How big data analytics capabilities drive supply chain resilience: The mediating roles of supply chain visibility and flexibility

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Abstract

Purpose – With the increasing adoption of big data analytics (BDA), academics and practitioners are examining how and under what conditions BDA capabilities enhance supply chain resilience (SCR). Drawing on dynamic capability theory (DCT) and inertia theory, this study investigates the differentiated impacts of BDA capabilities on proactive and reactive SCR. It further explores the mediating roles of supply chain visibility and flexibility, as well as the moderating role of firm size.

Design/methodology/approach – Survey data were collected from 277 Chinese manufacturing enterprises. Data were used to test the conceptual model, using the structural equation modeling-partial least square approach.

Findings – The results demonstrate that BDA capabilities positively influence reactive SCR, but their effect on proactive SCR is insignificant. Furthermore, visibility and flexibility mediate the relationship between BDA and SCR, exhibiting distinct mediating effects on proactive and reactive SCR. Additionally, the influence of BDA on visibility is more pronounced in large firms than in small firms, whereas its effect on flexibility is less significant in large firms compared to small firms.

Originality/value – First, this study extends understanding of BDA's distinct roles in the pre- and post-disruption contexts. Second, drawing on DCT, it uncovers the mediating effects of visibility and flexibility on the relationship between BDA and SCR, elucidating the differentiated mechanisms through which BDA delivers value to SCR. Finally, it highlights the moderating role of firm size in explaining the effects of BDA on visibility and flexibility, providing a richer and more detailed picture of how BDA impacts supply chain management.

Keywords: Big data analytics capabilities; supply chain resilience; visibility; flexibility; firm size

1. Introduction

Following the rapid expansion of big data, characterized by increasing volume, velocity, and variety, significant developments have been documented in technologies for data storage, analysis, and visualization. A growing number of firms are accelerating the deployment of their big data analytics (BDA) initiatives to provide critical insights that enhance competitive advantages and develop more resilient supply chains (Dennehy et al., 2021; Dubey, Gunasekaran, Childe, Fosso Wamba, et al., 2019; Wamba et al., 2017). While logistics firms with higher levels of big data usage may better respond to big disasters, a recent survey of Fortune 1000 companies demonstrates that—in spite of investment enthusiasm around big data—results vary significantly in terms of success (Bean, 2017). For example, Maersk, among the world's top ten logistics firms, actively used a high volume of data in operations to monitor COVID-19 trends to improve its digital platforms, maintain continuous business operations, and deliver goods to customers promptly in the pandemic context (Li et al., 2022). However, for some logistics firms in Hong Kong deploying big data, the abrupt and drastic loss in capacity caused by COVID-19 prompted spot charges to increase by 25–40% on some trade routes in comparison to 2019 (CILT, 2020). Given the inconsistent effectiveness of BDA implementation in supply chain management, it is crucial to explore how firms can effectively harness BDA to realize its full potential and create business value.

While BDA has largely been regarded as a breakthrough technological development in academic and business communities, there is an ongoing debate about whether and under what conditions such technologies can create business value and obtain long-lasting competitive advantage. On the one hand, scholars have revealed a positive correlation between BDA investments and outcomes such as enhanced supply chain agility (Mandal, 2019), flexibility (Edwin Cheng et al., 2022), and resilience (Bag et al., 2024; Dennehy et al., 2021). On the other hand, some researchers have argued that such BDA investments may not necessarily translate into enhanced operational efficiency, effectiveness, or supply chain performance (Edwin Cheng et al., 2022; Jum'a et al., 2023; Liu et al., 2023). These varying outcomes suggest that inconsistencies in the relationship between BDA and supply chain management may be attributed to multiple factors, including a limited understanding of its distinct roles in pre- and post-disruption contexts. The disruption mitigation framework allows classification of different resilience capabilities based on the prime impact time in relation to pre- and post-disruption contexts (Ali et al., 2017; Cheng and Lu, 2017). Following Chowdhury and Quaddus (2017), this study classifies supply chain resilience (SCR) into proactive and reactive types, reflecting their distinct roles in addressing challenges across these two phases. Proactive SCR enhances the ability of a system to maintain functions and operations against supply chain disruptions before they occur, whereas reactive SCR enables the system to quickly respond to and recover from supply chain disruptions after disruptions have occurred (Cheng and Lu, 2017). While several studies have focused on the role of BDA in relation to an independent and general SCR (Bag et al., 2024; Dennehy et al., 2021), limited attention has been paid to how BDA differently affects the two types of SCR. Proactive SCR focuses on long-term planning and risk mitigation, where the advantages of BDA may be less significant due to its predictive capabilities being constrained by the inherent uncertainty and complexity of supply chain operations. In contrast, BDA proves highly effective in the context of reactive SCR by enabling firms to rapidly detect disruptions, analyze root causes, and implement corrective actions—critical for minimizing downtime and ensuring rapid adaptation and recovery. Therefore, BDA should exert distinct roles in influencing proactive and reactive SCR. This distinction facilitates a comparative analysis of the differing antecedents that contribute to proactive and reactive SCR. Additionally, it engenders practical implications that can enable managers to strategically enhance capabilities aligned with the pre- and post-disruption phases.

While several studies have investigated the direct effect of BDA on SCR (Munir et al., 2024; Zamani et al., 2023), there remains a limited understanding of the mechanisms through which BDA investments contribute to SCR (Lee et al., 2024). Indeed, the challenge for most companies wanting to realize benefits of big data investments lies not in the technology itself but in the transformation of organizational capabilities (Mikalef et al., 2020). Dynamic capability theory (DCT) focuses on an organization's dynamic capability to create, deploy, and reconfigure resources to address changing opportunities and threats, leading to improved competitive advantages (Teece, 2007). According to DCT, a firm's resources or competencies—for example, BDA—yield competitive advantages only when they are integrated with higher-order organizational processes that enable the renewal of competencies to adapt to changing business environments (Mikalef et al., 2020). Dynamic capabilities facilitate the integration of BDA into decision-making and operational processes, enabling firms to anticipate disruptions (proactive SCR) and to reconfigure resources and capabilities to recover quickly from disruptions (reactive SCR). Mikalef et al. (2020) argue that big data investments alone are insufficient to provide competitive performance gains without the necessary transformation of organizational capabilities. Elsewhere, Bahrami and

Shokouhyar (2022) contend that BDA capabilities can only significantly influence performance when they are effectively transformed into dynamic capabilities. Therefore, dynamic capabilities may act as the critical link that leverages the potential of BDA to achieve improvements in SCR.

Based on this discussion, we explore the indirect effects of BDA on SCR. Following Wei and Wang (2010), we consider supply chain visibility as a dynamic capability by facilitating real-time information acquisition, enabling resource reconfigurability, and improving strategic performance. Similarly, supply chain flexibility serves as a dynamic capability that enables firms to absorb demand fluctuations, adapt to dynamic supply markets, and respond to unexpected supply shortages (Bag and Rahman, 2023). Therefore, we consider supply chain visibility and flexibility as dynamic capabilities that mediate the relationship between BDA and SCR. Through the lens of DCT (Teece, 2007), we examine the mediating effects of visibility and flexibility on the relationship between BDA and SCR.

Furthermore, not all firms benefit equally from big data investments because the influence of BDA on SCR largely depends on contextual factors such as firm size. Inertia theory suggests that large firms exhibit greater organizational inertia due to their rigid structures, which include multi-layered hierarchies and decentralized decision-making systems (Hannan and Freeman, 1984). In contrast, small firms, characterized by their simpler hierarchies and centralized decision-making systems, exhibit more flexibility and adapt more quickly to environmental changes (Corsi et al., 2019). Consequently, BDA affects supply chain management differently. In large firms, BDA is essential for real-time data sharing and cross-functional coordination, significantly enhancing visibility. However, their structural inertia limits flexibility, slowing their ability to adapt and reducing BDA's impact on increasing flexibility. Raguseo et al. (2020) suggest that BDA has a greater influence on the profitability of larger firms because they effectively integrate external market resources with their internal big data assets to generate value. This renders a "one-size-fits-all" strategy unsuitable for maximizing BDA benefits because strategies must align with the specific characteristics of firms of different sizes. Therefore, we explore the moderating effect of firm size on the relationship between BDA and visibility and flexibility.

Consequently, this study seeks to answer three research questions:

RQ1. What are the impacts of BDA capability on proactive and reactive SCR?

RQ2. How do supply chain visibility and flexibility mediate the relationship between BDA and SCR?

RQ3. How does firm size moderate the relationship between BDA and supply chain visibility and flexibility?

By answering these questions, our study makes three contributions to the literature. First, it extends understanding of BDA's distinct roles in the pre- and post-disruption contexts. Second, drawing on DCT, it uncovers the mediating effects of supply chain visibility and flexibility on the relationship between BDA and SCR, elucidating the differentiated mechanisms through which BDA delivers value to SCR. Finally, the study highlights the moderating role of firm size in explaining the effects of BDA on supply chain visibility and flexibility, providing a richer and more detailed picture of how BDA impacts supply chain management.

2. Literature review and theoretical background

2.1 Supply chain resilience

The concept of SCR has been widely discussed and debated in the literature. Traditionally, resilience has been understood as a system's ability to return to its original state following disruptions, as defined by Cheng and Lu (2017). This view emphasizes recovery within a proper time span after facing interruptions, particularly those with negative effects. However, there is growing recognition that resilience encompasses more than just recovery, extending to the capacity for adaptation and transformation in response to disruptions. For example, Ponomarov and Holcomb (2009) define SCR as the adaptive capability of a supply chain to prepare for unexpected events, respond to disruptions, and recover effectively. Wieland and Durach (2021) define SCR as the capacity of a supply chain to persist, adapt, or transform in the face of change. Recently, Jiang et al. (2024) have defined SCR as a firm's ability to prepare for, respond to, and recover from disruptions in its supply chains.

Scholars further debate whether SCR should focus solely on proactive capabilities or encompass both proactive and reactive elements. Several studies have emphasized proactive aspects of resilience, such as redundancy, integration, financial strength, and market capability (Erol et al., 2010; Jüttner and Maklan, 2011), while others define resilience as encompassing both proactive and reactive capabilities, including redundancy, agility, recovery time, cost, and response effort (Cheng and Lu, 2017; Christopher et al., 2004). Similarly, the proactive and reactive concepts of resilience are sometimes interchangeably defined in terms of pre-disaster resilient actions and post-disaster resilient actions (Wieland and Wallenburg, 2013). Additionally, several studies categorize SCR based on adaptation and transformation components (Grego et al., 2024; Wieland and Durach, 2021). However, these are not separate constructs but are embedded within the broader concept of reactive capabilities. Faruquee et al. (2024) explicitly identify adaptability as a fundamental aspect of reactive resilience, reinforcing its role in post-disruption recovery. Similarly, Lin et al. (2024) position transformation as integral to reactive resilience, describing how firms should restructure resource allocation and adjust business processes to restore normal operations, facilitating business transformation and subsequent innovation.

Given these debates, we adopt the definition offered by Chowdhury and Quaddus (2017), which conceptualizes SCR as the characteristics of a well-designed supply chain network with proactive and reactive capabilities that enable the supply chain's members to reduce the probability or the impact of disruptive events while facilitating the potential to achieve a new, stable, and sustainable state. While previous conceptualizations have primarily focused on SCR as encompassing adaptation and transformation (Grego et al., 2024; Wieland and Durach, 2021), our study adopts an alternative perspective that distinguishes between proactive capabilities in the pre-disruption stage and reactive capabilities in the post-disruption stage. This perspective offers a more practical and operationally actionable framework for managers, enabling them to align targeted strategies more effectively with distinct pre- and post-disruption phases. Proactive SCR enables firms to recognize, anticipate, and defend against the changing shape of risk before adverse consequences occur (Cheng and Lu, 2017). Once a disruption has occurred, reactive SCR enables firms to quickly respond to market needs during critical situations and recover from disruptions, restoring operations to their normal state or an even stronger position (Chowdhury and Quaddus, 2017). Therefore, we argue that supply chains require both proactive and reactive capabilities to effectively anticipate, respond to, and recover from disruptions across the pre- and post-disruption phases.

