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The impact of supply chain complexities on supply chain resilience: The mediating effect of big data analytics

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Abstract

Supply chains (SC) are increasingly complex and if the resulting complexity is not managed effectively, it could lead to adverse consequences for the firm. The effect big data analytics (BDA) can have on managing distinct types of SC complexity is not well understood in the extant literature. Based on a sample of 166 firms from Pakistan, this study empirically investigates the effects of BDA, and of structural and dynamic SC complexities, on SC resilience. The study also investigates the role of BDA as a mediator between SC complexities and SC resilience. We find that structural SC complexity positively affects SC resilience, while there doesn't seem to be a significant impact for dynamic SC complexity. We also find a mediating effect of BDA for structural and dynamic SC complexities on SC resilience. Our results contribute to the extant literature investigating BDA and SC resilience by offering a more nuanced understanding of distinct types of SC complexities. We establish a more critical understanding of the role of BDA in mediating the critical link between the two types of SC complexity and SC resilience. The proposed model highlights that there are both direct and indirect effects between structural SC complexity and SC resilience, however dynamic SC complexity only influences SC resilience via BDA. These findings provide strategic insights for SC executives as to where to invest in BDA to build much needed SC resilience.

Keywords Supply chain resilience, structural complexity, dynamic complexity, big data analytics, survey.

1. Introduction

With supply chains (SCs) nowadays becoming more global and, hence, exposed to a greater range of vulnerabilities and risk, their nature is also increasingly more complex, which in itself can lead to increased vulnerability (Bode et al., 2011; Birkie et al., 2017) and reduced ability to deal with disruptions. While the enhanced SC complexity is increasingly acknowledged in the operations management literature, with the structure of SCs viewed as a significant component of organizations' competitiveness (Vlajic et al., 2013), its impact on SC resilience is still not well understood. Some studies, for example, argue that higher SC complexity will increase vulnerability and lead to less resilient organizations (Habermann et al., 2015; Wiedmer et al., 2021). Others (Craighead et al., 2007; Birkie et al., 2017) argue that increased complexity can improve SC resilience by, for example, increasing its flexibility and redundancy dimensions. These mixed results in the extant SC resilience literature require further explorations of the concepts in greater detail, which is a gap our study aims to fulfil.

SC complexity stems from the internal operations employed, as well as from the interactions with external actors in the network (Dittfeld et al., 2018). The extant literature discusses different forms of SC complexities (Ates et al., 2021; Bode and Wagner, 2015; Aitken et al., 2016), previously categorized into "structural" and "dynamic" dimensions (Serdarasan, 2013; Dittfeld et al., 2018). The structural aspects of SC complexity relate to elements such as scale complexity, horizontal vs. spatial complexity, product complexity (Vachon and Klassen, 2002; Choi and Krause, 2006; Mason et al., 2007; Brandon-Jones et al., 2014; Bode and Wagner, 2015; Lu and Shang, 2017), while dynamic aspects emerge from interactions between actors within the network, such as delivery complexity, supplier volatility, demand volatility, etc. (Bozarth et al., 2009; Brandon-Jones et al., 2015; Campos et al., 2019; Giannoccaro et al., 2018). Furthermore, while reviewing relevant literature that investigates the relationship between SC complexity and resilience, contrasting schools of thought emerge. For example, increasing the number of nodes in the SC (structural complexity) may result in more frequent disruptions, increased operational loads in terms of transaction and coordination costs, and reduced visibility in the network (Brandon-Jones et al., 2014; Bode and Wagner, 2015 Birkie et al., 2017), which negatively impact resilience (Ali et al., 2017; Ali and Golgeci, 2019). Increased structural SC complexity, on the other hand, is also viewed as a strategic advantage to encourage innovation and a first line of defence to mitigate early disruptive effects (Lu and Shang, 2017; Chowdhury et al., 2019; Birkie and Trucco, 2020). The SC complexity construct is thus a multifaceted notion and its impact on resilience and firm outcomes needs further investigation (Ates et al., 2021; Wiedmer et al., 2021).

One of the likely causes of contradicting results when studying SC complexity in the resilience literature stems from the fact that most studies adopt a single perspective when investigating complexity, such as structural aspects, while the dynamic aspect is often neglected (Birkie and Trucco, 2020; Iftikhar et al., 2021). Scholars also identified different sub-dimensions of structural and dynamic SC complexity, which can have various effects on performance (for a comprehensive review, please refer to Ates et al. 2021). Structural complexity in SCs, for example, arises when firms employ a large number of suppliers, located in diverse geographical locations, as well as when firms serve a large customer base and / or offer a large variety of products (Vachon and Klassen, 2002; Bozarth et al., 2009; Bode and Wagner, 2015; Birkie et al., 2017; Birkie and Trucco, 2020). Dynamic complexity, on the other hand, emerges due to, for example, frequent changes in production scheduling, unreliable and late supplier deliveries, increased demand volatility, etc. (Vachon and Klassen, 2002; Brandon-Jones et al., 2015; Campos et al., 2018). Previous studies do not examine the combined interplay of the two distinct dimensions of SC complexity, structural and dynamic, on firm resilience (Birkie et al., 2017) and more empirical evidence is required to advance theory and provide managerial guidance.

In addition, due to the higher levels of uncertainty that can emerge from increased structural and dynamic SC complexity, fast and effective decision-making capabilities are required to increase resilience (Manuj and Sahin, 2011). The literature focusing on managing distinct types of SC complexities is very limited in this area (Aitken et al., 2016; Turner et al., 2018). Recently, Giannoccaro et al. (2018) studied the role of control in terms of coordination process to regulate the behaviour of nodes (suppliers) in the network to achieve specific goals. Furthermore, Ates and

Memis (2021) investigate the strategic purchasing functions employed to manage SC complexity, as well as purchasing performance. Surprisingly, in the context of digital technology, the role of big data analytics (BDA) has not received much attention in terms of its role in managing SC complexity to further improve firm resilience levels. While BDA, with its sophisticated technological capability, is acknowledged to improve organisations' information processing capacity, reduce ripple effects in SCs and improve organisations' ability to manage disruptions (Fan et al., 2015, Papadopoulos et al., 2017; Dubey et al., 2019; Ali et al., 2021), the role it can play in enabling organisations to manage SC complexity and assist in risk mitigation while enhancing resilience is not well understood. As such, our study aims to explore the mechanisms that firms can employ to better manage their SC complexity by investigating the intervening role of BDA on the relationship between distinct types of SC complexity and firm resilience. Specifically, we focus on the following research questions:

1- To what extent do distinct types of SC complexity (structural and dynamic) affect firm resilience?

2- What is the intervening role of BDA on the relationship between SC complexity and firm resilience?

To address these research questions, we frame our study on insights drawn from the contingency theory (CT) and the dynamic capability view (DCV) (Brandon-Jones and Knoppen, 2017; Gu et al., 2021). Together, the two theories suggest that firms can identify the potential of specific capabilities under dynamic environmental contexts. As BDA is acknowledged to play a vital role in dealing with SC disruptions, it should be viewed as a dynamic capability that can be leveraged by firms to improve their resilience when dealing with various SC complexity scenarios.

To address the two research questions, we adopt a survey methodology, with data collected from 166 firms, from an emerging & developing economy (Pakistan), where a significant lack of research has been identified (Iftikhar et al., 2021). Lempogo et al. (2021), for example, argue that in a world increasingly driven by data, most of the current research focuses on how developed economies are leveraging big data to achieve greater feats in various sectors of their economies. Unfortunately, the same cannot be said about the state of big data in the developing world, where investments in IT infrastructure are dangerously low. However, when adopted, BDA is proven to have a positive influence on the firm and supply chain performance of developing economies (Gunasekaran et al., 2018). In the context of Pakistan, very little empirical evidence has so far been put forward concerning the contribution of big data analytical capabilities towards firm performance and resilience, even though evidence indicates various industries have adopted and implemented big data analytics in the country (Latif et al., 2018). As such, Pakistan, a fast-growing market that displays similar traits to other emerging large country-markets such as Mexico, Brazil, Turkey, and Thailand, offers a substantial context for enlarging this stream of research since it has become crucial for firms operating in all sectors to develop BDA capabilities along with other competing economies. Like other key emerging markets, Pakistan is driven by the need to develop a technologically advanced business environment to compete in global markets.

Our research makes two key contributions to the literature related to supply chain complexity, resilience and big data analytics. First, we advance the discussion on distinct types of SC complexity (structural and dynamic) and highlight their divergent impacts on firm resilience. Specifically, we show that while structural complexity positively contributes to firm resilience, it also increases dynamic complexity, which is detrimental to firm resilience. Second, we find that BDA acts as an intervening variable between SC complexity and firm resilience. Furthermore, we examine whether the relationship between SC complexity and firm resilience is contingent on BDA. The emerging critical insights can assist managers in deciding where to invest in BDA to leverage resilience.

2. Theoretical Background & Hypotheses Development

This section discusses the theoretical foundations our study is built on and reviews the existing literature on SC complexity, BDA and firm resilience.

