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Enhancing innovativeness and performance of the manufacturing supply chain through datafication: The role of resilience

Shuang Tian [a], Lin Wu [a], Maria Pia Ciano [a], Marco Ardolino [b,*], Kulwant S. Pawar [a]

[a] Nottingham University Business School, NG8 1BB Nottingham, UK
[b] Rise Laboratory, Università degli Studi di Brescia, Via Branze 38, 25123 Brescia Italy

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ABSTRACT

The Covid-19 pandemic has extremely affected the manufacturing supply chain (SC) highlighting the need to deploy dynamic capabilities (DCs) such as supply chain resilience (SCRes) that enable companies to react rapidly and exploit intangible assets to support long-term performance. Concurrent with the needs dictated by the pandemic, companies are faced with rapid technological development driven by Industry 4.0. Massive amounts of information lead to the need for effective 'datafication', where information is standardized and recorded through technologies such as the Internet-of-Things (IoT), and processed by others like Artificial Intelligence (AI). In the disruptive context, companies can remain competitive by turning the crisis into an opportunity for innovation and improving their performance. This study thus explores the impact of datafication, represented by IoT and AI implementation, on manufacturing SC performance and innovativeness and investigates the role of SCRes. Analyzing data collected from 311 Chinese manufacturing companies reveals that datafication positively influences supply chain innovativeness and performance, in which SCRes plays a mediating role. The finding contributes to the ongoing debate on how digital technologies can help organizations improve DCs and achieve competitive advantage. This research also encourages companies, particularly those in developing countries, to take full advantage of Industry 4.0 technologies.

1. Introduction

The Covid-19 pandemic unleashed profound and far-reaching consequences both socially and economically. Despite concerted efforts by governments and businesses to limit the spread of the virus, its deleterious effect on the economy is expected to have long-term repercussions (Ahmed et al., 2023; Ardolino et al., 2022a; Chatterjee et al., 2022). Unlike some service operations (e.g., legal services, consultancy) which depend mainly on the information flow, manufacturing as a process where the effective flow of physical materials is a prerequisite for any value-adding activities. The Covid-19 outbreak prompted local governments to implement strict measures, including lockdowns and closures, which have severely limited the availability of labor, materials, and consumables and led to widespread shutdowns of factories and distribution facilities (Paul and Chowdhury, 2020; Pathy and Rahimian, 2023). Moreover, the implementation of contagion-limiting practices, such as social distancing and remote work, has also resulted in operational challenges, work schedule adjustments, and spatial reorganization (Ardolino et al., 2022b). Furthermore, the Covid-19 epidemic has significantly impacted consumption and demand trends and consumer behavior, challenging the planning of production processes (Diaz-Elsayed et al., 2020). Consequently, an urgent task for the manufacturing supply chain is to respond quickly and appropriately to the change caused by the disruption and maintain performance.

Frequent disruptions occurred in recent years have made the imperative to develop capabilities that enable a responsive and resilient manufacturing supply chain more urgent. Referred to as 'supply chain resilience' (SCRes) in the supply chain management (SCM) literature, this capability is considered crucial for organizations to adapt to changes and recover from damage in a timely manner (Christopher and Peck, 2004; Owida et al., 2022; Ribeiro and Barbosa-Povoa, 2018; de Sa et al., 2023). The ability of manufacturing companies to implement SCRes strategies is vital for their survival and achievement, particularly in unstable environments. It ensures that they can sustain adequate performance levels over short-, medium-, and long-term periods (Belhadi et al., 2021; Owida et al., 2022; Rahman et al., 2022). SCRes can be

* Corresponding author.
E-mail addresses: Shuang.Tian@nottingham.ac.uk (S. Tian), Lin.Wu@nottingham.ac.uk (L. Wu), Maria.Ciano@nottingham.ac.uk (M. Pia Ciano), marco.ardolino@unibs.it (M. Ardolino), Kul.Pawar@nottingham.ac.uk (K.S. Pawar).

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considered a type of dynamic capability (DC) (Kähkönen et al., 2021; Belhadi et al., 2022a), namely an ability to integrate, build and reconfigure the competencies to address changes (Teece et al., 1997). There has been much debate in literature on the crucial role of SCRes in coping with disruptive events such as the Covid-19 pandemic (Ozdemir et al., 2022; Queiroz et al., 2022a; Belhadi et al., 2021; Ivanov, 2020). However, although the pandemic has strongly affected the manufacturing supply chain, literature concerning DCs in the wider context of the SC, in particular SCRes, is still scarce (Ivanov, 2021; Kähkönen et al., 2021; Rahman et al., 2022).

Developing SCRes is by no means an easy task. Fortunately, industrial digital solutions empowered by modern digital technologies have brought hope (Agrawal et al., 2020; Ivanov, 2021; Gupta et al., 2022; Spieske and Birkel, 2021; Ardolino et al., 2022b). Digital technologies are found to enhance manufacturing SCRes, improving process efficiency, productivity, and worker safety (Ardolino et al., 2022b. Moreover, the use of digital technologies supported with experience and knowledge can improve supply chain memory to achieve resilience (Alvarenga et al., 2023). For example, IoT can enhance adaptability to changes by offering solutions that are secure, affordable, and capable of scaling, whereas conventional systems might hinder such flexibility and adjustments (Kopanaki, 2022). In addition, IoT sensors facilitate inventory management, traceability (Khan et al., 2022; Kayikci et al., 2022) and automate purchasing processes to maintain standard stock levels, reducing supply chain costs (Wu et al., 2020; Alsudani et al., 2023). When physical contact is limited, digital solutions can also enable distant operations, process mechanization, self-regulated machine performance, and a potential decrease in on-site staff in manufacturing operations (Ardolino et al., 2022a; Kamal, 2020). Also, Artificial Intelligence (AI) techniques such as machine learning and agent-based systems are crucial in supporting SCRes due to the large amount of data generated across supply chains that needs to be utilized (Belhadi et al., 2022). AI-powered image analysis can help monitor product quality and detect defects in manufacturing, reducing human supervision requirement and mitigating the risk of contagion (Di Vaio et al., 2020). Moreover, AI technologies have facilitated the development of novel methods in the supply chain, such as predictive analytics for risk assessment, machine learning algorithms to adapt to fluctuating market dynamics, and intelligent automation to increase efficiency, which all contribute to enhanced supply chain resilience (Ivanov, 2023, Zamani et al., 2022; Belhadi et al., 2022b).

The power of digital solutions to support manufacturers to cope with crises comes from digital technologies' ability to collect and analyze vast amounts of data accurately and efficiently. This process has been conceptualized in existing literature as "datafication," defined as the process of gathering, organizing, quantifying, and analyzing information to create knowledge and enhance economic value (Mayer-Schönberger and Cukier, 2013). Effective datafication is fundamental for the manufacturing supply chain as it supports the strategic actions of navigating disruptions and ensuring operational continuity (Bag et al., 2021; Mageto, 2021). In addition, it can assist businesses to maintain the flow of information and resources when coping with physical disturbances in the SC, enabling them to react to disruptions and restore operations timely (Yu et al., 2018). Despite the potential role datafication plays in the SC, existing literature on datafication reveals a persistent gap, as evidenced by Jones (2019), indicating the absence of a consistent and widely applicable operationalization of datafication. This limitation has hindered empirical advancements and impeded comprehensive understanding within the field (Holtzhausen, 2016). Our study aspires to bridge this gap by proposing an empirical operationalization of datafication based on its processes and functionalities of digital technologies. Specifically, we use the implementation of IoT (for data generation and collection) and AI (for data analysis and sensemaking) to represent the extent of datafication, which is further justified in the next section.

The ultimately purpose of manufacturing supply chains deploying datafication and developing SCRes is to maintain and improve performance in various environmental conditions. Supply chain performance (SCP) is a widely applied indicator in SCM literature to measure the overall efficiency and effectiveness of the SC during a certain period (Bahrami et al., 2022). SCP typically includes operational indicators such as speediness, sufficiency, on time delivery, and customer service of the supply chain (Gu et al., 2021). Existing studies show that inter-organizational and intra-organizational ICT use (Zhang et al., 2016), climate change risk (Er Kara et al., 2021) and lean six sigma practices (Selvaraju et al., 2019) are positively related to SCP. In fact, in turbulent times, organizations tend to adopt a cautious approach, prioritizing the preservation of their operations as measured by these basic aspects over investing in riskier endeavors such as exploratory innovations (Visser and Scheepers, 2021). However, at the same time, the long-lasting adverse effects of the pandemic necessitate that businesses deploy strategies for the short-, medium-, and long-term by embracing innovative solutions that can transform crises into value-creating opportunities (Hopkins, 2021). Given innovation's importance for organizational success and the macro-economic growth (Wong and Ngai, 2022), our study regards both SCP and supply chain innovativeness (SCI), typically measured by a SC's ability to introduce new products, services and processes (Panayides and Lun, 2009), as potential outcomes of datafication and SCRes in the short- and long-run.