In terms of the antecedents of SCR, previous studies have identified various enablers of SCR. For example, Dubey et al. (2020) find that blockchain-enabled swift trust enhances collaboration in disaster relief operations, improving SCR. Elsewhere, Queiroz et al. (2022) suggest that resource reconfiguration and a disruption-oriented supply chain approach positively influence SCR. Similarly, Zahid et al. (2022) argue that supply chain flexibility significantly enhances SCR. Among these enablers, BDA represents a critical factor that influences SCR by equipping firms with the ability to process, analyze, and leverage vast amounts of data, enhancing decision-making across supply chain operations. It supports proactive SCR by introducing real-time visibility into supply chain processes, forecasting potential disruptions, and facilitating preventive measures such as optimizing inventory and developing contingency plans. Furthermore, BDA is vital to enhancing reactive SCR because it enables firms to respond rapidly to disruptions via real-time monitoring, rapid root cause analysis, and dynamic resource reallocation.

2.2 Big data analytics capabilities

BDA capability refers to the ability of a firm to effectively deploy technology and talent to capture, store and analyze data, toward the generation of insight (Gupta and George, 2016). Notably, the classification of BDA capabilities is inconsistent in the literature. For example, Mikalef et al. (2019) use a combination of all three types of resources demanding investment by firms (i.e., tangible resources, human skills, and intangible resources). Alnuaimi et al.

(2021) propose BDA as a combination of two dimensions (i.e., technological capabilities and human capabilities). Su et al. (2022) identify BDA capability as being primarily composed of three types of resources (i.e., tangible resources, human skills, and intangible resources). Cheng et al. (2022) consider three dimensions of BDA capabilities (i.e., BDA infrastructure, BDA management capabilities, and BDA personnel expertise). Jiang et al. (2024) categorize BDA capabilities into technical skills, managerial skills, and data-driven culture. Consistent with Jiang et al. (2024), this study conceptualizes BDA as comprising three dimensions: managerial skills, technical skills, and data-driven culture. We focus more on human capabilities and intangible resources (managerial skills, technical skills, and a data-driven culture) compared to tangible resources because they are more difficult for competitors to replicate, enabling firms to develop valuable, inimitable resources that can provide sustainable competitive advantages. Tangible resources, such as financial resources, technology (e.g., software and hardware), and data, are commonly accessible and can often be imitated by competitors across most industries (Wamba et al., 2017). These resources are well-studied and commonly utilized within firms. By contrast, human capabilities and intangible resources are critical assets that offer uniqueness and drive competitive advantages. Therefore, we emphasize human capabilities and intangible resources (managerial skills, technical skills, and a data-driven culture) rather than tangible resources.

Technical skills enable firms to know how to use new forms of technology to extract intelligence from big data (Dubey et al., 2022). However, the technical skills alone cannot provide a long-term competitiveness, since they may become widespread within or across firms (Dubey, Gunasekaran, Childe, Blome, et al., 2019). These skills prepare and motivate firms to monitor changes in their routine or operating environments, facilitating a stable function despite disruptions (Jiang et al., 2024). Managerial skills are regarded as taken-for-granted norms through which managers implement their daily work and make decisions (Zouari et al., 2021). With effective managerial skills, firms are readier to manage existing new forms of technologies and associated knowledge base. Data-driven culture refers to the extent to which firm members make decisions based on the insights extracted from data (Gupta and George, 2016). A data-driven culture empowers firms to make decisions based on the information and knowledge derived from data through the use of BDA, effectively responding to supply chain disruptions (Dubey, Gunasekaran, Childe, Blome, et al., 2019).

Table 1 summarizes the effects of BDA on various outcomes, including corporate sustainability, supply chain performance, agility, flexibility, coordination, innovation, and SCR (Bag et al., 2024; Dubey, Gunasekaran, Childe, Fosso Wamba, et al., 2019; Edwin Cheng et al., 2022; Jum'a et al., 2023; Mandal, 2019; Wamba et al., 2017; Zamani et al., 2023). Among these outcomes, SCR is particularly critical because it enables supply chain members to minimize the likelihood of disruptions, maintain operational continuity, and promote a stronger, more sustainable state. For instance, during the COVID-19 pandemic, firms with high SCR leveraged BDA to monitor real-time disruptions to supplier networks, predict demand fluctuations, and reallocate resources effectively, maintaining service levels and customer satisfaction.

Table 1 also reveals an inconsistency in the relationship between BDA and supply chain management. While several studies highlight a positive correlation between BDA investments and outcomes such as supply chain performance, agility, flexibility, coordination, innovation, and SCR (Bag et al., 2024; Dubey et al., 2019; Wamba et al., 2017; Zamani et al., 2023), other research suggests that BDA investments may not always improve operational efficiency, effectiveness, or SCR in highly dynamic environments (Cheng et al., 2022; Jum'a et al., 2023; Liu et al., 2023). This inconsistency may be attributed to multiple factors, including the differing roles BDA plays in enhancing SCR during different phases of supply chain disruptions. Indeed, BDA may exert a stronger impact on reactive SCR than proactive SCR due to its ability to process large volumes of real-time data and support immediate decision-making. Proactive SCR emphasizes long-term planning and risk mitigation, where the benefits of BDA may be less pronounced because its predictive capabilities are limited by the uncertainty and complexity inherent in supply chain operations (Cheng and Lu, 2017). However, BDA proves particularly effective in reactive SCR because it enables organizations to rapidly detect disruptions, analyze root causes, and implement corrective measures—crucial for minimizing downtime and ensuring rapid adaptation and recovery. Consequently, BDA exerts a stronger impact on the immediate, action-oriented demands of reactive SCR than on supporting the anticipatory focus of proactive SCR. This differentiation highlights the need to strategically leverage BDA to optimize both the proactive and reactive aspects of SCR.

[INSERT TABLE 1 ABOUT HERE]

2.3 Dynamic capability theory

DCT focuses on an organization's dynamic capability to create, deploy, and reconfigure resources to address changing opportunities and threats, ultimately improving competitive advantages (Teece, 2007). Dynamic capabilities refer to an organization's ability to sense and shape opportunities and threats, seize opportunities, and maintain competitiveness by reconfiguring intangible and tangible assets (Teece, 2007). According to DCT, a firm's resources or competencies, such as BDA, yield competitive advantages only when they are integrated with higher-order organizational processes that enable adapting, integrating, and reconfiguring internal and external organizational competencies (Mikalef et al., 2020). Although previous studies have confirmed the direct relationship between BDA and SCR (Munir et al., 2024; Zamani et al., 2023), they have not adequately revealed the mechanism behind these relationships. According to DCT, the value of insights generated by BDA depends on a firm's ability to effectively sense, seize, and transform its operations—a process rooted in dynamic capabilities (Wamba et al., 2017). These capabilities facilitate the integration of BDA into decision-making and operational processes, enabling firms to anticipate disruptions (proactive SCR) and to reconfigure resources and capabilities to recover quickly from disruptions (reactive SCR). For example, a firm employing BDA to predict an imminent supplier failure can only capitalize on this insight if it possesses the dynamic capability to reallocate production, engage alternative suppliers, and adjust logistics in real-time (Dubey, Gunasekaran, Childe, Fosso Wamba, et al., 2019). Without such capabilities, the predictive power of BDA remains underutilized, limiting its strategic value (Bahrami and Shokouhyar, 2022). Therefore, dynamic capabilities act as a critical mediator between BDA and SCR.

In this study, we focus on two key dimensions of dynamic capabilities: sensing (via supply chain visibility) and reconfiguring (via supply chain flexibility). Drawing upon DCT (Teece, 2007), sensing refers to the ability to identify and shape opportunities and threats.

Supply chain visibility functions as a sensing capability, as it enables firms to detect and respond to such opportunities and threats through timely, high-quality information (Srinivasan and Swink, 2018; Wei and Wang, 2010). For example, a firm with high visibility can quickly sense disruptions, such as supplier delays. According to Wei and Wang (2010), visibility is a critical sensing capability that enhances firms' ability to acquire real-time external information and quickly recognize changes in the environment and supply chains.

Similarly, reconfiguring refers to the ability to reconfigure a firm's intangible and tangible assets to adapt to changing opportunities in the environment (Teece, 2007). Supply chain flexibility serves as a reconfiguring capability, as it allows firms to respond effectively to environmental changes through the reconfiguration of operational and supply chain routines (Bag and Rahman, 2023). For example, a highly flexible firm can quickly adapt its supply chain from automobile production to ventilator manufacturing, demonstrating its reconfiguring capability. Aslam et al. (2018) similarly position supply chain flexibility as a reconfiguring capability, allowing firms to reconfigure their resource base and supply chain structures to adapt to marketplace changes and deliver agile responses. Together, visibility and flexibility are essential prerequisites for building SCR, ensuring firms can both anticipate and respond effectively to disruptions (Jain et al., 2024; Zahid et al., 2022).

Drawing upon DCT (Teece, 2007), the processes of sensing, seizing, and transforming have distinct impacts depending on the stage of disruption. In the proactive stage (pre-disruption context), sensing and seizing capabilities enable firms to anticipate and identify potential disruptions, assess vulnerabilities, and enhance visibility to mitigate risks before they escalate. Proactive SCR reflects a forward-looking orientation, with dynamic capabilities facilitating preparation and preventive measures, ensuring the continuity of operations even in the face of uncertainty. In contrast, during the reactive stage (post-disruption context), the transforming capability plays a dominant role. Transforming capabilities allow firms to reconfigure resources, redesign supply chain processes, and recover swiftly following a disruption. Reactive SCR is inherently focused on immediate responses and adaptations, leveraging dynamic capabilities to restore functionality and adapt to the new conditions imposed by the disruption. This stage emphasizes the ability to act decisively and flexibly to minimize downtime and guide the system toward a stable and, potentially, improved state. Through the lens of DCT, this study provides a deeper understanding of the differential mechanisms through which BDA influences SCR at various temporal stages in terms of the proactive phase and the reactive phase. Furthermore, this study provides practical insights for firms, emphasizing the need to align their investments in BDA with the specific dynamic capabilities required at each stage of disruption. By tailoring strategies to these phases, firms can enhance both proactive and reactive resilience, improving their overall resilience.

Furthermore, recent studies increasingly highlight that the benefits of BDA are heavily influenced by contextual conditions, that is, a “one-size-fits-all” strategy does not suit all firms investing in BDA. A deeper exploration of contextual determinants is essential to guide managers in assessing whether BDA investments generate business value and how returns vary across different contexts. For example, Raguseo et al. (2020) have highlighted how larger firms are better able to integrate external resources with internal big data assets, creating valuable capabilities that strengthen the impact of BDA on profitability. According to inertia theory (Hannan and Freeman, 1984), larger firms face greater structural inertia due to their rigid structures and complex hierarchies constraining their ability to adapt quickly to environmental changes. Conversely, smaller firms, featuring flatter structures and lower levels of inertia, are more flexible and responsive to immediate market shifts (Corsi et al., 2019). These structural differences affect how firms derive value from BDA, rendering firm size a critical contingency in the realization of the benefits of BDA.

3 Hypothesis development

3.1 The influence of BDA capabilities on SCR

Drawing upon Jiang et al. (2024), we consider that BDA can be viewed as enablers of proactive and reactive SCR. By fostering a BDA, firms strengthen their ability to sense emerging opportunities and threats, seize opportunities before competitors. This ability enables the firm to recognize, anticipate and defend against the changing shape of risk before adverse consequences of disruptions occur. For example, in the retail sector, firms use BDA to monitor consumer behavior trends in real-time, enabling them to adjust inventory and production schedules to prevent shortages or overstocking. According to Ivanov and Dolgui (2021), BDA enhance a firm's proactive SCR as it enables firms to visualize their supply chains in real time, predict future impact and reactions, optimize strategic and logistical locational decisions for efficient contingency plan execution, and build firms' control towers. Manikas et al. (2023) argue that BDA capabilities strengthen a firm's ability to process information and reducing the level of supply or demand uncertainty in its supply chain networks, enhancing the firm's supply chain preparedness. Therefore, BDA significantly enhances proactive SCR by equipping firms with the tools to anticipate and mitigate risks, optimize decision-making, and improve preparedness for future disruptions.

Furthermore, BDA enables firms to respond quickly to market needs during critical situations and recover quickly from disruptions by processing large volumes of real-time data and supporting immediate decision-making. For instance, during the COVID-19 pandemic, firms leveraging BDA were able to analyze real-time data on supply chain disruptions and implement dynamic strategies to reroute shipments, adjust inventory levels, and manage demand fluctuations. According to Mikalef et al. (2020), BDA allows for the transformation of raw data into actionable insight in much shorter cycle times, contributing toward improved response speed, effectiveness, and efficiency when dealing with environmental changes. Moreover, Bag et al. (2023) contend that BDA enables firms to respond rapidly to disruptions and play a crucial role in disaster mitigation and recovery efforts. Therefore, BDA enhances reactive SCR by empowering firms to adapt quickly, minimize downtime, and recover effectively from unexpected disruptions. Based on these insights, we propose the following hypothesis:

H1: (a) BDA has a positive influence on proactive supply chain resilience; (b) BDA has a positive influence on reactive supply chain resilience.

