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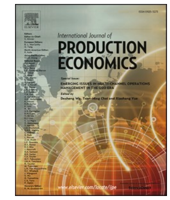

Unleashing supply chain agility: Leveraging data network effects for digital transformation☆

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ABSTRACT

The global manufacturing supply chain is undergoing a digital transformation (DT) powered by various digital technologies. In both stable and turbulent environments, DT helps safeguard supply chain performance by enhancing supply chain agility. While research on the use of digital technologies and their impacts on supply chains is growing, there is a lack of an overarching theoretical lens to synthesize their diverse functionalities, effects, and benefits. To address this gap, we adapt the concept of the data network effect to the supply chain context and propose that DT improves supply chain performance by enhancing supply chain resilience (SCRes) and robustness (SCRob) capabilities. To validate our hypotheses, we conducted a large-scale survey for data collection and performed Partial Least Squares Structural Equation Modelling (PLS-SEM) for data analysis. The results confirm the positive effect of DT on supply chain performance and the mediating roles of SCRob and SCRes. Our study contributes to the ongoing discussion on DT in the context of supply chains by introducing a novel theoretical perspective on the supply chain data network effect.

1. Introduction

As McKinsey (2020) found in a recent survey of cross-sectoral supply chain executives, over 70% of them had experienced disruptions to their supply chains during the Covid-19 pandemic, and in the food and consumer goods industries the percentage reached 100%. The detrimental impact has urged organizations to accelerate their digital transformation (DT) efforts, due to the novel opportunities that digital solutions can offer in the post-pandemic era (McKinsey, 2020; Cui et al., 2022). Against the background of Industry 4.0, companies are characterized by the increasing use of digital tools to transform their supply chain operating models, strategies, and the way they deliver value to customers (Hahn, 2020). DT encompasses a series of strategic changes made by the organization through the employment of digital technologies (Hess et al., 2016; Faruquee et al., 2021), and managers are motivated to embark on DT to address challenges their organizations face. For instance, successful DT is found to benefit the organization in terms of creativity (Mikalef and Gupta, 2021), internal and supply chain environmental integration (Benzidia et al., 2021), and competitive performance (Wamba and Guthrie, 2019), among others, and these benefits and opportunities would not be feasible in the past when digital technologies were not available.

Managing the supply chain is highly challenging, and frequent external disruptions further add to the intricacy. Under such circumstances, maintaining supply chain performance requires capabilities that can support supply chain operations in various environmental conditions. Literature has suggested that in uncertain environments, supply chains need to develop agile capabilities that enable them to recover quickly from the damage and to resist potential disruptions in the future (Nikookar and Yanadori, 2021). These capabilities are categorized as supply chain resilience (SCRes) and robustness (SCRob) respectively in the supply chain management literature and have gained extensive attention since the outbreak of Covid-19 (Brandon-Jones et al., 2014; Ivanov, 2020; Cui et al., 2022; Tian et al., 2024).

Developing capabilities such as SCRes and SCRob at the same time is never an easy task, but modern digital tools are believed to bring new opportunities (Appio et al., 2021). The profound and long-lasting impact of the pandemic and geopolitical risks has moved DT and the

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development of SCRes and SCRob to the top of the strategic agenda for all types of organizations and supply chains. DT, characterized by the implementation of various digital technologies, is turning unstructured, massive data into strategic organization resources. Such an ongoing phenomenon of collecting, analyzing, learning and transforming from data is termed by Gregory et al. (2021) as "data network effect", through which more data generated within an entity, the more value it can yield for the users. This is particularly relevant for supply chains, as companies have more digital tools available to collect and deal with big data and share data among themselves, more benefits can be generated to individual firms participating in a supply chain. For instance, P&G and its biggest customer Walmart achieved mutual benefits through technology-enabled data sharing, and more importantly, it motivated a healthy competition among Walmart's suppliers to innovate which further benefits the supply chain (Waller, 2013). However, the phenomenon of data network effect is severely under-researched in the supply chain management domain. It remains empirically unclear as what data network effect manifests in the context of supply chain management. We therefore propose that the simultaneous achievement of SCRes and SCRob is a form of data network effect, which then translates into enhanced supply chain performance. Our study aims to shed light on the burning research question:

Does DT create a data network effect in the supply chain, in the form of improved SCRes and SCRob capabilities and performance?

To address this question, we conduct a large-scale survey of Chinese manufacturers and perform structural equation modelling for data analysis. This study contributes to the DT literature by conceptualizing and operationalizing the concept and empirically validating its intended benefits in the supply chain context. Further, we aim to enrich the technology management studies by bringing in a new theoretical perspective, data network effect, to understand the implications of digital technologies more deeply. Practically, our study urgers supply chain managers to actively engage in DT by embracing emerging digital tools and pay particular attention to the development of capabilities that enable them to respond to and recover from disruptions.

The rest of the paper is structured as follows. Section 2 is a thorough review of relevant theories and concepts. That is followed by hypothesis development in Section 3. Section 4 then introduces the method employed and reports the data analysis results. Section 5 discusses the main findings and implications of the study and points out its limitations and directions for future research.

2. Theoretical background

2.1. Data-driven DT in the context of supply chain

Embedded in Industry 4.0, DT is defined as "a process that aims to improve an entity by triggering significant changes to its properties through combinations of information, computing, communication, and connectivity technologies" (Vial, 2019, p. 121). It was originally proposed as an organizational effort to improve business performance or create new business models through deploying digital technologies (Fitzgerald et al., 2013, p.2). Specifically, as Feliciano-Cestero et al. (2023) indicate, DT can either enable revolutionary methods of production or foster the development of new offerings. With supporting strategies and capabilities in place, digitally transformed organizations will potentially reshape the organizational structure and how they interact with stakeholders, which showcases DT's relevance to supply chain management. Understandably, the supply chain management research community is increasingly embracing DT by actively expanding its scope. A digitally transformed supply chain is perceived as a customer-centric platform where members actively exchange information empowered by digital tools to co-deliver user value (Ngo et al., 2023). Successfully transformed supply chains are therefore considered more effective and efficient due to timely data-driven decision-making. However, such transformation process cannot be taken for granted, which requires close and continuous cooperation among organizations within the supply chain built on high organizational flexibility, strong digital competences, and the same level of digital consciousness and motivation (Ngo et al., 2023).