Dynamic Capability View

Previous studies have argued that, in the wake of turbulent and disruptive events, the dynamic capability view (DCV) is a particularly relevant lens through which resilient organizational capabilities can be analysed (Teece et al., 1997). The DCV evolved from the resource-based view of the firm (RBV) (Bowman and Ambrosini, 2003), with its focus on organisations gaining competitive advantage by developing appropriate resources and capabilities. However, the RBV fails to appropriately address the way organisational resources and capabilities should change and evolve (dynamic perspective) to deal with volatile environments. This gap is addressed by the DCV, with its focus on the distinctive capabilities required to respond to highly turbulent events and volatile environments (Teece et al, 1997; Hamel and Välikangas, 2003). The main theme behind DCV is the organizational capabilities to integrate, build and reconfigure resources to respond to dynamic situations and uncertainties for a sustainable competitive advantage (Teece et al, 1997). In this context, BDA offers better situational awareness and augments decision makers' ability to make sense of rapidly changing situations, while helping to identify and guide the allocation of critical resources. BDA is therefore a continuous and dynamic process that, if formalised, would help businesses to become data-driven organisations capable of dynamically adapting to changing conditions (McAfee and Brynjolfsson 2012; Gunasekaran et al.; 2018).

The appropriateness of adopting the DCV in our study is further highlighted by the fact that the concept of resilience itself is perceived as a dynamic capability that organisations can adopt to deal with SC disturbances by changing organizational and SC structures, processes and functions to increase their ability to sense, respond and recover when faced with particular sources of volatility

(Brusset and Teller, 2016; Bag et al., 2019; Yu et al., 2019). The dynamic capability here refers to the ability of the supply network to evolve as it develops flexible and adaptive capabilities.

Contingency theory

Contingency theory (CT) encompasses the contextual settings in the firms' decision-making environment to attain superior performance (Donaldson, 2001; Ketokivi, 2006). The main idea behind CT is that firms must be adaptive and should configure themselves in accordance with the environment in which they operate. This is particularly relevant when studying SC complexity, as both structural and dynamic aspects can have a positive as well as a detrimental effect on various firm outcomes (Sirmon & Hitt, 2009; Grötsch et al., 2013; Brandon-Jones et al., 2014), and these outcomes are influenced by various environmental factors, such as geographical context, national culture, institutional conditions, as well as dynamic environmental aspects such as high complexity or uncertainty (Koufteros et al., 2005; Brandon-Jones and Knoppen, 2017). The relevance of contingency theory is thus particularly relevant for our study, which aims to examine the impact of distinct types of SC complexities on firm resilience, enabling organisations to continue to function in disruptive environments (Ali and Golgeci, 2019; Iftikhar et al., 2021). In the extant literature, the dynamic environmental contexts (SC complexity) are considered under contingency theory to further explore the potential of dynamic capabilities (Birkie et al., 2017; Gu et al., 2021). When dealing with high levels of SC complexity and unpredictable environments, firms need to have a clear understanding as to what capabilities are effective in increasing their resilience (Zollo and Winter, 2002; Winter, 2003).

2.1 Resilience in SCs

Firms experience disruptions on many levels, ranging from supply variability, parts quality problems, demand variability, cyber-attacks, to natural disasters, geopolitical uncertainties, pandemics, etc. These disruptions could affect SCs' performance significantly, as well as SCs' structural dynamics. For example, disruptions that could affect a firm's structural design and planning parameters are events such as strikes, tsunamis, floods and nuclear incidents impacting production facilities, volcanic eruptions (such as the Icelandic ash cloud) affecting air freight around the globe (Chopra and Sodhi, 2014; Behzadi et al., 2017; Stone and Rahimifard, 2018), traffic blockages, unreliable and untimely supplier deliveries impacting operational performance, etc. Further, these disruptive events could have cascading effects across various SCs and multiple business sectors. For example, the Japan 2011 earthquake caused severe disruptions for the automotive and electronics sectors' manufacturers and suppliers across the globe (Matsuo, 2015). Similarly, the current COVID-19 pandemic has led to unprecedented massive disruptions affecting a large number of industries due to lockdowns, strict government restrictions and uncertainty due to subsequent coronavirus waves (Queiroz et al., 2020). Such disruptions expose supply chain vulnerabilities and call for great resilience in SCs.

The focus on organisational and SC resilience in both literature and practice has been growing over the past few decades, acknowledging the fact that high impact disruptions can cause a ripple effect across SC actors, threatening their competitiveness and business continuity (Ivanov, 2017; Dolgui et al., 2018). Considering these impacts, SC managers are increasingly faced with the need to build resilient capabilities to sense, respond, resist and recover from such disturbances. These capabilities reflect proactive and reactive resilience approaches, where firms prepare themselves before the event occurs (Kleindorfer and Saad, 2005) and/or are able to deploy various practices and reconfigure their resources once the disruptive event takes place (Ambulkar et al., 2015).

Resilience, as such, is a multidimensional concept and its core purpose is to maintain a steady state by either returning to a pre disruption stage (Ponomarov and Holcomb, 2009) once a disturbance occurred or adapting to a new equilibrium stage (Tukamuhabwa et al. 2015). Studies have also framed resilience in terms of formative capabilities, such as flexibility, velocity, visibility, collaboration, etc (for a comprehensive review see Iftikhar et al., 2021). Resilience itself can thus be treated as an adaptive capability, enabling firms to respond to and recover from disruptive events to ensure business continuity and success (Gölgeci and Kuivalainen, 2019). It helps in resisting the adverse disruptive impact, withstanding the disruption, and hence effectively recovering within an acceptable time (Melnyk et al., 2014). Therefore, firms adopting a resilience strategy can be in a more advantageous position than their competitors when affected by disruptive events (Sheffi and Rice, 2005).

2.2 Supply Chain Complexity

Recent pandemic incidents highlight the necessity for a more in-depth examination of supply chain complexity (Choi et al., 2021). A large number of studies in the SC domain have investigated mitigation strategies without taking into account the complexity – disruption interaction (Chowdhury et al., 2021). The concept of "complexity science" is fragmented and has been examined by different disciplines, such as social sciences (Byrne, 2002), biology (Kauffman, 1993), and management sciences (McMillan, 2008). In management science, SC complexity has been studied through different theoretical lenses, for instance, complex adaptive systems (Choi and Krause, 2006; Day, 2014), contingency theory (Brandon-Jones et al., 2014; Birkie et al., 2017), system theory (Bode and Wagner, 2015; Dittfeld et al., 2018) and natural accident theory (Wiedmer et al., 2021). All of these theoretical lenses emphasise the multifaceted aspect of SC complexity, with numerousness, diversity, unpredictability, randomness, and uncertainty being the most often highlighted elements (Ates et al., 2021; Dittfeld et al., 2018).

In the SC literature, two established dimensions of complexity are structural and dynamic (Simon, 1962; Senge, 2006; Serdarasan, 2013; Bode and Wagner, 2015). *Structural complexity* (also known as static or detail complexity) emerges from the presence of various elements or sub-elements in the system under examination. The number of suppliers, customers, and products in a system, as well as their geographic dispersion, are among the variables that contribute to structural (static) complexity (Choi and Krause, 2006; Bozarth et al., 2009; Caridi et al., 2010). From an operations management perspective, d*ynamic complexity*, on the other hand, is driven by the dynamics of SC operations (Sivadasan et al., 2002; Bode and Wagner, 2015; Ates et al., 2021) and is also referred to as operational complexity (Wu et al., 2007). Aspects such as supplier delivery reliability and lead times incurred reflect dynamic aspects of operations (time and randomness), leading to dynamic complexities (Bozarth et al., 2009; Isik, 2010; Serdarasan, 2013).

The relationship between SC complexity and resilience is not straightforward and there are conflicting views in the literature. While some scholars have considered complexity as a barrier to increased firm performance (Heim et al., 2014; Birkie et al., 2017), others have viewed it as a source of competitive advantage and heightened resilience (Craighead et al., 2007). Table 1 explores the relationship between different SC complexity dimensions and firm outcomes, i.e., performance, disruptions, and resilience.

Table 1: Studies exploring the impact of SC Complexity and firm outcomes

Publication	SC Complexity Elements	Type of SC Complexity	Country/Region	Methodology	Impact on firm outcome (Firm Performance/Resilience/Disruptions)
Salvador et al. (2002)	Number of products and parts	Structural complexity	6 EU countries	Multiple case study	Negative influence on operational performance.
Vachon and Klassen (2002)	Number of suppliers & products	Structural complexity	Data collected from 19 countries	Survey	Negative influence on delivery performance (throughput time & lead time).
	Production scheduling changes, demand volatility, & late supplier deliveries.	Dynamic complexity			
Craighead et al. (2007)	Number of nodes, no. of forward flows and no. of backward flows.	Structural complexity	USA	Multiple case study	Complexity increases the severity of SC disruptions.
Bozarth et al. (2009)	Number of customers, no. of products & parts, no. of suppliers.	Structural complexity	7 countries - U.S., Japan, South Korea, Germany, Austria, Finland and Sweden.	Survey	Negative influence on manufacturing plant performance.
	Manufacturing schedule instability, unreliable supplier lead times, short product lifecycle.	Dynamic complexity			
Blackhurst et al. (2011)	Number of nodes in the SC, no. of parts, types of parts	Structural complexity	USA, South Korea, China	Multiple case study	Negative influence on supply resilience.
Vanpoucke et al. (2014)	Number of suppliers, percentage of international suppliers in the supply base.	Structural complexity	20 countries in America, Europe and Asia	Survey	Negative influence on market and financial performance.
Bode and Wagner (2015)	Number of first tier suppliers, no. of countries represented in the supply base.	Structural complexity	Germany, Austria and Switzerland.	Survey	Complexity increases the frequency of disruptions.
Brandon-Jones et al. (2015)	Number of supply chain players, varying level of technical capabilities by the suppliers.	Structural complexity	UK	Survey	Complexity increases the frequency of disruptions and reduce plant performance.

