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RESEARCH ARTICLE

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# How do digital technologies improve supply chain resilience in the COVID-19 pandemic? Evidence from Chinese manufacturing firms



**Abstract** Digital technologies (DTs) can assist businesses in coping with supply chain (SC) disruptions caused by unpredictability, such as pandemics. However, the current knowledge of the relationship between DTs and supply chain resilience (SCR) is insufficient. This study draws on information processing theory to develop a serial mediation model to address this deficiency. We analyze a sample set consisting of 264 Chinese manufacturers. The empirical results reveal that digital supply chain platforms (DSCPs), as well as supply chain traceability (SCT) and supply chain agility (SCA), fully mediate the favorable association between DTs and SCR. Specifically, the four significant indirect paths indicated that firms can improve SCR only if they use DTs to directly or indirectly improve SCT and SCA (through DSCPs). Our study contributes to the literature on resilience by examining the possible mechanism of mediation through which DTs influence SCR. The findings also offer essential insights for firms to modify their digital strategies and thrive in a turbulent environment.

**Keywords** digital technologies, supply chain resilience, information processing theory, COVID-19, China

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## 1 Introduction

Global supply chains (SCs) face unprecedented risks of disruption and unpredictability in today’s turbulent economy that can destroy businesses (Sawik, 2022). For example, many firms have been affected by the frequent closures of borders and lockdown measures because of the COVID-19 pandemic, which threaten their survival and sustainability (Sarkis, 2020). According to a recent report, 94% of Fortune 1000 firms have faced interruptions caused by COVID-19 (Sherman, 2020). Such interruptions dramatically and immediately impact the structure of the SC as they emerge from temporary inaccessibility to certain facilities, suppliers, distribution centers, and transportation links, resulting in the loss of gain, service quality, and productive forces for businesses (Dolgui et al., 2020; Ivanov, 2020). Supply chain resilience (SCR) is the capacity to foresee and overcome SC disruptions (Pettit et al., 2010). Firms need to promote resilience so that SCs can adequately react to disruptions (Shekarian et al., 2020). However, several firms lack the capacities necessary to manage risk and disruption as a result of the scale and complexity of the current global SCs (Faruquee et al., 2021). Therefore, academia and the industry are interested in the improvement of SCR.

In turbulent times, the deployment of digital technologies (DTs) is now one of the top popular academic subjects. DTs mean the collection of several new technologies in the modern industry, including big data analytics, the Internet of Things (IoT), and cloud computing, which allow connection, telecommunications, and computerization (Li et al., 2020). Although many scholars and practitioners argued that DTs may assist businesses in coping with SC disruptions (Li et al., 2022c; 2022d), the current knowledge of the relationship between DTs and SCR is insufficient. Some researchers found that the SC systems’ design can use DTs to make them resilient to disruptions such that they can quickly and efficiently recover

(Hosseini et al., 2019; Ivanov and Dolgui, 2021). In other words, competence in DTs results in their use to increase SCR to unpredictable disturbances (Balakrishnan and Ramanathan, 2021). Accenture (2020) also reported that in the three months following the COVID-19 outbreak, over 63% of firms that used DTs had recovered to pre-crisis productivity levels. However, some scholars claimed that the excessive development and use of DTs may place further financial constraints on struggling businesses (Li et al., 2020). Moreover, DTs are often viewed as risky owing to the potentially unpredictable parties with which the firm interacts and the environments in which it operates (Xue, 2014). Fay (2020) showed that many small firms risked insolvency owing to the irrational use of DTs when COVID-19 broke out. Mimecast (2021) also reported that 7.9% of digitally enabled firms suffered disruptions to their businesses that led to financial losses and other problems as a result of inadequate cyber-preparedness and training throughout the pandemic.

Given the above disparate views in the literature and practice, merely examining the direct association between DTs and SCR is insufficient. Academics must also investigate the underlying mechanisms underpinning this association. Information processing theory (IPT) suggests that firms can fruitfully be seen as information processing systems. Moreover, achieving compatibility between needs and information processing capabilities can help the firm improve its performance (Premkumar et al., 2005). To maintain SC stability, firms have been urged to extend their use of DTs and interact with their SC partners (Büyüközkan and Göçer, 2018; Li et al., 2020). Digital supply chain platforms (DSCPs) are the integrations of DTs into the SC, allowing communication between SC parties (Bruque Cámara et al., 2015). Li et al. (2020) also showed that the effect of DTs on the SC needs to be determined by establishing DSCPs. DSCPs provide a conduit for sharing information amongst SC participants, an important external information source. Moreover, establishing DSCPs enables the capture and storage of vast quantities of datasets, including superior collaboration and integration (Büyüközkan and Göçer, 2018). Supply chain traceability (SCT) measures the degree of information that a business harbors on the locations and processes of its items from their origin to their destination (Wowak et al., 2016). Supply chain agility (SCA) is a firm's capacity to adapt to market shifts (Blome et al., 2013). Tushman and Nadler (1978) used IPT to enhance information processing capabilities in conjunction with external information on the SC to facilitate information traceability, which can help firms respond rapidly to disturbances to restore regular operation. Hence, to better understand how DTs influence SCR, our major research question here is as follows: Do DSCPs, SCT, and SCA mediate the relationship between DTs and SCR?