So far, nascent research on DT in the supply chain context has started to yield valuable insights. For instance, Wang et al. (2024) illustrate the digital transformation of the food supply chain as composed of the initiation phase (defining objectives and principles of DT) and the technology implementation phase. Hartley and Sawaya (2019) elaborate how technologies can digitalize the business process of the firm. While diverse foci and findings remain highly inconclusive, researchers seem to agree on the essential roles of technology adoption in driving DT and improving various aspects of organizational performance (Lang et al., 2023; Wang et al., 2024; Yuan et al., 2024).

2.2. Driving DT through multiple digital technologies

The adoption of digital technologies by organizations is considered an important initial step for initiating DT (Shi et al., 2023). Currently, digital technologies that are driving organizations' DT include big data analytics, artificial intelligence (AI), blockchain, cloud computing, and the internet of things (IoT), all of which are increasingly being adopted by Chinese manufacturers (Chin et al., 2021). In normal or turbulent environments, these digital technologies show a promising role in supporting organizational and supply chain processes and achieving superior performance. These digital technologies work around a key organizational resource, data. While technologies such as IoT and big data analytics create and capture big data, AI is an effective tool to make sense of massive amounts of raw data. Raw data and processed data can then be safely stored by technologies such as blockchain and the cloud and shared among authorized parties. Wamba et al. (2020a, p.2) define big data analytics as "a holistic process that involves the collection, analysis, use, and interpretation of data for various functional divisions with a view to gaining actionable insights, creating business value, and establishing competitive advantage". As a powerful tool to make rapid and accurate sense of massive volumes and high velocity of data, the application of big data analytics has been found to bring firms and supply chains a wide range of benefits, including enhanced agility and adaptability (Wamba et al., 2020a), improve trust and collaboration among supply chain members (Dubey et al., 2019), bricolage capability and servitization (Chen et al., 2022), innovation capabilities and high-quality information (Bahrami and Shokouhyar, 2021), sustainability-related capabilities (Bag et al., 2021), as well as better overall organizational and supply chain performance (Gunasekaran et al., 2017).

IoT, one of the most prominent digital technologies in the industry 4.0 era, has been widely adopted by organizations especially manufacturers. The application of IoT significantly improves supply chain coordination as it enables human-to-object and object-to-object communications anytime and anywhere (Ben-Daya et al., 2019). IoT serves as a powerful tool to create and collect valuable big data, providing a solid basis for organizations' decision-making regarding risk management (Birkel and Hartmann, 2020).

AI refers to "the capability of machines to communicate with, and imitate the capabilities of, humans" (Toorajipour et al., 2021, p.502), and is capable of reshaping the creation and delivery mode of value for companies. Powered by big data analytics and IoT, AI has been found to contribute to resilient and sustainable supply chain management through its strong computational power, large datasets, and the development of novel learning algorithms (Belhadi et al., 2021; Benzidia et al., 2021; Pournader et al., 2021). AI-empowered learning from individual cases can feed instantly into the predictive models and be translated into current value of the product to all users (Gregory et al., 2022). As Tian et al. (2024) suggest, technologies like IoT and AI work together to complete the datafication process which is the first step of successful DT.

When items and their movements are datafied and information analyzed, the insights should be effectively stored and shared among supply chain partners. Blockchain is an important digital technology that can support this. According to Schmidt and Wagner (2019), blockchain is essentially a decentralized, consensus-driven ledger that records transactions in a way that is mostly immutable. The decentralized nature of blockchain has the potential to make the supply chain more efficient, transparent, visible, traceable, flexible, and sustainable (Wamba et al., 2020b; Kamble et al., 2021; Nandi et al., 2020).

Cloud computing provides a virtualized and distributed environment where resources are stored and made accessible on demand to authorized parties through web-based technologies (Maqueira et al., 2019). Since resources like data are usually not confined within organizational boundaries, cloud computing can enhance supply chain efficiency and improve decision-making (Bruque-Cámara et al., 2016). While various digital technologies offer distinct functionalities for managing supply chains, their combined use is aimed at better managing data to generate a data network effect within the supply chain (Gregory et al., 2021).

2.3. Data network effect

According to Saarikko et al. (2020), while increasing digital tools are available to organizations, the real challenge of their DT process lies in the lack of capability that can help them leverage digital technologies to change their existing business models. The data management process enabled by digital technologies is considered a starting point of DT (Wang et al., 2024). Our study proposes that DT can only be seen as happening in the supply chain when the data network effect starts to emerge following organizations' data management process enabled by their adoption of multiple digital technologies.

Building on the network effect literature and the unprecedented learning from data enabled by AI, data network effect refers to the phenomenon that the more user data a platform collects and the more it learns from the data, the more valuable the platform and its offerings become to each user (Gregory et al., 2021). Gregory et al. (2022) further clarifies the two conditions of data network effect. First, the resulting experience enhancement must be for all users of the platform and its offerings. Second, learning-driven experience enhancement should happen fast enough to allow for current value increase of the platform's offering. Departing from the traditional platform context, our study applies the data network effect concept to another format of platform, the supply chain.

A supply chain is a network of agents collaborating in a series of processes to deliver a product or service to end users. The agents in a supply chain differ from the users defined in a platform context (e.g., Huang et al., 2017), as the former are primarily contributing parties, while the latter are more often receiving parties. However, the mechanisms by which they derive utility values from the network can be shared (Gregory et al., 2021).