Based on the above discussions, despite the importance of datafication in the SC, how it affects SCI and SCP remains less clear (Flensburg and Lomborg, 2021; Arunachalam et al., 2018; Kache and Seuring, 2017). Furthermore, the scientific literature generally investigates SCRes as the final outcome of the application of digital technologies (Leoni et al., 2022; Nayal et al., 2023; Cui et al., 2023), however, the possibility of how enhanced SCRes capability can affect the performance and innovative of the manufacturing supply chain remains an under-investigated issue. Therefore, our study aims to address the following research questions (RQs):

RQ1: *How does datafication affect SCI and SCP under the circumstance of a major disruption?*
RQ2: *What is the role of SCRes in the relationship between datafication and SCI and SCP?*

To shed light on these questions, we draw upon the Dynamic Capabilities Theory (DCT) and the extant literature on SCM to develop a conceptual framework, and empirically validate it through a large-scale survey with Chinese manufacturing enterprises. Our study aims to offer novel insights to existing literature in several ways. First, based on existing conceptualization, our study operationalizes datafication empirically using two representative digital technologies for data creation and analysis, IoT and AI. This operationalization captures the essence of processes involved in datafication and serves as the foundation for understanding the role datafication plays in supply chains in turbulent environments. Second, our study provides empirical evidence on how datafication affects the performance and innovativeness of the manufacturing supply chain in the context of Covid-19. More importantly, we reveal the mediating role of SCRes capability. We showcase that SCRes is not merely an intangible outcome of successful datafication, but also serves as a bridging factor between datafication and more tangible outcomes such as SCP and SCI. Third, our discourse is placed within the DCT, acknowledging that businesses operate in ever-changing environments that necessitate resilient strategies, underscored by real-world experiences during the disruptive Covid-19 pandemic which shook global economic activities. Our results extend the use of DCT beyond the organizational boundary to the wider context of the SC. The remaining paper is organized as follows. Section 2 presents the theoretical background of the study, followed by Section 3 where hypotheses and the conceptual model are developed. Section 4 introduces the method, and Section 5 illustrates the results of data analysis. The key findings are discussed with reference to prior studies in Section 6. Section 7 concludes the paper by summarizing the

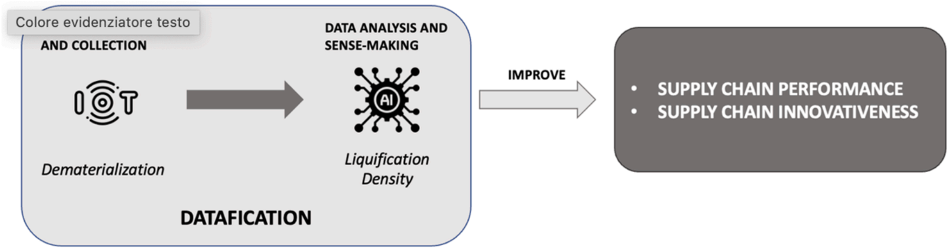

Fig. 1. Conceptual framework.

contributions and limitations of the study and opportunities for future research.

2. Theoretical background

2.1. Datafication

Data has become a vital capital driving organizational innovations (Sadowski, 2019). A data-driven culture is a crucial intangible asset to make effective use of data for decision-making in the SC (Gupta and George, 2016). Indeed, decision-making quality influences the global performance of the SC and decision-making based on empirical evidence rather than instincts ensures greater opportunities for improvement of business performance (Awan et al., 2021).

According to Mayer-Schönberger and Cukier (2013), datafication encompasses the structured processes of recording and quantifying different types of data for value-generating purposes, including standardization, typification, customization and optimization. It can also be seen as a technological process characterized by three founding aspects, namely, dematerialization, liquefaction and density (Lycett, 2013). Dematerialization emphasizes the capacity to disentangle a resource's informational component and its use in context from the physical world. Liquification follows dematerialization, where information is readily manipulated to unbundle the previously physically connected resources and activity sets. As the result of the value generation process, density is the optimal combination of resources mobilized for a certain environment, at a given time and location. While dematerialization provides the conceptual basis for data generation and collection, liquification and density, enabled by analytics, is the key to exploiting the value of data through analysis and sense-making. The result of analytics can be incorporated into complex organizational decision-making processes and empower value-driven actions. In this way, datafication becomes a true sense-making process driven by information technology (Lycett, 2013).

To delineate the processes of datafication, this study divides them into two macro-processes encompassing the above-mentioned concepts: 'data generation and collection' and 'data analysis and sensemaking'. To carry out these two macro-processes effectively, companies strategically adopt various digital technologies to keep abreast of datafication for better decision-making (Fan et al., 2015). Based on the functionalities of digital technologies, our study uses two representative technologies proven to create a synergic system for datafication, namely: IoT for data generation and collection, and AI for data analysis and sensemaking (Tzafestas et al., 2018; Kuzlu et al., 2021; Manavalan and Jayakrishna, 2019; Kumar et al., 2022). Fig. 1 illustrates the conceptual framework of the datafication process with the roles IoT and AI play, and the expected benefits to the implementing organization.

2.2. Operationalization of datafication: IoT and AI

Datafication has been well conceptualized in literature without a generally accepted operationalization. As mentioned above, our operationalization reflects the different processes and technologies involved in datafication. In fact, the use of multiple technologies in organizations has received much attention in the scientific literature recently, which has made valuable contributions to pressing issues such as sustainability (Lei et al., 2023; Liu et al., 2023), quality inspection (Sundaram and Zeid, 2023), knowledge management in the enterprises (Leoni et al., 2022; Zhang et al., 2022), and smart farming (Alves et al., 2023). It is evident that IoT and AI have been widely applied for the effective management of data especially in the manufacturing SC (Singh et al., 2023; Javaid et al., 2022), and it is appropriate to operationalize datafication using these technologies.

The Internet of Things (IoT) is the intricate interconnection of sensing and actuating devices, facilitating information collecting and sharing across platforms via a unified framework. This fosters a cohesive operational paradigm and drives innovative applications. The synergy between systems is achieved through seamless integration of extensive sensing, advanced data analytics, and efficient information representation, supported by IoT tools create data by efficiently tracking and tracing products and shipments, providing real-time data on the location of goods, their storage conditions and arrival time (Katsaliaki et al., 2021; Muñuzuri et al., 2020; Nozari and Nahr, 2022). It can also be applied to inventory management to enhance accuracy and reduce human involvement by tracking product flow via RFIDs, supply chain-based sensory networks and bar codes (Fan et al., 2015; Khan et al., 2022; Fang and Chen, 2022) enhanced transparency and resilience (Siriwardhana et al., 2020). Recently, digital solutions for process production and decision-making to accomplish energy efficiency, output optimization, and economically viable manufacturing have become a prominent research area. A comprehensive literature review by Tan et al. (2023) summarizes the current state of research on scheduling practices in the manufacturing industry within an IoT environment. It is agreed that IoT tools play a pivotal role in generating and recording big data, which serve as valuable input parameters for data analyzing technologies such as AI (Queiroz et al., 2021; Saravanan et al., 2022; Bi et al., 2023).

AI is currently one of the most widely applied technologies for data-driven decision-making for organizations (Baryannis et al., 2019; Ramirez-Asis et al., 2022). Ahmed et al. (2023) emphasized the paramount importance of real-time tracking of SC activities through IoT as the primary AI-based imperative for enhancing the survivability of manufacturing SCs. Younis et al. (2022) conducted a systematic literature review on AI, machine learning (ML), and SCM, revealing the benefits of digital solutions in reducing the bullwhip effect and enhancing efficiency. In contexts characterized by sudden fluctuations in demand patterns, SCs struggle to achieve adequate service level agreements with customers (Modgil et al., 2022). Thanks to the prediction capabilities of AI-based technologies, it is possible to make assumptions about how future events might affect SC operations (Pournader et al., 2021; Ganesh and Kalpana, 2022; Shah et al., 2023; Jauhar et al., 2023).

2.3. Supply chain innovativeness and performance

In the digital era, innovations are intricately linked to the corporate social networks, which encompass diverse interactions with stakeholders (Bhatti et al., 2022). Leveraging digital technologies, companies can gather substantial volumes of data through their own operations and social interactions, utilizing this information to make well-informed decisions regarding innovation (Bahrami et al., 2022; Chatterjee et al., 2022; Haefner et al., 2021). In this vein, SCI is considered as “a change (incremental or radical) within the supply chain network, supply chain technology or supply chain processes (or combinations of these) that can take place in a company function, within a company, in an industry or a SC to enhance new value creation for the stakeholder” (Arlbjørn et al., 2011, p. 8). SCI enables firms to strategically address and surpass the demand for enhanced competitiveness in the increasingly dynamic landscape, to achieve which data-driven decision-making and actions are crucial (Orlando et al., 2022; Feng et al., 2022; Hopkins, 2021).

