

Article

The Influence of Digital Transformation on the Reconfigurability and Performance of Supply Chains: A Study of the Electronic, Machinery, and Home Appliance Manufacturing Industries in China

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Abstract: In this era of intense global competition, supply chains are facing challenges in coping with emerging market issues. Within diverse industries worldwide, supply chains are experiencing accelerated reconfiguration, with one of the most notable transformations being the digitalization of supply chain operations. But the literature lacks empirical evidence about how digital transformation effectively contributes to it. Thus, this paper delves into the implications of the supply chain digital transformation (SCDT) and supply chain reconfigurability (SCR) on its overall performance. Cross-sectional data from 379 respondents in the machinery, electronics, and home appliance manufacturing industries were collected through a closed questionnaire. Utilizing a hybrid approach involving the Partial Least Squares Structural Equation Model (PLS-SEM) and fuzzy-set Qualitative Comparative Analysis (fsQCA), this study employs a cross-validation of the conceptual model. Initially, the PLS-SEM is employed to unveil the direct impact of SCDT on supply chain performance (SCP), as well as the intermediary effect of SCR. Building on this foundation, the fsQCA method is further utilized to investigate the configuration paths that enable enterprises to achieve high SCP under the combined influence of SCR and SCDT. The research results affirm the significant influence of SCDT on SCP. Likewise, the findings highlight the crucial intermediary role of SCR between SCDT and SCP. Ultimately, three distinct configurations driving high supply chain performance are identified: technical, management, and flexible configurations, each playing a unique role.

Keywords: digital transformation; reconfigurability; supply chain performance; PLS-SEM; fsQCA



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1. Introduction

The rise of digital technologies, such as cloud computing, big data, and artificial intelligence, has brought about a significant transformation across various industries. Digital transformation has become the foremost approach for enhancing competitiveness, exerting a profound impact on the business models of traditional enterprises [1]. Notably, companies worldwide, particularly in industrialized nations, are actively championing digital transformation initiatives. For instance, leading the forefront is Germany's Bosch and Siemens with the pioneering "Industry 4.0" initiative, while Japan is propelling the "Connected Industry" forward. Concurrently, emerging companies are increasingly recognizing digital transformation as a pivotal domain for their business strategies [2].

Digitization represents a contemporary approach to a new integrated business system that goes beyond the solitary and regional use of technology [3]. It extends to the systematic deployment of technology throughout the supply chain. In the evolving digital supply chain ecosystem, digitization provides crucial capabilities to adapt to dynamic changes in the business environment [4]. The integration of big data and analytics technologies

serves as the necessary tool for integrating the reconfigured structure. Digital supply chains enable enterprises to promptly respond by anticipating and identifying planned nonconformance or execution issues [5]. All things considered, these descriptions indicate that a digital supply chain can rapidly realign itself in reaction to a transient process breakdown. Moreover, when faced with more persistent shifts in customer needs, the supply chain may require more extensive structural adjustments [6].

Businesses must prioritize enhancing the flexibility and agility of their supply chains to effectively respond to dynamic market demands and drive digital transformation in order to maintain a competitive edge in today's rapidly evolving business landscape [7]. "The ability to change or reestablish to adapt to the changing environment" is now a critical factor influencing supply chain performance and operational efficiency. Leading companies such as Flextronics, Nike, and Nokia exemplify the significance of possessing a seamlessly operating supply chain network that can swiftly adapt to shifting market demands, optimize costs, and sustain production performance through strategic supplier network establishment and continuous supply chain reconfiguration [8,9].

Digitalization brings forth substantial benefits not only to manufacturing processes but also to various supply chain functions including procurement and distribution [10]. The implementation of digital technologies enables enhanced visibility across the supply chain, facilitating efficient planning and network design [11]. The intelligent integration of human resources, technological advancements, and streamlined processes leads to improved visibility, flexibility, and adaptability within supply chain operations [12].

The potential transformative impact of supply chain digital transformation on business operations is increasingly recognized by firms for its ability to enhance overall performance outcomes [13]. Driven by the fluctuation of demand and rapid technological progress, the inherent unpredictability of contemporary markets makes it necessary to establish a strategic transformation of the adaptable and reconfigurable supply chains. Despite this recognition, there remains a gap in the literature concerning the role of supply chain reconfigurability in influencing the relationship between digital transformation and performance [3,14]. Drawing insights from the Research Report on Digital Transformation of Enterprises in China issued by Tsinghua University Global Industry Research Institute, this study selects 25 supply chain enterprises related to the electronic, machinery, and home appliance manufacturing industries that have been significantly affected by the external market environment in recent years. This study reveals a positive correlation between SCDT and enterprise performance, with SCR playing a crucial role in amplifying the positive impact of digital transformation on enterprise performance. Furthermore, employing the configuration theory, this study delves into identifying optimal digital transformation strategies tailored to different enterprise types to enhance SCP. The findings offer valuable guidance for businesses aiming to reposition their supply networks, integrate digital solutions across supply chain functions, enhance supply chain management practices, and ultimately achieve superior performance outcomes.

The present study focuses on three crucial issues, seeking to shed light on the role of digital transformation in enhancing supply chain reconfigurability and performance:

- a. What is the role of digital transformation in improving supply chain reconfigurability and supply chain performance?
- b. How does supply chain reconfigurability correlate digital transformation and supply chain performance?
- c. What are the antecedent combinations that lead to superior high supply chain performance?

There are eight sections in this paper. Section 1 presents the empirical background and underscores this study's significance. Section 2 is the Literature Review. Section 3 introduces the Hypotheses Development. Section 4 presents the Data Collection and Methodology. Section 5 presents the Reliability and Validity Analysis, Common Method Bias, and Test of Hypotheses. Section 6 presents the Results of qualitative comparative

analysis of fuzzy sets. Section 7 presents the Conclusions drawn from the research findings, and Section 8 is the Discussion.

2. Literature Review

2.1. Digital Transformation

According to the research conducted by the German National Institute of Science and Engineering, Industry 4.0 can be categorized into three stages of development: informatization, digitalization, and digital transformation [15]. The process of digitalization involves the integration of cutting-edge technologies such as the Internet of Things, artificial intelligence, and big data with real production processes [4]. On the other hand, digital transformation refers to the pursuit of real-time visibility, future predictability, and self-adaptability within enterprises [13].

In the existing literature, scholars have expressed various perspectives on digital transformation [2]. Gregory et al. developed an eight-building-block framework that highlights the process of digital transformation [16]. Büyüközkan and Göçer identified three dimensions of digital transformation in the supply chain: supply chain management, digital transformation, and technology implementation [17]. They define it as an intelligent optimization technology system that processes data and facilitates the interaction among organizations using digital hardware and software. Digital technology improves the efficiency of the supply chain through various means, improves the traceability of the supply chain through the decentralization of blockchain, improves the transparency of the supply chain through recording real-time transaction data [18], improves the overall flexibility of the supply chain [19], and using big data technology analysis and machine learning [20]. Some scholars also analyze digital transformation from the perspective of digital operation management and digital system operation [21,22]. At present, research on the digital transformation of the supply chain mainly explores process optimization and network optimization, with limited emphasis on overall flexibility and supply chain reconfiguration. This signifies a gap in the literature and an opportunity for further exploration.