According to Gregory et al. (2021), three aspects are core to data network effect, namely data stewardship, user-centric design, and platform legitimation. These three play key roles in facilitating the achievement of data network effect through the use of AI in a platform. Similarly in the context of digitally transformed supply chain, these aspects are also crucial for the same purpose. First, data quality and quantity are vital inputs into and serve as a prerequisite for a successfully digitally transformed supply chain. As discussed above, the deployment of multiple digital technologies by supply chain partners enables data availability for sense-making and exchange of data within the supply chain. The enhanced data stewardship therefore ensures the accuracy and speed of the prediction models, which provide significant guidance for organizational decision-making across various environmental conditions. Second, the supply chain must be managed as a user-centric network to fulfil users' needs. Traditionally, the supply chain's objective is defined as meeting the end consumers' demand through the delivery of a product or service in the required quality and quantity, and at the right cost (Gu et al., 2021). Therefore, to accurately capture their real needs, end consumers need to be actively engaged in the design and production stages. However, when a supply chain is viewed as a digital platform, the concept of users becomes wider, including all organizations and individuals involved in the chain. A digitally transformed supply chain must be designed to empower all to co-create their own experiences, encouraging greater openness in data sharing (Gregory et al., 2021). The more data each party shares within the supply chain, the more valuable the supply chain becomes to everyone involved. A user-centric supply chain must ensure that every participating entity derives value from it, further strengthening the benefits of data stewardship. Last, platform legitimation is defined as actions taken by the platform to secure its key stakeholders' positive legitimacy evaluations (Gregory et al., 2021, p. 543), which aims to ensure responsible data use by the platform and the balancing of stakeholders' needs. This is crucial as organizations within a digitally transformed supply chain will need to open up their data assets to others while benefiting from access to shared data. Irresponsible or opportunistic behavior in data usage by any party can become a barrier that hinders others from participating in the supply chain. The continuous transformation of the supply chain and the realization of the data network effect can only be achieved when all parties align on proper digital conduct.

In sum, the use of multiple digital technologies not only drives the digital transformation of the supply chain but also enhances the data network effect by making data more accessible and creating conditions that foster improved data stewardship. Supply chain members gain a better understanding of their own operations and those of others. As a result, a digitally transformed supply chain can evolve into a digital platform allowing the actualization of two benefits. In addition to facilitating better coordination among entities to co-create and co-deliver value to all participants and end users, digitally transformed supply chain can potentially lead to the nurturing of agile supply chain capabilities.

2.4. DT-empowered agile supply chain capabilities

Agile supply chains are best known for their flexibility in adapting to various environmental conditions and effectively coping with changes (Aslam et al., 2018). One of the major benefits of DT in the supply chain and an important manifestation of the data network effect is the enhanced supply chain capabilities that secure performance across various environmental conditions. Managing complex supply chain systems in stable and turbulent environments requires different capabilities, including supply chain resilience (SCRes) and supply chain robustness (SCRob). Table 1 summarizes existing conceptualizations and operationalizations of SCRes and SCRob. While defined differently, the focus of SCRes is commonly placed on the ability of the system (e.g., firm, supply chain) to quickly recover from a disruption and adapt to the new situation. According to Tukamuhabwa et al. (2015), when disturbed, a resilient supply chain is able to return to the original state, or even achieve a better state, in a time- and cost-efficient manner. Therefore, SCRes requires rapid reactive responses, usually radical, made by the organization or supply chain to the disruptive forces.

SCRob differs from SCRes in that a robust supply chain is designed to withstand disruptions (Ivanov, 2020), reducing the need for radical changes when disruptions occur (Durach et al., 2015). A robust supply chain can "resist change without adapting its initial stable configuration" (Wieland and Wallenburg, 2012, p. 890). In other words, a robust supply chain can maintain a certain level of performance across all environmental conditions. Such an ability can only be achieved through constant, forward-looking and proactive small-scale adjustments in operations to absorb variances between operations and the external environment. Based on the conceptual difference between SCRes and SCRob, our study proposes the following definitions:

SCRes is the ability of the supply chain to make timely and cost-efficient

Table 1
SCRes and SCRob conceptualization and operationalization.

Study	SC Robustness	SC Resilience
El Baz and Ruel (2021)		
Definition	Ability of the supply chain to maintain its function despite internal or external disruptions. It is also frequently seen as the ability to resist the immediate impacts of a disruption.	Capability to anticipate and overcome disruptions and is defined as "the ability of a supply chain to return to normal operating performance, within an acceptable period of time, after being disrupted" with an objective to regain pre-disruption performance.
Operationalization	The ability of the supply chain to: - retain the same stable situation when disrupted; - develop a reasonable reaction to disruptions; - adapt through developing scenarios; - function despite damages.	The ability of the supply chain to: - cope with changes due to disruptions; - adapt to a disruption; - provide a quick response; - maintain high situational awareness.
Mackay *et al.* (2020r)		
Definition	The degree of system sensitivity when facing disruptions, which ensures the system's capability to absorb disruptions.	The supply chain's ability to withstand the effect of a disruption and recover within acceptable timeframe and within elastic boundaries.
Operationalization	SCRob's two dimensions: - resistance - avoidance	A post-disaster behavior of the system reflecting the ability to: - recover
Cohen and Kouvelis (2021)		
Definition	Operational flexibility to operate across a wide range of operating scenarios in the short term.	The ability to recover from current shocks, understand vulnerabilities and potential future shocks, and proactively mitigate their risks.
Gu *et al.* (2021)		
Definition		SCRes is the capability of the supply chain to recover from supply chain disruptions and maintain the continuity of material, information, and cash flow.
Operationalization		The ability of the supply chain to: - maintain high situational awareness at all times; - provide a quick response to supply chain disruptions; - cope with changes brought by the supply chain disruption; - adapt to the supply chain disruption easily; - recover to normal operations speedily after disruption.
Wong *et al.* (2020)		
Definition		SCRes prepares firms with capacity to cope with and recover from disruptions to the original state of operations. It reflects the ability to survive, adapt, respond, recover, and grow when confronted with change and uncertainty.
Operationalization		The ability of the supply chain to: - quickly return to its original state after being disrupted; - maintain a desired level of connectedness among members at the time of disruption; - maintain a desired level of control over structure and function at the time of disruption; - have the knowledge to recover from disruptions and unexpected events.
Brandon-Jones *et al.* (2014)		
Definition	SCRob refers to the ability of the supply chain to maintain its function despite internal or external disruptions.	The ability to quickly and successfully recover from a disruption and return to the original state of operating.
Operationalization	The ability of the supply chain to: - continue operations; - meet customer demand; - keep performance not deviated significantly from targets; - carry out its regular functions.	The ability of the supply chain to: - quickly restore material flow; - quickly recover normal operating performance; - easily recover to original state; - deal with disruptions quickly.
Tukamuhabwa *et al.* (2015)		
Definition		The adaptive capability of a supply chain to prepare for and/or respond to disruptions, to make a timely and cost-effective recovery, and therefore progress to a post-disruption state of operations – ideally, a better state than prior to the disruption
Operationalization		The adaptive capability of a supply chain to: - prepare for and/or respond to disruptions; - make a timely and cost-effective recovery. Therefore, progress to a post-disruption state of operations - ideally, a better state than prior to the disruption.
Our definition and operationalization in this study		
Definition	SCRob refers to the supply chain's ability to remain unimpacted by disruptions and therefore do not have to make radical changes to their operations.	SCRes is the ability of the supply chain to make timely and cost-efficient radical changes in their operations as a response to disruptions.
Operationalization	The ability to: - to retain the same operations; - to grant sufficient time for reactions; - to perform well in various scenarios without adaptations; - to carry out planned functions when disrupted.	The ability to: - quickly return to the original state; - maintain a desired level of connectedness; - maintain a desired level of control; - quickly recover after being disrupted.