3.2 The influence of BDA capabilities on supply chain visibility and flexibility

Drawing on DCT (Teece, 2007), a firm's resources or competencies—for example, BDA—yield competitive advantages only when they are integrated with higher-order organizational processes that enable the renewal of competencies to adapt to changing business environments. According to Wamba et al. (2017), BDA enhances firm performance by enabling the development of dynamic capabilities. Moreover, Mikalef et al. (2019) have argued that DBA contributes toward the processes of sensing, coordinating, learning, integrating and reconfiguring—key components of dynamic capabilities, ultimately enhancing innovation capabilities. In line with the literature (Wamba et al., 2017), we propose that BDA contributes to competitive advantage by effectively enhancing dynamic capabilities.

According to Wei and Wang (2010), supply chain visibility serves as a dynamic capability by facilitating real-time information acquisition, enabling resource reconfigurability, and improving strategic performance. BDA strengthens supply chain visibility by capturing and integrating real-time data from diverse sources, allowing firms to detect shifts in customer demand, monitor supplier activities, and anticipate potential disruptions as they emerge. Similarly, Bag and Rahman (2023) suggest that supply chain flexibility serves as a dynamic capability by enabling firms to absorb demand fluctuations, adapt to dynamic supply markets, and respond to unexpected supply shortages. BDA supports supply chain flexibility by rapidly reconfiguring resources—such as production capacity, distribution routes, or inventory allocations—in response to market fluctuations or unforeseen events. Consequently, BDA empowers organizations to remain vigilant of evolving market conditions and adapt their operations with agility, thereby enhancing both visibility and flexibility across the entire supply chain. Therefore, we hypothesize that:

H2: BDA has a positive influence on (a) supply chain visibility and (b) supply chain flexibility.

3.3 The mediating effect of supply chain visibility and flexibility

Drawing upon DCT (Teece, 2007), resources or competencies—for example BDA—generate competitive advantages only if they are embedded in higher-order organizational processes that continually renew and adapt these capabilities to evolving business environments. BDA enables firms to process and analyze vast amounts of data, generating insights into supply chain risks, inefficiencies, and opportunities (Cui et al., 2023). However, the value of these insights depends on a firm's ability to effectively sense, seize, and transform its operations—a process rooted in dynamic capabilities. Drawing upon DCT (Teece et al., 1997), dynamic capabilities facilitate the integration of BDA into decision-making and operational processes, enabling firms to anticipate disruptions (proactive SCR) and to reconfigure resources and capabilities to recover quickly from disruptions (reactive SCR). Therefore, dynamic capabilities act as the critical link that leverages the potential of BDA to achieve meaningful improvements in SCR across various disruption phases. Wamba et al. (2017) highlight the mediating role of dynamic capabilities in the relationship between BDA and firm performance. Similarly, Mikalef et al. (2019) suggest that a BDA contributes towards the processes of sensing, coordinating, learning, integrating and reconfiguring—key components of dynamic capabilities—thereby enhancing innovation capabilities.

Drawing upon DCT (Teece, 2007), supply chain visibility and flexibility serve as mediating mechanisms between BDA and SCR because they translate raw data and analytical insights into timely, adaptive actions—core components of dynamic capabilities. BDA's ability to gather, integrate, and analyze large-scale, real-time information strengthens the firm's visibility, which in turn enhances awareness of potential disruptions and opportunities. This increased visibility allows for proactive adjustments in strategy and resources—core dynamic capabilities that help shield the supply chain from shocks. Furthermore, BDA fosters flexibility by identifying precise areas for reconfiguration, enabling swift adaptations to shifting market conditions or unexpected events. As a result, the firm can quickly reallocate resources or modify processes, maintaining continuity and resilience. In essence, by facilitating accurate, up-to-date information flows (visibility) and agile responses (flexibility), BDA empowers firms to detect threats early and respond effectively, thereby bolstering their overall resilience in turbulent environments. Through the lens of DCT, we propose that supply chain visibility and flexibility acts as mediators between BDA and SCR. Therefore, we hypothesize that:

H3: Supply chain visibility mediates the relationship between (a) BDA and proactive supply chain resilience, (b) BDA and reactive supply chain resilience.

H4: Supply chain flexibility mediates the relationship between (a) BDA and proactive supply chain resilience, (b) BDA and reactive supply chain resilience.

3.4 The moderating effect of firm size

Drawing upon inertia theory (Hannan and Freeman, 1984), firm size is related with structural inertia, defined as resistance to organizational change. Large firms are characterized by stronger structural inertia due to their rigid structures, including multi-layered hierarchies, complex communication channels, and decentralized management decision-making systems (Qi and Yang, 2020). By contrast, small firms, with simpler hierarchies and flatter structures, exhibit greater flexibility and efficiency in responding to environmental changes (Qi and Yang, 2020). The multi-layered hierarchies in large firms requires substantial BDA investments to support real-time data sharing and cross-functional coordination, leveraging BDA to enhance visibility more effectively than in smaller firms. Conversely, flatter hierarchical structures in small firms may limit BDA's incremental impact on visibility, given that data is already broadly accessible throughout the organization—even without sophisticated analytics capabilities. Thus, BDA may exert a stronger positive effect on visibility in large firms than in smaller ones. However, the stronger structural inertia in large firms restricts their ability to adapt quickly to environmental changes, reducing the effect of BDA on flexibility. By contrast, small firms with lower structural inertia can rapidly adapt decision-making and marketing strategies when employing new technologies like BDA, enhancing its impact on flexibility. Thus, BDA may have a stronger positive effect on flexibility in small firms than in larger ones. Based on these distinctions, we propose the following hypotheses:

H5(a): The positive effect of BDA capabilities on supply chain visibility is stronger in large firms than in smaller ones.

H5(b): The positive effect of BDA capabilities on supply chain flexibility is stronger in small firms than in larger ones.

Accordingly, this study proposes the conceptual model shown in Figure 1.

[INSERT FIGURE 1 ABOUT HERE]

4. Research method

4.1 Data collection

This study conducted surveys across Chinese manufacturing firms in five geographic regions: Guangdong, Jiangsu, Shandong, Shaanxi, and Inner Mongolia. These provinces, representing northern, central, eastern, and southern China, exhibit diverse levels of disruption and capacities for returning to their original states. We randomly selected 600 companies within the sampling lists obtained according to suggestions from local governments. To ensure that the selected companies had experienced substantial supply chain disruptions, the survey included a preliminary screening question (i.e., Have you experienced a disruption in the supply chain during the past three years) designed to verify the occurrence of significant disruptions during the specified timeframe. Only those respondents who affirmed their experience with such disruptions were included in the final sample.

To mitigate common method bias, we have employed a multi-respondent survey design that sees two different respondents from each sample firm randomly selected to complete separate questionnaire volumes (Jiang et al., 2024). Volume A focuses on BDA capabilities and organizational contexts, while Volume B reveals the SCR, supply chain visibility, and flexibility of these firms. The questionnaire was translated and cross-checked by 2 bilingual professors and pretested with 5 managers. Respondents returned the overall questionnaires directly to the authors when they finished the survey. To enhance the response rate, we assured participants that they would receive a summary of the results to support their firms' SCR development. Surveys were sent via email to middle- and senior-level managers (e.g., CEOs, general managers, senior managers, or operations directors) with knowledge of their firms' internal operations and supply chain management. After excluding incomplete answers with excessive missing values, the final sample comprised 277 firms, yielding a response rate of 46.2%. Table 2 presents a summary of firms' characteristics, including industries, firm size, ownership structure, and respondents' positions.

[INSERT TABLE 2 ABOUT HERE]

4.2 Variables and measures

Measurement items are developed by modifying or adopting validated scales. The measurement items are listed in Appendix A. *Proactive SCR* was measured using four items, which were adapted from Brandon-Jones et al. (2014) and Cheng and Lu (2017). *Reactive SCR* was measured use four items derived from Ambulkar et al. (2015) and Cheng and Lu (2017). Following Gupta and George (2016) and Jiang et al. (2024), BDA has been conceptualized and developed as a second-order reflective construct comprising three first-order constructs, namely, technical skills, managerial skills, and data-driven culture. *Technical skills* were measured using five items, which were adapted from Gupta and George (2016). *Managerial skills* were measured using six items, which were adapted from Wamba et al. (2017). *A data-driven culture* was measured using five items, which were adapted from Gupta and George (2016). *Supply chain visibility* has been conceptualized and developed as a first-order reflective construct, with the five items adapted from Williams et al. (2013) and Srinivasan and Swink (2018). *Supply chain flexibility* was measured through five items, which were adapted from Nadkarni and Herrmann (2010). We operationalized five basic firm demographic variables as control variables: *firm size*, *firm age*, *industry type, firm ownership, and respondents' positions*. *Firm size* was calculated as the natural logarithm of the total number of employees. Following Millington et al. (2006), *firm age* was computed as the natural logarithm of the establishment year. Implementing new high technologies allows firms to have better capabilities than non-high technologies firms. Following Jiang et al. (2024), two dummy variables for *industry type* were used (1 = high-tech industry, 0 = otherwise). Moreover, compared to state-owned and collective enterprises, private enterprises were more flexible and responsive to consumer expectations, but foreign-invested enterprises were far more likely to be constrained to quality and process training to satisfy particular buyer demands (Millington et al., 2006). Thus, we created two dummy variables: *private enterprises* and *foreign-invested enterprises*. Finally, *respondents' positions* were used as control variables to address concerns about the influence of their knowledge on internal firms and supply chain management.

4.3 Nonresponse bias and common method bias

We implemented three approaches to assess whether nonresponse bias was significant in our sample data (Wagner and Kemmerling, 2010). First, we tested for nonresponse bias by comparing the responding firms' demographics to those of the nonresponding ones on the basis of firm size (number of employees) and firms age (the natural logarithm of the establishment year). Second, we compared responses for the first quartile and the late quartile respondents (Armstrong and Overton, 1977). Third, we conducted a follow-up approach by randomly selecting firms in our small samples of nonrespondents after the cutoff date. We compared the nonresponding firms' demographics to those of the responding ones of the main survey on the basis of firm size and firm age. In sum, the three findings suggest that nonresponse bias is not present in the sample data as all *t*-tests were nonsignificant.

Next, a common method bias (CMB) may become a concern, as all the variables are measured using a single method and data were collected from a single respondent. We check for CMB using two methods. First, following Williams et al. (2010), we included social media, defined as a venue that enables manufacturers to encourage suppliers to share their knowledge (Cheng and Krumwiede, 2018), as a marker variable being theoretically unrelated to substantive variables. This marker variable was used to compare the structural parameters both with and without this variable to identify the effects on the observed correlations

(Lindell and Whitney, 2001). Table 3 shows the differences between hypothetical correlations among substantive variables under two conditions: with or without marker variable. As shown in Table 3, this marker variable had insignificant correlations with supply chain visibility, flexibility, and proactive and reactive SCR (β = -0.046, -0.007, -0.041, -0.077; p > 0.05). Furthermore, as shown in Table 3, the original correlation was slightly improved but the significance remained relative unchanged after accounting for marker variable's effect. Thus, this finding suggests that CMB should not significantly affect the interpretation of our results.

[INSERT TABLE 3 ABOUT HERE]

Second, following Podsakoff and Organ (1986), a Harman's single-factor test was conducted to test the possible CMB. The results reveal that the most variance explained by a single factor is 35.04%, lower than 40%, suggesting that CMB was not a concern.

4.4 Reliability and validity

Following Nhat et al. (2022), we treated the loadings of the second-order latent variable as path coefficients between the first-order construct and the overall construct. Table 4 presents the analysis results, where all indicator loadings exceed 0.70, demonstrating acceptable indicator reliability (Fornell and Larcker, 1981). The Cronbach's alpha and composite reliability values of the first-order constructs are greater than 0.70, indicating sufficient internal consistency reliability.

[INSERT TABLE 4 ABOUT HERE]

To assess the validity of the BDA reflective scale, we followed Nhat et al. (2022) and created a "weighted" score for each dimension by multiplying its latent score with its partial squares weight. These scores were then compared with the overall composite score to check alignment. The results in Table 4 show that all correlations between the dimensions and the overall construct were significant, confirming the scale's convergent validity (β = 0.426, 0.421, 0.418, $p < 0.001$). Moreover, the average variance extracted (AVE) values for each first-order construct were above 0.50, further supporting convergent validity (Hair et al., 2017).