At the same time, we look at the operational performance of the supply chain through SCP, which encompasses the evaluation of how effectively and efficiently goods, materials, and information move through the processes within a SC, from suppliers to end customers. It evaluates the capacity of the SC to satisfy customer needs by ensuring product availability and prompt delivery (Gu et al., 2021). In the manufacturing SC, fluctuating market demands and growing competitive pressures are growing threats to maintaining SCP that require more creative and effective solutions (Ozdemir et al., 2022). In this study, we include both SCI and SCP as potential outcomes of datafication against the background of a major disruption, aiming to capture the maintaining of existing value and new value creation mechanisms that can be brought by digital transformation.

2.4. Dynamic capabilities theory

The DCT is rooted in the criticism and extenuation of the resource-based view (RBV) (Barney, 1991). Scholars have argued that RBV cannot be applied to dynamic markets where market players are not always distinguishable, market boundaries are not clear and changes often occur (Eisenhardt and Martin, 2000). Under such circumstances, the DCT proposes that business organizations engage in market competition based on new value creation strategies developed from inimitable, rare, valuable, and irreplaceable resources (Teece et al., 1997). According to the DCT, an organization is a dynamic system made up of resources, procedures, and activities (Gruchmann and Seuring, 2018). To quickly respond and adapt to changes from disruptive threats, organizations need to create or enhance dynamic capabilities (DCs) through adjusting their processes and resource base (Eisenhardt and Martin, 2000). The micro foundations of any DC should therefore include sensing, seizing and reconfiguring capabilities (Teece, 2007). Beyond the organizational level, the SC is a complicated system where DCs are needed to address internal dynamics and environmental changes (Fan and Stevenson, 2018). Therefore, even though the DCT is mainly applied at the organizational level, it is well suitable for assessing performance of the SC (Defee and Fugate, 2010; Ponomarov and Holcomb, 2009).

The emergence of Covid-19 intensifies the ever-changing environment where businesses are required to work together, combine, and rearrange both internal and external resources and abilities to minimize interruptions and disruptions (Ambulkar et al., 2015). Indeed, the DCT specifically emphasizes innovation and value creation (Katkalo et al., 2010) and is particularly relevant to our research questions and context as value creation and innovativeness often stem from adapting to changes in the external environment (Teece, 2007; Ellonen et al., 2009). Thus, the DCT is a suitable theoretical framework to examine how SCI and SCP can be enhanced by DCs in volatile market environments.

2.5. Supply chain resilience as a dynamic capability

SCRes is considered a form of DC and the DCT is increasingly embraced as the theoretical foundation of SCRes-related studies due to its power to help organizations cope with unavoidable risk factors, react to unexpected SC disruptions (Dubey et al., 2020; Ruel and El Baz, 2021; Silva et al., 2023; Belhadi et al., 2022a; Rahman et al., 2022; Brusset and Teller, 2017; Zamani et al., 2022), and cushion impacts from various sources(Ozdemir et al., 2022; Orlando et al., 2022).

The concept of resilience capability was first introduced by Lengnick-Hall et al. (2011), which explained how the capability equips an organization to react to destabilizing incidents that may pose a risk to its continued existence. In the supply chain context, SCRes, defined as capability of a system to return to its initial state or transition to a novel and more desirable state after being influenced by an external event, empowers businesses to identify risks proactively prior to unforeseen occurrences and cope with changes effectively (Christopher and Peck, 2004; Wieland and Durach, 2021). Chowdhury and Quaddus (2017) formulated a three-tiered SCRes framework based on the DCT, including supply chain design quality along with proactive and reactive abilities. SCRes focuses on the prompt foresight of risks, suitable gathering and utilization of resources, and the rearrangement of SC assets during emergencies. This capability aids in preserving a competitive edge and stable performance standards in an unpredictable setting, which builds on the micro foundations of DCs (Zhao et al., 2023).

The adoption of DCT as a theoretical basis to ground the performance implication of SCRes is quite diffused in scientific literature. For instance, Zhao et al. (2023) formulated a theoretical structure that demonstrates how supply chain digitalization promotes SCRes, subsequently impacting SCP, based on the DCT. Hamidu et al. (2023) adopted the same approach to investigate the effects of supply chain disruption on SCRes and SCP. Therefore, DCT is an appropriate lens through which the antecedents and outcomes of SCRes are examined.

3. Hypothesis development

3.1. Datafication and SCI and SCP

Based on the above, datafication is operationalized based on processes of data generation and collection, and data analysis and sense-making, using two representative technologies, IoT and AI. Datafication provides massive amounts of data resources and data-driven insights, which are crucial for innovativeness and performance of the manufacturing SC (Mention et al., 2019). As Harapko (2021) points out, as a sector heavily disrupted by the Covid-19 pandemic, the future of the manufacturing SC lies in digitalization. Specifically, IoT is capable of real-time monitoring in the SC (Weber, 2009), which enables real-time data capture and resolve information gaps that could cause misalignments in manufacturing SCs (Ping et al., 2018). The real-time data gathered through IoT technologies help track SC processes, improve the collaboration and coordination among resources (Mishra et al., 2016). Rich data and a sharing environment serve as an important condition for the manufacturing SC to identify problems swiftly and develop novel solutions (Ben-Daya et al., 2019).

On the other hand, IoT implementation can improve SC visibility and predictive ability through efficiently capturing real-time data, which is recognized by most manufacturers to be the priority for the post-Covid period (Harapko, 2021). IoT enables the monitoring of goods and the assessment of crucial metrics throughout the entire SC which improves the operations efficiency and risk management strategies (Birkel and Hartmann, 2020; Lee et al., 2022; Haghnegahdar et al., 2022). It has been demonstrated that data generated through IoT can provide unprecedented visibility across the entire SC, enabling early detection and response to both internal and external issues. For instance, Yuvaraj and Sangeetha (2016) integrated RFID with GPS technology to enable remote tracking and monitoring of goods. In addition, Hu et al. (2023) proposed an intelligent vaccine SC management system that incorporates IoT, machine learning and blockchain to achieve real-time monitoring of vaccine status. Furthermore, Mantravadi et al. (2023) proposed a framework for smart factory capabilities, based on Industrial Internet of Things (IIoT) connected manufacturing execution systems (MES) to enhance flexibility in manufacturing SCs. Based on the

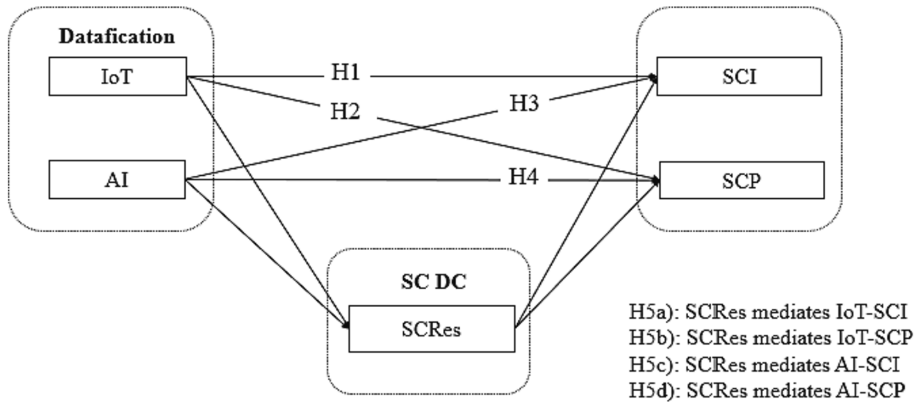

Fig. 2. Research model and hypotheses.

confirmed and proposed role IoT can play in the manufacturing SC, we propose that:

H1: IoT positively affects SCI.
H2: IoT positively affects SCP.

AI is another facet of datafication, which has been extensively adopted by manufacturers driven by the rapidly growing amount of data and its complexity (Sharma et al., 2022). AI technologies can better manage data flows in the SC (Baryannis et al., 2019) and help gain augmented knowledge from the external environment (Dubey et al., 2021). Moayedikia et al (2020) implemented AI in simulation modelling to improve decision-making through advanced perception of system behaviors. Furthermore, AI facilitated administrators to identify and anticipate disruptions that influence system operations and supported with system restoration in a more data-driven and responsive manner (Abedinnia et al., 2017; Sharma et al., 2022; Dey et al., 2023). Therefore, the adoption of AI-based technologies has the potential to accelerate decision-making by facilitating the development of new solutions (Wamba et al., 2020; Bhargava et al., 2022). Manufacturing SCs with integrated AI applications are in a better position to innovate due to the knowledge advantage AI technologies can offer (Modgil et al., 2022).