radical changes in their operations as a response to disruptions. SCRob refers to the supply chain's ability to remain unimpacted by disruptions and therefore do not have to make radical changes to their operations.

The simultaneous achievement of SCRes and SCRob capabilities enabled by data-driven DT of the supply chain is a typical manifestation of data network effect. SCRes and SCRob share common processes such as environmental scanning, sensing, and environmental sensemaking, and at the same time require distinct supporting capabilities.

Specifically, SCRes is supported by flexibility, rapid resource reconfiguring, responding and recovering, while SCRob requires continuous improvement, risk prevention and variance absorption. Therefore, agile supply chains with both capabilities are able to maintain performance in various conditions, which is largely a result of rich data resources and the associated learning co-contributed by supply chain partners. Entities involved in agile supply chains then enjoy the data network effect and secure their own performance against external disturbances.

3. Hypotheses

3.1. Data-driven DT and supply chain performance

Supply chain performance (SCP) refers to the extent to which the supply chain can meet customer needs in terms of product and service availability and on-time delivery at the lowest possible cost (Belhadi et al., 2021). In disastrous events, supply chains face serious challenges in terms of maintaining the promised service level due to changes in supply, demand, as well as logistics. Timely gathering, analysis and exchange of information along the entire supply chain and coordinated actions of all are thus crucial to maintain SCP, especially in unstable conditions.

Consumer satisfaction will drop if the supply chain fails to deliver on time (Gu et al., 2021), and this can be prevented with effective DT that enables and manifests data network effect. DT, with the use of digital technologies, provides data stewardship and supports organizational decision-making. For instance, information related to potential risks can be captured and communicated among supply chain partners through digital technologies in a timely fashion, which strengthens supply chain relationships and forms the basis for co-developing precautions (Nasiri et al., 2020). Honest and in-time communication of difficulties can adjust customer expectations during challenging times, preventing significant disappointment and unsatisfaction from happening. The acquisition of demand data can also be used to modify supply and production plans (Li et al., 2020). For firms involved in multiple supply networks, comprehensive planning and re-scheduling enabled by digital visualization can temporarily deal with supply shortages. Due to well-established digital infrastructure in many parts of the world, big data collection, analysis and virtual communications empowered by modern digital technologies have been made highly cost-efficient, saving expenses and increasing profit for organizations (Cui et al., 2022). The seamless connection between data collection, analysis and sharing technologies improves the user-centeredness of the supply chain, allowing all parties to contribute and benefit at the same time. This, along with well-implemented data rules and codes of conduct produces a virtuous cycle that keeps strengthening the value of the supply chain to each member. Therefore, we propose that enhanced SCP is a tangible manifestation of the data network effect enabled by DT.

H1. DT has a positive effect on SCP.

3.2. The mediation effect of agile supply chain capabilities

In terms of intangible manifestations of the data network effect, the development of agile supply chain capabilities, including both SCRes and SCRob, is important. As discussed earlier, developing SCRes and SCRob requires common capabilities, including environmental scanning, sensing, and environmental sensemaking, and these can be realized through the data stewardship provided by implementing multiple digital technologies. The basis of these capabilities lies in the acquisition and analysis of extensive market information, which is what the DT enabled data network effect can deliver. From a supply-side perspective, Yang et al. (2021) find a positive effect of DT on supply chain visibility. Specifically, the simultaneous deployment of IoT, blockchain, and cloud computing makes supply chain processes and actors visible and transparent through data generation and sharing, providing the condition for effective environmental scanning and opportunity- and threat-sensing (Xiong et al., 2021). Song et al. (2021) also gather empirical evidence that environmental scanning empowered by social media and big data analytics positively relates to the development of sensing capability. Dias and Lages (2021) validate the conceptualization of market sensing capability as including scanning, interpreting and responding, which are closely linked to information collection, data analysis and sense-making, and propose its contribution to successful data-driven decision-making in organizations. Further, blockchain ensures data quality and security, as all transactions are recorded in real time and cannot be altered (Baharmand et al., 2021), and such platform legitimation enables accurate sensemaking of the environment and data-driven decision-making. Overall, the ability of timely and precise understanding the environment is thus supported by the boosted data stewardship (Williams et al., 2013), and the user-centric design of the digital supply chain and the supply chain platform legitimation further strengthen the data stewardship.

Meanwhile, SCRes and SCRob require different foundational capabilities which rely heavily on the data network effect resulting from DT. SCRes is generally supported by flexibility, resource reconfiguration, and recovery. Big data analytics contributes to supply chain flexibility by effectively processing, visualizing and analyzing data, thereby enabling data stewardship and supporting data-driven decision-making on resource reconfiguration and faster adaptation to the changing environment (Koot et al., 2021; Yu et al., 2021; Faruquee et al., 2021; Dennehy et al., 2021). The use of AI, which is also significantly data-dependent, can contribute to supply chain agility by providing both flexibility and cost efficiency through machine learning (Toorajipour et al., 2021). Resource reconfiguration and recovery from disasters are built upon planning and preparedness, whose effectiveness depends on the reach and richness of data and the quality of algorithms, combined with high human intelligence (Faruquee et al., 2021). Well-planned DT, with appropriate human and organizational support, can contribute to data stewardship that preludes the data network effect and improve SCRes capability.