Therefore, this study assumes that the digital transformation of the supply chain primarily revolves around the actions of key enterprises. As such, this evolution encompasses not only the digital transformation of individual enterprises but also the digital modernization of core enterprises and those located at each juncture of the supply chain. Initially, the digital metamorphosis of the supply chain can be delineated into two primary dimensions: intra-nodal digital transformation within the supply chain and inter-nodal digital transformation linking each node in the supply chain. Intra-nodal digital transformation involves the modernization of core enterprises and their suppliers, a process mainly orchestrated by the core enterprises. This is succeeded by the digital evolution within each enterprise in the supply chain, serving as the foundation for the overall digital evolution of the supply chain. Subsequently, enterprises establish digital connections among all supply chain nodes through digital technologies and management practices, leading to the comprehensive digital transformation of the supply chain.

2.2. Supply Chain Reconfigurability

In the realm of supply chain reconfiguration research, scholars have predominantly focused on two main areas: the classification of reconfigurability characteristics and the development of reconfiguration strategies. Kelepouris et al. conducted a study that outlined the key features of reconfigurable manufacturing systems and proposed methods for integrating them into supply network firms to improve the network's capacity for effective reconfiguration [23]. Dolgui et al. put forward a novel concept of reconfigurable SC, also known as the X-network [24]. Ma et al. defined a reconfigurable supply chain as one that is cost-effective, responsive, sustainable, and resilient [9]. Chandra et al. described a reconfigurable supply chain as a flexible system capable of altering its structure to meet changing customer demands while optimizing resource utilization [25]. Addressing both supply chain reconfiguration and supplier selection challenges, Osman et al. developed a

bilinear goal programming model alongside a modified Benders decomposition algorithm aimed at enhancing customer satisfaction through improved delivery schedules and quantities in the face of growing demands [26]. Dev et al. proposed an innovative approach that combines decision tree learning with agent-based simulation as data mining tools to identify adaptive supply chain reconfiguration options [27]. Other scholars analyzed the dynamic reconfiguration [28,29], flexibility [30], and timeliness [31] within supply chains.

The advent of digital technology has revolutionized the concept of reconfigurable supply chains by enabling the efficient gathering, transmission, storage, and sharing of process data. This enhanced data capability fosters improved collaboration and communication among supply chain entities both upstream and downstream, in line with evolving market strategies [6]. Such advancements are pivotal in enhancing responsiveness and flexibility to address dynamic shifts in market demands. The ability to navigate through an increasingly volatile market landscape stands as a critical challenge that modern enterprises must confront. Primarily fueled by demand fluctuations and rapid technological advancements, the inherent unpredictability of contemporary markets necessitates a strategic shift towards establishing adaptable and reconfigurable supply chains. This strategic endeavor aims to bolster the organization's capacity to promptly respond and adapt to market dynamics, thus mitigating risks effectively and ensuring operational efficiency [32].

2.3. Supply Chain Performance

Supply chain performance entails the comprehensive assessment of the operational efficiency of the supply chain as a whole, individual enterprises within the supply chain network, and the collaborative dynamics among these enterprises aligned with supply chain objectives [33]. Scholars have underscored the vital role of performance management within the context of supply chain operations [34–36].

Various research studies have explored avenues to enhance supply chain performance, including strategic realignment coupled with proactive feedback mechanisms [33], collaborative innovation [37,38], data sharing [39,40], supply chain integration [41,42], practical supply chain initiatives [40], and the leveraging of digital technologies such as information technology [43], big data analytics [44,45], and blockchain technology [46] to optimize supply chain reconfiguration [38].

Predominantly, the existing literature has focused on elucidating how digital transformation catalyzes supply chain reengineering or how SCR drives performance enhancements. This study diverges by examining the impact of digital transformation on both supply chain reconceptualization and SCP, as well as delineating the intermediary role of supply chain restructuring in mediating the relationship between digital transformation and SCP. Furthermore, drawing upon configuration theory, this research delves into the exploration of three distinct high-SCP allocation strategies tailored for the nuances of varying industries.

2.4. Configuration Theory

Configuration theory, which originated in the 1960s, has garnered increasing attention from scholars. Its introduction into the management field by Miller (1987) has led to its wide application in areas such as innovation management, organizational behavior, and human resource management [47]. In a series of classic studies, Miller (1996) provided a systematic and detailed discussion on configuration theory [48]. At its core, configuration theory considers all factors that impact an organization as a whole. It aims to explore the interaction mechanisms among these factors and their respective roles within the organization, surpassing the limitations of traditional research that often focuses solely on individual factors. Alexander used configuration theory for reference to study the influence of alliance initiative on performance [49]. Andreas explored how the configurations resulting from the interplay of last-mile logistics practices and firm characteristics are associated with firm performance in an omni-channel context [50]. Mark demonstrated that configuration theory can be used to explore emerging configurations in a changing environment [51].

This study aims to investigate the driving factors of SCP in the context of digital transformation and identify the configuration path that facilitates SCP enhancement. While numerous scholars have explored the influencing factors of SCDT on performance, most related research primarily analyzes the net effect relationship between each influencing factor and performance. This approach stems from the recognition that performance improvement is the outcome of multifaceted synergy. Therefore, this study examines the complex driving mechanism of supply chain digital transformation on performance and combines its driving factors to analyze their combined effect. By doing so, it seeks to provide valuable insights for performance improvement and address the existing research gap, which mainly investigates the antecedents of supply chain digital transformation from a singular perspective.

3. Hypotheses Development

In the era of digitalization, key technologies such as the Internet of Things (IoT), artificial intelligence (AI), blockchain, and supply chain intelligent platforms play pivotal roles in advancing the digital transformation journey. The IoT technology facilitates the comprehensive digitalization and enhancement of intelligence throughout the supply chain processes. On the other hand, AI technology extends the service boundaries of supply chains, enabling a broader spectrum of services. Blockchain technology ensures the safety and security of supply chain applications, while supply chain intelligent platforms expedite the development of supply chain ecosystems [52].

