Big data analytics and supply chain learning: A serial mediation model for enhancing resilience and financial performance

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Abstract

The extant literature on big data analytics capability (BDAC) in the disruptions management area has largely overlooked the distinct role of exploitative and explorative supply chain learning (SCL) in enhancing supply chain resilience (SCRes) and financial performance (FP). This study addresses this gap by examining how BDAC strengthens both exploitative and explorative SCL to improve SCRes and FP. Using survey data from 188 firms from an emerging economy, structural equation modelling was used to test the hypothesised relationships. Our findings reveal that exploitative and explorative learning distinctly impact SCRes, while both are strengthened by BDAC. Although explorative learning does not directly influence SCRes, it enhances exploitative learning, indirectly affecting SCRes through sequential mediation. Finally, SCRes mediates the relationship between exploitative learning and FP, but no mediation effect is observed for explorative learning. This study offers a unique framework that highlights the critical role of BDAC in maximising the impact of both learning types to drive SCRes and FP.

Keywords: Supply chain learning, exploitation - exploration, big data analytics, supply chain resilience, financial performance.

1. Introduction

Building supply chain resilience (SCRes) is crucial in today's volatile environment (Bode & Wagner, 2015), where disruption events, such as the COVID-19 pandemic, the Russia-Ukraine conflict (Braun et al., 2023), and cyberattacks (Mascellino, 2023) can severely impact companies' bottom line, reputation, and customer satisfaction (Bode et al., 2011). Big data analytics capabilities (BDAC) offer a powerful tool to build SCRes (Ye et al., 2024) by quickly acquiring and processing huge volumes of data to provide real-time visibility and insight into complex supply chain networks. This enables companies to predict disruptions, identify alternatives, and facilitate coordinated responses (Sheng et al., 2021; L. Li, Ye, et al., 2022).

A growing body of literature indicates that firms with strong BDAC can better anticipate and adapt their SCs, leading to improved resilience (Zamani et al., 2023). For instance, Dubey et al. (2021) provide empirical evidence that advanced data mining and analytical capabilities have a significant positive impact on SCRes. Similarly, Bag et al. (2021) report that BDAC tools helped manufacturing firms restore and even increase resilience in the wake of the COVID-19 pandemic. Iftikhar et al. (2022) further highlight BDAC as a key enabler for coping with supply chain complexities and building resilience in uncertain environments. While these studies offer valuable insights for both academics and practitioners, they primarily focus on establishing a direct relationship between BDAC and SCRes, leaving a critical gap regarding the underlying mechanisms that translate BDAC investments into resilience outcomes. Extant literature on BDAC presents a multifaceted picture. On the one hand, research underscores its potential for improving performance and resilience (Raut et al., 2021; Wamba et al., 2017), yet on the other hand, several studies highlight the challenges and limitations associated with realising these benefits. For example, Boston Consulting

Group (BCG) report high rates of BDAC failure in achieving targeted outcomes (Forth et al., 2021). Other scholars point to the inflexibility of BDAC due to rigid systems (Ralston & Blackhurst, 2020), inadequate cyber preparedness, and insufficient technical infrastructure (Ye et al., 2024). These drawbacks not only hinder operational performance but also weaken a firm's ability to survive and recover from disruptions (Hanelt et al., 2021). This suggests understanding the underlying mechanisms and conditions through which firms successfully utilise BDAC to develop SCRes is of utmost importance. However, despite its significance, we know relatively little about these mechanisms. A recent systematic literature review by (Zamani et al., 2023) underscores that research on AI and BDAC for SCRes, while growing, remains fragmented and dispersed across various research streams. Notably, only 23 relevant studies were identified over a 10-year period, indicating that many aspects, particularly the mechanisms enabling BDAC-driven resilience, remain unexplored.

To address this gap and unlock the true potential of BDAC for building SCRes, this study posits that firms need to develop a culture of continuous learning within their supply chain operations (L. Chen et al., 2023; M. Wang et al., 2024). Learning within a supply chain refers to a routine of acquiring, developing, and sharing knowledge among supply chain partners (March, 1991; Yang et al., 2019). The existing literature discusses the two key types of supply chain learning (SCL): explorative and exploitative learning (Ojha, Acharya, et al., 2018). Exploitative learning focuses on refining existing processes for efficiency (Ojha et al., 2018). This learning type aligns well with BDAC's core strength of identifying patterns, highlighting inefficiencies, and enabling data-driven decision-making (Park et al., 2015). The integration of BDAC with exploitative learning may help firms identify reliable partners and optimise inventory levels based on historical demand patterns, thus helping firms build a strong foundation for SCRes. However, to build resilience, firms must not only optimise existing processes but also explore new possibilities, i.e., explorative learning (Lee & Rha, 2016). This involves activities such as experimentation, searching, and innovation to discover new solutions, ideas, or approaches (Kristal et al., 2010). Integrating explorative learning with BDAC may enable firms to proactively identify disruptions before they occur, for example, through social media sentiment analysis or weather forecasting (Papadopoulos et al., 2017). This process is important because dynamic SCs require learning-based adaptation to not only cope with disruptions but also continuously evolve to mitigate future risks (Azadegan et al., 2019).

In this study, we focus on SCL, which we define as the process where supply chain partners engage in knowledge creation, sharing and adapting to enhance their collective processes and outcomes (Cohen & Levinthal, 1990). While BDAC provides firms with real-time visibility and analytical insights, resilience depends on how well these insights are absorbed, shared, and transformed into adaptive strategies across the SC. SCL serves as the key conduit for this transformation by facilitating collective learning, process refinement, and proactive innovation (Dai et al., 2025; Munir et al., 2022). Without effective learning mechanisms, BDAC remains an untapped resource, providing insights without the organisational capability to implement them. We, therefore, posit that firms must develop both exploitative and explorative learning capabilities, by utilising both internal expertise and external knowledge sharing networks to translate BDAC into resilience (Zhao et al., 2023) . Therefore, we first investigate the following research question (RQ):

RQ1: To what extent does the integration of BDAC and the two distinct forms of SCL (exploitative and explorative learning) impact SCRes capability?

Building SCRes requires more than just adopting technology. It requires a dynamic learning environment that enables SCs to adapt, thrive, and survive in the face of disruptions (Azadegan et al., 2019; Conz & Magnani, 2020). Our research explores the critical, yet understudied, aspect of the learning process, that is, how SCL drives financial performance (FP) through SCRes. Firms employ exploitative and explorative learning capabilities to create efficient processes and cost-saving measures and develop new capabilities by innovating novel disruption mitigation strategies, respectively (Lee & Rha, 2016; O'Reilly & Tushman, 2008). This ensures that resilience is not undermined by disruptive events and further enhances FP (Conz & Magnani, 2020). However, these two SCL approaches have different resource allocation demands (O'Reilly & Tushman, 2008), which become more pronounced in resource-constrained environments. Existing research lacks empirical evidence on whether the two types of SCL exert distinct or complementary effects on the SCRes-FP relationship. For example, does exploitative learning lead to stronger FP through SCRes by reinforcing stable processes, or can explorative learning, despite its resource demands, unlock new opportunities for greater financial gains through SCRes? Understanding this distinction is important for firms seeking to enhance both operational efficiency and long term adaptability through resilient supply chain practices. Hence, we address this gap in the second question:

RQ2: How do distinct forms of SCL (exploitative and explorative learning) interact with SCRes capability to improve FP?

To answer our two RQs, we develop a unique framework grounded in the dynamic capabilities (DC) theory to understand how firms utilise various capabilities to continuously sense, seize, and reconfigure resources for competitive advantage in volatile environments (Bitencourt et al., 2020; Haarhaus & Liening, 2020; Teece, 2014). The lens allows us to explore the interplay between BDAC, exploitative and explorative learning, and their combined impact on SCRes capability and, ultimately, FP. Specifically, BDAC acts as a sensing mechanism, identifying opportunities and threats (L. Li, Ye, et al., 2022; Wamba et al., 2017). Exploitative learning based on BDAC insights plays a significant role in seizing these opportunities by refining existing processes. Meanwhile, explorative learning, empowered by BDA, enables resource reconfiguration by exploring new markets or sources of supply (Iftikhar, Purvis, et al., 2022). This dynamic interplay, in turn, contributes to SCRes, potentially leading to cost advantages and enhanced FP.