	Dependence on time delivery from suppliers, Shorter lead-time from suppliers.	Dynamic complexity			
Birkie et al. (2017)	Number of products, customers, brands; no. of suppliers and facilities.	Structural complexity	NA	Secondary data	Positively influence recovery performance after disruptions.
Bode and Macdonald (2017)	Number of SC players, detailed SC network spanning several scales.	Structural complexity	EU	Survey	Negative influence on firm's disruption response speed.
Campos et al. (2018)	Numerousness and variety within the SC.	Structural complexity	EU	Multiple case study	Complexity improves firm performance.
	Frequent changes to the SC elements or to their interconnections.	Dynamic complexity			
Giannoccaro et al. (2018)	Number of suppliers	Structural complexity	NA	Simulation, NK fitness landscape.	Negative influence on supply network performance.
	Degree of supply interactions	Dynamic complexity			
Chowdhury et al. (2019)	Number of buyers, suppliers, facilities; detailed SC network.	Structural complexity	Bangladesh	Survey	Complexity positively influences SC performance and resilience
Birkie and Trucco (2020)	Number of products, customers, brands; no. of suppliers and facilities.	Structural complexity	NA	Secondary data	Complexity positively influences recovery performance.
Dong et al. (2020)	Number of suppliers, no. of countries in the supply base, detailed SC network.	Structural complexity	USA	Secondary data	Negative influence on the firm's financial performance.
Wiedmer et al. (2021)	Number of suppliers, no. of logistics partners, no. of parts and components	Structural complexity	Japan, Germany and USA	Secondary data	Positive influence on disruption recovery; Negative influence on disruption impact.

The findings of previous studies that explored the impact SC complexity can have on a firm's ability to deal with disruptions are equivocal. Furthermore, scholars use different conceptualizations or dimensions of SC complexity in their studies, resulting in disparate results. For instance, increasing the number of nodes upstream in the SC (supply base) is reported to negatively impact SC resilience (Blackhurst et al., 2011), as increasing upstream SC complexity increases the frequency of disruptions (Bode and Wagner, 2015; Brandon-Jones et al., 2015) as well as the severity of disruptions (Craighead et al., 2007). Furthermore, increased supply base complexity reduces the likelihood of timely detection of disruptions (Bode and Macdonald, 2017). However, Birkie et al. (2017) and Chowdhury et al. (2019) find a positive relation between structural complexity and disruption recovery; SC complexity also shows a positive moderating role in minimising the negative ripple effects of disruptions (Birkie and Trucco, 2020); whereas, Wiedmer et al. (2021) find that while some aspects of SC complexity (high product complexity) contribute to an increase in disruption impact, others (such as a large number of logistics partners) have a positive effect on the speed of recovery. Ates and Memis (2021) argue that the way SC complexity is managed can also have a divergent impact on firm outcomes. Depending on the nature of practices adopted by firms to manage complex SC networks, they may be able to mitigate the negative effects of SC complexity on resilience (Aitken et al., 2016). However, extant studies on managing complexity for disruption recovery are scarce. In this regard, Masson et al. (2007) discussed the use of sourcing agents in low-cost countries to improve agility. Fernandez Campos et al. (2019) use multiple complexity management practices to improve performance, Giannoccaro et al. (2018) investigate the scope of control to manage upstream suppliers, and Ates and Memis (2021) investigate the moderating role of strategic purchasing to improve purchasing performance under SC complexity.

Understanding the relationship between resilience and complexity is made more difficult by the different conceptualizations of complexity that previous studies adopt. Earlier empirical studies mainly investigate the SC complexity dimension from a single perspective, predominantly structural (static). Craighead et al. (2007), for example, conceptualize SC complexity as the number of nodes and material flows within the supply chain in a single construct. They theorize that SC complexity increases the SC disruptions' severity, however, they find that increased mitigation capabilities moderate the relationship between complexity and disruption severity. Later, Brandon-Jones et al. (2014) found a negative moderating impact of SC complexity on SC resilience. Also, the level of structural complexity is found to increase the severity of the disruption experienced (Craighead et al., 2007; Brandon-Jones et al., 2015). However, Birkie et al. (2017) observe a positive moderating impact of structural SC complexity on the resilience and performance relationship. Recently, Chowdhury et al., (2019) find that SC complexity has a positive moderating effect on the relationship between SC resilience and performance, while Wiedmer et al. (2021) report a positive influence of SC complexity on disruption recovery, but a negative influence on disruption impact. The reason for the positive relationship identified between SC complexity and resilience is found to be the flexibility and redundancy characteristics in the static conceptualization of complexity. Based on the discussion above, we propose that:

H1 – Structural SC complexity positively affects SC resilience.

Our initial review of the literature highlights that many studies focus on structural dimensions of SC complexity, while the dynamic aspect of complexity is poorly understood, particularly in relation to the impact SC complexity can have on resilience. Furthermore, no prior work, to the best of our knowledge, has integrated both structural and dynamic aspects of SC complexity in examining SC resilience. This is a gap that our study aims to fill.

As such, the literature highlights that while global competition has influenced firms' appetite to increase their product ranges and capture new markets, increasing their SC structural complexity, this has also led to increased inter-connectedness (Choi and Krause, 2006; Giannoccaro et al., 2018) and hence given rise to heightened dynamic complexity. This has also resulted from firms understanding the importance of managing beyond tier 1 of their SCs, moving from managing dyadic relationships to triadic and multi-level relationships, where complex interconnectedness occurs among suppliers who might compete with each other and serve a diverse set of consumers (Wu and Choi, 2005). Based on this discussion, we propose that:

H2- Structural SC complexity positively affects dynamic SC complexity.

With the increase of nodes in the SC (structural aspect), interdependencies and interconnections increase (dynamic complexity), and this requires higher levels of coordination. To enable a higher degree of visibility and better decision making while dealing with high levels of SC complexity, aspects such as digital technologies adoption are acknowledged to enable a faster and more efficient response to nowadays dynamic environments (Zhan & Tan, 2020).

From a dynamic complexity perspective (Bozarth et al., 2009; Azadegan et al., 2013), earlier studies argue that complex SCs may experience reduced integration and collaboration with suppliers (Sheffi & Rice, 2005), which affect the agility and responsiveness capabilities of their SCs (Ashkenas, 2007; Collinson and Jay, 2012). Bozarth et al. (2009) highlight that longer lead times can increase a firm's dynamic complexity, experiencing a significantly larger bullwhip effect driven by longer replenishment lead times. Giannoccaro et al. (2018) explore supply network complexity at the level of supply interactions and find that when complexity increases, monitoring and managing a large number of interactions among SC partners becomes a difficult task (Cheng et al., 2014) and can adversely affect resilience (Chowdhury et al., 2019). It is also argued in the literature that supplier deliveries or lead times, which we use to operationalise dynamic complexity in our study, affect inventory management operations (Agarwal et al., 2009; Song et al., 2010) and lead to firms being unable to respond to disruptions adequately (Chang and Lin, 2019).

The literature on the effects of replenishment lead times is inconclusive. One school of thought, for example, posits that shorter lead times lead to firms being more flexible and more responsive in dealing with disruptions (Chopra and Sodhi, 2004). The idea behind this concept is that faster order replenishments and more reliable suppliers will lead to firms being less reliant on increasing inventory buffers to deal with uncertainty, increased flexibility, and greater resilience (Finke et al., 2012). Whereas, in a supply disruption scenario which occurs due to unreliable deliveries and long lead times, severe disruptive impacts are more likely to significantly affect an organisation (e.g., if upstream production halts, the backorder rate increases, while downstream stockout frequency and lost sales will rise (Simchi-Levi et al., 2002).

These mixed results in the literature highlight the need to further investigate the concept of dynamic SC complexity and its impact on resilience. In line with the current literature summarised above, we hypothesize the following:

H3 – The higher the dynamic SC complexity, the lower the SC resilience will be.

However, the extent to which increasing visibility through supply networks can help mitigate heightened structural and dynamic complexities in order to increase resilience has received limited attention in the extant literature. The role digital technologies such as Big Data Analytics can have in mitigating the detrimental effect of SC complexities on resilience needs further investigation.