As a representative black swan occurrence, which has now triggered SC disruptions, the COVID-19 epidemic has caused product delivery delays and product shortages (Tietze et al., 2022). China is a major developing country that has fared better in dealing with such disruptions than most other countries (Ye et al., 2022). Thus, we survey 264 Chinese firms in this study. The contribution of our findings to the literature on resilience is twofold. First, prior studies primarily focused on the role of certain DTs, such as cloud computing (Subramanian and Abdulrahman, 2017), in developing resilience. However, different DTs have their own advantages and disadvantages. Thus, firms seldom employ a onefold type of technology in their everyday operations and prefer a combination of DTs (Li, 2022). Unlike previous research, we examine DT use from a holistic perspective to enhance the present knowledge of SCR determinants. Second, some researchers have advocated integrating DTs into SCs (Li et al., 2022d). However, little research has examined how DTs affect SCR through important mediators associated with the SC. Utilizing IPT, the present study illustrates that DSCPs, SCT, and SCA fully mediate the relationship between DTs and SCR, thereby enhancing the understanding of the mechanism underlying the DTs–resilience association. In terms of management, our research provides managers with practical guidelines on how to use DTs to recover from disruptions by cooperating with business participants, which is crucial in light of SC management practices in times of interruptions in the global SC.

## 2 Theory and hypotheses

### 2.1 IPT

In IPT, the firm is an accessible socio–economic system for processing information that accommodates indeterminacy, where indeterminacy is defined as the distance between the quantities of information needed to accomplish a job at hand and the quantities of information at hand (Galbraith, 1974). Specifically, a firm can face internal or external indeterminacy (Wong et al., 2020). For instance, unexpected competition, changing client needs, and complicated inter-organizational relationships all are internal. External indeterminacy, such as the COVID-19 epidemic, is essentially unmanageable for a firm. The resilience in IPT functions as a stabilizing mechanism when disruptions occur (Wong et al., 2020). Accordingly, firms should improve their capabilities of SCR to address the growing demand for information processing in light of the growing indeterminacy or ambiguity (El Baz and Ruel, 2021).

In recent years, the expansion of DTs provides an excellent chance to experimentally test IPT in a novel context. According to some academics, DTs are critical to a firm's ability to digest information. Premkumar et al.

(2005) claimed that DT support facilitates access to information processing skills, and Melville and Ramirez (2008) emphasized the need to enhance information processing skills via investment in DT-enabled process optimization. Fairbank et al. (2006) claimed that DTs can be deployed inside organizations through information processing design to improve organizational stability. Li et al. (2020) regarded DTs as a part of the firm's internal information structure that reflects its information processing capabilities. In addition, DSCPs provide a conduit for information sharing between participants, which is a substantial source of external data. A combination of expanded information processing and sharing external information for the SC promotes the firm's resilience. By using IPT, our research explores how DTs are employed in SC partnerships and their ensuing influence on SCR.

## 2.2 Hypothesis development

Academics and industry alike have characterized SC operations as information-intensive processes, with DTs serving as the primary medium for information sharing throughout the SC during the COVID-19 pandemic (Cegielski et al., 2012; Li et al., 2022b; Ye et al., 2022). From the standpoint of IPT, DTs reflect the firm's information processing abilities to evaluate SC disruptions and make informed decisions. Through effective information processing, DTs assist in production planning and control choices to improve SC efficiency, lower costs, and increase profits (Yu et al., 2015; Nguyen et al., 2018; Joshi and Gupta, 2019). Therefore, DTs will likely enhance a firm's resilience by collecting and processing information to enable decisions on demand forecasting, product creation, and pricing optimization.

Firms can configure modernized systems to efficiently collect and process the information on SCs by integrating DTs, such as the IoT (Lee and Lee, 2015; Yang et al., 2017; Pan et al., 2021), cloud computing (Schniederjans and Hales, 2016), and big data analytics (Fosso Wamba et al., 2015). For example, every link in the SC may share data and interact with other links through the IoT (Ardolino et al., 2018; Frank et al., 2019). Cloud computing enables the real-time storage and analysis of data on the SC that can then be accessed as necessary (Bruque Cámara et al., 2015). Accordingly, the IoT and cloud computing may allow for the complete sharing, constant exchange, on-demand processing, and efficient deployment of the requisite information up and down the SC to boost organizational resilience. Furthermore, although vast volumes of data may be created, gathered, and integrated across the SC, big data analytics can assist businesses in identifying and extracting useful information to make scientific decisions in terms of SC disruptions (Gunasekaran et al., 2017). In short, greater information processing capabilities are critical for increasing production efficiency.