We investigate our model from a developing economy's perspective by collecting data from Pakistani firms operating in the manufacturing and service industries. Existing research on BDAC is predominantly focused on developed economies (Oesterreich et al., 2022) where firms benefit from better technological infrastructure, institutional support, and stable regulatory frameworks (Bag, Pretorius, et al., 2021). However, in developing economies, firm faces structural inefficiencies and resource constraints (Tukamuhabwa et al., 2017). Therefore, it is of significant importance to understand how firms in these contexts can utilise BDAC to enhance resilience. To address this contextual gap, we examine Pakistan as a relevant research setting for this study, as it is the fifth largest cotton producer in the world and a major textile producer (USDA, 2024). Pakistan's SCs are deeply embedded in global trade networks (ADB, 2022). Disruptions in these SCs can have significant ripple effects on international markets. Pakistan also faces significant challenges due to persistent infrastructure bottlenecks, logistics inefficiencies, inconsistent regulatory policies, and a lower rate of digital adoption (Asif et al., 2019). Given these constraints, we aimed to understand whether firms operating in such challenging environments must develop learning capabilities to translate BDAC investments into resilience. Our study extends the existing literature in several ways. Firstly, this study highlights the critical role of exploitative and explorative learning in the BDAC – SCRes relationship, addressing the gap in prior research that has largely overlooked these mechanisms. Secondly, we establish a unique empirical contribution by demonstrating how these two types of SCL, distinctively and sequentially influence (1) BDAC's impact on SCRes, and (2) SCRes's role in driving FP. Thirdly, we provide practical insights for supply chain managers, emphasising that successful BDAC implementation requires an investment in learning oriented capabilities to fully realise resilience and performance benefits.

The remainder of this paper is organised as follows. Section 2 presents the literature review, followed by the development of the hypotheses in Section 3. Section 4 outlines the research method before Section 5 presents the data analysis and results. Finally, Section 6 concludes with a discussion of theoretical and practical implications, limitations, and future research directions.

2. Literature review

2.1. Dynamic Capability Theory and Its Application to Big Data Analytics and Supply Chain Resilience

DC theory, an extension of the resource-based view (RBV), seeks to explain how firms can sustain competitive advantage (Augier & Teece, 2009; Mikalef & Pateli, 2017; Teece et al., 1997). DC refer to the abilities of a firm to "integrate, build and reconfigure internal and external competencies to address rapidly changing environments" (Teece *et al.,* 1997, p. 516). DC are considered higher-level capabilities that create, extend, and/or modify the resource base to build evolutionary fitness, foster innovation, and bring about changes in the market (Teece, 2014). Higher-level DC can be broken down into first-level and second-level forms in a hierarchical structure (L. Li, Ye, et al., 2022). While first-level DC allow the firm to reconfigure its resource base, second-level DC reconfigure first-level DC through different mechanisms (Schilke et al., 2018). By adopting this hierarchical structure, this study positions SCRes as a first-level DC and BDAC as a second-level DC.

SCRes is considered a first (lower) level DC (L. Li, Wang, et al., 2022), aiming to respond effectively to supply chain disruptions by quickly recovering and adapting to reach a more desirable state (Hendry et al., 2019; Stone & Rahimifard, 2018). In recent years, due to unprecedented turbulence from natural disasters, political upheavals, and high market dynamism, the concept of SCRes has risen to prominence as a critical capability for firm survival and performance (Roscoe et al., 2022). Considering it as a multidisciplinary concept, we rely on the dynamic conceptualisation of SCRes, defining it as “an adaptive capability that prepares supply chains for unexpected events and responds to and recovers from disruptions with connectedness and control” (Ponomarov & Holcomb, 2009, p. 131). This conceptualisation aligns closely with the DC theory, particularly the micro-foundations of sensing, seizing, and transforming (Teece, 2007). Specifically, sensing capabilities enable firms to detect disruptions swiftly; seizing capabilities empower rapid response and quick recovery; and transforming capabilities facilitate adaptive changes to processes and structures following disruptions (Ali et al., 2017; Hendry et al., 2019). Furthermore, contemporary views suggest SCRes is more than a reactive capability deployed to manage disruptions. It also enables firms to proactively realise the benefits of various opportunities that the environment presents, potentially allowing a firm to gain a competitive advantage by positioning itself better than rivals in the aftermath of a disruption (Ivanov, 2023; Sheffi & Rice, 2005). Thus, SCRes involves utilising internal and external resources to maintain operational continuity and emerge stronger during turbulent situations (Ambulkar et al., 2015; Golgeci & Kuivalainen, 2020; Scholten et al., 2019).

BDAC is considered a second (higher) level DC (Schilke *et al.,* 2018). From this perspective, BDAC is referred to as a firm's ability to effectively integrate and deploy a combination of tangible resources (such as data infrastructure and analytics platforms), human skills (including both technical and managerial expertise), and intangible resources (like organisational routines) to generate business value (Mikalef et al., 2019). This capability becomes dynamic because it enables the firm to transform these resources into actionable intelligence (Wamba et al., 2017). Indeed, firms with a high level of BDAC that utilise these insights can more effectively sense emerging market shifts and supply chain vulnerabilities, seize opportunities through more agile and informed decision-making, and reconfigure their operational routines. It is through this process that the strategic insights provided by BDAC help to build preventative, responsive, and recoverable capabilities, which all link to greater resilience (Li, Wang, et al., 2022).

Operations and Supply Chain Management (OSCM) scholars have positioned BDAC as a crucial element of a firm's decision-making when building proactive and forward-looking strategies, particularly in highly uncertain environments (Wamba *et al.,* 2017). However, most studies have been conducted in a developed country context. Firms in developing countries often encounter resource challenges that limit their ability to invest in BDAC; they can also lack the necessary infrastructure and face data integration and scalability challenges (Raut et al., 2021; Wamba et al., 2017). To avoid a bandwagon effect (Dennehy *et al.,* 2021), it is imperative to examine the mechanisms by which firms in specific developing countries can derive value from BDAC to enhance SCRes and FP. We seek to bridge this research gap by developing and testing a conceptual model that builds on the DC theory (Teece et al., 2007) and the concept of supply chain learning (Bessant et al., 2003; March, 1991) to understand the sequential mechanisms through which BDAC enhances SCRes and ultimately FP.

2.2. Supply chain learning

Learning is the process of detecting and correcting ineffective actions (Argyris, 1976). Organisational learning is the continuous process of refining an organisation's routines based on past successes to achieve its goals (Levitt & March, 1988). It involves setting new goals, focusing on different areas, i.e., *attention* rules, and figuring out better ways to solve problems, i.e., *search* rules. Over time, employees learn what actions lead to positive results, and the organisation as a whole adapts (Gavetti et al., 2012). Effective learning in firms is based on two pillars. First, developing a unique knowledge base, the "core competence" that drives competitive advantage. Second, fostering a long-term capacity for continuous learning across the organisation. This focus on becoming a "learning organisation" is crucial for sustained success (Bessant et al., 2003; Prahalad & Hamel, 2007).

The learning capability is critical for the development of a firm’s supply chain capabilities (Aslam, Khan, et al., 2020; Spekman et al., 2002). SCL, an extension of organisational learning, is the extent to which a firm manages its upstream and downstream learning processes with supply chain partners, ensuring that the firm, its suppliers, as well as its customers are managing learning targeted toward supply chain processes (Flint et al., 2008). SCL can occur through various modes. It can range from one-on-one interactions (e.g., customer-supplier) to multi-firm collaborations (e.g., supplier clubs, networks). Research suggests principles of individual learning can be applied to these inter-organisational settings (Bessant et al., 2003).