By contrast, SCRob stresses the maintenance of normal operations throughout without having to make substantial changes despite disruptions, which reflects the supply chain's ability to "absorb" variances on a continuous basis (Mackay et al., 2020). To achieve this, supply chains need the ability to sense and predict changes, and effectively incorporate them into their operations to develop preventive and preparative measures (El Baz and Ruel, 2021), where DT and the associated data network effect can contribute too. Seizing, as a crucial micro-foundation of dynamic capabilities, is essential for the development of absorptive and prevention capabilities (Teece, 2007). DT-enabled data stewardship can also enhance the ability of the supply chain to make effective prevention plans. For instance, with the capture and analysis of 10 years' transaction data, Alibaba is able to predict changes in Yu E Bao users' timing of moving money into and out of their accounts, and take action accordingly (Hassna and Lowry, 2018). Such actions taken are effective preventive or preparative measures that can protect the supply chain from being significantly disrupted by unexpected events. By constantly scanning the environment, sensing opportunities and changes, communicating them with partners in a timely manner, and incorporating them in their daily operations with the help of digital technologies, companies and supply chains are able to keep pace with the market trend and minimize the need for radical changes when confronted with disruptions.

DT-enabled data network effect, in the form of enhanced SCRes and SCRob capabilities, can then translate into maintained and even improved SCP during disruptions as well as in relatively stable times. While SCRes reflects the flexibility and adaptability of the supply chain (and all its members individually) when disruptions occur (Gu et al., 2021), SCRob reduces the vulnerability of the supply chain and increases its ability to avoid disruption (Wieland and Wallenburg, 2012). A digitally transformed supply chain is characterized by the widespread adoption of digital technologies by all parties involved, leading to the establishment of a platform where participants actively share data and leverage it to maximize their own benefits. This creates a virtuous cycle in which more data leads to a better user experience, further motivating users to be more open in sharing their data. As data-driven capabilities, SCRes and SCRob work together for the supply chain to perpetuate a high level of performance in various environmental conditions, meeting and even exceeding users' needs and requirements. We therefore propose that.

H2. SCRes mediates the DT-SCP link.

H3. SCRob mediates the DT-SCP link.

Fig. 1 illustrates the conceptual model and hypotheses.

4. Research methodology

4.1. The survey instrument

A survey-based quantitative approach was adopted to validate the research model based on established measurement scales. As the target respondents were mainly Chinese-speaking, a back-translation method involving two bilingual researchers (Bhalla and Lin, 1987) was applied to the questionnaire. The questionnaire was then reviewed by five industrial and six academic experts. Based on their feedback, minor modifications were made to ensure the clarity of questions and the face validity of the survey instrument.

To measure SCRes, four items were adapted from Wong et al. (2020) and Golgeci and Ponomarov (2013). Respondents were asked to indicate the degree to which their firms' supply chains can: (1) quickly return to the original state, (2) maintain a desired level of connectedness, (3) maintain a desired level of control, and (4) quickly recover when being disrupted. Measures of SCRob were adapted from El Baz and Ruel (2021). Respondents indicated the extent to which their supply chains are able to: (1) retain the same operations, (2) grant sufficient time for reactions, (3) perform well in various scenarios without adaptations, and (4) carry out planned functions when disrupted. Measures of SCP were based on Gu et al. (2021), capturing the supply chain's performance in (1) quickly modifying existing offerings, (2) developing new offerings, and (3) shortening length of the supply chain process, (4) overall speediness, (5) supply chain knowledge, (6) on-time delivery, and (7) customer service level. To measure DT, we followed Faruquee et al. (2021) and asked respondents to indicate the level of adoption of AI, big data analytics, IoT, blockchain and cloud computing in their supply chains. A seven-point Likert scale was applied to all questions, with 1 indicating "very low" and 7 "very high". The survey instrument is presented in the Appendix.

Firm size, industry type, location, and the level of involvement in global supply chains were dealt with as control variables. Theoretically, large firms tend to possess more resources in the form of qualified personnel and tacit knowledge, which contribute to capabilities such as SCRes and SCRob (Yang et al., 2021). Further, we acknowledge that sub-sectoral differences may have an influence on the result (Dubey et al., 2018; Faruquee et al., 2021; Yang et al., 2021). Therefore, a dummy variable of sub-sector was created to control the influence of sub-sectoral heterogeneity. Moreover, according to Bray et al. (2019), suppliers' physical proximity to the focal firm plays an important role in flows of materials, information, and capital along the chain. Therefore, the level of involvement in the global chain was also included as a control variable.

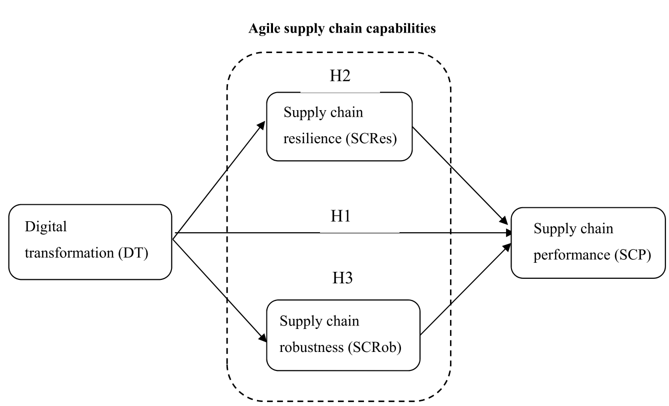

Fig. 1. Conceptual model.

4.2. Sampling and data collection

The unit of analysis in this study is the organization. A pilot study was conducted with 30 respondents before the survey was launched officially to ensure the readability, interpretability, and structural accuracy of the questionnaire. We collaborated with a professional market research company in China to collect data. Such professional support is a popular alternative to traditional approaches and has been increasingly used in recent studies (e.g., Faruquee et al., 2021; Revilla and Saenz, 2017). The questionnaire was emailed to key informants of companies, together with a cover letter with instructions, purpose of the survey, and assurance of confidentiality. To ensure the collection of high-quality data, quality check procedures were applied (Schoenherr et al., 2015). Stringent qualification criteria were established, restricting participation to senior executives or departmental heads of operations, supply chain, production, and procurement, who were believed to possess substantial knowledge of their companies' use of digital technology and operations. Respondents who did not pass through the qualifying checkpoints could not access the main survey.