Market information is also crucial for a firm. Ignorance of consumer behavior and market dynamics can lead to instability in the SC (Angelidou et al., 2022). For example, Kodak ignored market information and produced several films that were eliminated from the market, ultimately leading to bankruptcy. Mastering consumer demand is also key to maintaining normalcy downstream in the SC. The relevant DTs enable the quick monitoring and transfer of preferential customer demand to the firm to maintain uptime. Consequently, DTs can contribute to improving the firm's resilience. We propose the following hypothesis:

**H1:** Digital technologies positively influence supply chain resilience.

The term "traceability" means the act of identifying and verifying the elements of an SC and the order in which events have occurred (Skilton and Robinson, 2009). SCT is the tracking of the complete channel of the SC, that is, identifying the origin and characteristics of a specific product and collecting the history of a product's movement through the SC (Bechini et al., 2008). Specifically, SCT comprises tracing the origin of the acquired items along the SC, tracing stability throughout the SC and process of production, and monitoring the trends of market demand. SCT cannot be achieved without DTs. By using modern radio-frequency identification (RFID) and Global Positioning System technologies, for instance, blockchain technology may help in the development of SCs with robust traceability (Centobelli et al., 2021). Hence, we propose the following:

**H2:** Digital technologies positively influence supply chain traceability.

SCA refers to a firm's capacity to swiftly adjust its SC strategy and operations in reaction to market fluctuations and consumer demand (Christopher, 2000). The adoption of DTs is generally acknowledged as a crucial means of achieving SCA (Aslam et al., 2020). For example, Zara's deployment of RFID technology across its SC has afforded the excellent firm SCA in the apparel industry, resulting in a high degree of product control (Inditex, 2020). Amazon employed big data analytics to estimate pre-shipped items to distribution hubs before the final client puts an order, making the firm's SCs more agile (Lee, 2017). In this view, DTs primarily enhance SCA by facilitating the gathering of real-time information and promoting the exchange of information. Hence, we suggest the following hypothesis:

**H3:** Digital technologies positively influence supply chain agility.

The DSCP has evolved from traditional information and communication technology (Wang and Pettit, 2016). Firms are investing more in DTs to enhance their capabilities of internal data handling and making decisions as the foundation for building DSCPs (Li et al., 2020). Specifically, a firm can adequately coordinate the exchange and transmission of information with external suppliers and customers only when it has sufficient internal information processing capabilities (Shou et al., 2017). Businesses extend DTs across the SC, from raw material supply to final product delivery, particularly in highly linked sectors, to ensure compatibility with upstream and downstream processes. Otherwise, it will be difficult for the firm to thrive in a highly competitive market. Consequently, we hypothesize that the use of DTs leads to the enhancement of DSCPs:

**H4:** Digital technologies positively influence digital supply chain platforms.

We also contend that DSCPs are the basis for developing a traceable and agile SC. One of the most critical parts of SCT and SCA is the accessibility of information to SC members (Kim and Chai, 2017). SCT requires the accurate transfer of information upstream and downstream (Omar et al., 2022). DSCPs (e.g., blockchain systems) may promote safe information transfer between geographically distributed partners to enhance global commerce in areas, such as logistics operations, procurement, monitoring and tracing shipments, and trade financing. Utilizing the IoT and blockchain technology, Tian (2018) proposed a DSCP that links all possible locations in a food SC and enables the collection, transport, storage, inspection, and exchange of information across stakeholders to enhance the traceability of the quality and safety of food.

SCA necessitates greater collaboration and reliability among SC participants to minimize the total cost of responsiveness and reaction time and thus satisfy fluctuating consumer demand (Aslam et al., 2020). Having access to a vast amount of precise and up-to-date information on the SC helps firms accurately assess the upstream supply and downstream demand. This case in turn enables them to coordinate the actions of members of the SC and quickly react to market fluctuations (Christopher, 2000). The DSCP strengthens the relationship between upstream and downstream processes (Li et al., 2020). Procter & Gamble, for instance, employed a digital platform to exchange worldwide real-time order inventory, shipping, and payment information with all the members of its SC to construct agile SCs (Manuel Maqueira et al., 2019). Therefore, we propose the followings:

**H5:** Digital supply chain platforms positively influence supply chain traceability.

**H6:** Digital supply chain platforms positively influence supply chain agility.

DSCPs are intrinsically linked with the process management of the digital SC (Büyüközkan and Göçer, 2018). They include a variety of information sources and a strong capability to process internal information (Shou et al., 2017). Owing to the information-intensive nature of SC operations, SCR is dependent on a sufficient amount of information to facilitate production and sales. Moreover, DSCPs can connect organizations and integrate systems to help share information within the SC (Li et al., 2020).