Learning processes consist of exploring '*new possibilities'* and exploiting '*old certainties'* (March, 1991). Exploration is associated with managerial tendencies to search, innovate, discover, and experiment with new knowledge and competencies whilst taking a longer-term orientation. In contrast, exploitation is linked with the tendencies to refine, select, apply, improve, implement, and execute existing knowledge, competencies, technologies, processes, and products with a rather short-term focus (Benner & Tushman, 2003; Lavie et al., 2010; March, 1991). Both learning types are essential for an organisation's success (Tushman & O'Reilly, 1996). While both learning types are essential, they create a natural tension between short-term efficiency and long-term innovation, as they compete for scarce organisational resources, managerial attention, and strategic focus (March, 1991; Ojha et al., 2018; Partanen et al., 2020). This challenge has led to the concept of organisational ambidexterity, which is a firm's ability to effectively manage both exploration and exploitation (O'Reilly & Tushman, 2008). Ambidexterity can be achieved sequentially, where periods of exploration are followed by periods of exploitation. This temporal ambidexterity view suggests that instead of being purely competitive, the two learning types can be complementary over time (Tushman & O'Reilly III, 1996). Specifically, it allows for a process where the new knowledge and opportunities generated during an explorative phase can serve as direct inputs for a subsequent exploitative phase, where those opportunities are then refined and implemented (Aslam et al., 2022).

While the concept of temporal ambidexterity provides a strong theoretical basis for a sequential relationship, the specific mediating role of explorative and exploitative learning, linking BDAC to SCRes, has been largely overlooked in the prior literature. It is unclear if these two learning types act as distinct, parallel mechanisms or if they work sequentially, with one enabling the other. Also, the implications for resource-constrained firms in developing economies, where a pragmatic learning sequence might be critical for survival and resilience, have been largely overlooked (Aslam et al., 2022). Our study aims to address this multifaceted gap by proposing and testing a comprehensive model that examines both the distinct and sequential mediating roles of explorative and exploitative supply chain learning.

3. Hypotheses development

3.1. Big data analytics and supply chain learning

Emerging technologies, including BDA, facilitate SCL as they allow for the efficient search, acquisition, and use of data for both exploitative and explorative purposes (Liu et al., 2023). Furthermore, BDAC allows managers to avoid the "failure trap" (March, 1991) when exploring radical solutions, enabling them to pivot to new business models, create new routines and structures, experiment with new technologies, innovate by uncovering hidden patterns and weak signals from diverse and unstructured data sources (Sivarajah et al., 2024), and adapt to a new situation with a longer-term outlook (Mikalef et al., 2019). This facilitates the generation of novel insights necessary for adaptive responses. Similarly, managers can activate the power of BDAC to mitigate the "success trap" (March, 1991) in relying on exploitative activities to refine their existing knowledge base, competencies, technologies, and processes by using BDAC's predictive and real-time analytics capabilities to optimise current operations and routines (Sivarajah et al., 2024), as well as to elaborate on their existing mindset and decisions (Nakandala et al., 2023).

We posit that BDAC is positively associated with exploration and exploitation. BDAC allows firms to unearth customer requirements and hence potential business opportunities (Saeed et al., 2023), thereby fostering explorative learning. This capability also helps firms thrive during turbulent times (Mikalef and Pateli, 2017) by supporting adaptive responses

(Laguir et al., 2023). In parallel, the benefits of BDAC include driving successful organisational transformation, enabling data-driven decision-making, and facilitating the refinement of existing knowledge and processes (Pezeshkan et al., 2016), thus enhancing exploitative learning. Another key aspect of BDAC is its role in reconfiguring resources and capabilities to strengthen both learning types, ultimately maximising business value (Saeed *et al.,* 2023).

In summary, according to DC theory, BDAC allows organisations to sense changes in the market and industry landscape through the real-time analysis of large amounts of data. This improves a firm's capability to assess opportunities (exploration) and utilise existing resources in an optimal way (exploitation) following the firm's strategic objectives (Teece, 2007). Thus, by leveraging the full potential of big data, firms can strengthen their learning capabilities (exploitative and explorative) and successfully address dynamic and evolving environments. Hence, the following hypotheses are proposed:

H1a: Big data analytics capability is positively associated with exploitative learning.

H1b: Big data analytics capability is positively associated with explorative learning.

3.2. Big data analytics and supply chain resilience

Practitioners and scholars have called for the effective adoption of BDAC to foster SCRes capability to survive and maintain a competitive advantage in the face of disruptive events (Nakandala *et al.,* 2023). A growing focus has been on the connection between BDAC and SCRes, where a complementary relationship is thought to exist. That is, BDAC fosters supply chain visibility and flexibility, thereby contributing to enhanced SCRes (Bag, Dhamija, et al., 2021; Srinivasan & Swink, 2018).

Dennehy et al. (2021) emphasised that BDAC helps in developing SCRes by allowing firms to anticipate disruptions through sensing and forecasting disruptive events on the one hand and monitoring and tracking current firm activities on the other. BDAC is considered an intelligent tool and has been applied to different sectors, including the manufacturing sector (Wamba et al., 2020) and the emergency services sector (Wamba et al., 2015), to better manage operational uncertainties. Furthermore, by employing BDAC, firms can uncover potential vulnerabilities, explore alternative suppliers in the wake of disruption, and develop contingency plans (Prasad et al., 2018). This helps to develop an efficient response to disruptive events.

In accordance with the DC theory, which highlights firms' ability to adapt by leveraging resources, big data analytics enhances supply chain resilience through real-time insights, predictive analytics, and informed decision-making. This capability enables firms to anticipate disruptions, optimise responses, and recover swiftly, strengthening adaptability and operational continuity. Thus, big data analytics positively supports supply chain resilience. Based on the above discussion, the following hypothesis is proposed:

H2: Big data analytics capability is positively associated with supply chain resilience.

3.3. Supply chain learning and supply chain resilience

SCL is considered an antecedent of SCRes (Carayannis *et al.,* 2017; Scholten *et al.,* 2019), but mainly it is considered a monolithic construct. Indeed, scholars have argued that SCRes is a cyclical and cumulative capability developed through ongoing learning and adaptation in response to disruptions (Hendry *et al.,* 2019). More specifically, the ability to learn from past experiences, such as by applying knowledge to explorative or exploitative activities, influences the ability of firms to recover from disruption or transform their operations to reflect a new situation (Ali *et al.,* 2017). Liu *et al.* (2023) argued that firms manage uncertainty through two mechanisms. They can either increase their knowledge processing capacity or decrease their processing needs. This can be seen as a strategic choice between exploration, the pursuit of new knowledge to improve processing capacity, and exploitation, better utilising existing knowledge and reducing processing needs.

By deploying both exploration and exploitation, firms can improve their SCRes. The two learning types, however, contribute through different mechanisms when adverse events occur. Exploitation allows firms to maintain the stability and efficiency of operations. When faced with an adverse event, such as a sudden supplier failure, firms with strong exploitative learning capabilities can leverage their existing knowledge and routines to ensure resilience (Laguir *et al*., 2023). For example, they can efficiently execute pre-defined contingency plans, re-route orders to established secondary suppliers without significant delay, and apply proven problem-solving methods to quickly restore operational stability. Hence, exploitation will lead to SCRes (Gu et al., 2021).

On the other hand, exploration helps firms in searching for new knowledge to alter existing processes, business models, and products; as a result, firms that exhibit higher exploratory capabilities are able to engage in the adaptation phase of SCRes (Aslam et al., 2022). For instance, in the face of a sudden geopolitical tariff that makes a key material unavailable, explorative learning involves rapidly searching for and vetting entirely new materials or identifying and qualifying suppliers in different geographic regions that were not previously considered (Roscoe et al., 2022). Laguir *et al*. (2023) argued that this proactive search for novel solutions builds adaptive capacity and allows the supply chain to reconfigure itself to overcome the new challenge.

To summarise the above arguments from the DC theory, exploitative learning enhances SCRes by refining existing processes, improving efficiency, and strengthening operational stability. This allows firms to better manage known risks and disruptions. Conversely, explorative learning develops resilience by enabling innovation, identifying new opportunities, and adapting to unforeseen challenges. Together, these learning approaches build the capacity that ensures firms can both optimise current operations and innovate for future uncertainties, thereby enhancing overall SCRes. In light of this discussion, both types of learning have a positive influence on SCRes, leading to the following hypotheses:

H3a: Exploitative learning is positively associated with supply chain resilience.

H3b: Explorative learning is positively associated with supply chain resilience.