2.3 Big Data Analytics

Over the past few years, big data analytics (BDA) as an SC capability has gained a lot of attention for its ability to improve organizations' decision-making ability, particularly across organisational boundaries (McAfee and Brynjolfsson, 2012; Mikalef et al., 2020). It acknowledges that decision makers operate in a highly complex and competitive environment, therefore they cannot rely on tacit knowledge and their instincts alone to manage increasingly complex SCs. Formally, Romero, et al., (2016) define Big Data as a set of non-structured and complex data, which come from sensors, social media, applications and devices that work with the Internet and require technologies to store, manage, analyse and visualize the information. Sources of big data generation in a supply chain context are plentiful: financial data, supplier assessments, due diligence reports, weather data, forecast methods for maritime systems, business transactions or user generated content (George et al., 2014; Lamba and Singh, 2017). Similarly, it is applied in numerous sectors and requires quantitative computational techniques to unveil patterns and trends hidden in the data. Thus, in today's global world characterised by extremely complex supply networks, BDA has become an important tool available to decision-makers to extract valuable knowledge in order to better compete in dynamic business environments (Ali & Aboelmaged, 2021; Zhan & Tan, 2020). Table 2 summarises key findings from previous studies examining BDA adoption.

Table 2: Antecedents and outcomes of BDA adoption

Publication	Country/Region	Methodology/Approach	Antecedents of BDA	Outcomes of BDA
Chen et al. (2016)	USA	Survey	Grounded in technology-organization-environment (TOE) framework, technological factors directly influence, while organizational & environmental factors indirectly influence BDA adoption.	BDA positively influences business growth.
Schoenherr and Speier-Pero (2015)	USA	Survey	Various motivators and barriers in adopting BDA identified in SCM.	Improved SC efficiency, enhanced demand planning, increased visibility, faster response in dynamic environment.

Ramanathan et al. (2017)	UK	Qualitative	Various technological, organizational and environmental determinants for BDA adoption.	Poositive impact on business performance.
Chavez et al. (2017)	China	Survey	N/A	Positively influence on various manufacturing capability dimensions (quality, delivery, flexibility & cost).
Papadopoulos et al. (2017)	Nepal	Content Analysis	N/A	Enhanced sustainability.
Dev et al. (2019)	India	Fuzzy ANP, Simulation, TOPSIS	N/A	Improved key performance indicators in dynamic environments.
Dubey et al. (2018a)	India	Survey	N/A	Enhanced SC agility and competitive advantage.
Dubey et al. (2018b)	India	Survey	N/A	Positive influence on inter-organizational compatibility & resource complementarity.
Mandal (2018)	India	Survey	N/A	Positive influence on SC resilience dimensions.
Lai et al. (2018)	China	Survey	Perceived benefits and top management support positively influence BDA adoption; environmental factors positively moderate BDA adoption.	N/A
Dubey et al. (2019)	India	Survey	N/A	Positively influences SC resilience and competitive advantage.
Wu et al. (2019)	USA	Empirical data	N/A	Positively influence on process innovation which further improves firm productivity.
Singh and Singh (2019)	USA - EU	Survey	N/A	Positive influence on firm's knowledge management ability and enhanced resilience.
Moktadir et al. (2019)	Bangladesh	Delphi based AHP	Investment, technology, and organizational related barriers identified in adopting BDA.	N/A
Maroufkhani et al. (2020)	Iran	Survey	Technological, organizational and environmental factors significantly affect BDA adoption.	Positive influence on market and financial performance of SMEs.
Wamba et al. (2020)	USA	Survey	N/A	Positive influence on SC Ambidexterity and Organizational Performance.
Chen et al. (2020)	Taiwan	Qualitative	Identifies barriers in healthcare sector to adopt big data systems, and devise a strategy to overcome these barriers.	N/A

The extant operations and supply chain management academic literature on BDA is still developing and growing, while also attracting increasing recognition in practice (Dubey et al., 2019; Gu et al., 2021). The focus of BDA is towards creating actionable insights by collecting and analysing a large amount and variety of data (structured or unstructured) and enabling firms to develop competitive capabilities. Sanders (2014) argue that adopting BDA could result in more intelligent SCs and businesses could achieve tremendous benefits such as more efficient customer service, increased ability to attract potential customers and identify new markets and new service offerings, ability to better manage operational uncertainties (Opresnik and Taisch; 2015, Sanders and Ganeshan, 2018). In practice, BDA is considered a smart tool and has been employed in different sectors such as retail (Marr, 2016), manufacturing (Wilkins, 2013) and the public sector, such as emergency services (Wamba et al., 2015). To maximize the beneficial effect of BDA, researchers have identified two significant components which need to be present: the availability of well-trained workforce (Angrave et al., 2016; Marler and Boudreau, 2017) and suitable infrastructure for efficiently handling large amounts of information (Akter et al., 2016; Wang et al., 2018). These will enable firms to analyse large amounts of data from numerous sources, therefore the adoption of sophisticated quantitative techniques in BDA can improve visibility in the firm and across the SC (Belhadi et al., 2021), while supporting core supply chain processes and enabling the extraction of novel insights for decision making and provision of new service/products.

Furthermore, Waller and Fawcett (2013) highlighted that those firms which use advanced quantitative techniques such as simulation, optimization and statistical inference can generate useful insights for their decision-making process, leading to supply systems better equipped to deal with disturbances and increase their resilience. Adriana et al. (2014) argued that with the use of innovative technologies, it is possible to reduce the impact and magnitude of severe disruptions. Firms adopting these big data analytics innovative technologies have access to real-time critical information and hence can develop necessary measures to reduce disruption risks (Shamout, 2020). Using real-time analytics in SCs enhances visibility, transparency and ambidexterity in the network and can hence prevent internal and external disruptions from occurring and /or can limit their impact once they occur.

As such, operations and supply chain management literature argue that firms adopting BDA are able to better manage their SC risks, reduce sourcing costs and achieve improved organizational efficiency and resilience (Moretto et al., 2017; Gu et al., 2021; Ali & Govindan, 2021). In terms of managing SC activities, BDA is used for configuring supplier networks, capturing the dynamics of demand patterns, and developing customer networks (Prasad et al., 2018; Wang et al., 2016; Nguyen et al., 2017). This is essential as firms continue to require efficient decision-making processes and capabilities to not only stay ahead of the competition but also to remain resilient in continuously turbulent environments (Dubey et al., 2019; Singh and Singh, 2019). Moreover, big data driven decision making is useful for process improvement efforts, cost optimization, managing logistical activities, providing better inventory insights, monitoring suppliers' risk profiles, and helping in developing adequate contingency plans (Lamba and Singh, 2017; Tiwari et al., 2018; Ali et al., 2021).

However, while the literature acknowledges that real-time information sharing, along with data analytics capability, can enhance decision making and creates visibility across the network (Brandon-Jones et al., 2014; Schoenherr and Speier-Pero, 2015; Dubey et al., 2018), its impact on resilience is less well understood. By employing BDA capabilities across SC networks, managers could better identify potential risks in their SCs and hence can develop efficient measures to become highly responsive to disruptive events (Ivanov et al., 2017). Hence, we hypothesize that:

H4 – BDA positively affects SC Resilience.

The mediating role of Big Data Analytics

Since globalization has widened the number of SCs actors and the geographical spread of contemporary SCs, SCs' structural complexity has increased. SCs are now a complex system of suppliers, plants, distribution centres, warehouses and customers spread across nations and continents. These complex SCs are also capable to generate high volumes and a wide variety of data which increases the need to employ BDA to better deal with constantly arising challenges and to increase resilience. SC structural design pertains to strategic decisions such as the selection of partners in the network, as well as location decisions, both driven by the firm's long-term strategy. The application of BDA can enable the optimal design of the SC structure employed to achieve sustainable competitive advantage as well as increased resilience levels (Singh & Singh, 2019; Dubey et al., 2019). Wang et al. (2018), for example, develop a mixed-integer nonlinear model to rationalize locations for distribution centres, while incorporating transportation and warehousing cost parameters. BDA is also capable of providing foresight information on logistics routes and warehouse data (Jeble et al., 2018; Wamba et al., 2018). Wang et al. (2016) further argue that SC structural design requires a huge variety of data from retailers' aggregate demand, plant resource capacities, to transportation and operations cost for each location. The extended SC structure leads to higher complexity and its management will require extended information management capabilities (Wong et al., 2015). Owing to these BDA capabilities, we postulate that BDA plays an intervening role in the relationship between structural SC complexity and SC resilience. Therefore, we argue that:

H5. Big data analytics capabilities mediate the effect of structural SC complexity on SC resilience.

Furthermore, to sense, respond and recover from disruptions in the supply network, BDA can be employed, for example, through adopting SC mapping and enterprise social networking capabilities (Mubarik et al., 2021). These will help identify potential sources of uncertainties and strengthen supplier development efforts to cope with emerging disruptions (Souza, 2014). However, to reduce supply disruptions, a careful selection of suppliers is an important aspect of strategic sourcing (Romano and Formentini, 2012). In a global context, with a large number of potential suppliers, the selection process can be facilitated through adopting BDA. This will also enable the determination of optimum inventory levels with fluctuated demand while considering aspects such as lead time, delays and service level (Fernandes et al., 2013; Guo and Li, 2014). Due to the large volume and variety of operational data generated from various sources, such as supply-side (supplier production facility, warehouses) to demand-side (wholesalers, retailers, consumers) through storage nodes, adopting BDA tools is essential to build flexibility into the supply system. Thus, to examine the intervening effects of BDA on the relationship between dynamic SC complexity and SC resilience, the following hypothesis is proposed:

H6. Big data analytics capabilities mediate the effect of dynamic SC complexity on SC resilience.