IPT views SC platforms as a medium for information sharing among SC partnerships, which is a crucial source of external data. DSCPs promote effective interaction and SC integration to provide demand-based access to external data (Frank et al., 2019). SCR is enhanced by combining expanded internal information handling and external information exchange on the SC. Thus, we offer the following hypothesis:

**H7:** Digital supply chain platforms positively influence supply chain resilience.

SCT does not rely on a single entity but rather on all SC participants (Cousins et al., 2019). Monitoring and tracing goods and activities decrease the informational disparity between participants, the risk of opportunistic actions by upstream participants, and the unpredictability of downstream markets (Wowak et al., 2016). Without SCT, firms receive incorrect signals that may hamper efforts to improve the firm's resilience. The adoption of DTs with traceability can revolutionize the SC by removing the defects and inefficiencies of conventional SCs, thereby preventing disruptions (Centobelli et al., 2021). Consequently, we propose the following hypothesis:

**H8:** Supply chain traceability positively influences supply chain resilience.

SCA is also correlated favorably with SCR (Lee and Rha, 2016). SCA can help businesses quickly and accurately react to changing conditions and unanticipated events, such as interruptions (Najafi Tavani et al., 2014). SCA is particularly crucial during disruptions because it enables information exchange and cooperation among SC participants (Scholten et al., 2020). Firms with greater agility can provide better leverage collaboration up and down the SC to detect and respond to environmental hazards. We therefore propose the following:

**H9:** Supply chain agility positively influences supply chain resilience.

Figure 1 shows a summary of the research framework for this study based on the above considerations.

## 3 Methods

### 3.1 Data collection

China is the worldwide leader in manufacturing and the greatest technical innovator among the world's developing countries. China's industrial output increased from 16.98 trillion yuan in 2012 to 31.4 trillion yuan in 2021, and the share of the global manufacturing sector rose from approximately 20% to 30% (The State Council Information Office of PRC, 2022). We thus focus on Chinese manufacturing firms (Li et al., 2022d). China was the first country reported in the world to be affected by the COVID-19 epidemic, but many manufacturers in China

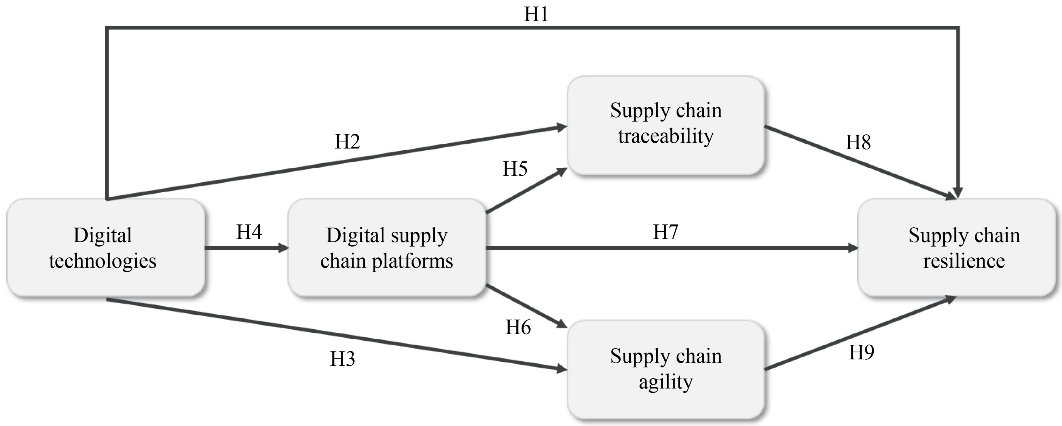


**Fig. 1** Theoretical model.

exhibited remarkable resilience (Wang et al., 2020). Thus, examining Chinese manufacturing organizations can help fulfill our study objectives and serve as a guide for firms in other countries undergoing comparable upheavals.

We employed a business research organization with a database containing information on more than 30000 Chinese businesses to help us quickly and accurately identify prospective firms. This questionnaire organization is competent, and its database is sufficient in size. The manufacturing industries in the database are from various regions of China and operate in numerous markets (e.g., manufacturing of computers, communications, and other electronic equipment). The organization sent personnel to assist with questionnaire distribution. All respondents to the questionnaires had to be management staff of Chinese manufacturing enterprises that had used a minimum of one sort of DT prior to the study. The organization randomly sent our questionnaire and the accompanying letter to the manufacturing firms in its database that fit the requirements of inclusion in our research. Participants that responded to the survey within the allotted deadline were rewarded with a gift. Having contacted 834 firms, the survey organization received 264 useable replies, with a response rate of 31.65%. The sample recovery rate is representative because we have very high requirements for the sample quality. Table 1 provides a profile of the respondent firms. Certain factors were examined as control variables in the model to determine their impact on the outcomes.