Discriminant validity was checked using several approaches following by Henseler et al. (2015) and Rönkkö and Cho (2022). Following Fornell and Larcker (1981), the square root of the AVE for each construct was compared with its correlations with other constructs. The results in Table 5 show that the diagonal values exceed the corresponding correlations, confirming discriminant validity. We also calculated Heterotrait-Monotrait (HTMT) ratio to measure discriminant validity between constructs. Table 6 shows that all HTMT values are below the recommended threshold of 0.85 (Hair et al., 2021), providing additional evidence of discriminant validity.

Finally, the variance inflation factor (VIF) was examined to assess the potential multicollinearity among the constructs. All VIF values were below the recommended threshold value of 5 (Hair et al., 2018), confirming that multicollinearity does not pose an issue in the research model.

[INSERT TABLE 5 ABOUT HERE]

[INSERT TABLE 6 ABOUT HERE]

4.5 Sample size requirements for statistical techniques

We employed variance-based, structural equation modeling (partial squares: PLS-SEM) using SmartPLS 4.0 software to assess the measurement and structural models. PLS-SEM was deemed more suitable for our study. This is because compared with covariance based structural equation modeling (CB-SEM), PLS-SEM was better for theory development and prediction purposes (Dash and Paul, 2021). In addition, PLS-SEM was more suitable for the complicated model with the existence of second-order constructs (Ooi et al., 2018).

Moreover, we followed Wong et al. (2024) and conducted a power analysis to check minimum sample size required for achieving the desired power. The G*Power software was employed to estimate the minimum sample size using an effect size, f^2 of 0.15, probability of error, $\alpha = 0.05$ and power level, $(1 - \beta) = 0.80$ with 4 as the number of predictors. Our sample size of 277 was higher than the minimum sample size of 85 to assess the proposed conceptual framework.

5. Results

5.1 Hypothesis testing

Figure 2 and Table 7 present the results. The coefficient of determination R^2 (coefficient of determination) was used to evaluate the model's explanatory power. The results show that visibility, flexibility, proactive SCR, and reactive SCR were explained by 21.4%, 19.0%, 25.4%, and 39.2%, respectively, of the variation in the conceptual model, exceeding the weak R^2 level of 19% (Chin, 1998). This means that these variables produce acceptable R^2 values and can be considered to represent a medium level of explanatory power. In addition to examining the R^2, the model was assessed by examining the Q^2 predictive relevance of exogenous variables. The results demonstrate that the Q^2 values for predictive relevance range from 0.014 to 0.677, all of which exceed zero, implying the predictive relevance of the structural model (Hair et al., 2017). Additionally, SRMR (standardized root means square residual) was used to test the validity of the structural model, producing a value of 0.095 (where < 0.12 indicates a well-fitting model) (Henseler et al., 2014).

Regarding the H1a and H1b proposed, as Figure 2 shows, BDA insignificantly influences proactive SCR ($\beta = 0.085, p > 0.05$) and exerts a positive and significant influence on reactive SCR ($\beta = 0.424, p < 0.001$). This means that H1a is not supported while H1b is supported. Given the H2a and H2b proposed, BDA positively and significantly affects both supply chain visibility and flexibility ($\beta = 0.465, p < 0.001; \beta = 0.434, p < 0.001$). Thus, H2a and H2b are supported.

To test the mediation effects, we adopted the bootstrapping procedure of using 5,000 sub-samples, an approach well suited to the PLS-SEM method. For the H3a and H3b proposed, supply chain visibility mediates the relationship between BDA and proactive SCR as well as reactive SCR ($\beta = 0.149, p < 0.001; \beta = 0.076, p < 0.05$). Thus, H3a and H3b are supported. For the H4a and H4b proposed, supply chain flexibility mediates the relationship between BDA and proactive SCR as well as reactive SCR ($\beta = 0.09, p < 0.001; \beta = 0.081, p < 0.01$). Thus, H4a and H4b are supported. Table 7 displays the results of these hypotheses.

[INSERT FIGURE 2 ABOUT HERE]

[INSERT TABLE 7 ABOUT HERE]

Regarding H5a and H5b, for large firms, BDA has a stronger influence on supply chain visibility compared to small firms. Conversely, BDA's influence on supply chain flexibility is less pronounced in large firms than in small firms. However, these differences simply indicate that the moderating effects are marginal. Thus, following the calculation procedure developed by Keil et al. (2000), the study examines the path coefficient differences between the structural models of the two subgroups to examine whether the moderating effects are substantive. The results appear in Table 8, which makes apparent that the path coefficient from BDA to supply chain visibility was significantly greater for large firms than for small firms (β_{large} = 0.493, β_{small} = 0.421, t_{spooled} = 8.40), providing empirical evidence for H5a. Meanwhile, the influence of BDA on supply chain flexibility is significantly greater for small firms than for large firms (β_{large} = 0.411, β_{small} = 0.465, t_{spooled} = -5.75), providing support for H5b. Therefore, we have confirmed significant differences in the preconditions of supply chain visibility and flexibility for firm of different sizes.

[INSERT TABLE 8 ABOUT HERE]

5.2 Robustness checks

We employed alternative methods and measures to assess the robustness of our results. To increase the reliability of our results, a Monte Carlo confidence interval (MCCI) method was used to verify the significance of indirect effects (MacKinnon et al., 2004). This MCCI method for assessing mediation is among the best methods to quantify coverage than the bias-corrected bootstrap and the Sobel method (Preacher and Selig, 2012). Following the procedure recommended by Bauer et al. (2006), we estimated the indirect effects by adopting the MCCI simulation with 20,000 replications. The unstandardized path estimates were used to calculate its 95% CI. As reported in Table 9, the results show that the 95% CI for the indirect effects of neither visibility nor flexibility contained zero, indicating that the indirect effects were significant at the 0.05 level.

Similar to visibility, alertness functions as a sensing capability, enabling firms to detect changes in both external and internal environments (Li et al., 2017). To maintain our model simplicity, we selected visibility as the representative variable for sensing capability. To ensure robustness, we conducted a test replacing visibility with alertness. The measurement of alertness was adapted from Li et al. (2017). As shown in Table 10, the results remained consistent with our original findings, confirming that sensing capability (alertness or visibility) more strongly mediates the relationship between BDA and proactive SCR, while flexibility (reconfiguring capability) plays a greater mediating role between BDA and reactive SCR. Given these consistent results, we retained visibility in the original model to maintain simplicity, while incorporating alertness in the robustness test to validate our findings.

[INSERT TABLE 9 ABOUT HERE]

[INSERT TABLE 10 ABOUT HERE]

5.3 Endogeneity test

To mitigate issues arising from reverse causality, this study collected data in two stages with a six-month interval between them. Moreover, this study performed an endogeneity test using social media use (Cheng and Krumwiede, 2018) as an instrumental variable. This choice of instrumental variables was justified due to the fact that adopting BDA techniques might be influenced by social media use, but SCR would remain unaffected, meeting the requirements for instrumental variables. Adopting a two-stage least squares (2SLS) approach and including these instruments into Table 11, the 2SLS results were similar with the original results. The endogeneity test thus strengthens the robustness of our results.

[INSERT TABLE 11 ABOUT HERE]

5.4 Post-hoc analysis

Following Li et al. (2013), *t*-tests were employed to examine the differential path coefficients, reinforcing the distinctions between relationships among the constructs. The results in Table 12 indicate that BDA capabilities exert a significantly stronger positive influence on reactive SCR compared to proactive SCR, with the difference being statistically significant ($p < 0.01$). Furthermore, the results show that visibility has a significantly stronger mediating effect on the relationship between BDA and proactive SCR compared to flexibility ($p < 0.01$). In contrast, flexibility exhibits a significantly stronger mediating effect on the relationship between BDA and reactive SCR compared to visibility ($p < 0.05$).

[INSERT TABLE 12 ABOUT HERE]

6. Discussion and conclusion

While interest in big data is continuously growing, the mechanisms and conditions under which it results in SCR remain largely unexplored in the empirical research context. The value of big data investments has also encouraged questioning from various perspectives. For example, it has been noted that only a small percentage of firms can realize the true potential of their big data investments (Mikalef et al., 2019). To address this issue, this study draws on DCT and inertia theory to investigate how BDA capabilities affect two types of SCR (i.e., proactive and reactive), as well as the mediating effects of visibility and flexibility. Furthermore, this study identifies firm size as a critical moderator in the relationship between BDA and visibility and flexibility.

First, the results demonstrate that BDA capabilities positively influence reactive SCR, but their effect on proactive SCR is insignificant. While several studies highlight the positive impact of BDA on supply chain management—including improvements in supply chain performance (Munir et al., 2022) and SCR (Bag et al., 2024; Dennehy et al., 2021; Zamani et al., 2023)—others argue that BDA investments do not consistently enhance operational efficiency or effectiveness (Edwin Cheng et al., 2022; Jum'a et al., 2023; Liu et al., 2023). These inconsistencies may result from multiple factors, with one key aspect being the differing roles that BDA plays at different stages of supply chain disruptions. Our study reveals that BDA is more effective at addressing the immediate, action-oriented demands of reactive SCR than the anticipatory requirements of proactive SCR.

This study highlights the mediating roles of visibility and flexibility in the relationship between BDA and SCR. While several studies have focused on the direct effect of BDA on SCR (Munir et al., 2024; Zamani et al., 2023), the mechanisms through which BDA capabilities translate into improved SCR remain less explored. By uncovering the mediating effects of visibility and flexibility, this study not only demonstrates how BDA capabilities enhance visibility and flexibility, which contributes to SCR, but also reveals their differentiated roles as mediators. Drawing on DCT, a firm's resources or competencies, like BDA, produce competitive advantages only when integrated with higher-order organizational processes that support renewing competencies to adapt to changing business environments (Wamba et al., 2017). Through the lens of DCT, visibility and flexibility serve as mediators in the relationship between BDA and SCR. Visibility, supported by BDA, provides real-time insights into supply chain operations, enabling firms to detect potential disruptions and assess their impacts. Flexibility, enhanced by BDA, enables the analysis of complex data to develop alternative strategies, optimize resource allocation, and reconfigure supply routes, empowering firms to adapt effectively to disruptions. Therefore, these capabilities link BDA to SCR, enhancing resilience across different timing conditions. This result aligns with the findings of Kähkönen et al. (2023), who emphasize that transforming capability enhances SCR, highlighting the importance of adaptive processes in enhancing SCR. Furthermore, the differentiated mediating effects of visibility and flexibility highlight their unique contributions to SCR. Visibility exerts a stronger mediating effect on the relationship between BDA and proactive SCR by providing transparency and enabling risk mitigation strategies before disruptions escalate. In contrast, flexibility plays a more significant mediating role in the relationship between BDA and reactive SCR because it supports real-time adaptation and recovery efforts during and after disruptions. This dual role of BDA, mediated by visibility and flexibility, helps explain its varying impact across different phases of supply chain disruptions.

This study reveals that BDA has a less pronounced influence on supply chain flexibility in large firms than in small firms. This finding aligns with Qi and Yang (2020), who have recognized that BDA is more profitable for small firms, as they face less required integration effort to realize synergies of social media diversity and big data analytics. However, the study also reveals that BDA exerts a stronger influence on supply chain visibility in large firms compared to small firms, thereby diverging from Qi and Yang (2020). Drawing on inertia theory, we argue that large firms, with greater structural inertia and more complex hierarchies, exhibit lower flexibility than small firms. Consequently, BDA is particularly beneficial for large firms in terms of enhancing visibility, because it simplifies the complex communication patterns that exist in multi-layered hierarchies. In contrast, the stronger structural inertia in large firms limits the effectiveness of BDA at improving flexibility.

6.1 Theoretical contributions

This study makes three theoretical contributes. First, this study elucidates the distinct roles of BDA in terms of shaping the two types of SCR. While BDA has largely been regarded as a breakthrough technological development in both academic discourse and organizational practice, a significant proportion of companies fail to realize competitive advantages from their investments in big data (Marr, 2016). Prior studies have primarily emphasized the positive impacts of BDA on supply chain management, which include enhanced agility, flexibility, and SCR (Bag et al., 2024; Dennehy et al., 2021; Edwin Cheng et al., 2022; Mandal, 2019). However, some studies suggest that BDA does not always translate into improved operational efficiency and effectiveness (Edwin Cheng et al., 2022; Jum'a et al., 2023; Liu et al., 2023). These discrepancies imply that the impact of BDA on enhancing SCR may depend on the different phases of supply chain disruptions. Notably, much of the existing research has treated SCR as a general construct (Bag et al., 2024; Dennehy et al., 2021), neglecting to distinguish between its proactive and reactive dimensions. Our results reveal that BDA positively and directly affects reactive SCR while exerting insignificant effects on proactive SCR. This contributes to understandings of the distinct role of BDA across various phases of supply chain disruptions, in terms of periods before and after disruptions.