3.4. Supply chain resilience and financial performance

SCRes can help firms respond to unforeseen challenges, such as geopolitical instability, economic fluctuations, or natural disasters without suffering extensive losses (Ali et al., 2017; Conz & Magnani, 2020). It can play a pivotal role in enhancing a firm's FP by enabling a swift adaptation to and recovery from disruptions and uncertainties (D. Li et al., 2018). By proactively mitigating risks, maintaining flexibility, and developing contingency plans, firms can consistently maintain production, reduce downtime, and protect their core business value from being damaged (Carvalho et al., 2012; Juan & Li, 2023). Also, by quickly adapting and reconfiguring resources, firms can manage sudden changes in supply and demand, reduce lead time fluctuations, and ensure on-time deliveries (Gligor & Holcomb, 2012; Iftikhar et al., 2021). Thus, SCRes could minimise the costs of disruptions and improve profitability in a dynamic business environment.

Researchers, however, have also argued that investing in SCRes involves a financial trade-off, such as between the costs of preparedness or mitigation and the costs of disruption (Jüttner et al., 2003). If this trade-off is not adequately managed, it may reduce overall FP. In highly turbulent environments, such as during the COVID-19 pandemic, some firms experienced significant financial losses and distortions in their logistics operations (Schleper et al., 2021). From the DC theory, SCRes enables firms to respond to disruptions, recover quickly, and maintain operational continuity. This reduces costs, minimises downtime, and ensures customer satisfaction, directly improving financial performance. By leveraging resilience as a DC, firms sustain competitive advantage, optimise resource utilisation, and capitalise on market opportunities, driving profitability and long-term financial success. Therefore, we propose the following hypothesis:

H4: Supply chain resilience positively influences financial performance.

3.5. Mediation effects

The argument for supply chain learning having a mediating effect on the relationship between BDAC and SCRes draws on two aspects of DC: evolutionary fitness and complementarity (Shi et al., 2024; Teece, 2007). Evolutionary fitness is the degree to which a capability allows a firm to earn a living. DC helps in attaining evolutionary fitness by helping firms shape their environment (Teece, 2007). Complementarity is the extent to which the worth of one capability increases due to another capability. Complementary capabilities are difficult to imitate due to the path-dependent nature of their developmental process and causal ambiguity (Teece *et al*., 1997). We argue that BDAC, SCL, and SCRes are complementary capabilities that allow firms to compete during disruptive times (Shi *et al.,* 2024).

BDAC acts as the foundational catalyst, providing the essential data and analytical power necessary for effective SCL. BDAC provides the data and tools that facilitate the search for new knowledge and the identification of vulnerabilities. This explorative learning then directly contributes to SCRes by enabling proactive risk mitigation and adaptation. Explorative learning, with the help of BDA, facilitates the search for alternative strategies, experimentation, and discovery, enabling firms to adapt to evolving market conditions and address to disruptive events (Osiyevskyy et al., 2020). Thus, explorative learning translates BDAC insights into innovation-based adaptive capabilities, enabling firms to anticipate and proactively manage disruptive risks (Blome et al., 2013; Lee & Rha, 2016). From the DC theory perspective, explorative learning aligns closely with dynamic sensing capabilities, empowering firms to innovate and proactively adapt their SCs. Conversely, exploitative learning mediates the BDAC-SCRes relationship differently, aligning more closely with dynamic seizing and reconfiguring capabilities due to its focus on speedy response (Gligor & Holcomb, 2012). Exploitative learning emphasises refining existing knowledge, processes, and routines using BDAC-generated insights, enabling incremental improvements, efficiency, and operational stability (Chandrasekaran et al., 2012; Zhu et al., 2021). Thus, exploitative learning empowers firms to optimise their current operations and swiftly adapt to disruptions, thereby enhancing SCRes. Building on the above, we propose the following hypotheses:

H5a: Explorative learning mediates the relationship between BDAC and SCRes.

H5b: Exploitative learning mediates the relationship between BDAC and SCRes.

In addition to examining the individual mediating roles of explorative and exploitative learning, we investigate whether the influence of BDAC on SCRes is sequentially mediated by explorative and exploitative learning. In addition to complementarity and evolutionary fitness, we build this hypothesis based on the notion of ‘capability levels’ in DC theory. Capability researchers suggest that the DC of a firm can be utilised to develop other dynamic capabilities (Collis, 1994; Helfat, 2010; Schilke, 2014). Notably, Collis (1994) proposed four levels of capabilities. The first level constitutes basic operational capabilities necessary for basic organisational functions. The second level focuses on "dynamic improvements" to existing activities. The third level enables firms to identify the value of new resources and formulate novel strategies ahead of competitors. Finally, the fourth level, characterised as "meta-capabilities," represents the "capacity to develop the capability to develop the capability that innovates faster (or better)" (Collis, 1994, p. 148). Similarly, Schilke (2014) proposed a two-level model: first-level DC that manifests in routines governing the reconfiguration of organisational resources, and second-level DC that modifies the capabilities at the first level. These frameworks highlight the ability of DC to act as catalysts for the development and evolution of other capabilities within an organisation.

This study proposes that BDAC functions as the higher-level DC in a firm, significantly influencing a firm's pursuit of supply chain exploration. We argue that this explorative learning is a necessary precursor to effective exploitative learning, a view supported by the concept of temporal ambidexterity, where firms may sequence learning activities over time (O’Reilly & Tushman, 2013). This sequential perspective is well-grounded in organisational learning theory. For instance, Rothaermel & Alexandre (2009, p. 203) state that "exploitation depends upon prior exploration," and Simsek et al. (2009, p. 883) note that, in technology-oriented firms, “exploration (discovering, acquiring, and developing new technologies) necessarily precedes exploitation (commercialising, applying, and leveraging new technologies).”

The mechanism for this sequence is one of knowledge conversion. Exploration is the pursuit of new, often transformational ideas, while exploitation involves the refinement and implementation of those ideas (Govindarajan & Trimble, 2010; Ojha, Struckell, et al., 2018). As Lavie et al. (2010) argued, exploration generates prospects for the firm to exploit. In the supply chain context, this means that gains from exploration (e.g., identifying a new logistics technology or an alternative supplier network) must be utilised and refined through exploitation (e.g., testing and implementing that technology or formalising new supplier contracts) to create value (Gualandris et al., 2018). Therefore, we argue that firms are most likely to realise the benefits of explorative learning for SCRes if they adopt this sequential approach.

According to the DC theory, BDAC enables firms to proactively sense and seize emerging opportunities and threats using data-driven insights. This capability facilitates both explorative and exploitative learning. Explorative learning, driven by BDAC, allows firms to experiment with novel approaches to SCRes, discovering new configurations and practices through data analysis. Exploitative learning, also guided by BDAC, focuses on refining and improving existing SCRes practices, increasing efficiency and effectiveness by leveraging data to optimise operations. This sequential process, where BDAC first develops exploration and then exploitation, ensures that firms not only discover innovative resilience strategies but also effectively implement and optimise them.

While the logic of temporal ambidexterity is established in the general management literature (O'Reilly & Tushman, 2013), its application has predominantly been studied in the context of well-resourced, high-tech firms in developed countries (Partanen et al., 2020). We argue that its implications for resource-constrained firms in developing economies, like

Pakistan, are not only unclear but potentially more critical. In these contexts, the threat of failure is particularly high due to limited financial and operational resources (Osiyevskyy et al., 2020). Pursuing simultaneous exploration and exploitation can be prohibitively expensive and risky (Wenke et al., 2021). Therefore, a sequential approach may represent a more pragmatic and effective strategy for survival and resilience. This knowledge gap may leave practitioners unsupported by research when allocating their resources. Despite its importance, the specific role of this sequential interplay as a mechanism linking BDAC to SCRes in this context has been overlooked (Aslam et al., 2022). We, therefore, propose evaluating the following hypothesis:

H6: BDAC positively influences SCRes sequentially through explorative and then exploitative learning.