At the same time, AI encompasses numerous adaptive and self-learning techniques, which can deal with multiple data resources and provide the SC with the capability to be self-adaptive and more agile (Modgil et al., 2022; Baryannis et al., 2019). The utilization of AI in decision-making for SC optimization can be categorized into optimization algorithms, expert decision systems, planning and scheduling methods, as well as simulation techniques (Pournader et al., 2021; Belhadi et al., 2022a). These techniques have been demonstrated to address various operational and SC optimization challenges (Kehayov et al., 2022; Moayedikia et al., 2020; Saghaei et al., 2020). Therefore, when faced with disruptions, SCs with higher AI adoption tend to be less affected and more likely to maintain the overall performance as they already have mitigation strategies in place enabled by accurate and timely sensemaking of data (Dubey et al., 2021; Leoni et al., 2022). Thus, we hypothesize that:

H3: AI positively affects SCI.
H4: AI positively affects SCP.

3.2. The mediating role of SCRes

In addition to the direct effect on SCI and SCP, datafication technologies are expected to have intangible benefits in the form of an important SC DC, SCRes. According to the DCT, DCs are the real source of organizational competitive advantage, and they can be built through effective organizational learning (Bingham et al., 2015; Ambrosini and Bowman, 2009; Ambrosini et al., 2009, which is increasingly enabled by digital tools (Mention et al., 2019; Warner and Wäger, 2019). In this research, SCRes is considered as a DC that helps the SC effectively adapting, responding, and recovering from disruptions, and improving financial and market performance (Yang and Hsu, 2018). IoT and AI have the potential to support SCRes through enhancing flexibility and responsiveness of the SC to mitigate disruptions. The information provided by IoT provides the condition for data-driven decision-making (Mishra et al., 2016), allowing the improvement of flexibility, adaptivity, agility and responsiveness of the SC to cope with market uncertainty (Winkelhaus and Grosse, 2020). As AI makes it easier for the SC to identify areas of disruption (Wamba et al., 2020), quick and effective actions can be taken and SCRes strengthened as a result. In summary, datafication can help firms improve their SC visibility, strengthen the ability of short-term predictions, and devise better control mechanisms and adaptive systems through collecting and making sense of big data, leading to stronger SCRes capability (Ralston and Blackhurst, 2020).

With the support of strong SCRes, when confronted with uncertainties and disruptions, organizations and SCs have extra capacity to engage in exploratory activities such as innovations. Innovation is a quest into the unknown, and it involves taking risks, searching, probing, and re-probing of opportunities, which requires strong resource commitment (Hopkins, 2021). Innovation in the SC cannot be exempt from the involvement of digital technologies capable of bringing improvements, as well as innovativeness in products, processes and services to customers capable of increasing customer satisfaction (Seo et al., 2014). Therefore, SCRes encourages information exchange, knowledge sharing, and provides financial foundation and a supporting climate for innovation.

Literature also shows that SCRes plays a fundamental role in reducing contingencies and maintaining SCP (Yu et al., 2019; Belhadi et al., 2021; Harapko, 2021). Pettit et al. (2010) argue that SCRes has a positive effect on the competitiveness and financial performance of manufacturing firms. Furthermore, SCRes has been found to improve the level of customer service of manufacturers (Srinivasan and Swink, 2018). According to Scholten et al. (2020), a resilient SC ensures agility, responsiveness, and visibility with respect to changing customer needs to maintain high performance. Therefore, the literature trend highlights the positive effect of SCRes on SCI and SCP, and we can assume that:

H5: SCRes mediates the relationship between a) IoT and SCI, b) IoT and SCP, c) AI and SCI, and d) AI and SCP.

Fig. 2 illustrates the conceptual model and hypotheses.

Table 1
construct measures.

Construct and measurement items	Factor loading	VIF	Source
Artificial intelligence (AI) (Cronbach's α = 0.845, AVE = 0.617, CR = 0.890)			
AI1-We possess the infrastructure and skilled resources to apply AI information processing systems.	0.816	1.899	Belhadi et al., (2021)
AI2-We use AI techniques to forecast and predict environmental behaviour.	0.746	1.585	
AI3-We develop statistical, self-learning, and prediction using AI techniques.	0.803	1.879	
AI4-We use AI techniques at all levels of the supply chain.	0.772	1.689	
AI5-We use AI outcomes in a shared way to inform supply chain decision-making.	0.790	1.790	
Internet of Things (IoT) (Cronbach's α = 0.838, AVE = 0.607, CR = 0.885)			
IoT1-We use automatic capture technology to monitor and track supply chain processes.	0.789	1.758	De Vass et al., (2018)
IoT2- We apply sensors and collect data on supply chain activities, processes, and their impact on the environment.	0.754	1.620	
IoT3-We use the IoT to help remotely monitor supply chain processes.	0.783	1.791	
IoT4-We use real-time information to optimize supply chain processes.	0.804	1.806	
IoT5-We leverage IoT big data analytics to make strategic and tactical decisions.	0.762	1.637	
Supply chain resilience (SCRes) (Cronbach's α = 0.775, AVE = 0.598, CR = 0.856)			
SCRes1- Our firm's supply chain can quickly return to its original state after being disrupted.	0.763	1.514	Wong et al., (2020); Gölgeci and Kuivalainen (2020)
SCRes2- Our firm's supply chain has the ability to maintain a desired level of connectedness among its members at the time of disruption.	0.729	1.385	
SCRes3- Our firm's supply chain has the ability to maintain a desired level of control over structure and function at the time of disruption.	0.821	1.720	
SCRes4- Our firm's supply chain has the knowledge to recover from disruptions and unexpected events.	0.776	1.517	
Supply chain innovativeness (SCI) (Cronbach's α = 0.819, AVE = 0.580, CR = 0.874)			
SCI1- We frequently try out new ideas in the supply chain context.	0.803	1.827	Panayides and Lun, (2009)
SCI2- We seek out new ways to do things in our supply chain.	0.768	1.700	
SCI3- We are creative in the methods of operation in the supply chain.	0.752	1.559	
SCI4- We often introduce new ways of servicing the supply chain.	0.758	1.593	
SCI5- Our new process introduction in the supply chain has increased over the last 5 years.	0.726	1.523	
Supply chain performance (SCP) (Cronbach's α = 0.782, AVE = 0.604, CR = 0.859)			
SCP1- We are satisfied with the speediness of the supply chain process.	0.804	1.669	Gu et al., (2021)
SCP2- Based on our knowledge of the supply chain process, we think that it is efficient.	0.759	1.528	
SCP3- Our supply chain has an outstanding on-time delivery record.	0.785	1.521	
SCP4- Our supply chain provides high-level customer services.	0.759	1.476	

4. Method

4.1. Context and data collection

To validate the proposed research model, a survey-based quantitative approach was employed. The Chinese manufacturing sector was targeted for three main reasons. Firstly, China is known as the world factory, whose manufacturing sector accounted for nearly one third of the world manufacturing output, according to pre-pandemic statistics (The World Bank, 2021). During the Covid-19 pandemic, while the sector was affected by shrinking external demand, sub-sectors such as healthcare manufacturing continued to operate at full capacity and be the world's biggest PPE supplier (Bradsher, 2020). Given its scale and contribution to the world economy and welfare, the sustainable development of the Chinese manufacturing sector requires more attention from academic researchers and practitioners. Secondly, the sector is currently undergoing digital transformation, where successful datafication serves as the basis (Fernández-Rovira et al., 2021). From a broader perspective, the national economy is projected to upgrade through integrating the digital economy and the real industry (Li et al., 2022). However, the process is still at its infancy, and most manufacturers, especially small and micro ones, still lack a clear understanding and plan regarding how digitalization goals can be achieved (Eloot, 2018). Therefore, our study provides timely guidance on how manufacturers can realise successful datafication. Thirdly, the Chinese manufacturing sector has long been known for low cost, and this competitive advantage is not sustainable and being lost to countries where cost of labour and materials is even lower (Bai, 2022). Therefore, urgent industrial upgrade enabled by innovation is needed. While the increased uncertainty and the associated stress and anxiety during turbulent times often forces organizations to be safe and cautious and reduces their motivations to innovate (Visser and Scheepers, 2021), our study focuses on SCI as an important way that can change the current geopolitical situation where countries fight for a shrinking pie and power new growth (Yang et al., 2020). Due to these reasons, the Chinese manufacturing sector serves as an optimal context for our study.

A web survey was adopted to collect data. Web surveys, compared to traditional paper-based surveys, offer a wide range of advantages to both researchers and respondents, including cost- and time-efficiency, as well as avoiding interviewer bias as the need for manual transfer of data is eliminated (Couper, 2000; Dillman et al., 2014). We surveys are also advantageous in terms of avoiding missing values in responses when all questions are set as compulsory. Data collection commenced in August 2021, through collaboration with a reputable Chinese consultancy firm known for its extensive industrial resources. We limited respondents to Operations, Supply chain, or IT managers from a random sample of 1,235 manufacturing companies across mainland China. Initially, an invitation letter was sent to these companies, explaining purpose of this study. Within 10 weeks, with two reminders, 820 manufacturing companies responded positively, indicating their interest in participating in the survey. Subsequently, emails containing the link to the survey and clear instructions were sent to these 820 companies. After an additional eight weeks, with another two polite reminders, 311 valid responses were obtained from the manufacturing firms, giving us a response rate of

Table 2
summary of sample demographics.