Second, using the lens of DCT (Teece, 2007), we highlight the distinct mediating roles of supply chain visibility and flexibility between BDA and SCR. While several studies have focused on the direct effect of BDA on an independent and general SCR (Iftikhar et al., 2022; Munir et al., 2024; Zamani et al., 2023), the mediating roles of supply chain visibility and flexibility in the relationship between BDA and SCR remain less explored and understood. Drawing upon DCT (Teece, 2007), our study shows that supply chain visibility and flexibility play distinct mediating roles in the relationship between BDA and SCR. Visibility has a stronger mediating effect in the relationship between BDA and proactive SCR than flexibility. In contrast, flexibility has a stronger mediating effect in relationship between BDA and reactive SCR compared to visibility. This distinction provides a deeper understanding of the differential mechanisms through which BDA influences SCR at various temporal stages, namely, during the proactive phase (pre-disruptions) and the reactive phase (post-disruptions).

Third, this study extends understanding of the relationship between BDA and supply chain visibility and flexibility by identifying firm size as a critical contingency. Prior research on BDA often adopts a "one-size-fits-all" approach, overlooking the heterogeneity among firms of different sizes. We highlight the moderating role of firm size in explaining the effects of BDA on supply chain visibility and flexibility, thereby clarifying the mixed findings regarding its benefits on supply chain management. Our findings demonstrate that the positive effect of BDA capabilities on visibility is stronger in large firms than in smaller ones, while the positive effect of BDA capabilities on flexibility is stronger in small firms than in larger ones. This finding provides a richer and more detailed picture of how BDA impacts supply chain management.

6.2 Managerial implications

This study offers three managerial implications. First, the findings emphasize that BDA directly enhances reactive SCR but does not have a significant direct effect on proactive SCR. Managers should recognize that BDA investments are particularly valuable for addressing immediate disruptions, especially compared to preparing for future uncertainties. In reactive scenarios, such as during supply chain disruptions, BDA enables real-time data analysis and decision-making to reconfigure resources quickly and recover operations. Managers should prioritize BDA tools and platforms that provide live monitoring, predictive analytics, and scenario planning to strengthen their firm's ability to respond effectively to disruptions. For instance, during the COVID-19 pandemic, companies such as Amazon utilized BDA tools to analyze real-time supply and demand fluctuations, enabling them to reroute shipments, adjust inventory levels, and meet sudden spikes in online orders. While proactive resilience is critical, firms must ensure that their BDA investments are complemented with capabilities that convert data insights into anticipatory actions, such as robust sensing mechanisms and scenario planning frameworks. For example, a retail firm could use predictive analytics to forecast seasonal demand surges and prepare stock levels accordingly.

Second, visibility has a stronger mediating effect on the relationship between BDA and proactive SCR, whereas flexibility plays a more prominent mediating role in the relationship between BDA and reactive SCR. Managers should leverage this insight to allocate resources strategically to enhance visibility and flexibility depending on the primary resilience goals. To improve proactive SCR, managers should focus on visibility-enhancing technologies, such as advanced tracking systems, supply chain control towers, and integrated platforms that provide real-time insights across the supply chain. These tools help firms anticipate potential risks and prepare mitigation strategies. For example, firms have invested in supply chain visibility platforms that integrate supplier and logistics data, enabling them to anticipate disruptions such as severe weather events and prepare mitigation strategies. For reactive SCR, flexibility is key. Managers should invest in capabilities that enable agile decision-making, such as dynamic inventory management systems, flexible supplier contracts, and workforce agility programs. Firms should establish systems that facilitate rapid adjustments to inventory levels, allowing for swift reallocation of resources to address fluctuating demands and unexpected disruptions. Furthermore, fostering strong, collaborative relationships with suppliers and logistics providers is essential to ensure responsiveness and shared capacity for quick reconfiguration of supply chain operations. By aligning visibility and flexibility investments with their resilience objectives, firms can maximize the benefits of BDA.

Third, firm size significantly shapes BDA's effectiveness in the context of supply chain management, with this study finding that BDA has a stronger influence on visibility in large firms but a less pronounced effect on flexibility. Large firms, especially multinational corporations, harness their extensive data repositories and complex BDA infrastructure to enhance visibility. For example, large firms use digital dashboards to monitor and share real-time supply chain data across its global network, facilitating cross-functional coordination and decision-making. Conversely, smaller firms, such as niche manufacturers, should focus on using BDA to enhance flexibility. These firms should prioritize agile tools and systems that enable quick adjustments to supply chain disruptions, such as on-demand forecasting and supplier reconfiguration. Tailoring BDA strategies to firm size allows managers to address inherent organizational challenges and capitalize on their respective strengths.

6.3 Conclusion and limitations

The findings indicate that BDA capabilities positively influence reactive SCR, but their effect on proactive SCR is insignificant. Furthermore, visibility and flexibility mediate the relationship between BDA and SCR, exhibiting distinct mediating effects on proactive and reactive SCR. Visibility exerts a stronger mediating effect on the relationship between BDA and proactive SCR, while flexibility plays a more significant mediating role in the relationship between BDA and reactive SCR. Additionally, the influence of BDA on visibility is more pronounced in large firms than in small firms, whereas its effect on flexibility is less significant in large firms compared to small firms.

This study has several limitations. First, the classification of BDA capabilities is inconsistent in the literature. Despite the significance of the three dimensions of technical skills, managerial skills, and a data-driven culture in the building of a BDA (Jiang et al., 2024), we recognize the need for a more comprehensive understanding of the dimensions of BDA, which include tangible resources. Second, our study classifies SCR into proactive and reactive dimensions, highlighting the distinct roles of BDA in the pre- and post-disruption stages. While existing literature suggests that reactive SCR encompasses both adaptation and transformation (Faruquee et al., 2024), the specific mechanisms through which BDA differentially influences these dimensions remain underexplored. Future research could delve deeper into how BDA shapes adaptation and transformation processes. Third, while our chosen mediators align with DCT, we intentionally excluded seizing capability to focus on comparing the distinct roles of visibility (sensing) and flexibility (reconfiguring). Sensing is critical in the pre-disruption stage (proactive capability), whereas reconfiguring is key in the post-disruption stage (reactive capability). This approach clarifies their distinct mediating roles in the relationship between BDA and SCR. However, additional constructs, such as seizing and absorptive capacity, may also offer valuable insights. Future research should explore these mediators to further understand the mechanisms through which BDA influences SCR.

References

Acciarini, C., Cappa, F., Boccardelli, P., and Oriani, R., 2023, How can organizations leverage big data to innovate their business models ? A systematic literature review, *Technovation*, 123, 102713.

Ali, A., Mahfouz, A., and Arisha, A., 2017, Analysing supply chain resilience: integrating the constructs in a concept mapping framework via a systematic, *Supply Chain Management: An International Journal*, 22(1), 16–39.

Alnuaimi, B. K., Background, T., and Collection, D., 2021, The role of big data analytics capabilities in greening e-procurement : A higher order PLS-SEM analysis, *Technological Forecasting & Social Change*, 169, 120808.

Ambulkar, S., Blackhurst, J., and Grawe, S., 2015, Firm's resilience to supply chain disruptions: Scale development and empirical examination, *Journal of Operations Management*, 34, 111–122.

Armstrong, J. S., and Overton, T. S., 1977, Estimating nonresponse bias in mail surveys, *Journal of Marketing Research*, 14(3), 396–402.

Aslam, H., Blome, C., Roscoe, S., and Azhar, T. M., 2018, Dynamic supply chain capabilities How market sensing, supply chain agility and adaptability affect supply chain ambidexterity Haris, *International Journal of Operations & Production Management*, 38(12), 2266–2285.

Bag, S., Dhamija, P., Luthra, S., and Huisingh, D., 2023, How big data analytics can help manufacturing companies strengthen supply chain resilience in the context of the COVID-19 pandemic, *The International Journal of Logistics Management*, 34(4), 1141–1164.

Bag, S., Gupta, S., Choi, T., and Kumar, A., 2024, Roles of innovation leadership on using big data analytics to establish resilient healthcare supply chains to combat the COVID-19 pandemic: A multimethodological study, *IEEE Transactions on Engineering Management*, 71, 13213–13226.

Bag, S., and Rahman, M. S., 2023, The role of capabilities in shaping sustainable supply chain flexibility and enhancing circular economy-target performance: an empirical study, *Supply Chain Management*, 28(1), 162–178.

Bahrami, M., and Shokouhyar, S., 2022, The role of big data analytics capabilities in bolstering supply chain resilience and firm performance: a dynamic capability view, *Information Technology and People*, 35(5), 1621–1651.

Bauer, D. J., Preacher, K. J., and Gil, K. M., 2006, Conceptualizing and testing random indirect effects and moderated mediation in multilevel models: new procedures and recommendations, *Psychological Methods*, 11(2), 142–163.

Bean, R., 2017, How companies say they're using big data, *Harvard Business Review*, April 28.

Brandon-Jones, E., Squire, B., Autry, C. W., and Petersen, K. J., 2014, A contingent resource-based perspective of supply chain resilience and robustness, *Journal of Supply Chain Management*, 50(3), 55–73.

Cheng, C. C. J., and Krumwiede, D., 2018, Enhancing the performance of supplier involvement in new product development : the enabling roles of social media and fi rm

capabilities, *Supply Chain Management: An International Journal*, 23(3), 171–187.
Cheng, J., and Lu, K., 2017, Enhancing effects of supply chain resilience: insights from trajectory and resource-based perspectives, *Supply Chain Management: An International Journal*, 22(4), 329–340.
Chin, W. W., 1998, The partial least squares approach to structural equation modeling, *Modern Methods for Business Research*, 295(2), 295–336.
Chowdhury, M. H., and Quaddus, M., 2017, Supply chain resilience: Conceptualization and scale development using dynamic capability theory, *International Journal of Production Economics*, 188, 185–204.
Christopher, M., Peck, H., Martin Christopher, and Peck, H., 2004, Building the resilient supply chain, *The International Journal of Logistics Management*, 1(11), 1829–1841.
CILT, 2020,*Impact of COVID-19 on Hong Kong's logistics industry*. https://ciltinternational.org/wp-content/uploads/2020/07/Impact-of-COVID-19-on-Hong-Kongs-Logistics-Industry-20200713.pdf
Corsi, C., Prencipe, A., and Capriotti, A., 2019, Linking organizational innovation, firm growth and firm size, *Management Research*, 17(1), 24–49.
Cui, L., Wu, H., Wu, L., Kumar, A., and Tan, K. H., 2023, Investigating the relationship between digital technologies, supply chain integration and firm resilience in the context of COVID-19, *Annals of Operations Research*, 327, 825–853.
Dash, G., and Paul, J., 2021, CB-SEM vs PLS-SEM methods for research in social sciences and technology forecasting, *Technological Forecasting and Social Change*, 173, 121092.
Dennehy, D., Oredo, J., Despoudi, S., and Fitzgibbon, M., 2021, Supply chain resilience in mindful humanitarian aid organizations : the role of big data analytics, *International Journal of Operations & Production Management*, 41(9), 1417–1441.
Dubey, R., Bryde, D. J., Dwivedi, Y. K., Graham, G., and Foropon, C., 2022, Impact of artificial intelligence-driven big data analytics culture on agility and resilience in humanitarian supply chain: A practice-based view, *International Journal of Production Economics*, 250, 108618.
Dubey, R., Gunasekaran, A., Bryde, D. J., Yogesh, K., Papadopoulos, T., Dubey, R., Gunasekaran, A., Bryde, D. J., and Yogesh, K., 2020, Blockchain technology for enhancing swift-trust , collaboration and resilience within a humanitarian supply chain setting, *International Journal of Production Research*, 58(11), 3381–3398.
Dubey, R., Gunasekaran, A., Childe, S. J., Blome, C., and Papadopoulos, T., 2019, Big data and predictive analytics and manufacturing performance: integrating institutional theory, resource-based view and big data culture, *British Journal of Management*, 30(2), 341–361.
Dubey, R., Gunasekaran, A., Childe, S. J., Fosso Wamba, S., Roubaud, D., and Foropon, C., 2019, Empirical investigation of data analytics capability and organizational flexibility as complements to supply chain resilience, *International Journal of Production Research*, 59(1), 110–128.
Dubey, R., Luo, Z., Gunasekaran, A., Akter, S., Hazen, B. T., and Douglas, M. A., 2018, Big data and predictive analytics in humanitarian supply chains: Enabling visibility and coordination in the presence of swift trust, *International Journal of Logistics*

Management, 29(2), 485–512.