Finally, we propose that SCRes mediates the relationship between (1) exploration and FP, and (2) exploitation and FP. As previously established, a firm's DC hold value when it enables competitive advantage during a supply chain disruption (evolutionary fitness). SCRes, nurtured by exploration and exploitation, equips a firm to navigate these disruptions and ultimately enhance its performance. The extant literature suggests that SCL explains how decisions taken by firms facilitate adaptive SCRes and firms' growth under a volatile and uncertain environment (Chowdhury & Quaddus, 2016; Scholten et al., 2019). We argue that a SCRes capability is influenced by exploitative and explorative learning (H3a and H3b) and that SCRes is linked to FP (H4). On the one hand, firms employing exploitation capitalise on what they do well in their supply chain and continue to do so during supply chain disruptions for improved performance (Ambulkar et al., 2023; Patel et al., 2013). These firms create efficient processes by achieving economies of scale, contributing to their competitive advantage (Adler et al., 2009). On the other hand, by employing exploration, firms seek new forms of competitive advantage through the development of new capabilities by making a deliberate effort to gain new knowledge (Ambulkar et al., 2023; Kristal et al., 2010).

Building on this foundation, SCRes ensures that the beneficial advantage accrued from SCL (exploitative and explorative) is not undermined by disruptive events but rather is leveraged to improve FP. Thus, the complementarity between SCL and SCRes capabilities offers a firm competitive advantage that manifests in improved FP. This implies that both exploitative and explorative learning may have indirect implications for FP through SCRes. Based on these arguments, we propose the following hypothesis:

H7: Supply chain resilience mediates the relationship between (a) exploitative learning and financial performance, and (b) explorative learning and financial performance.

To summarise, the hypothesised relationships between BDAC, SCL (explorative and exploitative), SCRes, and FP are depicted in the conceptual model (Figure 1).

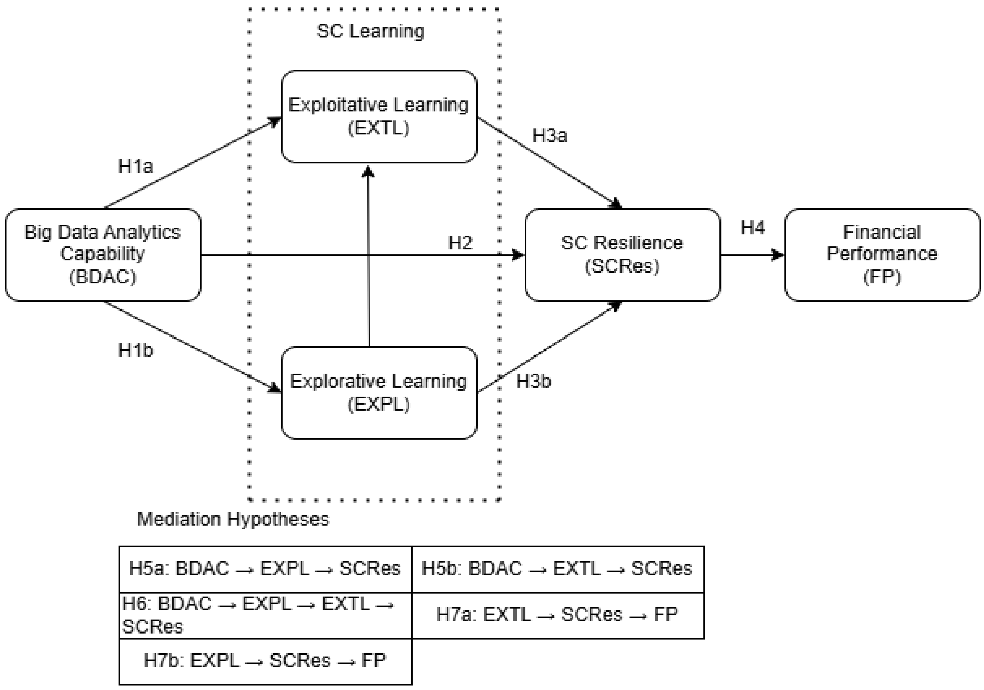

Figure 1: Conceptual model

4. Research method

A survey of supply chain professionals working in Pakistan was conducted to test our hypotheses. A positive paradigm is adopted that relies on observable and quantifiable measures (Zikmund et al., 2013) to ensure an objective approach to data collection. As a deductive and quantitative study, we followed established procedures in developing the survey instrument and utilised a simple random sampling method to select participants. This ensures all participants have an equal opportunity of being selected and that they are representative of the entire population, thus minimising selection bias. Below, we outline the data collection procedure, identify the study's empirical constructs, and discuss instrument development.

4.1. Data Collection

Survey responses were collected from experienced supply chain professionals working in Pakistani firms. Respondents have varying levels of managerial experience and work for organisations of different sizes in a range of manufacturing and service sectors. Table 1 demonstrates the heterogeneity of our sample.

Table 1: Demographic profile of respondents

	Frequency	Percentage
Annual Sales (PKR Millions)		
0 - 1000	56	30%
1001 - 2000	30	16%
2001 - 3000	31	16%
> 3001	71	38%
Designation		
Assistant Manager	85	45%
Manager	77	41%
General Manager/Director/CEO	26	14%
Experience		
Less than 11 years	106	56%
More than 11 years	82	44%
Age		

25 - 34	149	79%
35 - 44	26	14%
45 - 54	10	5%
Over 55	3	2%
Gender		
Male	162	86%
Female	26	14%
Firm Size		
500 - 1000 employees	48	26%
Below 500 employees.	64	34%
More than 1000 employees.	76	40%
Industry		
Manufacturing	114	61%
Service & Utility	74	39%
	N = 188	

A structured questionnaire was distributed to 1,000 firms, randomly selected from the Securities and Exchange Commission of Pakistan (SECP), to mitigate the potential bias. The SECP is the financial regulatory agency in Pakistan responsible for overseeing the corporate sector and capital markets. After multiple reminders (March to June 2021), we received 188 useful responses, i.e. an 18.8% response rate, which is sufficient to conduct a statistical analysis (Brusset & Teller, 2017; Gölgeci & Kuivalainen, 2020). Pakistan is an under-researched context despite the country's supply chain operations playing an immense role in the global market. The country's manufacturing and export sectors, particularly textiles, agriculture and pharmaceuticals, are integral to international markets. Any disruptive events in these SCs could have significant ripple effects on global supply chain operations. Hence, the Pakistani context provides an important opportunity to contribute to SCRes literature.

To ensure our sample size was adequate, we performed an *a priori* power analysis following the guidelines of Kock and Hadaya (2018). We used the inverse square root method as this method is considered to be more accurate and simpler to calculate the required sample size (Guenther et al., 2023; Wang et al., 2024). To achieve the statistical power of 0.80 at a

5% significance level, we set the minimum path coefficient to be detected at 0.20 based on similar studies in the literature (Aslam, Blome, et al., 2020; Mubarik et al., 2022). The inverse square root method suggests a minimum sample of 155. Therefore, our sample size of 188 is sufficient for the necessary analysis.

Non-response bias was examined following Armstrong and Overton (1977) by assuming late respondents are equivalent to non-respondents. In line with recent research (Chand et al., 2022; Iftikhar, Purvis, et al., 2022), we compared early and late respondents for each empirical construct. An independent sample t-test was conducted, with the results indicating no significant differences at a 5% significance level, suggesting that non-response bias is not a concern in this study.

4.2. Common method bias

Data were collected from one respondent per organisation, meaning there is the potential for common method bias (CMB) (Podsakoff et al., 2003). To avoid CMB, we adopted procedural remedies as suggested by Mackenzie and Podsakoff (2012). Proactively before the data collection to minimise the CMB issue, we ensured measurement items were drawn from established scales, guaranteed respondent anonymity, and divided the questionnaire into various sections by separating independent from dependent variables. Post data collection, to assess the CMB issue, we also used a theoretically unrelated marker variable (MV) (Lindell & Whitney, 2001). For this purpose, the manager's experience, provided by the responding managers, was considered as our MV. We checked its correlation with the variables in our hypothesised model and found non-significant correlations with the model variables. This suggests that the proposed model is free from the CMB issues.

We also conducted statistical tests to evaluate CMB. First, we carried out Harman's single-factor test, which showed that our first factor explained only 38.50% of the variance in the non-rotated solution, falling short of the cut-off value of 50% recommended by Podsakoff and Organ (1986). Second, we performed collinearity statistics by computing the variance inflation factor (VIF) with partial least squares (PLS) on all empirical constructs (as shown in Table II). According to Kock (2015), VIF values should be ideally ≤ 3.3 to be considered acceptable. None of our VIF values exceeded 2.5 (see Table 2). Therefore, we can conclude that CMB is not a significant threat to the validity of our study.