Manufacturing sub-sectors	Frequency	Percentage (%)
Dedicated and general-purpose equipment	35	11.25
Chemical raw materials and chemical products	16	5.14
Construction materials and furniture	28	9.00
Rubber and plastic products	9	2.89
Electronic and electrical equipment	70	22.51
Textile and apparel	25	8.04
Metal products, machinery and equipment	83	26.69
Food, tobacco, alcohol and beverages	22	7.07
Pharmaceutical products	16	5.14
Others	7	2.25
Company age	**Frequency**	**Percentage (%)**
>20 years	61	19.61
16–20 years	68	21.86
11–15 years	72	23.15
6–10 years	80	25.72
1–5 years	30	9.65
Company size (No. of employees)	**Frequency**	**Percentage (%)**
>3000	48	15.43
2001–3000	24	7.72
1001–2000	32	10.29
301–1000	133	42.77
21–300	72	23.15
<20	2	0.06
Company size (Annual turnover million CNY)	**Frequency**	**Percentage (%)**
>300	71	22.83
100–300	56	18.01
50–100	88	28.30
10–50	65	20.90
5–10	24	7.72
<5	7	2.25
Ownership	**Frequency**	**Percentage (%)**
State-owned	66	21.22
Private	173	55.63
Foreign	16	5.14
Joint venture	56	18.01

38 %, which is considered acceptable (Dillman et al., 2014). Due to the use of web survey where all questions were set compulsory, there was no missing data in the returned responses as the respondent would not be able to submit the response if they left any question unanswered.

4.2. Survey instrument

The survey instrument was developed based on well-established measurement scales from existing literature. The implementation of AI technology was measured by 5 items adapted from Belhadi et al. (2021), including the infrastructure and skills of applying AI, the use of AI for forecasting environmental changes, the development of statistical, self-learning for AI implementation, the application of AI across the SC, and the use of AI in shared decision-making in the SC. Another dimension of datafication, IoT implementation, was measure based on De Vass et al. (2018). Questions covered the use of automatic capture technology in the SC; the use of sensors for data collection in the SC; the use of IoT to monitor SC processes remotely; the use of real-time information for SC process optimization; and the use of IoT big data analytics in decision-making. Items measuring SCRes were adapted from Wong et al. (2020), including the SC's ability to rapidly move back to the original state of operations after being disrupted, the level of connectedness among SC members during disruptions, the level of control over SC structure during disruptions, and the SC's knowledge to recover from unexpected events. To measure SCI, 5 items were developed based on Panayides and Lun (2009), capturing the extent to which the firm's SC introduces new products, develops new ways of doing things, establishes new methods of operations, pilots new ways of servicing, as well as how new introductions have increased in the past 5 years. Lastly, SCP was measured using 4 items from Gu et al. (2021), including the SC's speediness, sufficiency, on time delivery, and customer service. A 5-point Likert scale was applied to all questions where 1 indicates strongly disagree and 5 strongly agree.

Two factors, company size (employee number) and age (total number of operating years), were included as control variables. As literature suggests, older and bigger businesses tend to enjoy extra resources than their smaller and younger counterparts (Gu et al., 2021), and are therefore more capable of investing in datafication and achieve higher performance. Therefore, the potential effect of both factors was controlled. Table 1 presents all constructs and their measurement items.

4.3. Common method bias (CMB) and non-response bias (NRB)

The unit of analysis in this study is the manufacturing organization. Considering that data collection was done through a single informant in every analytical entity, we conducted both procedural and statistical remedies to prevent and deal with the issue of CMB (Podsakoff et al., 2003). Ahead of the survey, a team of academics and experts (eight in total) was invited to review the content of the questionnaire and slight adjustments were made to ensure precise and accurate expression of items (Hair et al., 2014). Their suggestions were incorporated into the final survey. This allowed for clarification of some questions and items. In addition, as data collection took place in China, three multilingual academics back-translated the survey to confirm that the initial English version and the issued version in Chinese were identical in meaning. Regarding statistical remedies, we performed Harman's single factor test, the most commonly employed method of checking for CMB (Podsakoff et al., 2003). An un-rotated EFA was run with every eigenvalue-containing variable higher than 1. Results showed a total of 4 components, with the first one accounting for 37.380 % of the overall variation, lower than the 50 % variance threshold (Podsakoff et al., 2003). Therefore, CMB has limited effect on our study.

To verify whether NRB existed, we compared late and early respondents on firm characteristics to see whether they differed significantly (Armstrong and Overton, 1977). Paired *t*-test was conducted for key demographic variables. The comparison between the initial 50 reported responses and the concluding 50 revealed *p* values of 0.558 for company location, 0.349 for firm age, 0.084 and 0.162 for firm size (measured by employee number and annual turnover respectively), and 0.290 for ownership type. The results indicate no significant difference between early and late responses across the assessed demographic factors. Therefore, NRB does not present a severe threat to the reliability and generalizability of the outcomes of our research.

4.4. Data analysis

Partial least squares-structural equation modelling (PLS-SEM) was carried out to analyse the survey data and test the research hypotheses. In particular, the complex interrelationships between variables have been scrutinized using the software SmartPLS 3.0. According to Hair et al. (2014), exploratory models that seek to build theory instead of assessing existing theories are recommended to use PLS-SEM. Although our research model is supported by a well-established theory, the DCT, this study is still largely explorative as both antecedents (i.e., datafication) and outcomes (i.e., SCI and SCP) of a key DC (i.e., SCRes) are included, and this combination has not been validated in prior studies. Therefore, the use of PLS-SEM is considered appropriate for our study. We followed the general two-step procedure of PLS-SEM: 1) assessment of the measurement model, and 2) assessment of the structural model (Hair et al., 2019).

5. Results

5.1. Preliminary analysis

Preliminary analysis of the data shows that our sample is well represented. As can be seen in Table 2, the sample covers various manufacturing subsectors, and distributes across different size, age and

Table 3
Fornell-Larcker criterion results.

	AI	IoT	SCI	SCP	SCRes
AI	**0.786**				
IoT	0.562	**0.779**			
SCI	0.559	0.564	**0.762**		
SCP	0.604	0.604	0.642	**0.777**	
SCRes	0.541	0.568	0.560	0.654	**0.773**

Table 4
HTMT results.

	AI	IoT	SCI	SCP	SCRes
AI					
IoT	0.668				
SCI	0.668	0.680			
SCP	0.742	0.742	0.802		
SCRes	0.667	0.704	0.7	0.838	

Table 5
results of direct effects.

Structural path		*β*	*t*-value	*p*-value	f^2	Remarks
H1	IoT SCI	0.369	4.655	0.000	0.158	Supported
H2	IoT SCP	0.387	4.434	0.000	0.193	Supported
H3	AI SCI	0.353	5.374	0.000	0.145	Supported
H4	AI SCP	0.387	5.404	0.000	0.192	Supported
AGE SCI		0.006	0.114	0.910	0.000	
AGE SCP		0.002	0.033	0.973	0.000	
SIZE SCI		0.087	1.480	0.139	0.008	
SIZE SCP		0.018	0.327	0.744	0.000	

ownership groups. This provides a good basis for the subsequent data analysis.

5.2. Measurement model assessment

According to Hair et al. (2019), indicator loadings should be checked as the initial phase of reflective measurement model assessment. All assessment variables' standardized factor loadings, as shown in Table 2, are higher than 0.708, which means that the item explains more than 50 % of the indicator's variance and provides satisfactory item reliability. Following this, constructs' internal consistency and dependability were evaluated. As shown in Table 2, all composite reliability (CR) values are between 0.8 and 0.9, and Cronbach's α coefficients are above the suggested threshold of 0.7, indicating strong construct internal consistency and reliability.

The convergent validity of constructs was examined as the third step of the measurement model assessment. As Table 2 shows, the average variance extracted (AVE) values of all constructs are higher than the threshold of 0.5, indicating acceptable convergent validity. Discriminant validity, or how a construct is empirically different from other constructs in the structural model, was assessed as the last step using the Fornell-Larcker criterion and the heterotrait-monotrait (HTMT) ratio (Fornell and Larcker, 1981; Hair et al., 2019), displayed in Tables 3 and 4. As each construct's AVE value is larger than its squared correlations with other constructs, the Fornell-Larcker criterion is fully fulfilled. Moreover, all HTMT values are under the suggested level of 0.9, indicating that constructs in the model are not conceptually similar. In sum, the assessment of the measurement model generated satisfactory results, providing a solid foundation for the structural model assessment.