Edwin Cheng, T. C., Kamble, S. S., Belhadi, A., Ndubisi, N. O., Lai, K. hung, and Kharat, M. G., 2022, Linkages between big data analytics, circular economy, sustainable supply chain flexibility, and sustainable performance in manufacturing firms, *International Journal of Production Research*, 60(22), 6908–6922.

Erol, O., Sauser, B. J., and Mansouri, M., 2010, A framework for investigation into extended enterprise resilience, *Enterprise Information Systems*, 4(2), 111–136.

Faruquee, M., Paulraj, A., and Irawan, C. A., 2024, A typology of supply chain resilience : recognising the multi-capability nature of proactive and reactive contexts, *Production Planning & Control*, 35(12), 1503–1523.

Fornell, C., and Larcker, D. F., 1981, Evaluating structural equation models with unobservable variables and measurement error, *Journal of Marketing Research*, 18(1), 39–50.

Fosso, S., Maciel, W., Lunwen, M. Q., and Sivarajah, U., 2024, Big data analytics-enabled sensing capability and organizational outcomes : assessing the mediating effects of business analytics culture, *Annals of Operations Research*, 333(2), 559–578.

Grego, M., Magnani, G., and Denicolai, S., 2024, Transform to adapt or resilient by design ? How organizations can foster resilience through business model transformation, *Journal of Business Research*, 171, 114359.

Gupta, M., and George, J. F., 2016, Toward the development of a big data analytics capability, *Information and Management*, 53(8), 1049–1064.

Hair, J. F., Risher, J. J., and Ringle, C. M., 2018, When to use and how to report the results of PLS-SEM, *European Business Review*, 31(1), 2–24.

Hair, J., Hollingsworth, C. L., Randolph, A. B., and Chong, A. Y. L., 2017, An updated and expanded assessment of PLS-SEM in information systems research, *Industrial Management and Data Systems*, 117(3), 442–458.

Hair Jr, J. F., Hult, G. T. M., Ringle, C. M., Sarstedt, M., Danks, N. P., and Ray, S., 2021,*Partial least squares structural equation modeling (PLS-SEM) using R: A workbook*, Springer Nature.

Hannan, M. T., and Freeman, J., 1984, Structural inertia and organizational change, *American Sociological Review*, 49, 149–164.

Henseler, J., Dijkstra, T. K., Sarstedt, M., Ringle, C. M., Diamantopoulos, A., Straub, D. W., Ketchen, D. J., Hair, J. F., Hult, G. T. M., and Calantone, R. J., 2014, Common Beliefs and Reality About PLS: Comments on Rönkkö and Evermann (2013), *Organizational Research Methods*, 17(2), 182–209.

Henseler, J., Ringle, C. M., and Sarstedt, M., 2015, A new criterion for assessing discriminant validity in variance-based structural equation modeling, *Journal of the Academy of Marketing Science*, 43(1), 115–135.

Iftikhar, A., Purvis, L., Giannoccaro, I., and Wang, Y., 2023, The impact of supply chain complexities on supply chain resilience: the mediating effect of big data analytics, *Production Planning & Control*, 34(16), 1562–1582.

Ivanov, D., and Dolgui, A., 2021, A digital supply chain twin for managing the disruption risks and resilience in the era of Industry 4 . 0, *Production Planning & Control*, 32(9), 775–788.

Jain, N. K., Chakraborty, K., and Choudhury, P., 2024, Building supply chain resilience through industry 4.0 base technologies: role of supply chain visibility and environmental dynamism, *Journal of Business and Industrial Marketing*, 39(8), 1750–1763.

Jiang, Y., Feng, T., and Huang, Y., 2024, Antecedent configurations toward supply chain resilience : The joint impact of supply chain integration and big data analytics capability, *Journal of Operations Management*, 70(2), 257–284.

Jum'a, L., Zimon, D., and Madzik, P., 2023, Impact of big data technological and personal capabilities on sustainable performance on Jordanian manufacturing companies : the mediating role of innovation, *Journal of Enterprise Information Management*, 37(2), 329–354.

Jüttner, U., and Maklan, S., 2011, Supply chain resilience in the global financial crisis: an empirical study, *Supply Chain Management: An International Journal*, 4, 246–259.

Kähkönen, A. K., Evangelista, P., Hallikas, J., Immonen, M., and Lintukangas, K., 2023, COVID-19 as a trigger for dynamic capability development and supply chain resilience improvement, *International Journal of Production Research*, 61(8), 2696–2715.

Keil, M., Tan, B. C., Wei, K.-K., Saarinen, T., Tuunainen, V., and Wassenaar, A., 2000, A cross-cultural study on escalation of commitment behavior in software projects, *MIS Quarterly*, 24(2), 299–325.

Lee, V. H., Foo, P. Y., Cham, T. H., Hew, T. S., Tan, G. W. H., and Ooi, K. B., 2024, Big data analytics capability in building supply chain resilience: the moderating effect of innovation-focused complementary assets, *Industrial Management and Data Systems*, 124(3), 1203–1233.

Li, L., Gong, Y., Wang, Z., and Liu, S., 2022, Big data and big disaster : a mechanism of supply chain risk management in global logistics industry big disaster, *International Journal of Operations & Production Management*, 43(2), 274–307.

Li, Xixi, Hsieh, J. P.-A., and Rai, A., 2013, Motivational differences across post-acceptance information system usage behaviors: An investigation in the business intelligence systems context, *Information Systems Research*, 24(3), 659–682.

Li, Xun, Wu, Q., Holsapple, C. W., and Goldsby, T., 2017, An empirical examination of firm financial performance along dimensions of supply chain resilience, *Management Research Review*, 40(3), 254–269.

Lin, J., Wu, S., and Luo, X. R., 2024, How does big data analytics capability affect firm performance ? Unveiling the role of organisational resilience and environmental dynamism, *European Journal of Information Systems*, Online, 1–27.

Lindell, M. K., and Whitney, D. J., 2001, Accounting for common method variance in cross-sectional research designs, *Journal of Applied Psychology*, 86(1), 114–121.

Liu, H., Lu, F., Shi, B., Hu, Y., and Li, M., 2023, Big data and supply chain resilience : role of decision-making technology, *Management Decision*, 61(9), 2792–2808.

MacKinnon, D. P., Lockwood, C. M., and Williams, J., 2004, Confidence limits for the indirect effect: Distribution of the product and resampling methods, *Multivariate Behavioral Research*, 39(1), 99–128.

Mandal, S., 2019, The influence of big data analytics management capabilities on supply chain preparedness, alertness and agility: An empirical investigation, *Information Technology and People*, 32(2), 297–318.

Manikas, I., Sundarakani, B., and Shehabeldin, M., 2023, Big data utilisation and its effect on supply chain resilience in Emirati companies, *International Journal of Logistics: Research and Applications*, 26(10), 1334–1358.

Marr, B., 2016,*Big Data in Practice: How 45 Successful Companies Used Big Data Analytics to Deliver Extraordinary Results* (B. Marr (ed.)), John Wiley & Sons.

Mikalef, P., Boura, M., Lekakos, G., and Krogstie, J., 2019, Big data analytics capabilities and innovation: the mediating role of dynamic capabilities and moderating effect of the environment, *British Journal of Management*, 30(2), 272–298.

Mikalef, P., Krogstie, J., Pappas, I. O., and Pavlou, P., 2020, Exploring the relationship between big data analytics capability and competitive performance: The mediating roles of dynamic and operational capabilities., *Information & Management*, 57(2), 103169.

Millington, A., Eberhardt, M., and Wilkinson, B., 2006, Supplier performance and selection in China, *International Journal of Operations and Production Management*, 26(2), 185–201.

Munir, M. A., Hussain, A., Farooq, M., Rehman, A. U., and Masood, T., 2024, Building resilient supply chains: Empirical evidence on the contributions of ambidexterity, risk management, and analytics capability, *Technological Forecasting and Social Change*, 200, 123146.

Munir, M., Shakeel, M., Jajja, S., and Chatha, K. A., 2022, Capabilities for enhancing supply chain resilience and responsiveness in the COVID-19 pandemic : exploring the role of improvisation , anticipation , and data analytics capabilities, *International Journal of Operations & Production Management*, 42(10), 1576–1604.

Nadkarni, S., and Herrmann, P., 2010, CEO personality, strategic flexibility, and firm performance: The case of the Indian business process outsourcing industry, *Academy of Management Journal*, 53(5), 1050–1073.

Nhat, A., Le, H., Xuan, H., Phong, D., Ming, J., and Cheng, S., 2022, Dataset for cognition processes , motivations , spatial presence experience , and customer engagement in retail mobile apps, *Data in Brief*, 42, 108198.

Ooi, K., Hew, J., Lin, B., and Hew, J., 2018, Unfolding the privacy paradox among mobile social commerce users : a multi-mediation approach, *Behaviour & Information Technology*, 37(6), 575–595.

Podsakoff, P. M., and Organ, D. W., 1986, Self-reports in organizational research: problems and prospects, *Journal of Management*, 12(4), 531–544.

Ponomarov, S. Y., and Holcomb, M. C., 2009, Understanding the concept of supply chain resilience, *The International Journal of Logistics Management*, 20(1), 124–143.

Preacher, K. J., and Selig, J. P., 2012, Advantages of Monte Carlo confidence intervals for indirect effects, *Communication Methods and Measures*, 6(2), 77–98.

Qi, J., and Yang, C., 2020, Business value of big data analytics : A systems-theoretic approach and empirical test, *Information & Management*, 57(1), 103124.

Queiroz, M. M., Wamba, S. F., Branski, R. M., Sao, U. De, and Escola, P., 2022, Supply chain resilience during the COVID-19 : empirical evidence from an emerging economy, *Benchmarking: An International Journal*, 29(6), 1999–2018.

Raguseo, E., Vitari, C., and Pigni, F., 2020, Profiting from big data analytics : The moderating roles of industry concentration and firm size, *International Journal of*

Production Economics, 229, 107758.
Rönkkö, M., and Cho, E., 2022, An updated guideline for assessing discriminant validity, *Organizational Research Methods*, 25(1), 6–14.
Srinivasan, R., and Swink, M., 2018, An investigation of visibility and flexibility as complements to supply chain analytics: An organizational information processing theory perspective, *Production and Operations Management*, 27(10), 1849–1867.
Su, X., Zeng, W., Zheng, M., Jiang, X., Lin, W., and Xu, A., 2022, Big data analytics capabilities and organizational performance : the mediating effect of dual innovations, *European Journal of Innovation Management*, 25(4), 1142–1160.
Teece, Dacvid J., 2007, Explicating dynamic capabilities: The nature and microfoundations of (sustainable) enterprise performance, *Stragic Management Journal*, 28, 1319–1350.
Teece, David J., 2007, Explicating dynamic capabilities: The nature and microfoundations of (sustainable) enterprise performance, *Strategic Management Journal*, 28(13), 1319–1350.
Teece, David J., Pisano, G., and Shuen, A., 1997, Dynamic capabilities and strategic management, *Strategic Management Journal*, 18(7), 509–533.
Wagner, S. M., and Kemmerling, R., 2010, Handling nonresponse in logistics research, *Journal of Business Logistics*, 31(2), 357–381.
Wamba, S. F., Gunasekaran, A., Akter, S., Ren, S. J. fan, Dubey, R., and Childe, S. J., 2017, Big data analytics and firm performance: Effects of dynamic capabilities, *Journal of Business Research*, 70, 356–365.
Wei, H. L., and Wang, E. T. G., 2010, The strategic value of supply chain visibility: Increasing the ability to reconfigure, *European Journal of Information Systems*, 19(2), 238–249.
Wieland, A., and Durach, C. F., 2021, Two perspectives on supply chain resilience, *Journal of Business Logistics*, 42(3), 315–322.
Wieland, A., and Wallenburg, C. M., 2013, The influence of relational competencies on supply chain resilience: a relational view, *International Journal of Physical Distribution & Logistics Management*, 43(4), 300–320.
Williams, B. D., Roh, J., Tokar, T., and Swink, M., 2013, Leveraging supply chain visibility for responsiveness: The moderating role of internal integration, *Journal of Operations Management*, 31(7–8), 543–554.
Williams, L. J., Hartman, N., and Cavazotte, F., 2010, Method variance and marker variables A review and comprehensive CFA marker technique, *Organizational Research Methods*, 13(3), 477–514.
Wong, L. W., Tan, G. W. H., Ooi, K. B., Lin, B., and Dwivedi, Y. K., 2024, Artificial intelligence-driven risk management for enhancing supply chain agility: A deep-learning-based dual-stage PLS-SEM-ANN analysis, *International Journal of Production Research*, 62(15), 5535–5555.
Zahid, A., Noor, P., Jaafar, I., Mohezar, S., Muhammad, A., Mubarik, S., and Shahbaz, M., 2022, Multi - dimensional supply chain flexibility and supply chain resilience : the role of supply chain risks exposure, *Operations Management Research*, 15, 307–325.
Zamani, E. D., Smyth, C., Gupta, S., and Dennehy, D., 2023, Artificial intelligence and big data analytics for supply chain resilience : a systematic literature review, *Annals of*

Operations Research, 327(2), 605–632.
Zouari, D., Ruel, S., and Viale, L., 2021, Does digitalising the supply chain contribute to its resilience ?, *International Journal of Physical Distribution & Logistics Management*, 51(2), 149–180.