With the help of the research company, the questionnaire was emailed to a total of 760 randomly selected manufacturing enterprises across mainland China in August 2022. After two and half months and four polite reminder emails, 257 complete responses were returned and

Table 2
Sample demographics.

Industry	%		%
Electrical machinery and equipment	17.1	*Sales (mRMB)*	
Special equipment	13.6	<5	2.3
Metal, mechanical and engineering	32.3	5–10	6.6
Building materials and furniture	4.7	10–50	19.5
Food, beverage, alcohol and cigarettes	8.6	50–100	29.2
Chemicals and petrochemicals	6.2	100–300	19.1
Fabric	9.7	>300	23.4
Rubber and plastics	3.5		
Others	4.3		
Number of employees	%	*Region*	%
<21	0.8	Yangzi river delta	32.7
21–300	21.8	Pearl river delta	18.7
301–1000	42.0	Bohai Bay economic rim	10.5
1001–2000	12.1	Middle South China	16.0
2001–3000	7.4	Northeast China	10.1
>3000	16.0	Other areas in China	12.0
Ownership	%		
Private	54.5		
State-owned	20.2		
Joint venture	19.1		
Foreign	6.2		
Tenure of respondent in organization (years)	%	*Position of respondent in organization*	%
1–5	9.0	Chief executive officer (CEO)	3.5
6–10	23.7	Senior managers/ departmental heads	96.5
11–15	24.1		
16–20	23.4		
>20	19.8		

considered valid, representing a response rate of 33.8%. Table 2 shows the demographic statistics of the sample.

4.3. Non-response bias (NRB) and common method bias (CMB)

Following Armstrong and Overton (1977), NRB was assessed by comparing firm characteristics of early (119) and late responses (138). T-test results show no significant difference between these two groups of responses in terms of firm annual revenue, level of global supply chain involvement, location and ownership type ($p = 0.449$, $p = 0.137$, $p = 0.111$, $p = 0.828$, respectively). Thus, non-response bias is not a serious concern in our study.

To control for CMB, we followed Podsakoff and Organ (1986) to place conceptually related variables far apart in the questionnaire to avoid unconsciously consistent responses. To test whether CMB affected the results, we performed Harman's single-factor test. Eleven factors with eigenvalues above 1.0 emerged, explaining 65.1% of the total variance, with the first factor explaining 28.4%. Hence, CMB is not a serious problem.

4.4. The measurement model

Partial least squares structural equation modeling (PLS-SEM) was performed using Stata 18.0 to analyze data. First, confirmatory factor analysis (CFA) was carried out to assess convergent validity and discriminant validity of the constructs. Items with low factor loadings were removed from subsequent analysis, and the remaining items for each construct are presented in Table 3. Model fit indices, including $\chi^2 = 1883.675$, df $= 136$, root mean square error of approximation (RMSEA) $= 0.057$, comparative fit index (CFI) $= 0.947$, and standardized root mean square residual (SRMR) $= 0.045$, indicate a good fit between the collected data and the proposed model (Hu and Bentler, 1999).

Following the standard procedure of PLS-SEM (Hair et al., 2019), we first assessed the measurement model through item reliability, construct reliability and validity. As shown in Table 3, the standardized factor loadings for all measurement items exceed the threshold of 0.7, indicating good item reliability. Cronbach's α values of all variables are above 0.7, composite reliability (CR) values are greater than 0.8, and average variance extracted (AVE) values are above 0.5, indicating sufficient reliability and validity of constructs (Hair et al., 2019). Discriminant validity is established for all constructs, as shown in Table 4. The square root of the AVE for each construct is greater than its correlations with other variables.

Table 4
Square root of AVE and correlation matrix of constructs.

		1	2	3	4
1	Digital transformation (DT)	N/A			
2	Supply chain resilience (SCRes)	0.589***	N/A		
3	Supply chain robustness (SCRob)	0.555***	0.770***	N/A	
4	Supply chain performance (SCP)	0.638***	0.690***	0.660***	N/A
	Square root of AVE	0.726	0.777	0.791	0.760

Note(s): sample size = 257, $*p < 0\ 0.05$; $**p < 0\ 0.01$; $***p < 0\ 0.001$.

Table 5
Estimation results.

Panel A: Structural model results

Hypothesis	Path	Coefficient	p-value	Result	Model fit
					R^2_a
H1	DT → SCP (Direct)	0.317	0.000	Supported	0.575
	DT → SCP (Indirect)	0.320	0.000		0.575
	DT → SCP (Total)	0.638	0.000		0.575
H2	DT → SCRes	0.589	0.000	Supported	0.345
	SCRes → SCP	0.320	0.000		0.575
H3	DT → SCRob	0.555	0.000	Supported	0.306
	SCRob→ SCP	0.238	0.000		0.575

Panel B: Parallel mediating effects

IV MV DV	coefficient	SE	p-value	95% CI: Confidence Interval
DT - > SCRes - > SCP (H2)	0.188***	0.050	0.000	[0.089 0.287]
DT- > SCRob - > SCP (H3)	0.127**	0.043	0.003	[0.044 0.211]
DT- > Total indirect effect of SCRes and SCRob- > SCP (H1)	0.315***	0.062	0.000	[0.192 0.437]

Note(s): 5000 bootstrap sample size is used for the PLS-SEM estimation. Firm size, industry type, location and the level of involvement in global supply chains are treated as control variables. They are not found significantly related to the DVs and are not reported here.
$^{\dagger}p < 0.1$, $*p < 0.05$, $**p < 0.01$, $***p < 0.001$.

Table 3
Constructs and indicators.

Construct	Indicator*	Cronbach's α	Composite Reliability (CR)	AVE	Factor loading
Digital transformation (DT)	DT1	0.776	0.848	0.527	0.732
	DT2				0.738
	DT3				0.743
	DT4				0.716
	DT5				0.700
Supply chain resilience (SCRes)	SCRes1	0.780	0.859	0.604	0.743
	SCRes2				0.719
	SCRes3				0.837
	SCRes4				0.805
Supply chain robustness (SCRob)	SCRob1	0.801	0.869	0.625	0.756
	SCRob2				0.805
	SCRob3				0.764
	SCRob4				0.836
Supply chain performance (SCP)	SCP4	0.756	0.845	0.578	0.799
	SCP5				0.752
	SCP6				0.761
	SCP7				0.727

Note(s): Original measurement items for each construct are shown in the Appendix.