Based on the above literature review, Figure 1 presents the conceptual framework for this study. It consists of 4 factors: Structural Supply Chain Complexity (Structural SCC), Dynamic Supply Chain Complexity (Dynamic SCC), Big Data Analytics (BDA) and Supply Chain Resilience (SC Resilience).

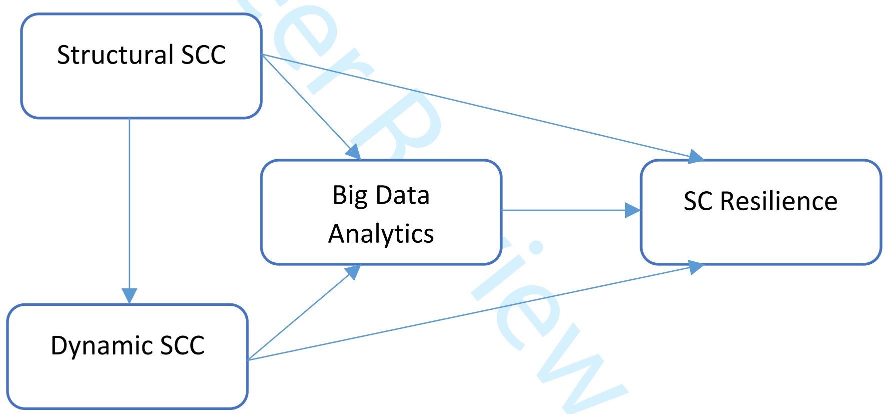

Figure 1: Conceptual Model

3. Methodology

3.1 Sample and data collection

This research was conducted in Pakistan, a developing emerging economy. As highlighted in the Introduction, developing economies are perceived to be more oriented towards SC failures and adversity, which amplifies the uncertainties that firms are likely to be exposed to, which further emphasises the need for research on resilience in these contexts. Furthermore, most of the research on SC resilience has previously been conducted in developed economies, with emerging and developing economies have attracted limited focus. At the time data was collected (2019-2020), Pakistan was facing political instability and economic hardships, which can negatively impact firm performance. In this context, firms can become more rigid in their resource allocation and utilization, which make studies on resilience particularly relevant, especially when it comes to investing in and developing advanced analytical capabilities, such as BDA. Firms' reluctance to invest in digital technologies may hamper their resilience capabilities, hence why studies investigating the role BDA plays in enhancing SC resilience are particularly timely.

The target population in our survey were full-time professionals with at least 2-3 years of experience in SCM. Relevant work experience was mandatory to get reliable responses from the participants in the survey. Further, during the preparation of the survey, we validated the content through a series of meetings with two academics. Before rolling out the survey, we also pre-tested the questionnaire with five industry experts from the SCM field. Their experience allowed for improved clarity of the constructs used (Chen and Paulraj, 2004). The entire questionnaire was administered in the English language, as it is also the second official language in Pakistan firms.

Further, to assure reliable responses from the respondents, we approached participants through a professional social networking platform, LinkedIn, and the professional network of APICS. In total, 1020 survey links were sent to the participants (700 email invitations & 320 LinkedIn invitations). Responses were collected over 16 weeks, from August 2019 until January 2020. To improve the response rate, participants were sent fortnightly reminders. We received 166 usable responses, with an effective response rate of 16.27%. This response rate is deemed adequate to conduct statistical analysis (Brusset and Teller, 2017; Han et al., 2017).

The sample demographic of the responding firms was fairly distributed among different sectors of manufacturing (56%) and service (35%), which is essential for results generality. All participants held different managerial positions in the SC field and possessed multiple years of experience. The survey answers also had a good representation of participants from different firm sizes, with different annual sales levels, thus capturing heterogeneous groups of people and firms. Further detail of the participants' profiles is presented in Table 3.

3.2 Non-response and common method bias

We performed a non-response bias test, as suggested by Armstrong (1977), where we compared the early and late respondents. For non-response bias, we performed an independent t-test on the key research constructs and found no significant differences among early and late respondents. Hence, no evidence of non-response bias was found in our study. Further, as seen in Table 3, the heterogeneous profile of respondents and firms instils confidence in the survey results. Due to the adoption of a survey methodology for data collection, we also address the common method bias issue. We applied Harman's single factor test of CMB (Podsakoff et al., 2003), to examine whether a single factor could explain the majority of the variance. During the exploratory factor analysis for the non-rotated solution, our first factor explained 34.30% of the variance, which does not represent the majority of the total variance. Further, the analysis revealed that 4 factors with

Eigenvalues above 1.0 explained 64% of the total variance. Also, no one single factor explained the majority of the variance (>50%) (Podsakoff and Organ, 1986; Gölgeci and Kuivalainen, 2019).

Next, we examined the correlation matrix computed through partial least squares (PLS) to see if any of the construct variables are extremely highly correlated (> 0.90) (see Table 6), which indicates the possibility of common method bias (Pavlou et al., 2007). We did not find any highly correlated constructs. We also conducted the second test by performing collinearity statistics, thus the variance inflation factor (VIF) computed with partial least square (PLS) on all the key constructs. If all VIFs resulting from a full collinearity test are either equal to or lower than 3.3 then no common method bias exists (Kock, 2015). In our case, we did not find any VIF exceeding 3.3, therefore, we can conclude that our model has no significant problems associated with common method bias.

Profile	Number	Percentage
Industry Sector		
Manufacturing	92	55%
Others	16	10%
Service	58	35%
Gender		
Male	156	94%
Female	10	6%
Designation		
Manager	128	77%
Senior Manager	24	14%
General Manager	8	5%
Director	6	4%
Experience		
3 - 5	55	33%
6 - 8	29	17%
9 - 11	30	18%
>11	52	31%
Firm Size		
Below 500 employees	53	32%
500 - 1000 employees	41	25%
> 1000 employees	72	43%
Annual Sales		
Less than $1 million	19	11%
$1 - 50 million	49	30%
$51 - 500 million	45	27%
$501 million - $1 billion	22	13%
Greater than $1 billion	31	19%

Table 3: Descriptive statistics of participants

3.3 Construct Operationalization

For this study, we used established and validated scales from the literature for the proposed constructs. Constructs were measured through multiple items on a 5 – point Likert type scale, with 1 representing "Strongly disagree" and 5 representing "Strongly agree". In all of the scales, minor modifications were made based on the feedback from the pre-test run to improve the model performance. We measured Big Data Analytics (Akter et al., 2016; Dubey et al., 2019), Structural SC Complexity (Bozarth et al., 2009; Bode and Wagner, 2015), Dynamic SC Complexity (Bozarth et al., 2009; Brandon-Jones et al., 2014), and SC Resilience (Gölgeci and Ponomarov, 2015; Brusset and Teller (2017). The values of the measurement model are provided in Table 5. As suggested by Churchill (1979), we followed the scale development methodology for instrument development by conducting a literature review and pretesting the instrument among academics and practitioners as discussed in the earlier section.

The construct BDA examines the extent to which firms are adopting this highly sophisticated technology in their decision making. Respondents were asked to what extent they: used advanced analytical techniques; extracted information from a variety of sources; used visualization techniques for complex scenarios; have integrated these applications with the decision maker's device. Then, the SC Complexity construct was conceptualized from a structural and dynamic perspective. The items selected in the structural dimension represent the detailed level of complexity in the supply network. The dynamic dimension represents the delivery reliability of the suppliers based on the lead times. Finally, SCRE measured the resistance, responsiveness, and redundancy elements in a single construct (see Table 4).

3.4 Partial Least Square SEM method

For this study, we adopted the partial least square (PLS) structural equation modelling (SEM) technique. This technique is considered more suitable and recommended where the primary goal of the research is prediction and a theory building exploratory investigation (Chin, 1998). PLS application in SC literature is not uncommon and has recently been applied in various research papers (Birkie et al., 2017; Brusset and Teller, 2017). Also, the PLS-SEM technique has some distinctive benefits compared to the covariance-based SEM technique. For example, it has less restrictive assumptions on the sample size as it uses the ordinary least square regression, therefore a smaller sample size (< 200) is suitable for the data analysis (Reinartz et al., 2009; Hair et al., 2011). Furthermore, moderation and mediation effects could be analysed more effectively (Wetzels et al., 2009), with fewer restrictions on distributional assumptions (Tenenhaus et al., 2005; Peng and Lai, 2012). We deployed SmartPLS 3.0 software and used its bootstrapping technique to generate the standard path coefficients, coefficient of determination, and t values with 5000 subsamples from the dataset.

4. Empirical analysis and results

4.1 Reliability and Validity

To assess the PLS results, we first examine the measurement model and then the structural model. At first, for the reliability indicator, all of the outer loadings are higher than 0.70 which is the suggested limit (Hulland, 1999) and also their t – values are highly significant at $p < 0.001$ (see Table 4). However, only one item's outer loading (dynamic SC complexity) is 0.634. Since our research is exploratory in nature, this limit is also acceptable (Han et al., 2017). Further, to check the construct reliability for all the factors, we examine the composite reliability values. The composite reliability (CR) for all the scales ranges from 0.783 to 0.883. This range meets the requirement of being higher than 0.70 (Fornell and Larcker, 1981) (see Table 5).