The rapid evolution of digital technologies has brought about a revolution in supply chain management practices in recent years [53]. The advent of digital solutions has addressed the need for more efficient transportation, real-time tracking, and traceability, enhancing the autonomy and reconfigurability of supply chains [54]. Data analysis has emerged as a crucial factor in decision-making processes related to procurement forecasting, route optimization, and inventory management [55]. Furthermore, intelligent operations have paved the way for customizable and reconfigurable supply chain systems. In the face of global crisis and evolving customer demand, the competition between supply chains has intensified significantly. Enterprises are compelled to reconfigure resources in response to shifting market conditions in order to manage risks stemming from supply chain disruptions [56]. Environmental changes often precipitate supply chain disruptions, imperiling organizational stability and disrupting production processes. Therefore, organizations typically need to reorganize their resources to establish coordination across internal and external networks in order to recover from the disruption [2].

The integration of cloud-based platforms, collaborative software, and communication tools enables seamless information sharing and coordination across the entire supply chain ecosystem. This improved collaboration fosters agile decision-making and allows for rapid reconfigurations in response to market changes or unforeseen events, such as natural disasters or supply disruptions [2]. Digital transformation has facilitated the collection and analysis of vast amounts of supply chain data. Advanced analytics techniques, such as machine learning and predictive modeling, can leverage these data to provide valuable insights into SCP and predict potential disruptions or opportunities. By harnessing these predictive insights, organizations can proactively reconfigure their supply chains to meet changing customer demands, mitigate risks, and optimize inventory levels. Furthermore, the adoption of digital transformation has empowered organizations to gain real-time visibility into their supply chain processes, from sourcing to delivery [19]. With the help of technologies like IoT devices, sensors, and RFID tags, companies can track inventory levels, monitor shipment progress, and collect data on various aspects of the supply chain. This enhanced visibility allows organizations to identify bottlenecks, optimize processes, and make informed decisions quickly, leading to improved reconfigurability [57]. The attainment of real-time visibility, data-driven decision-making, enhanced collaboration, automation, and agility has equipped organizations with the capability to swiftly and effectively reconfigure

their supply chains quickly and effectively [3]. Based on the aforementioned perspectives, we propose the following assumptions:

Hypothesis 1. *The impact of supply chain digital transformation on the reconfigurability of the supply chain is expected to be positive.*

The digitization of supply chains holds the potential to significantly enhance the operational efficiency of enterprises by improving the quality and availability of information [58]. From the perspective of data quantity, the embedding of the IoT technology has unearthed a wealth of previously untapped data throughout the supply chain, enriched the information pool accessible for enterprise decision-making, and thus improved the efficiency of supply chain resource allocation [59]. In terms of data quality, the incorruptible nature of blockchain technology and the decentralized validation method present a viable solution to ensuring the credibility of information within the chain, thereby enhancing the precision of enterprise decision-making processes [60]. From the perspective of automation, the adoption of supply chain automation reduces dependence on intermediary involvement in decision-making. For example, smart contract technology can automatically promote the ownership transfer and streamline payment processes in the supply chain, thereby boosting operational efficiency [61]. Furthermore, in the realm of intelligence, taking the food supply chain as an example, the smart packaging system embedded with the Internet of Things technology can automatically monitor the food state and respond immediately through independent decision-making (such as absorbing chemical derivatives of food). This enables the swift mitigation of unexpected food safety issues as they arise [62]. From the visual point of view, within the virtual network of IoT-based supply chains, enterprises can swiftly capture demand signals from each node, empowering expedited decision-making processes to be undertaken promptly in response [63]. Drawing from these viewpoints, we put forward the following assumption:

Hypothesis 2. *The impact of supply chain digital transformation on the performance of the supply chain is expected to be positive.*

To thrive and stay competitive in today's dynamic business landscape, companies must continually adapt their supply chains to meet evolving market demands. The establishment of an adaptive supply chain is crucial for business success. In evaluating a company that adopts an adaptive supply chain strategy, reconfigurability stands out as a key performance indicator [9].

Scholars proved that reconfigurability has an important influence on performance [56,64]. A highly reconfigurable supply chain is well positioned to respond quickly and effectively to market fluctuations, such as shifts in customer demands, emerging trends, or competitive pressures [9]. This capability enables organizations to adjust their production, distribution, and sourcing strategies promptly, ensuring that they can meet changing customer requirements and capitalize on new opportunities. Such responsiveness contributes to improved customer satisfaction, increased sales, and enhanced overall SCP. Through reconfigurability, organizations can optimize their resources, including inventory, production capacity, and transportation [24]. By dynamically adjusting these resources based on demand fluctuations, organizations can minimize excess inventory, reduce carrying costs, and improve operational efficiency. This optimization of resources leads to cost savings, increased productivity, and improved overall SCP.

Many researchers or managers choose to redesign or redistribute factories, warehouses, and production capacity to enhance performance. In the study of supply chain reconfiguration, the ability to redesign and redistribute is vital, as it can reduce supply chain risks and improve performance outcomes [23]. Companies need to reconfigure their resources to cope with supply chain interruption, and reconfiguration serves as a crucial mechanism for managing interruptions and establishing resilient supply chains. In instances where the

supply chain faces disruptions such as earthquakes and epidemics, the ability to reconfigure and utilize resources becomes the key factor to recover from such disruptions.

Recent studies have categorized measurement indicators for supply chain reconfigurability into six key areas: modularity, integrity, convertibility, diagnosability, scalability, and customization [9,65]. These indicators assist decision makers in assessing their supply chain's capability to address events that might impact its performance.

SCP represents a significant aspect of supply chain management, which plays a vital role in supply chain operation and management. It is crucial to gauge the extent to which supply chain objectives are achieved and to offer decision-making support to businesses. A reconfigurable supply chain enables organizations to be responsive, adaptable, and agile in the face of market changes and disruptions. It leads to optimized resource utilization, improved collaboration, innovation, and customer satisfaction, ultimately resulting in superior SCP. Building upon this, our suggestion is as follows:

Hypothesis 3. *The impact of supply chain reconfigurability on the performance of the supply chain is expected to be positive.*

In order to ensure the continuous improvement in SCP in the changing market environment, enterprises have embraced digital technologies such as cloud computing, Internet of Things, and big data to make the supply chain reconfigurable [64]. By introducing collaborative platforms, a reconfigurable supply chain is designed. The rapid and effective reconfiguration of the supply chain not only provides a competitive advantage for the company itself but also guarantees that node enterprises can effectively cope with the shortage of materials.

A reconfigurable supply chain is a flexible chain that can optimize resources without compromising operational efficiency while responding to changing customer needs and operating environments [66]. Previous studies have explored reconfiguration in establishing logistics chains and networks capable of adapting to changes [67]. The reconfiguration of supply chains primarily encompasses the production system, information system, and business processes. In fact, business processes play a vital role in ensuring the establishment of reconfigurable chains [68].

To establish a more flexible and agile system for resource reconfiguration, companies must modify physical, organizational, and information technology characteristics, thereby extending the system's life cycle [55]. Some scholars view reconfigurability as a central element for establishing a digital, resilient, sustainable, and efficient supply chain. They illustrate the interconnectedness of these requirements within a framework known as the X-network [24]. By leveraging digital technologies and data-driven approaches, organizations can enhance their supply chain's flexibility, adaptability, and responsiveness to changing market conditions.