**Table 1** Profiles of respondent firms

| | Frequency | Percentage |
|---|---|---|
| **Firm size** (number of employees) | | |
| < 100 | 26 | 9.8% |
| 100–299 | 61 | 23.1% |
| 300–499 | 56 | 21.2% |
| 500–999 | 53 | 20.1% |
| 1000–1499 | 34 | 12.9% |
| 1500–1999 | 10 | 3.8% |
| ⩾ 2000 | 24 | 9.1% |
| **Firm age** (years established, to 2021) | | |
| < 5 years | 14 | 5.3% |
| 5–10 years | 57 | 21.6% |
| 10–15 years | 90 | 34.1% |
| 15–20 years | 64 | 24.2% |
| 20–25 years | 26 | 9.8% |
| 25–30 years | 6 | 2.3% |
| > 30 years | 7 | 2.7% |
| **Ownership** | | |
| State-owned | 35 | 13.3% |
| Privately-owned | 197 | 74.6% |
| Foreign | 6 | 2.3% |
| Collectively-owned | 26 | 9.8% |
| **Manufacturing sector** | | |
| Textile | 34 | 12.9% |
| Chemical | 26 | 9.8% |
| Steel | 22 | 8.3% |
| Automobile | 12 | 4.6% |
| Electronics | 37 | 14.0% |
| Food | 21 | 8.0% |
| Machinery | 85 | 32.2% |
| Pharmaceutical | 13 | 4.9% |
| Others | 14 | 5.3% |

## 3.2 Measures

Our measurement items were developed from the literature on SC management and information systems. All of them were rated using a seven-point Likert scale, ranging from “1 = strongly disagree” to “7 = strongly agree”. Specifically, four items were adapted from Faruquee et al. (2021) to assess DTs, reflecting how well they were at adopting these new technologies in the SC. To measure DSCPs, three items were adapted from Li et al. (2020). We also adapted four items from Cousins et al. (2019) to measure SCT and four items from Aslam et al. (2018) to measure SCA. Furthermore, to measure SCR, four items were adapted from Brandon-Jones et al. (2014). Tables A1 and A2 (Appendix A) present the details of each item.

### 3.3 Non-response and common method biases

We tested for the non-response bias by contrasting the first and fourth quarters of replies in relation to the mean values of the firms' size and age (Armstrong and Overton, 1977). The result revealed no statistically significant differences ($p > 0.10$) between these groups. Furthermore, we used two methods to test for the common method bias. First, we used Harman's single-factor model, which consists of loading all items into a single component for confirmatory factor analysis (Podsakoff et al., 2003). The model fit indices were $\chi^2 = 566.491$, $df = 152$, $\chi^2/df = 3.727$, incremental fit index (IFI) = 0.832, comparative fit index (CFI) = 0.83, and root mean-squared error of approximation (RMSEA) = 0.102, suggesting that the model was unacceptable. Second, we used the marker variable technique (Lindell and Whitney, 2001). We designated the respondent's shoe size as a marker variable as it should ideally be unrelated to the primary variables. The relationships between the marker and other research variables were determined to be insignificant (Table 2). Moreover, correcting for the common method bias had a small effect on the statistical significance of the correlations between variables (Li et al., 2022a). Consequently, the results revealed that the common method variance did not constitute a threat to our study.

## 4 Results

### 4.1 Scale validity and reliability

Confirmatory factor analysis was conducted using the maximum likelihood method to assess the reliability and validity of the constructs. The results, including $\chi^2 = 180.219$, $df = 142$, $\chi^2/df = 1.269$, IFI = 0.985, CFI = 0.984, and RMSEA = 0.032, suggest the model is acceptable. The majority of factor loadings and Cronbach's alpha for each variable were over 0.7, indicating strong reliability (Fornell and Larcker, 1981). We then calculated the composite reliability (CR) and the average variance extracted (AVE) of each construct, which were over 0.7 and 0.5, respectively, indicating strong CR and convergent validity (Fornell and Larcker, 1981). Finally, we compared whether the square roots of the AVEs were greater than the inter-construct correlations to evaluate discriminant validity (Fornell and Larcker, 1981). Table 3 shows the results. In short, all constructs satisfied the criteria for indicator reliability, CR, convergent validity, and discriminant validity.

### 4.2 Hypothesis testing

Multicollinearity tests were performed on the structural model in three subparts prior to its assessment. Multicollinearity concerns can arise in research models containing many exogenous constructs that are predicted by endogenous constructs (Ning et al., 2021). Thus, we calculated the variance inflation factor (VIF) of all exogenous constructs in the model. When the VIF value was less than 10, multicollinearity was not an issue (Hu et al., 2017). In the structural model, the range of VIF values from 1.559 to 2.320 indicated that multicollinearity was not an issue.

We used the SPSS (Statistic Package for Social Science) to test our hypotheses. The hypotheses were examined by using estimates of the path coefficient and results of bootstrapping from our research model, as presented in Table 3. Hierarchical regression analysis showed that all hypotheses are supported. Concretely, the results showed that DTs favorably enhance SCR ($\beta = 0.451$, $p < 0.001$), SCT ($\beta = 0.292$, $p < 0.001$), SCA ($\beta = 0.210$, $p < 0.001$), and DSCPs ($\beta = 0.576$, $p < 0.001$). Therefore, H1, H2, H3, and H4 are supported. SCT is positively influenced by DTs ($\beta = 0.292$, $p < 0.001$) and DSCPs ($\beta = 0.456$, $p < 0.001$). Hence, H2 and H5 are supported. SCA is positively influenced by DTs ($\beta = 0.210$, $p < 0.001$) and DSCPs ($\beta = 0.439$, $p < 0.001$). Thus, H3 and H6 are supported. SCR is positively influenced by DSCPs