For convergent validity, the average variance extracted (AVE) values need to be higher than 0.5 (Bagozzi and Yi, 1988; Hair et al., 2011; Fornell and Larcker, 1981). Our AVE values range from 0.549 to 0.766. To verify the discriminant validity, Fornell and Larcker (1981) recommend that the square root of the AVE for each construct needs to be greater than its highest correlation with the other constructs in the measurement model. The square roots of AVE values can be seen in Table 6 in diagonal, which satisfies this criterion. Additionally, we also confirmed that all of the outer loadings of the constructs were higher than the cross-loadings of other constructs (Chin, 1998). Therefore, it can be concluded that this model shows sufficient validity.

Additionally, apart from the reliability and validity investigation, we also examined the multicollinearity of the constructs. The collinearity statistics of variance inflation factors (VIF) for all of the constructs of our model remain under the acceptable limits of 5 (Hair et al., 2006) (see Table 7), therefore, no multicollinearity issue was found among the constructs.

Latent Constructs	Loadings	t - value	p - value
Big Data Analytics			
1. We use advanced tools and analytical techniques (e.g. simulation, optimisation, regression) to take decision.	0.726	13.9	< 0.001
2. We use information extracted from various sources of data to make decision.	0.76	16.225	< 0.001
3. We use data visualisation technique (e.g. dashboards) to assist users or decision-maker in understanding complex information.	0.827	20.173	< 0.001
4. Our dashboards display information which is useful for carrying out necessary diagnosis.	0.817	19.952	< 0.001
5. We have connected dashboard applications or information with the manager's communication devices.	0.748	15.757	< 0.001
SC Resilience			
1. Our firm is able to adequately respond to unexpected disruptions by quickly restoring its product flow.	0.782	15.774	< 0.001
2. Our firm is well prepared to deal with financial outcomes of potential supply chain disruptions.	0.801	14.673	< 0.001
3. Our firm has the ability to maintain a desired level of control over structure and function at the time of disruption.	0.785	12.395	< 0.001
4. We deploy alternative plans associated with identified risks.	0.742	15.199	< 0.001
Structural SC Complexity			
1. Our firm serve large number of customer base.	0.904	39.976	< 0.001
2. Our firm has large number of first tier suppliers.	0.845	19.288	< 0.001
Dynamic SC Complexity			
1. We seek short lead times in the design of our supply chains	0.634	4.566	< 0.001
2. Our company strives to shorten supplier lead time, to avoid inventory & stockout	0.833	11.344	< 0.001
3. We can depend upon on time delivery from our suppliers	0.743	8.905	< 0.001

Table 4: Indicator reliability – Outer loading factors

Table 5: Measurement model summary

Constructs	CR	AVE
Big Data Analytics	0.883	0.603
Dynamic SC Complexity	0.783	0.549
SC Resilience	0.86	0.605
Structural SC Complexity	0.867	0.766

CR - Composite Reliability; AVE - Average Variance Extracted

Table 6: Fornell-Larcker Criterion

Constructs	Big Data Analytics	Dynamic SC Complexity	SC Resilience	Structural SC Complexity
Big Data Analytics	**0.776**			
Dynamic SC Complexity	0.298	**0.741**		
SC Resilience	0.511	0.302	**0.778**	
Structural SC Complexity	0.338	0.249	0.439	**0.875**

4.2 Evaluation of the structural model – Hypothesis testing

Following the assessment of the measurement model, the assessment of the structural model was then performed. In Table 8, we summarise the results of the structural model tested through the PLS-SEM analysis. Our results present the standard path coefficients, *t* – values and bias – corrected 95% confidence interval with the level of significance by adopting the bootstrapping technique. We have shown the direct and indirect effects (mediation) of BDA on the relationship between dynamic SC complexity and SC resilience.

Table 7: VIF Analysis Results

Constructs	Item	VIF
Big Data Analytics	BD-1	1.585
	BD-2	1.627
	BD-3	3.156
	BD-4	3.318
	BD-5	1.736
SC Resilience	SCRE-1	1.621
	SCRE-2	1.727
	SCRE-3	1.638
	SCRE-4	1.385
Structural SC Complexity	NC-1	1.401
	NC-2	1.401
Dynamic SC Complexity	NC-3	1.182
	NC-4	1.247
	NC-5	1.184

Table 8 examines the hypothesized linkages of the direct effects of BDA, structural SC complexity and dynamic SC complexity on SC resilience, and of structural SC complexity on dynamic SC complexity. The indirect effects of Structural and Dynamic SC complexity on SC resilience through BDA were also examined. After 5000 bootstrapped resamples, the test results of the hypothesis of the direct effects (H4 - β=0.388, $p < 0.001$; H1 - β=0.278, $p < 0.01$; H2 - β=0.255, $p < 0.01$) are found to be supported, whereas, (H3 - β=0.110, $p > 0.10$) is not significant and not supported. Further, the 95% confidence interval of H3 is [-0.074, 0.284] and due to the inclusion of zero the direct effect of dynamic SC complexity over SC resilience is not significant (Preacher and Hayes, 2008). These are interesting findings and, in the subsequent section, a detailed discussion is carried out.

Next, we also tested the indirect effects as shown in the structural mediation model (Fig 2) and the results are tabulated in Table 8. We tested the indirect effect of structural SC complexity on SC Resilience through BDA (H5 - β=0.108, p < 0.01). As recommended by Hayes and Scharkow (2013) we also reported bias-corrected bootstrap confidence interval to detect mediation effects, hence the 95% confidence interval range for H5 was [0.050, 0.174]. Another hypothesis of the impact of dynamic SC complexity on SC resilience through BDA was also examined with (H6 - β=0.087, p < 0. 1) and bias-corrected 95% confidence interval [0.018, 0.178]. Since none of the hypotheses contains zero between the lower and upper limits of the confidence interval, both of the indirect effects (H5 & H6) are significant and supported. There is one partial mediation and one full mediation found for structural and dynamic SC complexity over resilience through BDA respectively. It can be seen from Table 8 that the direct effect between DSCC and SCRE is not significant and not supported, whereas the indirect effect through BDA is significant and supported. Therefore, a full mediation effect can be found in the model. The model reflects the importance of big data analytics in improving resilience for supply networks experiencing structural and dynamic complexities. The model thus suggests that in supply networks with increased structural and dynamic SC complexities, firms require big data analytics as a moderator to experience an increase in SC resilience.

Table 8: Hypothesis results.

Hypothesis	**Path Coefficient**	***t*-statistics**	***p*-values**	**Lower bound 95% CI[a]**	**Upper bound 95% CI[a]**	**Decision**
Direct Effect Results						
H1. SSCC -> SCRE	0.278	2.883	0.004^{*}	0.093	0.471	Supported
H2. SSCC -> DSCC	0.255	2.777	0.006^{*}	0.060	0.421	Supported
H3. DSCC -> SCRE	0.110	1.185	$0.236^{n.s}$	-0.074	0.284	Not Supported
H4. BDA -> SCRE	0.388	4.833	0.000^{*}	0.216	0.530	Supported
Indirect Effects (Mediation) Results						
H5. SSCC -> BDA -> SCRE	0.108	2.825	0.005^{*}	0.050	0.174	Supported (**Partial Mediation**)
H6. DSCC -> BDA -> SCRE	0.087	1.908	0.078^{**}	0.018	0.178	Supported (**Full Mediation**)

Note – BDA – Big Data Analytics, SSCC – Structural Supply Chain Complexity, DSCC – Dynamic Supply Chain Complexity, SCRE – Supply Chain Resilience. * Significant at α < 0.05, ** α < 0.10 (2-tailed test), n.s – not significant, a – bias-corrected.

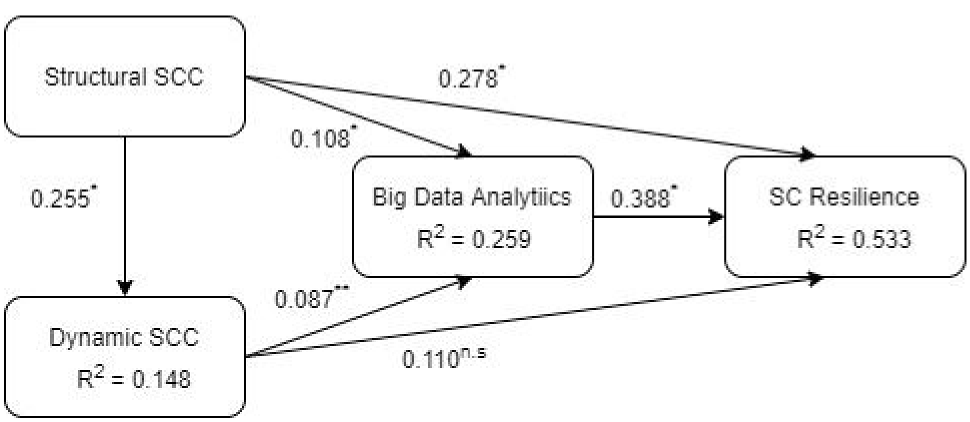

Figure 2: Structural model results, ** $p < 0.10$, * $p < 0.05$, N.S – Not Significant.