Digital transformation empowers organizations to transition from traditional, forecast-driven supply chains to more agile and demand-driven models [13]. By integrating customer data, market trends, and real-time demand signals, companies can dynamically adjust their supply chain configurations to meet evolving customer expectations. This shift towards agility and responsiveness allows organizations to reconfigure their supply chains rapidly and efficiently to address new product launches, seasonal fluctuations, or unexpected changes in demand. Based on this reasoning, we propose the following:

Hypothesis 4. *Supply chain reconfigurability as a mediator.*

The conceptual framework is presented in Figure 1.

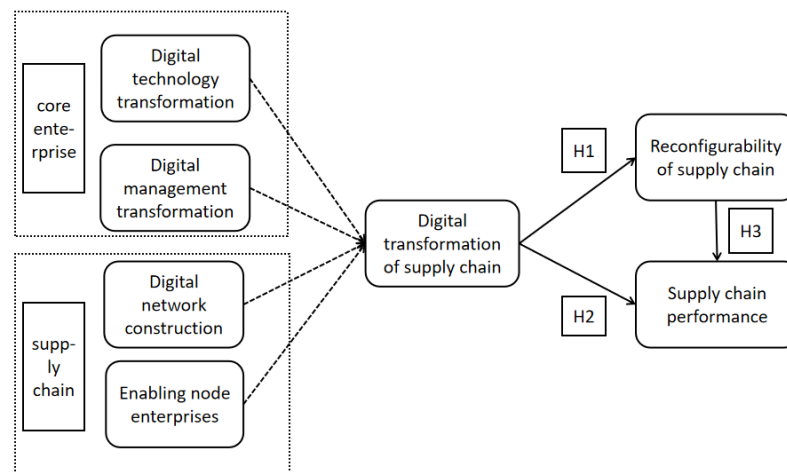


Figure 1. Research model.

4. Data Collection and Methodology

4.1. Data Collection

There are several reasons for the selection of data. Firstly, the manufacturing industry is a crucial component of the real economy, and the Chinese Municipal Government has emphasized the need to expedite the digital development of the real economy, particularly in the manufacturing industry. This includes upgrading data elements to the same status as traditional economic elements such as land, labor, and capital. Secondly, the digital economy in China has witnessed an annual growth rate of 11.24%, emerging as a significant driver of economic growth [69]. Lastly, Chinese enterprises have shown great enthusiasm for digital transformation and are actively seeking ways to bring it into supply chain practices [70]. To ensure the credibility and relevance of the data, this study selected 25 supply chain enterprises from the electronic, machinery, and household appliance manufacturing industries. These industries have experienced noticeable impacts from the external market environment in recent years. The selection of enterprises was based on data from the Research Report on Digital Transformation of China Enterprises, published by the Tsinghua University Global Industry Research Institute. A closed questionnaire survey was conducted among employees within these enterprises, with a focus on technology adoption and digital transformation. Preliminary screening was carried out to filter the sample enterprises, considering factors such as enterprise sizes, properties, and ages in order to ensure sample diversity. Enterprises with incomplete information were excluded to maintain the effectiveness of questionnaire distribution and recovery. Initially, a total of 490 responses were collected from respondents of listed manufacturing, retail, and catering enterprises in China. Rigorous data quality control measures were then implemented, resulting in a final sample size of 379 for the questionnaire survey. The majority of these employees are located in Beijing, Tianjin, and Shijiazhuang. The questionnaire can be found in the attached Appendix A.

4.2. Data Cleaning

The formal questionnaire survey commenced in June 2023, with questionnaire collection concluding in September 2023. An electronic questionnaire was developed using the Questionnaires system and distributed online. Two primary channels were utilized for questionnaire distribution: (1) dissemination through alumni and other related resources and (2) distribution via the resources and contacts of the intern's respective company. A total of 586 questionnaires were distributed, from which 33 respondents completed the questionnaire at random. Missing information was addressed by filling in identical responses, resulting in 379 valid questionnaires. The survey achieved a recovery rate of 64.7%.

4.3. Analytical Methods

In this research, the investigation of established correlations was conducted following the application of the Partial Least Squares Structural Equation Modeling (PLS-SEM) analytical method. PLS-SEM was chosen due to its capability to forecast complex models and evaluate complex relationships by circumventing issues related to viable solutions and additional component indeterminacy. This methodology is highly favored in research for its effectiveness in handling such complexities [69]. The estimation of our model was performed in a two-stage approach: the initial stage involved the inspection of the measurement model to identify reliability and validity statistics, while the subsequent stage focused on analyzing the structural model to confirm the proposed hypotheses [71]. Thus, using SmartPLS 3.0 software, both the measurement and structural models underwent rigorous testing, with parameters estimated through the bootstrap procedure [14]. The detailed profiles of the respondents are presented in Table 1, showcasing a comprehensive overview of the participant demographics. The dataset comprised a total of 379 respondents, among which 60.9% possessed an undergraduate degree, while 12.2% held a master's degree or higher qualification. Regarding the respondents' supply chain experience, 6.9% had amassed over fifteen years of expertise, 34.6% had less than three years of experience, 27.7% had a range of three to eight years of experience, and 30.8% reported experience spanning eight to fifteen years. The distribution of enterprise sizes among the respondents was as follows: 7% were classified as large-sized enterprises, 49% as medium-sized, and 44% as small-sized enterprises. When examining the industry types represented in the respondent pool, home appliance manufacturing enterprises accounted for 32%, machinery manufacturing enterprises for 47%, and electronics manufacturing enterprises for 21%. Table 1 also shows the distribution of specific roles within the respondents, with 5.5% identified as Supply Chain Specialists, 4.7% as Supply Chain Managers, 17.6% as R&D Specialists/Engineers, 21.3% as Manufacturing Engineers, and 25.0% as Logistics Planning Staff. Our questionnaire was mainly aimed at small- and medium-sized enterprises in the above three industries. Most of the participants have worked in this industry for a long time and accumulated some experience. Only a few people do not participate in supply chain operation, and the data quality is relatively high.

Table 1. The profile of respondents.

Characteristics	Types	Frequency	Percentage (%)
Job position	Supply Chain Specialist	21	5.5
	Supply Chain Manager	18	4.7
	R&D Specialist/Engineer	67	17.6
	Manufacturing Engineer	81	21.3
	Logistics Planning Staff	95	25.0
	Other	97	25.6
	Total	379	100
Firm size	0~500	168	44
	500~1000	186	49
	1000~3000	25	7
	Total	379	100
Experience (years)	0~3	131	34.6
	3~8	105	27.7
	8~15	117	30.8
	15~35	26	6.9
	Total	379	100
Education	Specialized college	102	26.9
	Bachelor's degree	231	60.9
	Master's degree	46	12.2
	Total	379	100

5. PLS-SEM Analysis

5.1. Reliability and Validity Analysis

The reliability index is a commonly used statistical index, which can be used to test whether the random error of a sample is the same as the total error [72]. In practice, the reliability index is often used as the statistical quality index of samples to evaluate their reliability. Cronbach's α and combination reliability (CR) are generally used for evaluation [73].