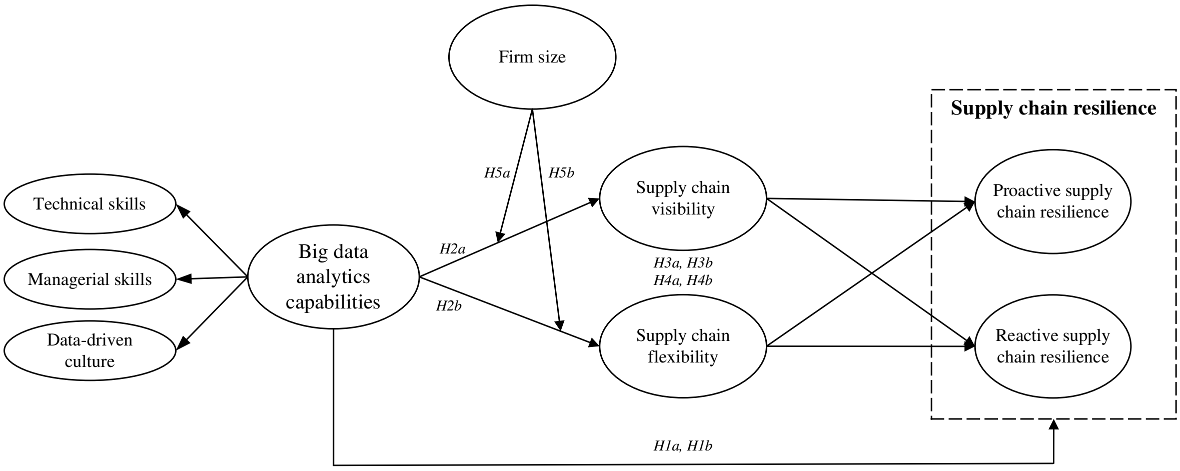

Figure 1 Conceptual model

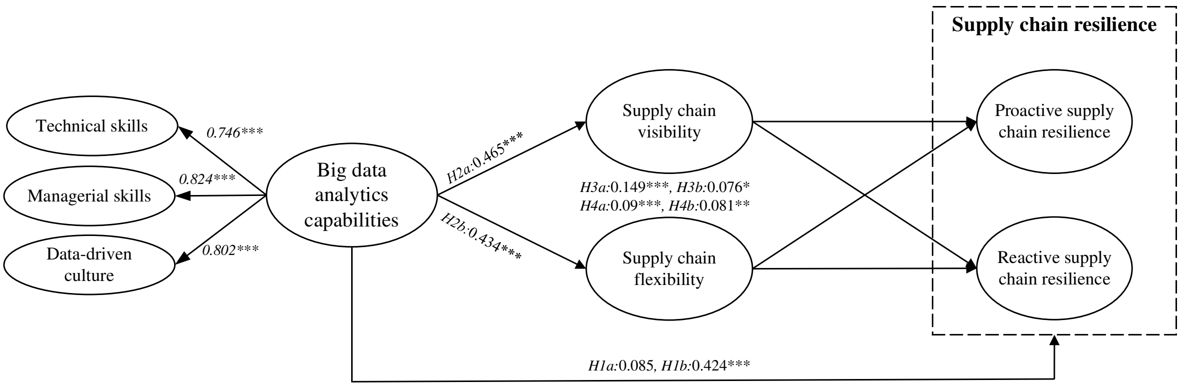

Figure 2 The model estimation results

Note: ***Significant at the 0.001 level, **Significant at the 0.01 level, *Significant at the 0.05 level.

Table 1 BDA and their outcomes

Independent variables	Dependent variables	Mediators	Moderators	Findings	Theory	Authors
BDA	Firm performance	Dynamic capabilities	None	BDA enhances firm performance through dynamic capabilities, enabling agility and innovation.	DCT	(Wamba et al., 2017)
BDA	Coordination	Visibility	Swift trust	BDA significantly improves visibility and coordination in humanitarian supply chains, with swift trust mediating the relationship.	Resource-based view (RBV)	(Dubey et al., 2018)
Institutional pressures	Cost performance, Operational performance	Tangible resources, human skills, big data predictive analytics (BDPA) capabilities	Big data culture	Institutional pressures significantly influence resource selection. Big data culture positively moderates the impact of resources on BDPA adoption. BDPA improves cost and operational performance.	Institutional theory, RBV	(Dubey, Gunasekaran, Childe, Blome, et al., 2019)
BDA	Competitive advantage	SCR	Flexibility	BDA enhances competitive advantage by enhancing SCR.	Information processing theory (IPT)	(Dubey, Gunasekaran, Childe, Fosso Wamba, et al., 2019)
BDA	Supply chain agility	None	None	BDA planning, BDA coordination and BDA control are critical enablers of supply chain agility	DCT	(Mandal, 2019)
BDA	Innovation	Dynamic capabilities	Environment	Dynamic capabilities indirectly influence the relationship between BDA and innovation capabilities	DCT	(Mikalef et al., 2019)
BDA	Competitive performance	Dynamic, marketing, technological capabilities	None	BDA strengthen dynamic capabilities, positively impacting marketing and technological capabilities	DCT	(Mikalef et al., 2020)
BDA	SCR	Organizational mindfulness (OMIN)	OMIN	BDA positively affects SCRE, and OMIN mediates this relationship.	DCT	(Dennehy et al., 2021)
BDA	Circular economy practices, sustainable performance	Sustainable supply chain flexibility	None	BDA drives circular economy practices and sustainable performance through supply chain flexibility as a mediator.	DCT	(Edwin Cheng et al., 2022)
BDA	Supply chain performance (SCP)	SCR, supply chain innovation (SCI)	None	BDA capabilities improve SCP through the mediating effects of SCR and SCI.	DCT	(Bahrami and Shokouhyar, 2022)
BDA	Supply chain performance	Anticipation and improvisation, SCR and responsiveness	None	Data analytics capability enhances resilience and responsiveness through anticipation and improvisation.	DCT, IPT	(Munir et al., 2022)
AI-Driven	Humanitarian	Humanitarian	Institutional	AI-BDAC enhances HSCP	Practice-	(Dubey et

BDA culture (AI-BDAC)	supply chain performance (HSCP)	supply chain agility (HSCA), Humanitarian SCR (HSCR)	complexity (IC)	through HSCA and HSCR. IC negatively moderates the relationship between HSCA/HSCR and HSCP.	based view	al., 2022)
Structural and dynamic supply chain complexity	SCR	BDA	None	Structural complexity enhances resilience, while dynamic complexity negatively impacts it unless mediated by BDA.	DCT, Contingency theory	(Iftikhar et al., 2023)
BDA	Business model innovation (BMI)	None	None	BDA supports BMI by enabling value creation, value capture, and value delivery.	None	(Acciarini et al., 2023)
Top management support	SCR	Big data adoption	Dynamic environment	Support from management accelerates the adoption of BDA, enhancing SCR.	None	(Liu et al., 2023)
BDA, Artificial intelligence (AI)	SCR	None	None	AI and BDA have been reported to improve SCR.	RBV	(Zamani et al., 2023)
BDA	SCR	Supply chain innovation (SCI), Supply chain responsiveness	Innovation leadership (IL)	BDA enhances supply chain responsiveness and SCI, while IL strengthens these effects. Both SCI and supply chain responsiveness contribute to SCR.	IPT	(Bag et al., 2024)
BDA-enabled sensing capability	Organizational outcomes: customer linking capability, firm performance, market performance, strategic business value	Analytics culture	None	BDA-enabled sensing improves organizational outcomes such as financial and market performance, mediated by analytics culture.	DCT	(Fosso et al., 2024)
Supply chain ambidexterity , risk management (SCRM)	SCR	Supply chain analytics capability (SCAC)	None	SCAC plays mediating effect between SC ambidexterity and SCR as well as between SCRM and SCR.	DCT	(Munir et al., 2024)

Table 2 Profiles of sample firms

Characteristics of firms	Frequency	Percentage
Industry		
Machinery	45	16.3
Electrical machinery and equipment	40	14.5
Communication and computer-related equipment	36	13.0
Chemical and related products	25	9.0
Metal products	22	7.9
Instruments and related products	22	7.9
Non-metallic mineral products	18	6.5
Transport equipment	18	6.5
Rubber and plastics	13	4.7
Food and beverage	12	4.3
Textile	11	4.0
Pharmaceutical and medical	8	2.9
Others	7	2.5
Number of employees		
1-49	31	11.2
50-99	37	13.4
100-299	52	18.8
300-999	45	16.2
1,000-1,999	40	14.4
2,000-4,999	40	14.4
Over 5,000	32	11.6
Ownership structure		
Private enterprises	138	49.8
State-owned and collective enterprises	76	27.5
Foreign-invested enterprises	63	22.7
Respondent 1's position		
CEOs/general managers	27	0.10
Senior managers	141	0.51
Middle management like operations directors	109	0.39
Respondent 2's position		
CEOs/general managers	11	0.04
Senior managers	160	0.58
Middle management like operations directors	106	0.38

Table 3 Test for CMB: correlations between substantive variables and marker variables

Without marker variable	Coefficient	Standard deviation	T statistics	P values	2.50%	97.50%
BDA -> Proactive	0.085	0.08	1.066	0.287	-0.058	0.25
BDA -> Reactive	0.424	0.075	5.691	0	0.284	0.559
BDA -> Visibility	0.465	0.054	8.681	0	0.355	0.568
BDA -> Flexibility	0.434	0.056	7.804	0	0.328	0.544
Visibility -> Proactive	0.32	0.071	4.52	0	0.172	0.452
Visibility -> Reactive	0.164	0.068	2.419	0.016	0.036	0.302
Flexibility -> Proactive	0.207	0.058	3.568	0	0.093	0.322
Flexibility -> Reactive	0.187	0.059	3.155	0.002	0.08	0.317
With marker variable	**Coefficient**	**Standard deviation**	**T statistics**	**P values**	**2.50%**	**97.50%**
BDA -> Proactive	0.109	0.091	1.192	0.234	-0.058	0.303
BDA -> Reactive	0.463	0.074	6.261	0	0.325	0.605
BDA -> Visibility	0.486	0.061	7.903	0	0.36	0.597
BDA -> Flexibility	0.438	0.062	7.059	0	0.315	0.552
Visibility -> Proactive	0.308	0.07	4.383	0	0.164	0.439
Visibility -> Reactive	0.159	0.067	2.388	0.017	0.035	0.298
Flexibility -> Proactive	0.201	0.059	3.394	0.001	0.09	0.319
Flexibility -> Reactive	0.186	0.059	3.148	0.002	0.08	0.309
Media -> Proactive	-0.041	0.057	0.72	0.472	-0.153	0.057
Media -> Reactive	-0.077	0.07	1.093	0.275	-0.215	0.06
Media -> BDA	0.465	0.054	8.654	0	0.363	0.571
Media -> Visibility	-0.046	0.072	0.637	0.524	-0.183	0.104
Media -> Flexibility	-0.007	0.071	0.106	0.916	-0.153	0.132