5.3. Structural model assessment

We utilized AMOS software for a comprehensive model analysis. The fitness values obtained from various indices (RMSEA = 0.04, RMR = 0.06, GFI = 0.92, AGFI = 0.90, NFI = 0.90, CFI = 0.97) consistently reside within the recommended acceptable ranges (Kline, 2023; MacCallum et al., 1996; Tabachnick et al., 2013; West et al., 2012; Diamantopoulos and Siguaw, 2000). This alignment underscores the model's congruence with the survey data and its commendable fitness.

Before testing the structural relationships, it is also important to check for collinearity and make sure it does not affect the regression results. As all VIF values are less than 3 (Table 2), multicollinearity is not a serious concern. The structural model was then assessed through the

Table 6
results of mediation effects.

Structural path		*β*	*t*-value	*p*-value	Remarks
H5a	IoT → SCRes → SCI	0.101	3.285	0.001	Supported
H5b	IoT → SCRes → SCP	0.144	3.610	0.000	Supported
H5c	AI → SCRes → SCI	0.085	2.645	0.008	Supported
H5d	AI → SCRes → SCP	0.121	3.329	0.001	Supported

Table 7
Summary of direct, indirect and total effects.

	SCRes	SCI	SCP
IoT			
Total effect	0.386*** (4.485)	0.367*** (4.582)	0.387*** (4.461)
Direct effect	0.386 (4.485)	0.266*** (3.295)	0.243** (2.867)
Indirect effect	–	0.101*** (3.285)	0.144*** (3.610)
AI			
Total effect	0.324*** (3.792)	0.355*** (5.563)	0.387*** (5.437)
Direct effect	0.324*** (3.792)	0.270*** (4.905)	0.267*** (4.303)
Indirect effect	–	0.085** (2.645)	0.121*** (3.329)
SCRes			
Total effect		0.261*** (4.148)	0.372*** (5.968)
Direct effect		0.261*** (4.148)	0.372*** (4.148)
Indirect effect	–	–	–

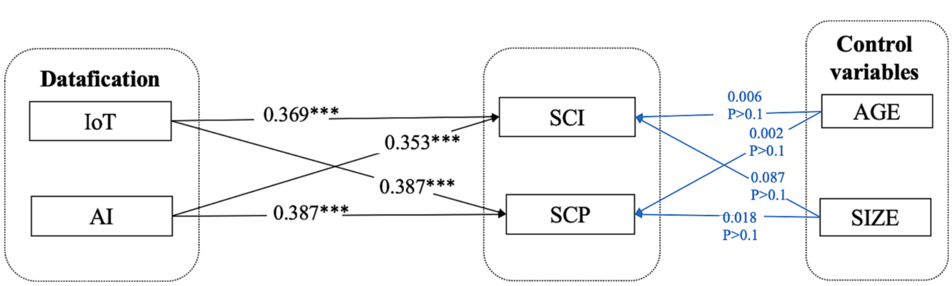

Fig. 3. Structural model results for direct effects (*p < 0.05, **p < 0.01, ***p < 0.001).

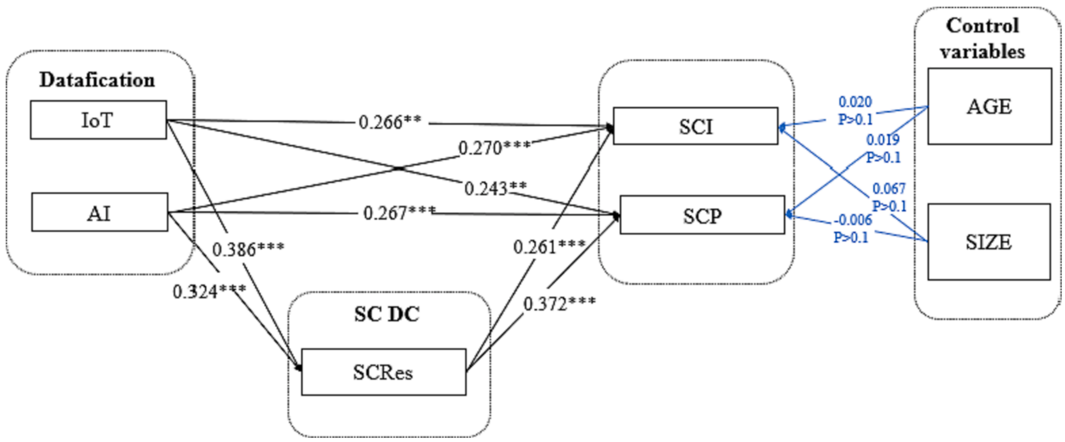

Fig. 4. Structural model results for mediation (*p < 0.05, **p < 0.01, ***p < 0.001).

Table I
Evaluation of nonlinear effects.

	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T statistics	*P* value	Ramsey's RESET
QE (AI) -> SCP	0.015	0.018	0.045	0.328	0.743	F (2, 305) = 0.163, *P* = 0.849
QE (IoT) -> SCP	0.044	0.046	0.049	0.892	0.373	
QE (SCRes) -> SCP	0.007	0.005	0.045	0.148	0.883	
QE (AI) -> SCI	0.035	0.036	0.046	0.758	0.448	
QE (IoT) -> SCI	−0.008	−0.008	0.041	0.206	0.837	F (2, 305) = 0.628, *P* = 0.534
QE (SCRes) -> SCI	0.035	0.031	0.048	0.737	0.461	
QE (AI) -> SCRes	0.036	0.041	0.047	0.768	0.443	
QE (IoT) -> SCRes	0.021	0.023	0.039	0.542	0.588	

Table II
Evaluation of unobserved heterogeneity through FIMIX-PLS.

Criteria	Number of segments				
	1	2	3	4	5
AIC (Akaike's information criterion)	2081.306	1884.04	1853.386	1820.17	**1792.21**
AIC3 (modified AIC with Factor 3)	2092.306	1907.04	1888.386	1867.17	**1851.21**
AIC4 (modified AIC with Factor 4)	2103.306	1930.04	1923.386	1914.17	**1910.21**
BIC (Bayesian information criterion)	2122.443	**1970.055**	1984.279	1995.94	2012.858
CAIC (consistent AIC)	2133.443	**1993.055**	2019.279	2042.94	2071.858
HQ (Hannan-Quinn criterion)	2097.749	1918.422	1905.706	1890.428	**1880.406**
MDL5 (minimum description length with factor 5)	**2374.994**	2498.116	2787.85	3075.021	3367.449
LnL (LogLikelihood)	−1029.653	−919.02	−891.693	−863.085	**−837.105**
EN (normed entropy statistic)	0	0.557	0.505	0.507	**0.584**
NFI (non-fuzzy index)	0	**0.631**	0.504	0.487	0.535
NEC (normalized entropy criterion)	0	137.823	153.801	153.392	**129.405**

Table III
Evaluation of Endogeneity Bias via Durbin and Wu-Hausman Tests.

Relationship	**Durban and Wu-Hausman**	**Conclusion**
IoT- SCI	$0.3709^{n.s}$	No bias present
IoT-SCP	$0.9323^{n.s}$	No bias present
IoT-SCRes	$0.6686^{n.s}$	No bias present
AI- SCI	$0.2346^{n.s}$	No bias present
AI-SCP	$0.7991^{n.s}$	No bias present
AI-SCRes	$0.8765^{n.s}$	No bias present
SCRes- SCI	$0.3614^{n.s}$	No bias present
SCRes-SCP	$0.9953^{n.s}$	No bias present

Note(s): n.s = not significant.

coefficient of determination (R^2), the blindfolding-based cross-validated redundancy measure Q^2, and the statistical significance and relevance of the path coefficients (Hair et al., 2019). R^2 is a measurement of the model's explanatory performance (Rigdon, 2012), and values of 0.75, 0.50, and 0.25 show significant, medium, and low levels of in-sample predictive power (Henseler et al., 2009). In our study, the R^2 values for SCI, SCP, and SCRes are 0.446, 0.550, and 0.394, showing the model's middling explanatory ability.

The Q^2 value, a measure of the predictive accuracy of PLS route modelling, incorporates elements of out-of-sample prediction and in-sample explanatory power, with values greater than 0, 0.25, and 0.50 indicating the model's low, medium, and high predictive relevance (Hair et al., 2019). The Q2 values for SCI, SCP, and SCRes, respectively, are 0.250, 0.321, and 0.230, showing medium to high degrees of predictive accuracy.

We conducted a bias-corrected and accelerated (BCa) bootstrapping algorithm with 311 cases and 5,000 subsamples to test the proposed effects. Results of the direct effects, as presented in Table 5 and Fig. 3, reveal no significant effect of the control variables (age and size) on the dependent variables, SCI and SCP. The regression coefficients (β) and associated *t*-values and *p*-values for both control variables show no statistical significance. These findings indicate that variations in age and company size do not influence the observed relationships between the

Table IV
Results of the Gaussian Copula Approach.