4.5. The structural model

We then ran the structural model using 5000 bootstrap samples, and the results of the path coefficients are shown in Table 5. In Panel A, the direct effect of DT on SCP is significantly positive ($b = 0.317$, $p < 0.001$), supporting H1. DT is also found to be significantly related to both SCRes and SCRob ($b = 0.589$, $p < 0.001$; $b = 0.555$, $p < 0.001$, respectively). Both SCRes and SCRob positively relate to SCP ($b = 0.320$, $p < 0.001$; $b = 0.238$, $p < 0.001$, respectively). Additionally, the indirect effect of DT on SCP is positive and significant ($b = 0.320$, $p < 0.001$). Therefore, H2 and H3 are supported, indicating a partial mediation effect of SCRes and SCRob on the DT-SCP relationship.

We followed Preacher and Hayes (2008) by using a parallel mediation model since our proposed model includes two mediators. We ran the analysis with 5000 bootstrap samples, and the estimation results are shown in Panel B of Table 5. The results indicate significant indirect effects of the independent variable, DT, on a firm's SC performance through SCRes and SCRob ($b = 0.188$, $p < 0.001$; $b = 0.127$, $p < 0.01$), further supporting H2 and H3.

4.6. Robustness checks

To check the robustness of the results, we conducted further tests to eliminate potential biases. First, we used ordinary least squares (OLS) regressions as an alternative method to assess the sensitivity of the PLS-SEM model. Firm size, industry type, location, and the level of involvement in global supply chains were included in the estimation. As shown in Table 6, in Model 3, the effect of DT on SCP is significantly positive ($b = 0.669$, $p < 0.001$), supporting H1. In Models 1 and 2, DT is significantly related to both SCRes ($b = 0.556$, $p < 0.001$) and SCRob ($b = 0.512$, $p < 0.001$). In Models 6 and 7, both SCRes and SCRob are found to positively relate to SCP ($b = 0.216$, $p < 0.001$; $b = 0.195$, $p < 0.001$, respectively). When SCRes and SCRob are treated as mediators, the effect of DT on SCP is weakened but remains positive and significant ($b = 0.140$, $p < 0.001$; $b = 0.155$, $p < 0.001$, respectively), indicating a partial mediation effect of SCRes and SCRob on the DT-SCP relationship. Therefore, H2 and H3 are supported.

To further assess the robustness of the results, we applied cluster analysis to classify firms based on their DT levels. This approach has been widely used in similar studies for robustness checks (e.g., Karahanna et al., 2019). Following Sullivan et al. (2023), we first predetermined the number of clusters by dividing firms into three groups: low-level, medium-level, and high-level of DT. We then applied the k-means algorithm to generate three-cluster solutions. Using cluster membership as a control variable, we found that firms with high level of DT exhibited a higher degree of SCRes and SCRob, as well as better SCP. However, the difference between the low and medium DT level groups was not significant in terms of SCP. Overall, our robustness tests remained qualitatively consistent with the main analysis in terms of significance and direction.

5. Discussion

Through a novel theoretical perspective of the data network effect, our study empirically validates the effect of DT on SCP, through the mechanisms of improved agile capabilities of SCRes and SCRob. We operationalize DT as the implementation of a wide portfolio of digital technologies, including big data analytics, IoT, AI, blockchain, and cloud computing. We propose that the data network effect is generated through data creation and collection, data analysis and sense-making, and data-sharing among supply chain members, in the form of enhanced supply chain capabilities (intangible) and performance (tangible). Our result is consistent with past studies which have confirmed the positive effect of DT on capabilities and performance (e.g., Belhadi et al., 2022; Li et al., 2023; Yuan et al., 2023). However, our study is novel in terms of employing the perspective of data network effect to explain how DT improves the common and distinct underlying capabilities of SCRes and SCRob at the same time and consequently influences SCP in various environmental conditions. Therefore, this study makes significant contributions to the supply chain management literature and practice.

5.1. Theoretical contribution

First, our study contributes to the DT literature, especially in the context of supply chain management. While a growing body of research is interested in exploring the implications of DT in supply chains, it remains unclear what DT really means. In other words, more knowledge is needed for clarifying what a digitally transformed organization or supply chain is like and what the process of DT exactly entails. Our study

Table 6
Regression results.

DV	SCRes	SCRob	SCP	SCP	SCP	SCP	SCP
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
Constant	−0.728[d]	−0.800[d]	0.189	−0.583[b]	−0.619[b]	−0.474[b]	−0.485[b]
	(0.291)	(0.353)	(0.279)	(0.255)	(0.266)	(0.232)	(0.236)
Control variable							
Firm size	0.083[b]	0.071[a]	−0.023	−0.029	−0.023	−0.025	−0.021
	(0.041)	(0.048)	(0.039)	(0.037)	(0.039)	(0.034)	(0.034)
Global chain involvement	0.055	0.090	−0.039	0.123[c]	0.121[b]	0.096[b]	0.092[b]
	(0.055)	(0.056)	(0.052)	(0.047)	(0.050)	(0.043)	(0.044)
DT	0.556[d]	0.512[d]	0.669[d]			0.140[d]	0.155[d]
	(0.053)	(0.055)	(0.051)			(0.019)	(0.021)
SCRes				0.309[d]		0.216[d]	
				(0.048)		(0.024)	
SCRob					0.293[d]		0.195[d]
					(0.036)		(0.024)
N	257	257	257	257	257	257	257
R2	0.407	0.359	0.308	0.352	0.380	0.420	0.406

Note(s): Standard errors are in parenthesis. The coefficients of industry type and location are control in all models, but since they are both a range of dummy variables, we do not report them in the table.
Standard errors are in parenthesis.
[a] $p < 0.1$.
[b] $p < 0.05$.
[c] $p < 0.01$.
[d] $p < 0.001$.

proposes that DT is an ongoing data-driven process, where multiple digital technologies continuously work around and with data to nurture and propel data network effect. Specifically, different digital technologies serve different purposes for DT and data network effect. For instance, IoT and big data analytics create and capture data, AI analyzes and makes sense of data, and blockchain and the cloud store and share data. The co-implementation of these technologies strengthens data stewardship, user-centeredness and the governance legitimation of the supply chain, creating an environment for data network effect to emerge. Empirically, we operationalize the DT process as the implementation of a wide portfolio of digital technologies that cover all these sub-processes. Our study therefore contributes to the DT literature by providing an account that is novel in conceptualization and feasible in operationalization (Vial, 2019).