Cronbach's α values of all variables in this study are greater than 0.7; the parameters are as follows: the $\bar{r}$ is average nonredundant indicator correlation coefficient, and K represents the construct's number of indicators, which is defined as Formula (1):

$$\text{Cronbach's } \alpha = \frac{K \cdot \bar{r}}{1 + (K - 1) \cdot \bar{r}} \quad (1)$$

The CRs are greater than 0.7 [74], which can prove that the internal consistency of the data is good and the combined reliability is high. In Formula (2), l_k symbolizes the standardized outer loading of the indicator variable k of a specific construct measured with K indicators, $\text{var}(ek)$ denotes the variance of the measurement error, which is defined as $1 - l_k^2$, and ek is the measurement error of indicator variable k .

$$CR = \frac{\left(\sum_{k=1}^K l_k\right)^2}{\left(\sum_{k=1}^K l_k\right)^2 + \sum_{k=1}^K \text{var}(ek)} \quad (2)$$

Validity is generally used to indicate whether the measured content is consistent and appropriate with the content to be measured [75], and this is one of the key signs to determine whether data are valid or not. In Table 2, the factor loading values (FL) are higher than 0.6, significant at the 0.01 level [72]. The average variance extracted (AVE) is more than 0.5 in Table 3, which is calculated as Formula (3). The square root of the AVE is greater than the correlation coefficient between variables, which shows that the scale used in this study has good discrimination validity [73]. Furthermore, Fornell and Larcker testing and the heterotrait–monotrait ratio values (HTMT) are lower than 0.85, which meets the threshold standard [72]. The results are presented in Table 4.

$$AVE = \frac{\left(\sum_{k=1}^K l_k^2\right)}{K} \quad (3)$$

Table 2. Fornell–Larcker criteria.

	DTT	SCR	DNC	DMT	ENE	SCP
DTT	0.905					
SCR	0.375	0.897				
DNC	0.299	0.413	0.811			
DMT	0.316	0.244	0.307	0.928		
ENE	0.191	0.309	0.044	0.257	0.822	
SCP	0.288	0.455	0.397	0.173	0.404	0.732

Table 3. Validity and reliability of the constructs.

Construct	Items	FL	CB	Rho-A	CR	AVE
Core Enterprise Digital Technology Transformation	DTT-1	0.844 ***	0.791	0.757	0.830	0.718
	DTT-2	0.748 ***				
	DTT-3	0.840 ***				
Core Enterprise Digital Management Transformation	DMT-1	0.829 ***	0.826	0.928	0.821	0.692
	DMT-2	0.822 ***				
	DMT-3	0.855 ***				
	DMT-4	0.853 ***				
Supply Chain Digital Network Construction	DNC-1	0.932 ***	0.813	0.913	0.944	0.811
	DNC-2	0.882 ***				

Table 3. *Cont.*

Construct	Items	FL	CB	Rho-A	CR	AVE
Enabling Node Enterprises	ENE-1	0.943 ***	0.776	0.921	0.936	0.766
	ENE-2	0.939 ***				
Supply Chain Performance	SCP-1	0.848 ***	0.911	0.799	0.855	0.829
	SCP-2	0.800 ***				
	SCP-3	0.829 ***				
Reconfigurability of Supply Chain	SCR-1	0.891 ***	0.957	0.942	0.841	0.708
	SCR-2	0.864 ***				
	SCR-3	0.863 ***				

*** <0.001; rho_A were used to assess the reliability and validity of constructs and items.

Table 4. Hetrotrait–monotrait ratio (HTMT).

	DTT	SCR	DNC	DMT	ENE	SCP
DTT						
SCR	0.389					
DNC	0.241	0.126				
DMT	0.373	0.273	0.186			
ENE	0.198	0.097	0.289	0.271		
SCP	0.296	0.352	0.188	0.361	0.289	

5.2. Nonresponse Bias and Common Method Bias

In survey-based research, the evaluation of nonresponse bias and common method bias holds significant importance. To assess the potential nonresponse bias, our study built upon Armstrong and Overton's notion of uniformity between nonrespondents and late respondents [74]. The tests showed no significant divergence between early and late respondents, which demonstrates the nonexistence of nonresponse bias.

To mitigate the influence of common method bias on the conclusion of this study, proactive measures and retrospective testing were employed. For preemptive actions, this study's objectives were explicitly outlined in the initial section of the official survey questionnaire to prevent any misinterpretation of the measurement themes. Furthermore, a business security confidentiality agreement was agreed upon by the survey team and the participating enterprises, allaying respondents' apprehensions [76]. Employing a post hoc validation approach, this study utilized the Harman single-factor test to detect common method deviations within the dataset. The methodology hinges on the principle that in factor analysis, a dominant common factor or excessive variance explained by a single factor indicates a notable common method bias. Generally, when the unrotated variance explained by the primary factor falls below 40%, it suggests the absence of significant common method biases. In light of this criterion, the unrotated principal component analysis in our study reveals that the first factor only explains 25.6% of the variance, well below the 40% threshold, signifying the absence of pronounced common method deviations in the collected data.

5.3. Test of Hypotheses

This study employed partial least squares path modeling to evaluate its hypotheses [77]. Table 5 and Figure 2 display the structural model's outcomes derived from the PLS-SEM study.

Table 5. Hypothesis testing.

Hypotheses	β	<i>t</i> Value	<i>p</i> Value	Results
H1 DT→SCP	0.276	2.732	0.000	Accepted
H2 DT→SCR	0.505	7.925	0.000	Accepted
H3 SCR→SCP	0.329	3.361	0.000	Accepted

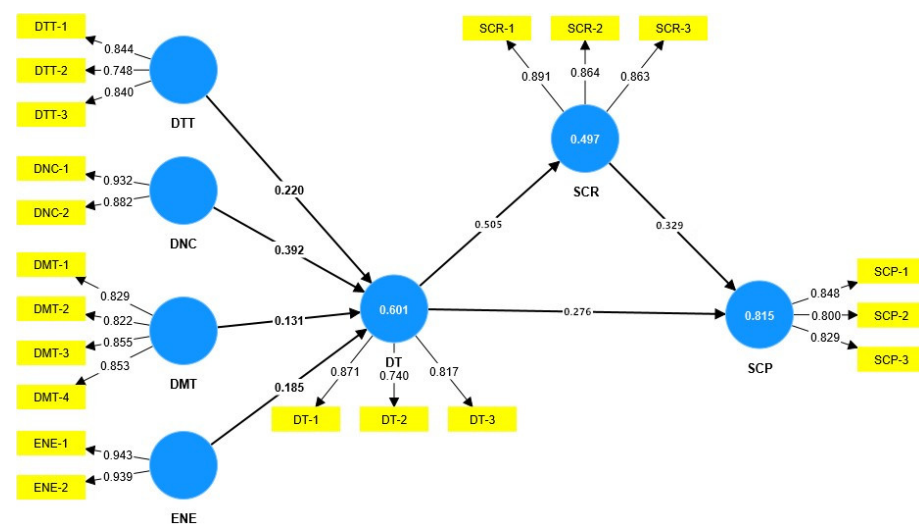


Figure 2. Structural model.