5. Discussion and implications

5.1 Discussion of results

We found that structural SC complexity (H1) has a positive effect on SC resilience. Our finding thus suggests that structural SC complexity (emerging from a large number of suppliers and customers in the supply network), which in turn leads to increased redundancy and flexibility in SCs (Chowdhury et al., 2019), increases SC resilience. This result is in contrast to previous studies such as Brandon Jones et al. (2015), who found that an increase in supply base complexity leads to an increase in the frequency of disruptions the SC is exposed to, hence reduced SC resilience. Our results highlight that a higher number of suppliers and customers can provide considerable flexibility in sourcing and/or channels to market and, as such, increased ability to deal with SC disruptions (Wagner and Bode, 2006; Tang and Tomlin, 2008). Furthermore, alternative sources of supply can increase inventory and capacity flexibility, which can both further reduce SC vulnerability and increase resilience (Li and Amini, 2012).

Our study also found that structural SC complexity increases dynamic SC complexity (H2). This finding suggests that, as the structure of an SC increases, the increased number and variety of components leads to higher levels of dynamic SC complexity. The dynamic complexity, or operational complexity, arises due to the uncertainty associated with time and randomness (Bozarth et al., 2009; Serdarasan, 2013). We infer from this result that an increase in structural SC complexity may lead to reduced control over processes, and ambiguity (Isik, 2010). In line with Dittfeld et al. (2018), uncertainty is an implied element of dynamic SC complexity; in a network characterised by structural complexity, without increased visibility supported by predictive analytics the resulting uncertainty related to aspects such supply side material availability, for example, disturbs and destabilises the organisation's operation management activities, such as planning and scheduling.

As for dynamic SC complexity, we found no significant direct effect on resilience (H3). This suggests that firms, in their search for more resilient SCs, can benefit more from developing structural complexity in their supply network (a large number of suppliers and customers) rather than relying on dynamic complexity emerging from highly collaborative efforts and interactions with flexible and reliable SC partners. Though surprising, such patterns of behaviour have been previously reported in the SCM literature. Masson et al. (2007), for example, found that when organisations need to respond to demand volatility at short notice, they rely on sourcing intermediaries to switch their sources of supply at short notice, rather than draw on sources of flexibility built-into their extant supply network. A further justification for this is provided by the fact that, as firms have focused over the past few decades on implementing lean practices in their supply networks, which are focused on increasing efficiency by reducing as much as possible slack resources such as spare capacity or just-in-case inventory (Song et al., 2010), the resulting SCs are inherently lacking flexibility. Furthermore, the trade-off between flexibility and efficiency has received increasing attention in managerial practice (Prahalad and Krishnan, 2002; Kaplan and Norton, 2008). As a result, when organisations need to display high levels of resilience by responding to quick changes in demand patterns, for example, they will need to seek this flexibility outside their current network, rather than relying on the extant SC partners. Hence, the severity of the initial disruption could be lessened by assuring multiple sourcing strategies, which in itself is an established contingency strategy (Chang and Lin, 2019). Further, our results related to the impact of dynamic SC complexity on resilience are consistent with Colicchia et al. (2010), who found that supply lead times are considered as sources of vulnerabilities for SCs, which can significantly impact their resilience.

We also explored in our study how big data analytical capabilities impact SC resilience and our findings confirm H5. This is consistent with extant literature which argues that different forms of supply chain visibility influence the development of big data analytical capabilities (Srinivasan and Swink, 2018), which in turn increase the resilience of supply networks (Brandon Jones et al., 2014). Big data analytics also improves decision making through real time information sharing and SC visibility, leading to higher resilience levels.

The model we adopted in our study aimed to also explore the intervening (mediation effects) of big data analytics on the relationship between structural and dynamic SC complexities and resilience, and both were found to be significant. The positive mediation effects of BDA in this study for SC complexities and resilience confirm earlier findings that adopting BDA creates flexibility and visibility into supply systems and can support early identification of potential risks (Adriana et al., 2014; Ivanov et al., 2017; Dubey et al., 2018). Our findings suggest that, despite the reduced level of collaboration associated in previous literature with a higher level of SC complexity (the higher the number of nodes, the weaker the resulting collaborative efforts), BDA through real-time information sharing and visibility can lead to more responsive measures to avoid disruptive events.

5.2 Contributions to Theory

The global nature of nowadays supply chains and associated complexity have compelled firms to adopt innovative and sophisticated technologies, such as big data analytics, to better manage the structural and dynamic complexity of their supply networks and better deal with increased vulnerabilities. In this context, our study makes several contributions to the extant SCM literature by exploring BDA and its potential role in increasing supply chain resilience. While earlier studies have provided some initial conceptual development and understanding of the link between SC complexity and resilience (Birkie et al., 2017; Chowdhury et al., 2019) and big data analytics (Dubey et al., 2019), our research's contribution lies in the reconceptualization of supply chain complexity (structural and dynamic). Our research also contributes to the extant literature by establishing a critical understanding of the role of BDA in mediating the critical link between two types of SC complexities (structural and dynamic) and SC resilience. Our results highlight that there are both direct and indirect effects between structural SC complexity and SC resilience, however dynamic SC complexity only influences SC resilience via BDA. These findings provide strategic insights to supply chain executives as to where to invest in BDA to build much needed supply chain resilience.

While the literature investigating the impact of SC complexity on resilience is limited, it is also biased towards focusing on structural complexity. In our study, we extend the concept and integrate the dynamic aspect of complexity in our model to acknowledge the importance of understanding how different types of SC complexities affect resilience so that appropriate capabilities could be adopted at the firm/supply chain level. We draw on the contingency theory but also extend it and adapt alongside it the dynamic capability view. The combined framework highlights the impact of SCC on resilience and offers a much more nuanced view in relation to the interactions between structural SC complexity and dynamic SC complexity, as well as their different cause-effect relationships on resilience. We find that, while structural SC complexity positively influences SC resilience, dynamic SC complexity does not appear to have a significant impact. As highlighted in the previous section, this result needs to be interpreted in contrast to earlier research, where dynamic complexity emerged as a primary driver for disruptions frequency (Brandon Jones et al., 2015), which could lead to reduced SC resilience.

Secondly, the extant literature of BDA in SCM has previously focused mainly on predicting firms' performance (Iftikhar et al., 2021; Chavez et al., 2017; Chen et al., 2015; Jeble et al., 2018), and on the antecedents or determinants of BDA adoption (Maroufkhani et al., 2020; Waller and Fawcett, 2013). However, the mediating role of BDA between SC complexity and SC resilience was overlooked in the extant literature. Our model breaks down SC complexity into structural and dynamic complexity and shows how both types of complexities interact with each other, as well as how the relationship between SC complexity and SC resilience is contingent on BDA. Our study thus reflects the importance of big data analytics in improving resilience for supply networks experiencing structural and dynamic complexities. When present, high levels of complexity can increase resilience, provided that firms focus on developing advanced analytical capabilities that will enable them to counteract the potential difficulties and uncertainties associated with managing complex supply networks. These findings, collectively, have significant implications for theory and practice, while providing new potential research avenues and guiding SC managers in their quest to build more resilient supply chains.

As such, our study is one of the first ones to empirically validate the mediating effect of BDA on the relationship between distinct SC complexities and resilience. Hence, this study provides tangible evidence that supports the mediating role of BDA in the impact on SC resilience for both structural and dynamic SC complexities. Our theoretical model also motivates the top management in E&DE to adopt BDA in enhancing firm resilience performance despite their inherent SC complexities. We, therefore, contribute to the current literature by exploring the BDA role in mitigating SC complexities and enhancing firm resilience performance.

However. we also acknowledge that successful implementation of BDA can be challenging in developing and developed countries (Moktadir et al., 2018; Ferraris et al., 2018). While our study is the first one, to our knowledge, that investigates the interplay between SC complexity – BDA – resilience in an E&DE context, we also acknowledge that results may vary for future studies looking at other E&DE contexts, based on varying organizational culture and knowledge predictors. Therefore, we suggest future studies should examine in depth the extent to which these factors can influence results.

5.3. Contributions to Practice

Our research has also important implications from a practical perspective. First, our study confirms that BDA enhances resilience in SCs in emerging & developing economies, considering distinct types of SC complexities. Firms operate in an increasingly hostile environment in these economies. Under these circumstances, top management can be sceptical to adopt innovative technologies without tangible evidence for the impact their adoption might have on the performance of SCs. Our research clarifies that firms must invest in innovative technologies to build BDA capabilities, which will help to minimize risks associated with structural and dynamic SC complexities. Generally, in Emerging and Developing Economies, the adoption of BDA is in its early stages, therefore the results give a clear idea of the positive impact BDA has on SC resilience. As SC complexity increases, the amount of data (structured & unstructured) generated also increases, and BDA plays a significant role in enabling firms to gain new insights from data, make rapid decisions, and develop effective interventions to better respond to disruptive events, hence leading to enhanced resilience. This means that SC managers must develop a data-driven and digital culture which might not be common in E&DEs. Literature suggests that firms must change the managerial mindset related to relationship management (e.g a move away from adversarial relationships to collaborative partnerships) to increase the impact that the adoption of BDA capabilities can have on organisational performance (Maroufkhani et al., 2020).