Further, our study contributes to the intellectual development of digital technology research, in particular from the phenomenon and theorizing of data network effect. Originating from the platform literature, data network effect is proposed to explain the enhanced value of a platform and its offerings to users as a result of the platform collecting and learning from mounting user data (Gregory et al., 2021). While the importance and occurrence of data network effect is increasingly acknowledged (e.g., Haftor et al., 2021, 2023), related theoretical and empirical development is largely absent from the area of supply chain management, despite the growing emphasis on the use of digital technologies by researchers from the supply chain management community. Therefore, our study serves as a pioneer to extend the data network effect concept to the supply chain context, and empirically validates the DT-enabled data network effect through enhanced CSP (tangible) and the improved agile capabilities (intangible). To guard performance against various environmental conditions, supply chains need to have both SCRes to respond effectively to disruptions and SCRob to maintain operations. Our study, through a thorough review of key literature on SCRes and SCRob, clarifies their underlying processes and how they work together to achieve supply chain management objectives. SCRes and SCRob are connected by sharing common supporting capabilities such as environmental scanning, sensing, and environmental sensemaking. Meanwhile, they also require distinct foundational capabilities. For instance, SCRes requires rapid resource reconfiguration while SCRob stresses variation absorption. Our study acknowledges that both SCRes and SCRob are data-driven capabilities and explains how DT can enhance them from the lenses of data stewardship, user-centric design, and platform legitimation. Specifically, the use of data capture and sensemaking tools, such as IoT and AI, enhances quality and quantity of data. Data sharing technologies like blockchain strengthen the governance legitimation of the supply chain while simplifying data access for users. DT can therefore enhance the performance of the supply chain directly and through improved supply chain agility.

5.2. Practical implications

This study also offers important management insights for practitioners. First, advancements in digital technologies provide new opportunities for firms and their supply chains to generate and deliver value which might not have been feasible before. Therefore, companies are advised to actively engage in DT to deploy the new strategic resource, i.e., data. Especially in the current business environment, where unprecedented events have disrupted the physical supply chain, managers are urged to utilize digital tools to maintain a seamless information chain. It is worth noting that digital technologies form a digital ecosystem to generate and connect data, and companies within a supply chain are advised to co-develop DT strategies and actively engage in the DT process. To fully realize the power and benefits of the data network effect, managers involved in the supply chain must carefully develop their data strategies. This ensures that all participants in the supply chain can achieve further benefits despite ongoing and often unexpected changes in the environment.

Second, the recent business environment is becoming more dynamic, and the need for agility is pushed to the forefront of supply chain management. Whereas some changes can be foreseen, others, such as the global pandemic and natural disasters, are hard to predict and prepare for. Therefore, in addition to their day-to-day operational practices, managers are advised to focus on the intangible assets, i.e., the development of agile capabilities, as a way of maintaining and improving performance in both normal and catastrophic times. It is crucial that companies understand different types of capabilities and unleash any synergies in their existing resources to nurture multiple capabilities together. For instance, DT can be utilized to advance SCRes and SCRob capabilities simultaneously, due to the affordance of digital technologies to help firms predict environmental changes and make adaptations accordingly, by capturing and making sense of big data. Therefore, managers are advised not to focus only on tangible indicators and quick returns in their decision-making. Attention should also be paid to intangible aspects such as capabilities, which may take time to be transformed into quantifiable benefits.

5.3. Limitations and future research directions

Despite the high conceptual novelty of our study and valuable contributions to the literature, it is not without limitations. First, we relied on self-reported, subjective data collected through a survey, which may not have captured the whole picture on the issues of interest, due to respondents' cognitive and knowledge bias and limits. Therefore, future studies are encouraged to make efforts to triangulate data sources. Second, our survey was conducted in a single country and in a single sector, and the findings may not be readily generalizable to other contexts. Therefore, the developed model should be validated in other contexts in the future. Third, in addition to SCRes, SCRob and SCP, data network effect can take other forms. We call for more works that empirically validate the existence of the data network effect.

CRediT authorship contribution statement

Lin Wu: Writing – original draft, Methodology, Formal analysis, Conceptualization. **Jimmy Huang:** Writing – review & editing, Writing – original draft, Project administration, Conceptualization. **Miao Wang:** Validation, Supervision, Project administration, Funding acquisition. **Ajay Kumar:** Writing – review & editing, Supervision, Project administration.

Data availability

Data will be made available on request.

Appendix

Measures
Digital Transformation (DT)
Extent of technology adoption in the supply chain:
DT1: Artificial intelligence (AI)

(continued on next page)

(*continued*)

Measures
DT2: Blockchain
DT3: Cloud computing
DT4: Internet of things (IoT)
DT5: Big data analytics
Supply chain resilience (SCRes)
SCRes1: Our supply chain can quickly return to its original state after being disrupted
SCRes2: Our supply chain has the ability to maintain a desired level of connectedness among its members at the time of disruption
SCRes3: Our supply chain has the ability to maintain a desired level of control over structure and function at the time of disruption
SCRes4: Our supply chain has the knowledge to recover from disruptions and unexpected events
Supply chain robustness (SCRob)
SCRob1: For a long time, our supply chain retains the same stable situation as it had before some changes occur
SCRob2: When changes occur, our supply chain grants us much time to consider a reasonable reaction
SCRob3: Without adaptations being necessary, our supply chain performs well over a wide variety of possible scenarios
SCRob4: For a long time, our supply chain is able to carry out its function despite some damage done to it
Supply chain performance (SCP)
SCP1: Our supply chain has the ability to quickly modify products to meet customers' requirements
SCP2: Our supply chain allows us to quickly introduce new products into our markets
SCP3: The length of the supply chain process is getting shorter
SCP4: We are satisfied with the speediness of the supply chain process
SCP5: Based on our knowledge of the supply chain process, we think that it is sufficient
SCP6: Our supply chain has an outstanding on-time delivery record
SCP7: Our supply chain provides high-level customer services

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