Based on the outcomes of the hypothesis test, every hypothesis is validated. The results shows that DT and SCP have a positive correlation ($\beta = 0.276$, $p = 0.001$); DT explains 27.6% of SCP ($R^2 = 0.276$), so hypothesis H1 is accepted (DT→SCP). DT is positively linked with SCR ($\beta = 0.505$, $p = 0.000$), so H2 is accepted. Similarly, SCR is significantly associated with SCP ($\beta = 0.329$, $p = 0.001$); thus, H3 is accepted (SCR→SCP) [73].

Furthermore, it is observed that SCR mediates the relationship between SCDT and SCP, suggesting that SCR should be implemented to enhance SCP ($\beta = 0.431$, t -statistics = 4.367, $p \leq 0.05$), as shown in the results presented in Table 6. In addition, Table 5 shows that the coefficient of H1 is not only significant but also less important than other coefficients. This reflects the intermediary role of SCR. According to Lowry and Gaskin [78], there are three mediation effects: no mediation, partial mediation, and complete mediation. Part of the mediation reflects the significance of direct and indirect effects between variables. This strengthens the intermediary role of SCR in the relationship between SCDT and SCP.

Table 6. Mediating effects.

Relationship	β	t Value	p Value	Results
SCDT→SCR→SCP	0.431	4.367	0.000	Partial mediation

6. fsQCA Test

The methodology employed in this study leverages fuzzy-set Qualitative Comparative Analysis (fsQCA) to evaluate the relationships among variables under investigation. Initially, fsQCA constructs a truth table utilizing fuzzy sets, subsequently determining the attribute sets of each causal condition based on the truth table's calculations. The subsequent step involves streamlining the amalgamation of these causal characteristics through Boolean algebra [79]. This analytical approach often delves into the impact of predefined causal conditions by analyzing the logical operations between combination relationships and variables. Given the continuous nature of variable attributes across various scenarios in practical applications, the binary variable system typically utilized in conventional QCA approaches may not be optimal for this study. In particular, conventional QCA (csQCA) mandates the utilization of binary variables for both antecedent and outcome variables, rendering fsQCA more appropriate for our purposes due to its flexibility in handling continuous variables. Since all variables in our research are continuous, the fsQCA methodology aligns seamlessly with our analytical requirements, providing a robust framework for our analysis [80].

Traditional statistical analysis methods, such as regression analysis, focus on examining the isolated effect of a single independent variable on the dependent variable. While this approach provides valuable insights, it is limited in capturing the intricacies of complex causal relationships. For instance, methods like structural equation modeling assume a unidirectional linear relationship between causal variables, treating each variable as independent with causal symmetry [81,82]. Such methodologies primarily assess the marginal net effects between variables, overlooking the intricate interplay among antecedent factors. In reality, the dynamics influencing supply chain flexibility are multifaceted and not solely attributable to individual factors but rather a combination of various elements. Hence, analyzing net effects alone proves insufficient in elucidating this complex phenomenon. Consequently, a comprehensive exploration of antecedent variables necessitates investigating their combined effects to offer a more nuanced understanding of the factors influencing supply chain flexibility [83]. Contrastingly, the QCA method builds upon an adequacy analysis foundation. It introduces a systemic perspective, conceptualizing outcomes as configurations formed by diverse combinations of conditional elements. By synthesizing the strengths of quantitative inquiry and case study methods, QCA enhances and complements results derived from statistical approaches like structural equation modeling. This method is particularly adept at exploring the intricate causal complexities inherent in concurrent multiple causality, causal asymmetry, and multi-scheme equivalence, making it ideally suited for delving into the complexity of factors impacting supply chain flexibility.

6.1. Variable Selection and Calibration

Before fsQCA standardization analysis, the original case data need to be calibrated to a set membership score. fsQCA allows case data to be calibrated to a set membership score ranging from 0.0 to 1.0 [74,84]. Firstly, three anchor points are set for structural calibration, namely, the thresholds for complete membership, intersection, and total non-membership. Subsequently, the fsQCA calibration formula is employed for calibration. In this study, the quantile method was selected by referring to the previous research methods. The anchor points for the thresholds of full membership, intersection, and full non-membership were determined as the 95%, 50%, and 5% quantiles, respectively, for the five antecedents and one result variable [85]. To minimize missing cases, this study revised the anchor point value within the range of 0.001 according to the actual repetition of variables so as to ensure the inclusion of as many valid case data points as possible. For example, in the actual data calibration process, the 5% quantile value employed for digital technology was adjusted from 1.000 to 1.001 [86]. As the sample data are derived from questionnaires, it was necessary to calculate the average value of all the items under each variable to represent the value of the variable. Subsequently, the variable calculation command in fsQCA 3.0 was executed for calibration based on the variable anchor point.

6.2. Necessity Conditions Analysis

Before the QCA standard analysis, it is essential to perform a univariate necessity analysis to ascertain the factors that are indispensable in driving the outcomes. The necessity test focuses on assessing the relationship between the set of outcomes and a single set of conditions. A condition can be deemed necessary if the consistency level approaches 0.9 and demonstrates adequate coverage. Once these criteria are met, it signifies that the condition significantly influences the results [87].

According to the results in Table 7, it can be concluded that in the univariate necessity analysis of high supply performance, the coincidence rate of the results of DTT, DMT, and DNC all exceeds 0.9. Therefore, it can be judged that DTT, DMT, and DNC are the necessary conditions for high supply chain performance. This assertion is further confirmed by PLS-SEM empirical analysis, which demonstrates that the path coefficients are both substantial and statistically significant. However, it is worth noting that the consistency rates of the single variable necessity analysis for ENE and SCR are 0.873 and 0.725, respectively, falling below the threshold value of 0.9. This suggests that these variables alone are inca-

pable of forming a necessary condition for high SCP, indicating relatively weak explanatory power for the outcome variables.

Table 7. Necessity conditions.