		Original sample (O)	Sample mean (M)	Standard deviation	T statistics	*P* values
Gaussian copula of model 1 (endogenous variables; AI)	GC (AI) -> SCP	0.094	0.101	0.159	0.593	0.553
	GC (AI) -> SCI	0.163	0.155	0.163	0.996	0.319
	GC (AI) -> SCRes	0.223	0.222	0.181	1.23	0.219
Gaussian copula of model 2 (endogenous variables; IoT)	GC (IoT) -> SCP	0.132	0.125	0.149	0.881	0.378
	GC (IoT) -> SCI	−0.011	−0.015	0.139	0.081	0.936
	GC (IoT) -> SCRes	0.091	0.087	0.14	0.655	0.512
Gaussian copula of model 3 (endogenous variables; SCRes)	GC (SCRes) -> SCP	−0.012	0.027	0.248	0.048	0.961
	GC (SCRes) -> SCI	0.21	0.208	0.258	0.812	0.417
Gaussian copula of model 4 (endogenous variables; AI, IoT)	GC (AI) -> SCI	0.211	0.203	0.164	1.29	0.197
	GC (AI) -> SCP	0.025	0.042	0.159	0.156	0.876
	GC (AI) -> SCRes	0.214	0.214	0.195	1.1	0.271
	GC (IoT) -> SCI	−0.086	−0.087	0.139	0.615	0.539
	GC (IoT) -> SCP	0.123	0.11	0.154	0.797	0.426
	GC (IoT) -> SCRes	0.015	0.015	0.155	0.099	0.921
Gaussian copula of model 5 (endogenous variables; AI, SCRes)	GC (AI) -> SCI	0.114	0.1	0.141	0.803	0.422
	GC (AI) -> SCP	0.121	0.105	0.146	0.826	0.409
	GC (AI) -> SCRes	0.223	0.222	0.181	1.23	0.219
	GC (SCRes) -> SCI	0.147	0.159	0.251	0.584	0.559
	GC (SCRes) -> SCP	−0.079	−0.025	0.246	0.32	0.749
Gaussian copula of model 6 (endogenous variables; IOT, SCRES)	GC (SCRes) -> SCI	0.278	0.285	0.275	1.012	0.312
	GC (SCRes) -> SCP	−0.141	−0.074	0.266	0.531	0.595
	GC (IoT) -> SCI	−0.09	−0.1	0.141	0.638	0.523
	GC (IoT) -> SCP	0.172	0.142	0.156	1.101	0.271
	GC (IoT) -> SCRes	0.091	0.087	0.14	0.655	0.512
Gaussian copula of model 7 (endogenous variables; AI, IOT, SCRES)	GC (IoT) -> SCI	−0.131	−0.139	0.149	0.878	0.38
	GC (IoT) -> SCP	0.157	0.127	0.163	0.964	0.335
	GC (IoT) -> SCRes	0.015	0.015	0.155	0.099	0.921
	GC (SCRes) -> SCI	0.218	0.236	0.266	0.817	0.414
	GC (SCRes) -> SCP	−0.164	−0.091	0.262	0.626	0.531
	GC (AI) -> SCI	0.164	0.152	0.15	1.093	0.274
	GC (AI) -> SCP	0.06	0.058	0.148	0.407	0.684
	GC (AI) -> SCRes	0.214	0.214	0.195	1.1	0.271

variables. As to the main effects, it is evident that the implementation of IoT is positively related to SCI ($\beta = 0.369$, $t = 4.655$, $p = 0.000$) and SCP ($\beta = 0.387$, $t = 4.434$, $p = 0.000$), supporting H1 and H2. In terms of AI, results suggest that it positively relates to both SCI ($\beta = 0.353$, $t = 5.374$, $p = 0.000$) and SCP ($\beta = 0.387$, $t = 5.404$, $p = 0.000$), and H3 and H4 are also supported.

Results for the mediation effect assessment are presented in Table 6, Table 7 and Fig. 4. As shown, IoT ($\beta = 0.386$, $t = 4.485$, $p = 0.000$) and AI ($\beta = 0.324$, $t = 3.792$, $p = 0.000$) are positively related to SCRes with high significance. Meanwhile, SCRes positively relates to SCI ($\beta = 0.261$, $t = 4.148$, $p = 0.000$) and SCP ($\beta = 0.372$, $t = 5.968$, $p = 0.000$). The direct effects of IoT and AI on SCI and SCP remain significant after the mediator was added. The indirect path coefficients for IoT-SCRes-SCI and IoT-SCRes-SCP are 0.101 ($t = 3.285$, $p = 0.001$) and 0.144 ($t = 3.610$, $p = 0.000$), indicating that SCRes partially mediates the effect of IoT implementation on SCI and SCP. Meanwhile, the indirect path coefficients for AI-SCRes-SCI and AI-SCRes-SCP are 0.085 ($t = 2.645$, $p = 0.008$) and 0.121 ($t = 3.329$, $p = 0.001$), demonstrating a partial mediating role of SCRes in AI-SCI and AI-SCP links. In sum, H5a, b, c, d are all supported.

5.4. Robustness test

We followed Sarstedt et al., (2020) for structural model robustness checks. First, we checked if the model contains non-linear relationships through adding quadratic effects in the PLS-SEM model and Ramsey's regression specification error test (RESET) (Wooldridge, 2016). The outcomes of this analysis, as illustrated in Table I in Appendix A, strongly endorse a linear association among variables in our model as all p values exceeding 0.05.

We then checked if unobserved heterogeneity is present and affects the robustness of our result using the finite mixture PLS (FIMIX-PLS) approach, adhering to the multi-method framework by Sarstedt et al. (2017). According to Table II in Appendix A, Akaike's information criterion modified with factor 3 (AIC3) suggests a five-segment solution, while the consistent Akaike's information criterion (CAIC) favors a two-segment solution. Additionally, modified AIC with factor 4 (AIC4) and Bayesian information criteria (BIC) propose alternative segment solutions. Collectively, these analyses lack a definitive consensus on a specific segmentation solution, indicating that unobserved heterogeneity does not pose a threat to the reliability of our results.

Potential endogeneity, stemming from the structural error correlation between endogenous variables, can introduce bias to the structural model result (Queiroz et al., 2022a). To assess and address this, we conducted the Durban and Wu-Hausman test before evaluating the structural model, as per precedents in literature (e.g., de Sousa Jabbour et al., 2022). Finding no evidence of endogeneity, we further addressed this concern in the PLS-SEM model using the Gaussian copulas approach (Park and Gupta, 2012). Following Hult et al.'s (2018) guidance, we verified the non-normal distribution of endogenous variables (AI, IoT and SCRes) through Kolmogorov-Smirnov and Shapiro-Wilk tests (Sarstedt and Mooi, 2014), revealing non-normal distribution across all variables. Subsequently, bootstrapping analysis, as recommended by Hult et al. (2018), yielded no statistically significant copula terms. Therefore, we can conclude that endogeneity is not a significant concern in our study. Detailed results of these tests are presented in Table III and Table IV in Appendix A.

6. Discussion

6.1. Direct effect of datafication on SCI and SCP

With increasing recognition of the importance of data, datafication, which refers to the process of transforming something into data, is considered a crucial element in successful digital transformation (Mejias and Couldry, 2019; Sadowski, 2019). Especially in more competitive and uncertain times, digital technology-supported collection and analysis of big data plays a crucial role in organizational and supply chain level decision-making (Fernández-Rovira et al., 2021). Result of our study confirms the positive effect datafication, as represented by the use of two digital technologies, IoT and AI, on the innovativeness and performance of the manufacturing SC during a major disruption. IoT tools, such as RFID, foster innovation in sourcing by monitoring inventory and consumption levels and enabling real-time decision-making on pricing and inventory management strategies (Fan et al., 2015; Li and Li, 2017), which is particularly useful in case of sudden changes in the market. IoT platforms, the main application of Logistics 4.0, increases visibility and reduces error based on inventory inaccuracies (Winkelhaus and Grosse, 2020). During the pandemic, this has particularly helped the manufacturing sector, especially the vaccine or medicine cold chain logistics (Halim et al., 2021). Our study therefore reinforces that SCI can only be achieved with timely and meaningful access to data and with an interconnection between sensing and actuating devices in platforms that allow data sharing by providing a common view, precisely what the IoT provides (Kalaitzi and Tsolakis, 2022).

The acquisition and management of heterogeneous information provided by the IoT improves communications and cooperation across the manufacturing SC and confers greater trust between actors, leading to improved overall performance (Feng et al., 2022). Considering on-time delivery and customer satisfaction as performance, Tsang et al. (2021) proposes an IoT-based system architecture that collects real-time information including location and environmental monitoring. The data is processed with genetic algorithms to determine the quasi-optimal vehicle routing solutions to cope with accidents and unforeseen events during delivery and maintain the desired level of customer satisfaction. Therefore, in extremely uncertain environments such as the pandemic, IoT technologies can help maintain SC operations through data-driven decision-making.