4.3. Measures for the construct

The research framework used empirical constructs from the extant literature and previously validated item scales on a 5-point Likert scale from strongly disagree (1) to strongly agree (5) – see Table II. The empirical constructs are all lower-order reflective constructs.

The construct, *big data analytics capability,* is an independent variable that was measured using 8 items adapted from Dubey *et al.* (2021), Wang and Byrd (2017), and Yu *et al.* (2021). The selected items reflect the key elements of BDAC, measuring it holistically, including the use of advanced analytical techniques (e.g., simulation, optimisation, regression) to derive insights, the integration of data from multiple sources to enhance accuracy and efficiency, and the application of data visualisation tools (e.g., dashboards) to facilitate quick and informed decision-making. The mediating variables, *explorative learning* and *exploitative learning,* each used 4 items adapted from Donate and Guadamillas (2011) and Revilla et al. (2010), with refinements based on broader literature. Explorative learning captures a firm's ability to engage in creative problem-solving, experimentation, and knowledge acquisition through both internal and external interactions. Exploitative learning, in contrast, focuses on utilising, refining, and applying existing knowledge to enhance operational efficiency and respond to competitive conditions. The dependent variable, *SCRes,* was measured using 5 items adapted from Ambulkar et al. (2015) and Gölgeci and Kuivalainen (2020) capturing a firm's ability to respond, adapt, and recover from supply chain disruptions, and *FP* was measured using 3 items adapted from Tseng (2014) and Iftikhar *et al.* (2021), capturing a firm's profitability, return on investment, and sales growth relative to competitors.

4.4. Pretesting the survey instrument

Two industry professionals and two academics were consulted on the items and constructs. Their feedback was used to improve the scale items. The measurement items' reliability was then assessed, and all constructs had a Cronbach's alpha value greater than 0.7 (Hair et al., 2011). Finally, a pre-test was conducted with 30 industry professionals to further improve the instrument (I. J. Chen & Paulraj, 2004). The pre-test results were not included in the main survey and analysis.

Table 2: Scale Item Analysis and Reliability Measures

Construct	Scale Items	Factor loading	Cronbach's Alpha	Composite Reliability	Average Variance Extracted
Big Data Analytics	Utilise advanced tools and analytical techniques (e.g., simulation, optimisation, regression) to make informed decisions.	0.769	0.907	0.925	0.607
	Extract information from various sources of data to facilitate effective decision-making.	0.692			
	Apply data visualisation techniques (e.g., dashboards) to assist users or decision-makers in understanding complex information.	0.834			
	Predict patterns within each channel in response to specific supply chain requirements for optimal performance.	0.800			
	Analyze data in near-real or real-time, enabling timely responses to unexpected events and changes in the supply chain.	0.796			
	Provide systemic and comprehensive reporting to recognise viable opportunities for improvement in supply chain channels and services.	0.817			

	Support data visualisation tools that empower users to easily interpret and understand analytical results.	0.781			
	Provide near-real or real-time information on public operations and services within the organisation and across other supply chain systems/organisations.	0.737			
Exploratory Learning	Our organisation actively arranges coaching and training sessions for 'thinking outside the box' activities and creative problem solving.	0.737	0.71	0.82	0.533
	Our organisation regularly conduct departmental meetings to discuss market trend to solve supply chain problems creatively.	0.736			
	In the buyer supplier relationship, our organisation convert technical know-how of the supplier into our new products and processes.	0.753			
	Our organisation works in partnership with international customers to solve problems creatively.	0.694			
Exploitative Learning	Our organisation has developed processes for using existing knowledge to solve current problems.	0.839	0.829	0.886	0.661
	Our organisation has developed processes to locate and apply existing knowledge to changing competitive conditions.	0.843			
	Our organisation has methods to analyze and critically evaluate existing knowledge to generate patterns and knowledge for current use.	0.787			
	Our organisation is equipped with the ability to apply existing knowledge to adjust current direction.	0.781			
Supply Chain Resilience	We are able to adequately respond to unexpected disruptions by quickly restoring its product flow.	0.747	0.861	0.900	0.644
	We are well prepared to deal with financial outcomes of potential supply chain disruptions.	0.778			
	We are able to provide a quick response to the supply chain disruption.	0.820			
	We are able to adapt to the supply chain disruption easily.	0.838			
	We are able to cope with changes brought by the supply chain disruption.	0.825			
Financial Performance	In comparison with the competition, we have improved the firm's profit margin.	0.827	0.748	0.855	0.663
	In comparison with the competition, we have improved the firm's return on investment.	0.813			
	In comparison with the competition, we have improved the firm's sales growth.	0.803			

5. Results and analysis

We utilised the partial least square (PLS) structural equation modelling (SEM) technique, as recommended for predictive and theory-building exploratory studies (Richter et al., 2016) and as used in previous business management studies (Cegarra-Navarro et al., 2024; Chand et al., 2022), given its suitability for handling complex relationships. PLS-SEM has several advantages over covariance-based SEM, including less restrictive sample size assumptions as it employs ordinary least square regression, making it suitable for smaller sample sizes, i.e., < 200 (Hair et al., 2011; Reinartz et al., 2009). Additionally, PLS-SEM allows for a more effective evaluation of mediation effects with fewer restrictions on distributional assumptions (Peng & Lai, 2012; Tenenhaus et al., 2005). We employed SmartPLS 4.0 software and utilised its bootstrapping technique to generate standard path coefficients, the coefficient of determination, and t values with 5,000 subsamples.

5.1. Measurement validation

To assess the model's robustness, we conducted a comprehensive analysis of its psychometric properties. This involved evaluating Cronbach's alpha (α), factor loadings, composite reliability (CR), and average variance extracted (AVE) (see Table II). Our results revealed strong evidence for the model's reliability and validity. Specifically, all factor loadings exceeded the recommended threshold of 0.5, ranging from 0.692 to 0.843, indicating that each item significantly contributes to its respective construct. Furthermore, Cronbach's alpha values for all constructs were well above the 0.7 benchmark, ranging from 0.71 to 0.907, demonstrating high internal consistency. Composite reliability (CR) values ranged between 0.82 and 0.925, exceeding the 0.7 threshold, further supporting the model's reliability. Lastly, all constructs exhibited convergent validity, with AVE values ranging from 0.533 to 0.663, surpassing the minimum criterion of 0.5.

We also checked the discriminant validity of each empirical construct (see Table 3). Fornell and Larcker (1981) recommended that the inter-correlation values of each construct should be smaller than the square root of the AVEs of each construct in each row and column. The square root of AVE, shown on the diagonal in Table 3, satisfies this criterion.

Collectively, these findings attest to the measurement model's robustness and confirm the reliability and validity of the scale items for further analysis.

Table 3: Fornell-Larcker criterion

Construct	BDAC	Fin Perf	Exploit Learn	Explor Learn	SCRes
BDAC	0.779				
Fin Perf	0.581	0.814			
Exploit Learn	0.625	0.645	0.813		
Explor Learn	0.665	0.614	0.692	0.730	
SCRes	0.654	0.693	0.635	0.556	0.802

5.2. Hypothesis testing

Our hypothesis test results are summarised in Table 4, where we present the standard path coefficients, t-statistics, and significance values. The results show the direct and indirect effects (mediation) of exploitative and explorative learning on the BDAC-SCRes and SCRes-FP relationships.