**Table 2** Correlation matrix and discriminant validity

| | Mean | Standard deviation | 1 | 2 | 3 | 4 | 5 |
|---|---|---|---|---|---|---|---|
| 1. Digital technologies | 5.598 | 0.862 | **0.736** | | | | |
| 2. Digital supply chain platforms | 5.641 | 0.877 | 0.599** | **0.767** | | | |
| 3. Supply chain traceability | 5.789 | 0.889 | 0.533** | 0.588** | **0.773** | | |
| 4. Supply chain agility | 5.671 | 0.783 | 0.531** | 0.629** | 0.682** | **0.725** | |
| 5. Supply chain resilience | 5.531 | 0.846 | 0.499** | 0.575** | 0.589** | 0.644** | **0.742** |
| 6. Marker variable | n/a | n/a | 0.006 | −0.026 | 0.000 | 0.011 | 0.067 |

Notes: **$p < 0.01$; the square root of AVEs are in the diagonal.

**Table 3** Estimated results

| | Digital supply chain platforms | Supply chain traceability | Supply chain agility | Supply chain resilience | |
|---|---|---|---|---|---|
| | Model 1 | Model 2 | Model 3 | Model 4 | Model 5 |
| **Constant** | 2.090*** | 1.864 | 2.000*** | 2.895*** | 0.955*** |
| **Control variables** | | | | | |
| Firm age | −0.022 | 0.002 | −0.049 | −0.052 | −0.025 |
| Firm size | 0.051 | −0.031 | 0.025 | 0.063 | 0.038 |
| State-owned | −0.041 | −0.178 | 0.031 | −0.180 | −0.142 |
| Privately-owned | −0.080 | −0.004 | 0.015 | −0.146 | −0.118 |
| Food | 0.269 | −0.254 | −0.074 | 0.326 | 0.292 |
| Textile | 0.366 | −0.259 | 0.121 | 0.025 | −0.121 |
| Chemical | 0.424 | −0.232 | −0.044 | 0.167 | 0.055 |
| Steel | −0.020 | −0.093 | 0.105 | −0.014 | −0.028 |
| Automobile | −0.224 | 0.200 | 0.367 | 0.040 | −0.044 |
| Electronics | 0.517* | −0.154 | 0.152 | 0.384 | 0.146 |
| Machinery | 0.306 | −0.169 | 0.061 | 0.254 | 0.138 |
| Pharmaceutical | 0.351 | −0.151 | 0.054 | 0.247 | 0.098 |
| **Independent variable** | | | | | |
| Digital technologies | 0.576*** | 0.292*** | 0.210*** | 0.451*** | 0.086 |
| **Mediating variable** | | | | | |
| Digital supply chain platforms | | 0.456*** | 0.439*** | | 0.155* |
| Supply chain traceability | | | | | 0.184** |
| Supply chain agility | | | | | 0.376*** |
| Degrees of Freedom | 13 | 14 | 14 | 13 | 16 |
| $R^2$ | 0.406 | 0.417 | 0.451 | 0.287 | 0.153 |
| $F$ value | 13.158*** | 12.710*** | 14.615*** | 7.745*** | 16.391*** |

Notes: $^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$.

($\beta = 0.155$, $p < 0.05$), SCT ($\beta = 0.184$, $p < 0.01$), and SCA ($\beta = 0.376$, $p < 0.001$). Hence, H7, H8, and H9 are supported.

## 4.3 Mediation analysis

According to the preceding analysis, DTs positively influence SCR. However, how DSCPs, SCT, and SCA mediate the link between DTs and SCR requires further analysis. Hence, we used the PROCESS macro in SPSS 25.0 for mediation analysis by setting 5000 bootstrap samples and a 95% bias-corrected confidence interval (Hayes, 2017). We set DTs as the independent variable; DSCPs, SCT, and SCA as three mediating variables; firm age, firm size, ownership, and the manufacturing sector as control variables; and SCR as the dependent variable.

Tables 3 and 4 present the results of stepwise hierarchical regression and bootstrapping as supplied by the PROCESS macro. When no putative mediators existed, DTs had a beneficial effect on SCR ($\beta = 0.451$, $p < 0.001$); however, this effect became insignificant ($\beta = 0.086$, $p > 0.1$) when the presumed mediators were present. On the contrary, DSCPs ($\beta = 0.155$, $p < 0.05$), SCT ($\beta = 0.184$, $p < 0.01$), and SCA ($\beta = 0.376$, $p < 0.001$) showed positive links with SCR. According to hierarchical stepwise regression, the aforementioned results indicate the full effects of the mediation of DSCPs, SCT, and SCA. To verify robustness, Table 4 displays the results of the bootstrap method. As the 95% confidence interval for the direct path contains 0, whereas that for the four indirect paths does not contain 0, these results reaffirm the fully mediated role of DSCPs, SCT, and SCA.