Antecedent Conditions	SCP	
	Consistency	Coverage
DTT	0.926	0.893
~DTT	0.528	0.886
DNC	0.919	0.921
~DNC	0.531	0.836
DMT	0.928	0.891
~DMT	0.469	0.915
ENE	0.873	0.792
~ENE	0.569	0.906
SCR	0.725	0.661
~SCR	0.693	0.708

Configuration analysis aims to study the adequacy of different configurations composed of multiple antecedents for producing the desired outcomes. Through the lens of set causal logic, this paper discusses whether the configuration set, composed of multiple antecedents, is a subset of the result variable set. Each configuration represents different conditions that lead to the same result. For this study, a consistency threshold of 0.8, PRI value of 0.7, and frequency threshold of 10 were employed. These settings generate three output solutions: reduced solution, intermediate solution, and complex solution. Usually, the configuration analysis is used for conducting configuration analysis. According to the QCA results proposed by Ragin et al. [75], Table 8 is drawn, revealing that there is no singular configuration that ensures high performance in the supply chain.

Table 8. Results—intermediate solution.

Conditions	SCP		
	M1	M2	M3
DTT	◎	⊗	●
DMT	●	◎	●
DNC	●	●	
ENE	⊗	●	⊗
SCR			◎
Consistency	0.973	0.969	0.958
Raw coverage	0.741	0.637	0.692
Unique coverage	0.071	0.089	0.013
Solution consistency		0.928	
Solution coverage		0.891	

Note(s): ● black dot indicate peripheral conditions, ◎ large circles indicate core conditions, blank space indicates “do not care”, and ⊗ indicates absent.

Technical: The antecedent configuration of M1 entails “digital technology-digital management-digital network”, with digital technology serving as the core condition, while digital management and digital network construction act as the auxiliary conditions. The consistency of this configuration is recorded at 0.973, original coverage at 0.741, and the unique coverage at 0.071. Predominantly seen in industries such as the science and technology promotion and application service industry and electronic equipment manufacturing, this configuration elucidates the operational dynamics of said industries. Leveraging insights from product life cycle research and development data alongside meticulous process management, organizations can amplify part reuse rates, enhance research and development efficiency, and streamline physical experiments by shifting towards

simulation-driven design paradigms. This strategic shift not only curtails research and development costs but also fosters collaborative research across geographically dispersed teams. Furthermore, pioneering enterprises have spearheaded the integration of blockchain technology into supply chain management processes to address carbon emissions concerns. By harnessing the potential of blockchain technology, these enterprises bolster their supply chain resilience, consequently mitigating carbon emissions and fostering environmentally sustainable practices.

Management: The antecedent configuration of M2 is defined as “digital management-digital network-empowerment node enterprise” in the field of management. Here, digital management stands as the core condition, while digital technology and the establishment of a digital network serve as supplementary factors. The consistency of this configuration is 0.969, enabling an explanation of approximately 63.7% of cases, with 0.89% of cases uniquely clarified through this configuration path. Typical cases of this configuration include home appliance manufacturing and mechanical equipment manufacturing. Midea exemplifies this model with its provision of a complete smart home solution, empowering the monitoring of diverse smart home devices. Similarly, the Japanese machine tool company MAKINO has implemented an intelligent production system hinged on industrial Internet technologies. This has led to enhanced transparency and traceability in the production process, coupled with the optimization of workflow and equipment functionality through data-driven insights, thereby bolstering product quality and performance. The FMS system instituted by MAKINO now comprehensively enables digital oversight across planning, logistics coordination, product administration, and processing program structuring.

Flexible: The antecedent configuration of M3 is characterized by the sequence “Reconfigurability-Digital Technology-Digital Management”, with reconfigurability acting as the central element, while digital technology and digital management serve as supplementary factors. This arrangement demonstrates a high degree of coherence, registering a consistency score of 0.958. This setup accounts for approximately 69.2% of observed cases, with a distinct subset (0.13%) exclusively explicable through this specific pathway. Illustrative instances showcasing this configuration include Sinosteel, Caesar Air Compressor Company, and Michelin Company. Sinosteel originated from the amalgamation of various trading and manufacturing entities previously under the jurisdiction of the Ministry of Metallurgy. Before 2004, the organization boasted a vast network of 76 secondary branches. Following subsequent restructuring and consolidation efforts, Sinosteel evolved into a fully-fledged supply chain service provider offering comprehensive support and system integration services tailored for iron and steel manufacturers. Kaiser Air Compressor Company, based in Germany, successfully transitioned from merely retailing air compressors to delivering air compression services enriched by the implementation of the information system. Moreover, SHANGPIN’s ability to discern and embrace the industry’s evolving trajectory via digital supply chain transformations enabled the strategic realignment and optimization of pertinent assets, thereby bolstering supply chain efficacy through astute reconfigurations.

7. Conclusions

In this paper, the PLS-SEM and fsQCA method were used to explore influencing factors and antecedent configuration of SCP in the digital age. The key findings and implications are summarized as follows.

Firstly, employing PLS-SEM, the research analyzed the proposed relationships. The results affirm a substantial and significant impact of digital transformation on SCP [55,60]. This study reveals that the implementation of digital transformation within the supply chain enhances operational efficiency and reduces costs by eliminating inefficiencies. Furthermore, SCR emerges as a crucial intermediary between SCDT and SCP, underscoring the need for reconfiguration to bolster SCP. Moreover, this research sheds light on the pivotal role of digital transformation in augmenting the adaptability and performance

of the supply chain. The integration of technologies such as big data, IoT, and cloud computing enables the analysis of existing data to aid decision-making during unforeseen events, ultimately empowering enterprises to overcome challenges [21,45]. Consequently, this study underscores the significance of digital supply chain transformation in fortifying supply chain reconfiguration.

Secondly, through further fsQCA, DTT, DMT, DNC, ENE, and SCR alone do not constitute essential conditions for SCP. For example, M1 lacks ENE, and high SCP can still be achieved by relying on DTT, DMT, and DNC. This diversity in digital transformation approaches across supply chain enterprises, whether technically or management-oriented, does not impede organizations from achieving high supply chain resilience through varied configurations.

Lastly, three distinct high-SCP-driven configurations emerged, categorized as technical, management, and flexible orientations. Industries associated with technology focus predominantly on science and technology promotion alongside electronic equipment manufacturing [87]. Embracing digital technologies such as intelligent manufacturing enables the replacement of manual operations with automated processes, thus driving cost efficiency, enhanced predictive capabilities, and streamlined supply chain management practices. Management-centric industries, including home appliance and mechanical equipment manufacturing sectors, leverage technologies like 5G and Internet of Things to bolster equipment connectivity, facilitate remote monitoring, and optimize supply chain operations. A transition towards “service + manufacturing” models sees investments in customer-centric services, production efficiency enhancements, and targeted promotions [88]. Meanwhile, flexible-related industries encompass steel, machinery, and equipment sectors, signifying diverse avenues for digital transformation and adaptability within various industrial contexts.