AI, another facet of datafication, is also found to contribute to SCI and SCP in our study. Haefner et al. (2021) show that AI systems can develop and generate innovative ideas. These systems can identify and evaluate information that can be channeled into the development of ideas and can then evaluate and select different creative or exploratory ideas. Likewise, they can identify and compare different problems or opportunities for new ideas generation. According to Dwivedi et al. (2021), AI overcomes some computational and creative limitations of humans, opening up new fields of application. Their study also reports data on the expected AI-driven innovation boost, namely the creation of 133 million new jobs globally by 2022 and contributing 20 % of China's GDP by 2030. Our study adds to this stream of literature by proving empirical evidence on how AI's adoption in the organization offers wider benefits in terms of SCI.

Our finding also supports the widely agreed view that AI improves performance and enables multi-period planning that considers production and inventory levels, shipping methods and times, and customer service. For example, AI helps to analyze real-time data from the SC to identify bottlenecks and mitigate potential risks (Ye et al., 2022). It helps companies to monitor the status of their suppliers during Covid-19 and act in case of problems by selecting alternative suppliers that can ensure stability in the delivery of raw materials, so as not to jeopardize their performance towards the end customer. Also, the AI research stream focusing on the last mile delivery is growing rapidly since it is highly affected by the Covid-19 disruptive changes (Srinivas and Marathe, 2021). AI can provide supporting tools, including optimized vehicle routing which calculates the most optimal delivery route, and data mining through predictive intelligence algorithms (Jucha, 2021).

6.2. The mediating role of SCRes

While discussing the positive effect of datafication on the innovativeness and performance of the supply chain, the mechanism through which this is realized is worth noting. Our study finds that the improved dynamic capability of SCRes, serves as one of the underlying factors through which firms materialize the desired benefits of datafication. The result is consistent with existing studies such as Gani and Rahman (2022) which demonstrates a mediating role of SCRes in the supply chain capabilities -sustainable SCP link.

A manufacturing firm adopting IoT and AI tools is able to manage and transform the various and numerous collected data into useful knowledge to deal with disruptions (Dolgui and Ivanov, 2020), which can circulate within the SC and strengthen SCRes. Effective datafication can enhance SC mapping by increasing SC visibility and resilience (Fertier et al., 2021; Oliveira-Dias et al., 2022). Furthermore, digital technologies such as AI, big data, and IoT can enable powerful predictive capabilities for developing platforms that guarantee high levels of automation in decision-making (Calatayud et al., 2018). For example, IoT deployment can help managing issues related to both overstock and stockouts in sectors such as the food SC (Njomane and Telukdarie, 2022). That helps the development and deployment of digital solutions to enable flexible decisions to empower agile logistics and SCRes for smart production (Fertier et al., 2021).

During the pandemic, firms are driven to engage in datafication and digital transformation to improve their SCRes and maintain operational performance (Belhadi et al., 2021). IoT and AI are crucial to identify potential areas of disruption, as effective datafication enables companies to collect and process information more efficiently, thus facilitating the orchestration of resources and processing of information and improving real-time coordination of SC processes (Xu et al., 2021). Datafication represents the technological base on which firms build SCRes, an indispensable capability in times of crisis (Ruel and El Baz, 2021; Fertier et al., 2021).

SCRes enables companies to minimize the negative effects of disruptions, maintain business continuity, optimize resource use, and ensure delivery to customers without hindrance or excessive delays (Ambulkar et al., 2016; Queiroz et al., 2022b). In this respect, Liu et al. (2018) highlight the positive financial results deriving from the exploitation of SCRes, thanks to more quickly and effective responses to disruptions in comparison with competitors, higher market share, and enhanced goodwill and profitability. Consequently, SCRes has shown a direct positive impact on SCP by ensuring consistent service and stock availability and improving the ability to face various external threats (Liu and Lee, 2018; Liu et al., 2018). Moreover, SCRes enables better predictions concerning operational vulnerability with the consequent improvement of SCP (Chowdhury and Quaddus, 2017).

7. Conclusions

7.1. Theoretical contribution

Our study makes two significant contributions to the literature. First, our study is among the earliest to operationalize the concept of datafication empirically. Flensburg and Lomborg (2021), through analyzing the state-of-the-art of datafication studies, point out the lack of quantitative approaches. This is partially attributed to the lack of an agreed operationalization of datafication. Through an in-depth understanding of the macro-processes involved in datafication, we summarize them into data generation and collection, as well as data analysis and sense-making. Based on the functionalities of digital technologies and the way they work around data, IoT and AI are selected to represent these two processes. Our approach to operationalizing datafication will inspire future attempts for the same, and more importantly, pave the way for more empirical studies in the field and advance knowledge development on datafication and digital transformation. In addition, our study provides quantitative empirical evidence on how datafication can improve innovativeness and performance of the manufacturing SC against disruptions through nurturing an important DC, SCRes.

In the context of datafication, our study then extends the DCT beyond the organizational boundary to the SC context. Researchers consider DCs as the cluster of capabilities which enable organizations to adjust their resource base to respond to environmental changes more effectively (Teece et al., 1997). Additionally, DCs enable a firm to use its resources to reconfigure its operational abilities and generate new capabilities, which provide a strategic advantage over other industry players (Beske et al., 2014). Coupling SCM and the DCT, our study proposes SCRes as a form of SC DC, and this combination broadens the theoretical connotation of each other. In particular, the study's exploration into the influence of SCRes on the interconnectedness between datafication and SCP and SCI has revealed novel insights within DCT and its application in SCM studies. Far from being simply an end result of successful datafication, SCRes emerges as a pivotal bridging factor that unites datafication with SCI and SCP. Our findings underscore the importance of SCRes in enhancing the synergy between data-driven technologies and strategic manufacturing processes, thereby opening new avenues for innovation and efficiency in the industry.

7.2. Managerial implications

This research also offers significant managerial implications for the manufacturing SC. According to a recent survey targeting at senior manufacturing supply chain executives by Ernst & Young, 72 % of manufacturers have been negatively impacted by the pandemic (Harapko, 2021). Recognizing the need for a more efficient, visible, resilient and sustainable manufacturing SC in the future, manufacturers have reached a consensus to develop a SC that is digital and autonomous. Consistent with this survey, our study highlights the critical managerial actions required to leverage digital technologies effectively and address the challenges arising from dynamic environments. First, our study emphasizes the strategic utilization of digital technologies for datafication, thereby strengthening the SCRes capability in the manufacturing sector. Through successful datafication, manufacturers can enhance the accuracy and transparency of their SCs, resulting in improved efficiency across the firm, supplier, distributor, and retailer nodes. The availability and precise analysis of data facilitate rapid responsiveness to disruptions. To achieve this, managers of manufacturing SCs are strongly encouraged to adopt understand the importance of data in their operations and select appropriate digital tools such as IoT and AI to harness big data.

Second, new digital technologies, on the one hand, represent a huge opportunity for manufacturers to develop competitive advantages and improve efficiency, while on the other, require significant time and financial efforts in their implementation. Our research unveils the tangible and intangible benefits arising from datafication; however, it is also important to acknowledge the inherent risks, such as data breaches and security infringements, that may result from mismanagement. In addition, digitalization among manufacturing subsectors and between the upstream and downstream SC differs significantly, and is found particularly challenging for SMEs (Li, 2022). Therefore, we encourage manufacturing enterprises to develop skills (e.g., human resources, mindset change) for datafication and digital transformation, and nurture capabilities during the process for better outcomes.

7.3. Limitations and future research

Despite significant theoretical and practical contributions, our study has certain limitations. Specifically, we only considered two representative digital technologies, IoT and AI, to operationalize datafication based the macro-processes involved and these two technologies' demonstrated ability to synergize and form a cohesive datafication system. As explained earlier, IoT represents data generation and collection, and AI processes the big data and makes sense of it for decision making. However, Industry 4.0 is distinguished by swift technological progress. This surge in innovation has enabled manufacturers to access a plethora of digital technologies, including but not limited to cloud computing, blockchain, digital twins, additive manufacturing, virtual reality, and more. These technologies are intricately intertwined with the utilization of vast amounts of data in various different operational capacities. Therefore, future studies are encouraged to show a deeper understanding of datafication and the macro-processes, especially with respect to the context (e.g., manufacturing), and use different technologies to operationalize it. Furthermore, our research is limited to the manufacturing sector of a single country. To enhance the generalizability of findings, further work should expand the research setting to encompass multiple countries and industries.

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CRediT authorship contribution statement

Shuang Tian: Conceptualization, Formal analysis, Writing – original draft. **Lin Wu:** Conceptualization, Methodology, Writing – review & editing. **Maria Pia Ciano:** Visualization, Writing – review & editing. **Marco Ardolino:** . **Kulwant S. Pawar:** Supervision.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

Appendix A. Robustness checks

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