**Table 4** Effects of digital collaboration capability on supply chain resilience

| Paths | Effect | BootSE | BootLLCI | BootULCI |
|---|---|---|---|---|
| DTs → DSCPs → SCR | 0.091 | 0.051 | −0.018 | 0.181 |
| DTs → SCT → SCR | 0.055 | 0.030 | 0.002 | 0.117 |
| DTs → SCA → SCR | 0.081 | 0.029 | 0.032 | 0.146 |
| DTs → DSCPs → SCT → SCR | 0.049 | 0.023 | 0.002 | 0.094 |
| DTs → DSCPs → SCA → SCR | 0.097 | 0.028 | 0.050 | 0.160 |

## 5 Discussion

Considering the inconsistency in the accounts of the relationships between DTs and the firm's resilience in the literature (Xue, 2014; Hosseini et al., 2019; Accenture, 2020; Fay, 2020; Ivanov, 2020; Li et al., 2020; Balakrishnan and Ramanathan, 2021; Mimecast, 2021), we investigate the factors that influence the relationship between them. We seek an answer to this research question: Do DSCPs, SCT, and SCA act as mediators between DTs and SCR? By assuming the perspective of IPT and utilizing data from 264 Chinese manufacturers, we examined the relationships among DTs, DSCPs, SCT, SCA, and SCR. Several noteworthy findings are mentioned below.

First, as in a majority of prior research (Gunasekaran et al., 2017; Hosseini et al., 2019; Accenture, 2020), we found that DTs can enhance a firm's resilience. The reason is that DT enables information transfer within and between firms. In other words, DTs reflect organizations' information processing abilities to analyze SC interruptions and make educated judgments. They facilitate operational management through efficient information processing to enhance SC efficiency, reduce costs, and increase profitability (Yu et al., 2015; Nguyen et al., 2018). In summary, our results corroborate the findings in many prior investigations.

Second, we found that DSCPs, SCT, and SCA completely mediate the positive effect of DTs on a firm's resilience. Specifically, the four significant indirect paths indicated that only firms that use DTs to directly or indirectly (through DSCPs) improve SCT and SCA can achieve adequate resilience. The reason is that DSCPs need higher resilience through SCT and SCA. If digital firms solely prioritize DSCPs and disregard the significance of SCT and SCA, then they may not be able to handle disruptions to the SC.

Finally, some real cases can support our findings to some extent. For example, Siemens and System Applications and Products (SAP) have demonstrated our results with practice. In particular, Siemens Digital Logistics focused on digitizing logistics operations and claimed to be the top DT supplier in global SC management (Siemens, 2013). Meanwhile, SAP is the market-share leader in Enterprise Resource Planning and a worldwide digital platform supplier to deliver cutting-edge technologies, particularly artificial intelligence, IoT, big data, and advanced analytics (Gillis, 2022). During the COVID-19 pandemic, Siemens and SAP established a strategic alliance to accelerate the digitalization of Industry 4.0 to strengthen SCR (DiNunzio, 2020). This cooperation enables many firms who utilize DTs in the epidemic to have digital supply platforms that match their situations, making SCA and SCT and thereby allowing SCR.

### 5.1 Theoretical implications

This study provides two theoretical contributions. First, earlier studies generally emphasized the impact of certain DTs, such as cloud computing (Subramanian and Abdulrahman, 2017), in building resilience. However, each DT has its own benefits and drawbacks. Hence, businesses rarely use just one kind of technology in everyday operations and prefer a combination of DTs (Li, 2022). In contrast to previous research, we examined the use of DTs from a comprehensive perspective, thereby enhancing the current knowledge of the determinants of the firm's resilience.

Second, although some researchers advocated incorporating DTs into SCs (Li et al., 2022d), little research has examined how DTs influence the firm's resilience through several essential SC mediators. Using the information processing theory, we demonstrated that DSCPs, SCT, and SCA fully mediate the link between DTs and the firm's resilience, thereby expanding our understanding of the mechanism underlying this association.

### 5.2 Managerial implications

In terms of management, we provide practical guidelines for managers to use DTs to recover from disruptions with SC partners, which is particularly beneficial and crucial in light of SC management practices subjected to global SC disruptions. We next discuss the management implications of using DTs to enhance SCR in a turbulent market. First, we see a beneficial association between DTs and the firm's resilience. Accordingly, firms should implement multiple DTs, rather than examine a single DT, to enhance their SCR owing to the individual advantages and disadvantages of each DT. This process can help overcome the handicap and spillover effect of DTs on the resilience to SC disruptions (Chiarini, 2021).

Second, the effect of DTs on the firm's resilience is fully mediated by DSCPs, SCT, and SCA. Firms should not only implement DTs but also apply DSCPs and make efforts to enhance SCT and SCA. In addition, SCT and SCA play a greater mediating role than DSCPs in the use of DTs to enhance SCR. If firms emphasize only DSCPs, and overlook the importance of SCT and SCA, they may be incapable of handling interruptions in the SC. Therefore, firms should invest in enhancing SCT and SCA rather than solely prioritizing DSCPs.