The findings reveal a positive and significant relationship between BDAC and exploitative learning based on the path coefficient and p-value ($\beta = 0.470$, $p < 0.001$) and between BDAC and explorative learning ($\beta = 0.667$, $p < 0.001$). Thus, *H1a and H1b are supported.* The path coefficient from BDAC to SCRes ($\beta = 0.250$, $p < 0.001$) is positive and significant. Thus, *H2 is supported.* Path coefficients from exploitative learning to SCRes are positive and significant ($\beta = 0.542$, $p < 0.001$), whereas path coefficients from explorative learning to SCRes are positive but not significant ($\beta = 0.012$, $p = 0.892$). Thus, *H3a is supported* but *H3b is not supported.* We also analysed the path coefficient from SCRes to FP, which was found to be positive and significant ($\beta = 0.695$, $p < 0.001$). Thus, *H4 is supported.*

Furthermore, we analysed the mediation (indirect) effects of the two SCL types. The path coefficient for the influence of explorative learning on the BDAC-SCRes relationship is positive but not significant (β = 0.014, p = 0.894). Thus, *H5a is not supported.* In contrast, the path coefficient for the influence of exploitative learning on the BDAC-SCRes relationship is positive and significant (β = 0.254, p < 0.001). Thus, *H5b is supported.* Meanwhile, the sequential mediation hypothesis from explorative learning to exploitative learning is positive and significant (β = 0.136, p < 0.001). Thus, *H6 is supported.* Finally, the mediation effects of exploitative and explorative learning on the SCRes-FP relationship were also tested. The path coefficient for the influence of exploitative learning on the SCRes-FP relationship is positive and significant (β = 0.376, p<0.001), whereas the path coefficient for the influence of explorative learning on the SCRes-FP relationship is positive but not significant (β = 0.014, p = 0.892). Thus, *H7a is supported* but *H7b is not supported.* The implications of these results will be discussed in the final section of this paper. Overall, the findings indicate that exploitative learning plays a mediating role in the BDAC-SCRes relationship and subsequently impacts FP. While explorative learning does not directly enhance SCRes (H3b, H5a, H7b not supported), it indirectly contributes through a sequential effect on exploitative learning, highlighting the need for temporal ambidexterity to achieve resilience and superior performance outcomes.

To control for potential confounding effects, firm size, firm sales, and sector type were included as dummy variables. The results indicate that firm size (p = 0.467), firm sales (p = 0.943), and sector type (p = 0.606) had no significant effect on SCRes. However, firm size (p = 0.048) and firm sales (p = 0.012) exhibited a significant impact on FP, while sector type remained non-significant (p = 0.198). The inclusion of these control variables neither alters the significance nor changes the direction of the hypothesised relationships.

Table 4: Structured model statistics

Hypothesis	Coefficient	p-value	T-value	Result
Direct hypotheses				

H1a: Big data analytics -> Exploitative learning	0.470	p<0.001	6.415	Supported
H1b: Big data analytics -> Explorative learning	0.667	p<0.001	13.365	Supported
H2: Big data analytics-> Supply chain resilience	0.250	p<0.001	2.869	Supported
H3a: Exploitative learning -> Supply chain resilience	0.545	p<0.001	7.085	Supported
H3b: Explorative learning -> Supply chain resilience	0.012	p=0.893	0.136	Not supported
H4: Supply chain resilience -> Financial performance	0.695	P<0.001	16.864	Supported
Mediation Hypothesis (Indirect effects)				
H5a: Big data analytics -> Explorative learning -> Supply chain resilience	0.014	p=0.895	0.132	Not supported
H5b: Big data analytics -> Exploitative learning -> Supply chain resilience	0.254	p<0.001	5.241	Supported
H6: Big data analytics -> Explorative learning -> Exploitative learning -> Supply chain resilience	0.136	p<0.001	3.689	Supported
H7a: Exploitative learning -> Supply chain resilience -> Financial performance	0.376	P<0.001	6.751	Supported
H7b: Explorative learning -> Supply chain resilience -> Financial performance	0.014	P=0.892	0.135	Not Supported

5.3. Robustness tests

Endogeneity was evaluated to ensure the robustness of our results. The Kolmogorov-Smirnov test with Lilliefor's correction confirmed that the variables potentially exhibiting endogeneity bias were non-normally distributed, as their p-values were <0.05 (Sarstedt & Mooi, 2014). We then followed Hult *et al.* (2018) by conducting the Gaussian Copula (GC) test using Smart PLS 4.0. We applied this test by using the constructs' standardised composite scores to compute the Gaussian copula for the partial regressions within our structural model (Hult et al., 2018).

The GC method detects endogeneity by introducing a 'copula term' (e.g., GC (BDAC) in Table 5) that captures the dependence between the potentially endogenous regressor and the error term. This copula term is generated by applying the inverse normal cumulative density function Φ^{-1} to the empirical cumulative density function H(x) of the regressor (Hult et al., 2018), which can be expressed as $c^{x} = \Phi^{-1}[H(X_1)]$ (Papies et al., 2017).

If the path coefficient for this copula term is statistically significant, it indicates the presence of endogeneity in the model; a non-significant coefficient suggests that endogeneity is not a major concern for that variable (Becker et al., 2022; Hair et al., 2019). To provide a comprehensive assessment, we followed the practice of testing various combinations of potentially endogenous variables (Hult et al., 2018). This allows for checking if endogeneity arises from multiple sources simultaneously or from specific individual regressors, thus assessing the model's robustness under different endogeneity assumptions. As shown in Table 5, the p-values of all respective copula terms were insignificant (>0.05), meaning there is no evidence of endogeneity.

Overall, to minimise the potential endogeneity risks in addition to the GC method, we took a series of precautions, following the recommendations of Guide & Ketokivi (2015) (see Sections 4.1 and 4.2). We also considered whether the dependent variable could have influenced the independent variable, resulting in reverse causality (Damali et al., 2016). As shown in Section 3.2, BDAC typically precedes and enables the development of capabilities like SCRes. however, the literature is silent on the reverse sequence. Our primary endogeneity was checked through the GC approach, which did not indicate the presence of endogeneity in our model.

Table 5: Endogeneity test results

Variable	Model 1 (endogenous variable: BDAC)		Model 2 (endogenous variable: EXTL)		Model 3 (endogenous variable: EXPL)		Model 4 (endogenous variable: SCRes)	
	Coeff.	P values	Coeff.	P values	Coeff.	P values	Coeff.	P values
BDAC	0.259	0.201	0.052	0.583	0.049	0.645	0.054	0.610
EXTL	0.111	0.217	0.053	0.979	0.111	0.225	0.112	0.221
EXPL	0.282	0.000	0.278	0.000	0.329	0.207	0.274	0.000
SCRes	0.420	0.000	0.423	0.000	0.421	0.000	0.343	0.236
GC (BDAC)	-0.218	0.206						
GC (EXTL)			0.059	0.652				
GC (EXPL)					-0.047	0.854		
GC (SCRes)							0.084	0.727

Variable	Model 5 (endogenous variable: BDAC, EXTL)		Model 6 (endogenous variable: BDAC, EXPL)		Model 7 (endogenous variable: BDAC, SCRes)		Model 8 (endogenous variable: BDAC, EXTL, SCRes)	
	Coeff.	P values	Coeff.	P values	Coeff.	P values	Coeff.	P values
BDAC	0.308	0.114	0.276	0.187	0.345	0.126	0.379	0.079
EXTL	-0.051	0.625	0.111	0.210	0.109	0.225	-0.023	0.701
EXPL	0.281	0.000	0.237	0.481	0.272	0.000	0.272	0.000
SCRes	0.421	0.000	0.417	0.000	0.199	0.583	0.216	0.526
GC (BDAC)	-0.258	0.117	-0.232	0.185	-0.292	0.120	0.128	0.406
GC (EXTL)	0.157	0.335					-0.320	0.075
GC (EXPL)			0.046	0.735				
GC (SCRes)					0.229	0.352	0.213	0.416

Variable	Model 9 (endogenous variable: EXTL, EXPL, SCRes)		Model 10 (endogenous variable: BDAC, EXTL, EXPL)		Model 11 (endogenous variable: BDAC, EXPL, SCRes)		Model 12 (endogenous variable: BDAC, EXTL, EXPL, SCRes)	
	Coeff.	P values	Coeff.	P values	Coeff.	P values	Coeff.	P values
BDAC	0.059	0.566	0.317	0.117	0.356	0.125	0.385	0.085
EXTL	0.054	0.968	-0.047	0.652	0.108	0.220	-0.020	0.718
EXPL	0.348	0.160	0.255	0.424	0.242	0.449	0.255	0.405
SCRes	0.335	0.237	0.418	0.000	0.197	0.574	0.213	0.522
GC (BDAC)			-0.265	0.119	-0.301	0.117	-0.324	0.081
GC (EXTL)	0.053	0.663	0.152	0.358			0.124	0.422