8. Discussion

8.1. Theoretical Implications

The emerging economies are developing towards a circular economy model and have experienced various interruptions [89–91]. Therefore, the proposed model in this study describes the transformation of digital technology, management, network construction, and reconfiguration in the context of emerging economies such as China. It addresses the existing research gap, as the study of SCDT has predominantly focused on developed economies in the Western world [1,16]. By constructing a model that explores the influence of SCDT on enterprise performance and supply chain reconfiguration, the theory of SCDT can be further supported and expanded. This will not only help to clarify the mixed research outcomes related to the impact of digital transformation on supply chain reconfiguration but also enhance the value of the existing literature.

Furthermore, numerous scholars have examined the factors influencing the performance of the digital transformation of the supply chain. Most of the related research has primarily concentrated on discussing the individual impact of each factor on performance, thereby disregarding the potential confounding effects of enterprise characteristics [14,33,37,55]. We argue that configuration theory provides a suitable lens to explain not only which parameters should be bundled but rather how they should be synergistically matched with certain contingent firm characteristics for leveraging. Configuration analysis with fsQCA is a method that is increasingly being applied in various fields [92]. This study considers SCDT as diverse in nature, using the configuration theory and employing fsQCA to study the path to improving the performance of supply chains under digital transformation, which overcomes the shortcomings of single factor. The model is divided into three different high-supply-chain-performance-driven configurations: technical, management, flexible. It expands the research scope and application scenarios of configuration theory.

8.2. Practical Implications

The conceptual framework presented in this study aims to provide supply chain managers with a deeper understanding of how digital transformation can enhance, as well as the key factors that influence SCP in the digital era. During the process of transformation, it may be necessary to rebuild the supply chain and redefine its parameters. Managers should reconstruct the supply chain appropriately while ensuring efficiency. Digital technology enables managers to evaluate the rapid response ability of the supply chain to emergencies, such as replacing a node in the supply chain, integrating new products and technologies, and responding quickly to the needs of downstream customers. Ultimately, the performance indicators are utilized to evaluate the supply chain's ability to adapt to this new structure.

A digital supply chain is a collaborative effort that seamlessly links suppliers to end customers through digital information systems in the process of supply chain management. It enhances data availability and furnishes upstream suppliers with a wealth of market intelligence. Data analysis also has emerged as a crucial factor in decision-making processes related to procurement forecasting and inventory management. Intelligent operations have made the customizable and reconfigurable supply chain systems possible [93,94]. Nevertheless, a dearth of existing research often hampers enterprises' comprehension of the digital supply chain, leading to challenges in navigating the transformation journey. This study reveals that the digital transformation of supply chains is an important means to improve the dynamic capability of supply chains and the key to the growth and success of enterprises, which provides theoretical reference for manufacturing enterprises to carry out digital transformation of supply chains. On one front, supply chain reconfiguration can be propelled through digital transformation initiatives, thereby ameliorating overall supply chain performance. Concurrently, leveraging the lens of the digital supply chain bolsters enterprises' competitive edge. By remodeling their primary supply chains, companies bolster transmission efficiency across all supply chain nodes, thus amplifying the catalytic impact of digital transformation on enterprise performance. Harnessing digitalization to craft products that cater to diverse customer needs can fortify the industry at large amidst the burgeoning era of digital economy [95,96].

This study examines the essence of the digital supply chain through a comprehensive analysis of relevant theories, documents, and empirical data. It argues that digital transformation in the supply chain encompasses more than the mere adoption of digital technologies. It involves the integration of both internal and external resources, as well as the identification and utilization of opportunities and capabilities to adapt to the digital environment. This paper also offers specific recommendations for the digital transformation of the supply chain based on different types of enterprises, namely those characterized by management focus, technological expertise, and flexibility. These suggestions hold significant theoretical implications for guiding the digital transformation of supply chains in the manufacturing sector of China.

8.3. Limitations and Future Research Directions

While this study presents valuable contributions to both theoretical understanding and practical applications, it is important to acknowledge several limitations that should be taken into account. Firstly, it is important to note that the sample used in this research is exclusive to the electronic, machinery, and home appliance manufacturing industries within China. To enhance the generalizability of the findings, future research endeavors should encompass diverse samples from various regions to validate the applicability of the conclusions across different stakeholders. Secondly, this study predominantly relies on survey methodology for data collection and analysis. For future investigations, it is advisable to explore alternative data collection methods such as case studies or longitudinal data integration in conjunction with surveys. By incorporating different data collection approaches, a more comprehensive and nuanced understanding of the research phenomenon can be achieved. Thirdly, this study approaches digital transformation in a generalized

manner, without specific delineation of the diverse digital tools and strategies that firms may employ with their suppliers and customers. Subsequent research should delve into the impact of specific and emerging digital transformation tools (e.g., big data analytics, blockchain technology) on supply chain dynamics. This focus on detailed exploration can provide deeper insights into the implications and ramifications of digital transformation on supply chain operations. Despite rigorous efforts to design robust questionnaires and implement stringent data collection protocols, there remains the possibility of response bias in non-anonymous questionnaires. To address this concern, future studies could explore the inclusion of multi-source and secondary data to corroborate the findings and ensure research robustness. By incorporating a diverse range of data sources, researchers can fortify the validity and reliability of their conclusions.

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Appendix A

Table A1. Questionnaire constructs.

Main Variables	Items	Statement	References
Core Enterprise Digital Technology Transformation	1	Core enterprises have applied technologies such as big data, cloud computing, blockchain and Internet of Things.	[20]
	2	The digital technology of core enterprises is more perfect than other enterprises in the supply chain.	
	3	Core enterprises have invested heavily in digital technology.	
Core Enterprise Digital Management Transformation	1	Core enterprises can analyze customer behavior in real time.	[16]
	2	Core enterprises have certain information exchange ability.	
	3	The introduction of blockchain technology improves the traceability of products and improves the communication efficiency between upstream and downstream of supply chain.	
	4	The production equipment related to the production process introduces the Internet of Things technology.	
Supply Chain Digital Network Construction	1	The upstream and downstream of the supply chain are closely linked through technologies such as the Internet of Things or blockchain.	[5]
	2	A perfect digital supply chain network has been formed.	

Table A1. Cont.

Main Variables	Items	Statement	References
Enabling Node Enterprises	1	Digitalization of core enterprises has a driving effect on enterprises at all nodes.	[52]
	2	Digital transformation of core enterprises has improved the performance of node enterprises.	
Supply Chain Performance	1	Operational Performance: Stable customer relationship.	[33,40]
	2	Financial Performance: The product has a large market share or a high sales growth rate.	
	3	Quality performance: Our product quality assurance.	
Reconfigurability of Supply Chain	1	We can successfully reconfigure supply chain resources to generate new productive assets.	[56,65]
	2	We can effectively integrate and combine existing resources to form a new combination.	
	3	We can deal with most emergencies by restructuring the supply chain.	

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