## 6 Conclusions

DTs assist businesses in coping with SC disruptions caused by the unpredictable, such as some pandemics. However, the current knowledge of the relationship between DTs and the firm's resilience is insufficient. To address this deficiency, we draw on IPT to develop a serial mediation model. The empirical findings obtained from a survey of 264 Chinese manufacturers showed that DSCPs, SCT, and SCA completely mediate the favorable association between DTs and SCR. Specifically, four key indirect channels indicated that firms can only achieve better SCR if they employ DTs to directly or indirectly (through DSCPs) increase SCT and SCA. We contribute to the research on resilience by highlighting the potential mechanism of mediation by which DTs affect SCR. In addition, our results offer organizations vital insights for adapting their digital strategies to prosper in an unstable market.

Despite the significant contributions of this study, additional investigation is needed. First, the firms examined in this research were all from the manufacturing sector, but we are also concerned with the impact of DTs on the resilience of service firms. During the pandemic, a large number of service-based firms ceased operation. We plan to consider a larger industrial context and investigate crucial factors that might strengthen the service sector's resilience in future work. Second, we did not rigorously explain the moderating mechanisms involved when illustrating the mediating effect between DTs and SCR from the standpoint of IPT. Our future research will also investigate the factors that modulate the association between DTs and SCR. Third, some control variables were not considered in this study, such as total revenue or total sales. In future research, we will try to define total revenue or total sales as control variables to explore whether the results would differ. Fourth, our data were cross-sectional data, showing certain limitations in inferring causality. Future research can enrich and verify our findings by using broader approaches, such as case studies and experimental methods. Finally, the global spread of the COVID-19 pandemic has posed a danger to the global SCR. DTs are increasingly utilized worldwide. We will explore the situation in other nations in future research.

## Appendix A

**Table A1** Measurement items

| Construct | Items |
|---|---|
| Digital technologies (Faruquee et al., 2021) CR = 0.826; AVE = 0.542; Cronbach'salpha = 0.826 | • Artificial intelligence: Factor loading = 0.719<br>• Cloud-based e-procurement: Factor loading = 0.749<br>• Big data analytics: Factor loading = 0.767<br>• Internet of Things: Factor loading = 0.709 |
| Digital supply chain platforms (Li et al., 2020) CR = 0.811; AVE = 0.589; Cronbach's alpha = 0.810 | • Digital platforms with suppliers: Factor loading = 0.800<br>• Digital platforms with customers: Factor loading = 0.738<br>• Digital platforms with other company units: Factor loading = 0.763 |
| Supply chain traceability (Cousins et al., 2019) CR = 0.856; AVE = 0.597; Cronbach's alpha = 0.856 | • We know the sources of our raw materials: Factor loading = 0.755<br>• We track the processes involved in producing product throughout our complete supply chain: Factor loading = 0.774<br>• We trace the origins of our purchases through the entire supply chain: Factor loading = 0.803<br>• We know what chemicals or elements are in our purchased components: Factor loading = 0.759 |
| Supply chain agility (Aslam et al., 2018) CR = 0.816; AVE = 0.526; Cronbach's alpha = 0.813 | • Our supply chain can adapt services and/or products to new customer requirements quickly: Factor loading = 0.730<br>• Our supply chain can react to new market developments quickly: Factor loading = 0.740<br>• Our supply chain can react to significant increases and decreases in demand quickly: Factor loading = 0.648<br>• Our supply chain can adjust product portfolio as per market requirement: Factor loading = 0.778 |
| Supply chain resilience (Brandon-Jones et al., 2014) CR = 0.931; AVE = 0.551; Cronbach's alpha = 0.829 | • Material flow would be quickly restored: Factor loading = 0.758<br>• It would not take long to recover normal operating performance: Factor loading = 0.727<br>• The supply chain would easily recover to its original state: Factor loading = 0.733<br>• Disruptions would be dealt with quickly: Factor loading = 0.751 |

**Table A2** Confirmatory factor analysis

| Item | Factor loadings | Cronbach's alpha | CR value | AVE value |
|---|---|---|---|---|
| DT1 | 0.719 | 0.860 | 0.826 | 0.542 |
| DT4 | 0.749 | | | |
| DT5 | 0.767 | | | |
| DT6 | 0.709 | | | |
| DSCP1 | 0.800 | 0.810 | 0.811 | 0.589 |
| DSCP2 | 0.738 | | | |
| DSCP3 | 0.763 | | | |
| SCT1 | 0.755 | 0.856 | 0.856 | 0.597 |
| SCT2 | 0.774 | | | |
| SCT3 | 0.803 | | | |
| SCT4 | 0.759 | | | |
| SCA1 | 0.730 | 0.813 | 0.818 | 0.526 |
| SCA2 | 0.740 | | | |
| SCA3 | 0.648 | | | |
| SCA4 | 0.778 | | | |
| SCR1 | 0.758 | 0.829 | 0.931 | 0.551 |
| SCR2 | 0.727 | | | |
| SCR3 | 0.733 | | | |
| SCR4 | 0.751 | | | |

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