GC (EXPL)	-0.072	0.704	0.027	0.837	0.031	0.812	0.018	0.895
GC (SCRes)	0.092	0.750			0.228	0.366	0.213	0.422

GCbdac: Gaussian Copula term for BDAC; GCextl: Gaussian Copula term for EXTL; GCexpl: Gaussian Copula term for EXPL; GCscres: Gaussian Copula term for SCRes

6. Discussion and conclusions

6.1. Theoretical implications

We make several significant contributions to OSCM research. First, we extend the SCRes literature by empirically discovering that BDAC, as a higher-level capability, enables SCRes, a lower-level capability, specifically through the mediating role of SCL. While prior studies often assume a direct relationship between BDAC and SCRes (Dubey et al., 2021; Bag, 2021; Iftikhar et al., 2022), we posit an indirect, mediated relationship facilitated by SCL. Specifically, BDAC provides the data and analytical power (the "what") to identify potential risks and areas for improvement. However, it is SCL that enacts the learning processes and activities ("the how") to translate these insights into actionable knowledge and capabilities that ultimately bolster SCRes. Our findings highlight that effective SCL is essential to fully realising the resilience-enhancing potential of BDAC.

Second, we broaden the understanding of how different types of SCL exert distinct and sequentially linked effects on the BDA-SCRes relationship. *Concerning exploitative learning*, our results underscore its strong and significant mediating role in enhancing SCRes. In line with prior findings (e.g., Nakandala et al., 2023; Ivanov & Dolgui, 2020), our study indicates that a firm's learning orientation towards effectively utilising its existing knowledge is crucial for adapting and improving resilience, a point further illustrated by the ability to implement data-driven demand forecasting during disruptions (Ivanov & Dolgui, 2020).

In contrast, our findings concerning *explorative learning* challenge the common assumption of its direct positive influence on SCRes (Laguir et al., 2023). This finding allows us to contribute a significant boundary condition to the ambidexterity literature. While prior studies have rightly highlighted the benefits of ambidextrous strategies that include exploration, e.g., Kristal et al. (2010), our results suggest the pathway through which exploration adds value may be context dependent. Our explanation is aligned with the organisational learning literature on the trade-offs between exploration and exploitation (March, 1991). This suggests that simply utilising exploratory initiatives may not automatically translate into enhanced resilience. Exploration is inherently risky, resource-intensive, and its benefits are often long-term and uncertain (Rosenbusch et al., 2011; Wenke et al., 2021). In the specific context of our study – resource-constrained firms in a volatile developing economy environment – the high immediate costs and delayed benefits of exploration may prevent it from translating directly into resilience. Scholars have suggested that investing limited resources in these risky ventures (exploratory initiatives) increases the transaction cost and lowers the probability of success (Kocabasoglu-Hillmer et al., 2023; Song & Di Benedetto, 2008). Firms in such contexts may rationally prioritise the immediate, short-term efficiency gains from exploitative learning to ensure immediate survival. Our finding that exploration's effect is indirect (by enabling exploitation) clarifies the pragmatic, sequential mechanism through which it contributes to resilience under specific conditions of scarcity and uncertainty.

We also provide compelling evidence for the *sequential mediating effect of* SCL, where explorative learning serves as a critical antecedent for exploitative learning, ultimately enhancing SCRes. We reveal that while explorative SCL may not directly influence SCRes, it can lay the foundation by identifying novel opportunities and innovative solutions that exploitative SCL subsequently refines and implements to achieve resilience (Lavie et al., 2010; Lee & Rha, 2016). This sequential learning model adds to current understanding of organisational ambidexterity by explicitly incorporating temporal ambidexterity (e.g., Aslam et al., 2022, O'Reilly & Tushman, 2013), highlighting that exploration and exploitation may unfold sequentially rather than simultaneously. Moreover, by introducing a novel sequential mediation model (BDAC → Exploration → Exploitation → SCRes), we extend the ambidexterity literature within the specific context of SCRes. In highly uncertain environments, exploration driven by BDAC enables firms to proactively identify emerging threats and market shifts. This exploratory phase then informs subsequent exploitative activities, ensuring that innovative strategies and operational efficiencies developed through exploitation are precisely targeted at overcoming disruptions. Thus, our study empirically demonstrates that prioritising exploratory learning through the effective utilisation of BDAC significantly strengthens firms' resilience capabilities.

Finally, we identified the distinct pathways through which exploitative and explorative learning contribute to FP. We found that SCRes fully mediates the relationship between exploitative SCL and FP, highlighting the critical role of operational efficiency and disruptive mitigation in driving financial outcomes. This finding aligns with existing ambidexterity literature, which emphasises the direct and immediate returns associated with exploitative activities, especially during turbulent conditions (Ambulkar et al., 2023). In contrast, the absence of a mediating effect for explorative SCL indicates that exploration’s financial benefits may be realised through alternative mechanisms, such as innovation, new product development, etc. rather than directly through enhanced resilience (Conz & Magnani, 2020). This reinforces some of our results (H3b and H6) and highlights the challenges firms face in pursuing explorative initiatives during crises, as resource constraints and immediate recovery pressures often restrict investments in long-term exploratory activities. While explorative learning is undoubtedly valuable for long-term growth and adaptability, our findings suggest that its impact on FP may not be as direct or immediate as that of exploitative learning. Future research should investigate the complex interplay between these two learning types and their distinct contributions to various aspects of firm performance.

6.2. Managerial implications

Our findings also offer important managerial insights. Managers should adopt a temporally sequenced learning strategy aligned with the principles of DC. While BDAC provides data-driven insights, these insights must be channelled through structured learning mechanisms to realise improvements in both resilience and financial performance. Specifically, we recommend that firms initially utilise BDAC to trigger explorative learning, enabling them to sense risks, identify new opportunities, and experiment with innovative strategies. This early-stage exploratory focus allows firms to generate novel insights and lay the groundwork for adaptation. However, our findings underscore that explorative learning alone may not yield immediate resilience or financial gains. Without subsequent exploitative learning to refine and institutionalise exploratory insights, firms risk remaining in a perpetual search mode, delaying tangible operational improvements. Managers must therefore transition from exploration to exploitation, using BDAC to consolidate and routinise innovations within resilient supply chain processes. This temporally phased approach not only enhances SCRes but also enables firms to optimise limited resources to achieve short-term stability and long-term innovation.

Finally, our study encourages managers to recognise that resilience-building is not just a matter of investing in technology, but rather it is also about developing an adaptive learning environment. Beyond immediate disruption responses, firms must utilise BDAC to foster continuous learning and cross-functional collaboration, ensuring that insights are not siloed but rather shared across supply chain networks. In resource-constrained environments, this requires a mindset that views resilience as a capability distributed across partners, where coordinated learning and data sharing become critical enablers of both operational stability and long-term competitiveness.

6.3. Limitations and future research directions

We have presented the sequential interplay between explorative and exploitative learning practices in a cross-sectional study. Future research could collect data longitudinally to understand the dynamic nature of explorative and exploitative learning practices concerning supply chain disruptions. Moreover, it would be valuable to investigate the impact of isolated and simultaneous explorative and exploitative learning practices in lessening the disruptive impact, both upstream and downstream (Aslam et al., 2022; Bode et al., 2011). Meanwhile, while our Pakistan-based sample offers valuable initial insights, future research should test and refine our model in other economic contexts, including developed countries with more mature technological infrastructures and potentially greater access to resources. This will be essential for assessing the generalisability of our findings and identifying the contextual boundaries within which these relationships hold true. Due to our cross-sectional data, we cannot empirically rule out the possibility of reverse causality. Therefore, we suggest that future research uses longitudinal data to further examine the causal dynamics within the BDAC and SCRes relationship.

Finally, we used single respondents to assess the empirical constructs. Researchers have argued that this approach has the potential for bias (Kaufmann & Saw, 2014), including social desirability bias. Therefore, future research could adopt a multi-respondent approach to obtain a broader range of perspectives and enhance the robustness and validity of the findings. Future research could also benefit from adopting an experimental design approach to establish causal relationships between BDAC, SCL and SCRes. Because experimental design could provide deeper insights into these variables.

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