Table 4 Results of validity and reliability analysis

Construct	Items	Factor loading	Cronbach's alpha	Composite reliability	AVE	VIF
Proactive SCR (1 = strongly disagree, 7 = strongly agree) (Brandon-Jones et al., 2014; Cheng and Lu, 2017)	PSCR1	0.924	0.933	0.936	0.833	4.677
	PSCR2	0.899				4.040
	PSCR3	0.908				3.769
	PSCR4	0.921				4.058
Reactive SCR (1 = strongly disagree, 7 = strongly agree) (Ambulkar et al., 2015; Cheng and Lu, 2017)	RSCR1	0.919	0.947	0.949	0.862	3.783
	RSCR2	0.937				4.634
	RSCR3	0.933				4.457
	RSCR4	0.925				4.205
Technical skills (1 = strongly disagree, 7 = strongly agree) (Gupta and George, 2016)	TS1	0.938	0.928	0.929	0.874	3.974
	TS2	0.931				3.399
	TS3	-				-
	TS4	0.935				3.727
	TS5	-				-
Managerial skills (1 = strongly disagree, 7 = strongly agree) (Gupta and George, 2016)	MS1	-	0.924	0.924	0.867	-
	MS2	-				-
	MS3	-				-
	MS4	0.940				3.858
	MS5	0.932				3.583
	MS6	0.922				3.474
Data-driven culture (1 = strongly disagree, 7 = strongly agree) (Gupta and George, 2016)	DC1	0.910	0.915	0.917	0.854	2.877
	DC2	0.940				3.749
	DC3	0.922				3.218
	DC4	-				-
	DC5	-				-
Visibility (1 = not at all, 7 = great extent) (Srinivasan and Swink, 2018; Williams et al., 2013)	V1	0.870	0.937	0.943	0.800	3.143
	V2	0.909				2.963
	V3	0.899				3.523
	V4	0.898				3.553
	V5	0.895				3.426
Flexibility (1 = strongly disagree, 7 = strongly agree) (Nadkarni and Herrmann, 2010)	FL1	0.886	0.928	0.931	0.777	3.443
	FL2	0.878				3.346
	FL3	0.890				3.176
	FL4	0.887				3.678
	FL5	0.866				3.369
Reflective Construct	Items	Outer Weight	T statistics	P values	VIF	Mean
BDA	Technical	0.426	13.362	0	1.260	0.426
	Managerial	0.421	16.882	0	1.487	0.421
	Culture	0.418	14.762	0	1.438	0.418

Table 5 Mean, standard deviations and correlations of the variables

Constructs	1	2	3	4	5	6	7	8	9	10	11	12	13
1.Proactive	0.913												
2.Reactive	0.429	0.929											
3.Technical skills	0.288	0.421	0.935										
4.Managerial skills	0.238	0.509	0.413	0.931									
5.Data-driven culture	0.256	0.433	0.377	0.523	0.924								
6.Visibility	0.386	0.385	0.435	0.326	0.341	0.894							
7.Flexibility	0.299	0.397	0.309	0.332	0.39	0.188	0.881						
8.Firm size	0.009	0.008	0.01	0.012	0.062	0.125	0.026	1					
9.Firm age	0.069	0.057	-0.071	0.055	-0.045	-0.005	-0.031	0.388	1				
10.Industry type	0.091	0.016	-0.058	-0.009	0.097	0.008	0.016	0.024	0.038	1			
11.Private	0.068	0.067	0.054	0.024	0.086	0.02	0.053	-0.178	-0.117	-0.002	1		
12.Foreign	0.069	0.006	0.048	0.101	0.011	0.038	-0.003	0.056	0.06	0.042	-0.541	1	
13.Position	0.055	-0.035	-0.037	0.008	-0.056	-0.105	-0.058	-0.088	-0.056	0.034	-0.032	0.032	1

Note: The square root of AVE value is on the diagonal.

Table 6 Discriminant validity of HTMT

Variables	1	2	3	4	5	6	7	8	9	10	11	12
1.Proactive												
2.Reactive	0.456											
3.Technical skills	0.308	0.447										
4.Managerial skills	0.255	0.542	0.444									
5.Data-driven culture	0.277	0.464	0.408	0.568								
6.Visibility	0.41	0.405	0.464	0.348	0.365							
7.Flexibility	0.32	0.42	0.33	0.357	0.422	0.2						
8.Firm size	0.016	0.016	0.023	0.013	0.065	0.128	0.028					
9.Firm age	0.07	0.059	0.075	0.057	0.047	0.02	0.04	0.388				
10.Industry type	0.094	0.018	0.06	0.03	0.101	0.037	0.027	0.024	0.038			
11.Private	0.071	0.068	0.055	0.028	0.09	0.022	0.055	0.178	0.117	0.002		
12.Foreign	0.07	0.031	0.05	0.105	0.023	0.039	0.022	0.056	0.06	0.042	0.541	
13.Position	0.057	0.039	0.038	0.02	0.059	0.108	0.06	0.088	0.056	0.034	0.032	0.032

Table 7 Results of hypothesis test

Structural paths	Coefficient	Standard deviation	T statistics	P values	2.50%	97.50%
Direct effects						
BDA → Proactive	0.085	0.08	1.066	0.287	-0.058	0.25
BDA → Reactive	0.424	0.075	5.691	0	0.284	0.559
BDA → Visibility	0.465	0.054	8.681	0	0.355	0.568
BDA → Flexibility	0.434	0.056	7.804	0	0.328	0.544
BDA → Technical skills	0.746	0.039	19.21	0	0.656	0.814
BDA → Managerial skills	0.824	0.026	31.241	0	0.761	0.867
BDA → Culture	0.802	0.03	26.574	0	0.734	0.855
Mediating effects						
BDA → Visibility → Proactive	0.149	0.034	4.347	0	0.08	0.213
BDA → Visibility → Reactive	0.076	0.031	2.418	0.016	0.017	0.135
BDA → Flexibility → Proactive	0.09	0.028	3.249	0.001	0.04	0.149
BDA → Flexibility → Reactive	0.081	0.029	2.816	0.005	0.032	0.146

Table 8 Path coefficient comparison between large and small firms

	Large firms (*N*=157)	Small firms (*N*=120)	$t_{spooled}$
BDA→Visibility	0.493***	0.421***	8.40
BDA→Flexibility	0.411***	0.465***	-5.75

Note: ***Significant at the 0.001 level.

Table 9 Robust test for indirect effects based on Monte Carlo CI simulation

Indirect effects paths	Unstandardized coefficient	Monte Carlo 95 % CI	
		Lower level	Upper level
BDA→ Visibility→ Proactive	0.083	0.378	0.501
BDA→ Visibility→ Reactive	0.051	0.378	0.501
BDA→ Flexibility→ Proactive	0.060	0.406	0.529
BDA→ Flexibility→ Reactive	0.055	0.406	0.529

Table 10 Robust test: substituting alertness for visibility

Structural paths	Coefficient	Standard deviation	T statistics	P values	2.50%	97.50%
Direct effects						
BDA → Proactive	0.15	0.098	1.526	0.128	-0.029	0.344
BDA → Reactive	0.394	0.084	4.661	0	0.224	0.55
BDA → Alertness	0.576	0.055	10.526	0	0.47	0.68
BDA → Flexibility	0.435	0.056	7.776	0	0.328	0.545
BDA → Technical skills	0.741	0.041	17.863	0	0.647	0.814
BDA → Managerial skills	0.826	0.025	33.098	0	0.775	0.868
BDA → Culture	0.804	0.031	25.708	0	0.735	0.856
Mediating effects						
BDA → Alertness → Proactive	0.096	0.043	2.248	0.025	0.001	0.166
BDA → Alertness → Reactive	0.083	0.04	2.075	0.039	0.008	0.162
BDA → Flexibility → Proactive	0.076	0.028	2.661	0.008	0.025	0.142
BDA → Flexibility → Reactive	0.084	0.028	2.947	0.003	0.038	0.154

Table 11 2SLS Model testing for endogeneity

Variables	(1) BDA	(2) Proactive	(3) Reactive
Firm age	-0.064	0.149	0.144
	(0.084)	(0.105)	(0.102)
Firm size	0.012	-0.008	-0.022
	(0.032)	(0.043)	(0.037)
Private	0.283*	0.300	0.095
	(0.134)	(0.170)	(0.146)
Foreign	0.241	0.318	-0.011
	(0.137)	(0.202)	(0.171)
Industry type	-0.019	0.210	0.036
	(0.109)	(0.146)	(0.129)
Position	-0.061	0.119	-0.036
	(0.079)	(0.105)	(0.096)
Media	0.346***		
	(0.056)		
BDA		0.252	0.519**
		(0.146)	(0.179)
_cons	3.746***	3.013***	2.167*
	(0.450)	(0.874)	(0.996)
N	277	277	277
R^2	0.236	0.123	0.312
adj. R^2	0.216	0.100	0.294

Note: ***Significant at the 0.001 level, **Significant at the 0.01 level, *Significant at the 0.05 level.

Table 12 Post-hoc analysis results

Hypotheses	Path Coefficient	Results	Conclusion
H1a vs. H1b	βBDA→Proactive vs. βBDA→Reactive = 0.085 vs. 0.424***	$p < 0.01$	βBDA→Proactive < βBDA→Reactive
H3a vs. H4a	βBDA→Visibility→Proactive vs. βBDA→Flexibility→Proactive = 0.149*** vs. 0.09***	$p < 0.01$	βBDA→Visibility→Proactive > βBDA→Flexibility→Proactive
H3b vs. H4b	βBDA→Visibility→Reactive vs. βBDA→Flexibility→Reactive = 0.076* vs. 0.081**	$p < 0.05$	βBDA→Visibility→Reactive < βBDA→Flexibility→Reactive

Note: ***Significant at the 0.001 level, **Significant at the 0.01 level, *Significant at the 0.05 level.

Appendix A. List of measurement items

Measurement
Proactive supply chain resilience (Brandon-Jones et al., 2014; Cheng and Lu, 2017)
When facing supply chain disruption:
PRO1: Operations would be able to continue
PRO2: We would still be able to meet customer demand
PRO3: Our performance would not deviate significantly from targets
PRO4: The supply chain would still be able to carry out its regular functions
Reactive supply chain resilience (Ambulkar et al., 2015; Cheng and Lu, 2017)
REA1: We are able to adapt to the supply chain disruption easily
REA2: We are able to provide a quick response to the supply chain disruption
REA3: We are able to cope with changes brought by the supply chain disruption
REA4: We are able to recover normal operating performance easily
Technical skills (Gupta and George, 2016)
TS1: We provide necessary training for our employees related to big data analytics
TS2: We hire new employees for big data analytics team based on their big data analytics skills
TS3: Our big data analytics staff has the right skills to accomplish their jobs successfully
TS4: Our big data analytics staff has suitable education to fulfill their jobs
TS5: Our big data analytics staff holds suitable work experience for undertaking their jobs successfully
Managerial skills (Gupta and George, 2016)
MS1: Our big data analytics managers have the ability to understand and appreciate the needs of other managers
MS2: Our big data analytics managers can work with other functional managers of their own organization
MS3: Our big data analytics managers can coordinate big-data-related activities in ways that support other partners
MS4: Our big data analytics managers can anticipate future challenges
MS5: Our big data analytics managers have a good sense of where to use big data
MS6: Our big data analytics managers can interpret the analyses obtained using complex analyses and offer inputs which are useful for swift decision making
Data-driven culture (Gupta and George, 2016)
DC1: We consider data as an asset
DC2: We base most of the decisions on data rather than instinct
DC3: We are willing to override our intuition when data contradict our viewpoints
DC4: We continuously assess our strategies and take corrective action in response to the insights obtained from data
DC5: We continuously coach our people to make their decisions based on data
Supply chain visibility (Srinivasan and Swink, 2018; Williams et al., 2013)
The extent to which the following information is visible to us in the following areas:
V1: Sales information
V2: Demand forecast information
V3: Market level demand information
V4: Customer inventory information
V5: Promotional information
Supply chain flexibility (Nadkarni and Herrmann, 2010)
SCF1: We regularly share information and costs across business activities
SCF2: We frequently change our strategies and structures to derive benefits from environmental changes
SCF3: Our strategy emphasizes exploiting new opportunities arising from environmental variability
SCF4: Our strategy reflects a high level of flexibility in managing political, economic, and financial risks
SCF5: Our strategy emphasizes versatility and empowerment in allocating human resources
Social media use (Cheng and Krumwiede, 2018)
MU1: We use social media to its fullest potential for supporting our own work
MU2: We use all capabilities of social media in the best fashion to help us on the job
MU3: Our use of social media is pretty much integrated as part of our normal work routine
Supply chain alertness (Li et al., 2017)
SCA1: We can detect sudden changes in demand
SCA2: We can detect threats to supply chain network
SCA3: We can identify new technologies for increasing supply chain visibility
SCA4: We can detect unexpected changes in physical flow throughout the supply chain