Managers also need to better understand the importance of adopting advanced information technology when developing resilience strategies, particularly when dealing with high levels of complexity in their SCs. In addition to the insights that BDA directly impacts SC resilience, our study further identifies three pathways that firms can adopt to utilise BDA to build SC resilience (see Figure 2): A) From Structural SC complexity to BDA to SC resilience; B) From Dynamic SC complexity to BDA to SC resilience; C) From Structural SC Complexity to Dynamic SC Complexity to BDA to Resilience. This provides clear pathways for operations and supply chain managers in terms of where and how they should allocate critical resources to enhance SC visibility and tackle the disturbances brought by the associated SC complexities. For example, managers can now have better insights into how the level of complexity in supply chain networks (structural and dynamic) can affect the resilience strategies employed, which is particularly relevant when responding to unforeseen events, such as the COVID-19 pandemic (Chowdhury et al., 2021).

Particularly, firms might benefit in the long term from maintaining buffers of inventory and capacity to quickly recover from the disruption impact of longer lead times or unreliable deliveries and increase their flexibility. This trade-off between efficiency and flexibility is well established in the operations and SCM literature but requires further investigations in the context of mitigating the impact of structural and dynamic SC complexity on resilience, particularly when firms are beginning to establish BDA capabilities in their supply chains.

6. Conclusions

Over the last couple of years, the concept of BDA has gained importance for supply chain management, at the tactical, operational and strategic levels (Wang et al., 2016). In today's highly competitive world, BDA has become an innovative organizational capability that could contribute to improved robustness of demand prediction and reduced bullwhip effect (Arunachalam et al., 2018).

Our study set out to investigate the impact of SC complexity on SC resilience. More specifically, we examine whether this relationship is contingent on BDA. Via a survey of 166 firms in Pakistan, our study is one of the first studies to examine the impact of structural and dynamic SC complexities on resilience, particularly from an E&DE perspective. While a small number of past studies have highlighted the positive impact BDA can have on SC resilience, our paper further extends this understanding by exploring its role in mediating the relationship between structural and dynamic complexity and SC resilience, thus making significant contributions to theory and practice. We find that structural SC complexity positively affects SC resilience, while there doesn't seem to be a significant impact for dynamic SC complexity. We also find a mediating effect of BDA for structural and dynamic SC complexities on SC resilience. Our results contribute to the extant literature investigating BDA and SC resilience by offering a more nuanced understanding of distinct types of SC complexities. Our research also contributes to the extant literature by establishing a critical understanding of the role of BDA in mediating the critical link between two types of SC complexities and SC resilience. The proposed model highlights that there are both direct and indirect effects between structural SC complexity and SC resilience, however dynamic SC complexity only influences SC resilience via BDA.

Our study also brings into focus some of the associated difficulties of managing SC complexity and adopting BDA capabilities in E&DE economies. Thus, we call for further studies to particularly focus on the supply chain resilience domain from a cultural perspective. Previous authors have highlighted that organizational capabilities in SC resilience management should not be applied universally, across different cultural contexts (Manhart et al., 2020). Some cultures can be more relationally oriented by, for example, practising collective working and investing in team building and, as a result, they might display higher resilience levels. Contextual factors in E&DE economies, such as limited access to resources, infrastructure, and expertise, and poor SC governance, can, in turn, increase specific SC complexities and this may hinder resilience. Further research is however needed to understand the role that relational, governance, and regulatory factors could play in improving or hindering resilience in these economies.

In our study, we specifically examined the mediation effects of BDA on SC complexities and SC resilience. Future research should examine the relationship of other dynamic capabilities and resources between these concepts. Hence, a deeper understanding of the underlying relationship mechanism between the explored concepts of BDA, SC complexity and resilience could be established. Further, for dynamic SC complexity, we particularly examined it from the perspective of lead time and supplier delivery reliability. Expanding the span of dynamic SC complexities could further explain some of the more surprising findings in this study. We also suggest further research into SC complexity from horizontal, vertical and spatial conceptualization perspectives, to explore the extent to which it can affect SC resilience. Future studies could also develop the model of combined interplay of structural and dynamic complexities with the relationship between resilience and firm performance. Since complexity is in itself a complex construct, we further suggest exploring the role of BDA from the complex adaptive systems perspective by adopting a simulation approach, which is also considered suitable in the disruption management discipline (Giannoccaro and Iftikhar, 2020).

A further limitation of our research arises from the construct development of big data analytics. Since this research area is growing and nascent, further conceptual developments might lead to different conclusions as different measuring scales continue to emerge. Furthermore, the study design employed was limited to an emerging and developing economy. While this is an under-researched context that warrants further investigations, our findings may not be generalizable to other economic regions.

References

Adriana, L., Irineu de, B., Jr., Eduardo Queiroz, P., Tábata Rejane, B., Hugo Tsugunobu Yoshida, Y., (2014), Literature review of humanitarian logistics research: trends and challenges. Journal of Humanitarian Logistics and Supply Chain Management 4, 95-130.

Agarwal, S., Sengupta, R. N., & Shanker, K. (2009). Impact of information sharing and lead time on bullwhip effect and on-hand inventory. European Journal of Operational Research, 192(2), 576-593.

Aitken, J., Bozarth, C. and Garn, W. (2016), To eliminate or absorb supply chain complexity: a conceptual model and case study, Supply Chain Management, 21(6), 759-774.

Akter, S., Wamba, S. F., Gunasekaran, A., Dubey, R., & Childe, S. J. (2016). How to improve firm performance using big data analytics capability and business strategy alignment?. International Journal of Production Economics, 182, 113-131.

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

Ali, I., & Gölgeci, I. (2019). Where is supply chain resilience research heading? A systematic and co-occurrence analysis. International Journal of Physical Distribution & Logistics Management, 49(8), 793-815.

Ali, I., Arslan, A., Khan, Z., & Tarba, S. Y. (2021). The role of Industry 4.0 technologies in mitigating supply chain disruption: empirical evidence from the Australian food processing industry. IEEE Transactions on Engineering Management, 1-11.

Ali, I., & Aboelmaged, M. G. S. (2021). Implementation of supply chain 4.0 in the food and beverage industry: perceived drivers and barriers. International Journal of Productivity and Performance Management.

Ali, I., & Govindan, K. (2021). Extenuating operational risks through digital transformation of agri- food supply chains. Production Planning & Control, 1-13.

Ambulkar, S., Blackhurst, J., & Grawe, S. (2015). Firm's resilience to supply chain disruptions: Scale development and empirical examination. Journal of operations management, 33, 111-122.

Angrave, D., Charlwood, A., Kirkpatrick, I., Lawrence, M., & Stuart, M. (2016). HR and analytics: why HR is set to fail the big data challenge. Human Resource Management Journal, 26(1), 1-11.

Armstrong, R. (1977). THE RIGHT TO LIFE. Journal of Social Philosophy, 8(1), 13–19.

Arunachalam, D., Kumar, N., & Kawalek, J. P. (2018). Understanding big data analytics capabilities in supply chain management: Unravelling the issues, challenges and implications for practice. Transportation Research Part E: Logistics and Transportation Review, 114, 416–436.

Ashkenas R. Simplicity-minded management. A practical guide to stripping complexity out of your organization. Harv Bus Rev. 2007 Dec;85(12):101-9, 146.

Ateş, M. A., & Memiş, H. (2021). Embracing supply base complexity: the contingency role of strategic purchasing. International Journal of Operations & Production Management, 41(6), 830-859.

Ateş, M. A., Suurmond, R., Luzzini, D., & Krause, D. (2021). Order from Chaos: A Meta-analysis of Supply Chain Complexity and Firm Performance. Journal of Supply Chain Management, e12264.

Azadegan, A., Patel, P.C., Zangoueinezhad, A. and Linderman, K. (2013), "The effect of environmental complexity and environmental dynamism on lean practices", Journal of Operations Management, 31(4), pp. 193-212.

Bag, S., Gupta, S., & Foropon, C. (2019). Examining the role of dynamic remanufacturing capability on supply chain resilience in circular economy. Management Decision. 57(4), pp. 863-885.

Bagozzi, R. P., & Yi, Y. (1988). On the evaluation of structural equation models. Journal of the academy of marketing science, 16(1), 74-94.

Behzadi, G., O'Sullivan, M. J., Olsen, T. L., Scrimgeour, F., & Zhang, A. (2017). Robust and resilient strategies for managing supply disruptions in an agribusiness supply chain. International Journal of Production Economics, 191, 207-220.

Belhadi, A., Kamble, S., Fosso Wamba, S., & Queiroz, M. M. (2021). Building supply-chain resilience: an artificial intelligence-based technique and decision-making framework. International Journal of Production Research, 1-21.

Birkie, S. E., & Trucco, P. (2020). Do not expect others do what you should! Supply chain complexity and mitigation of the ripple effect of disruptions. International Journal of Logistics Management, 31(1), 123-144.

Birkie, S. E., Trucco, P., & Campos, P. F. (2017). Effectiveness of resilience capabilities in mitigating disruptions: leveraging on supply chain structural complexity. Supply Chain Management: An International Journal. 22 (6), 506-521.

Blackhurst, J., Dunn, K. S., & Craighead, C. W. (2011). An empirically derived framework of global supply resiliency. Journal of business logistics, 32(4), 374-391.

Bode, C., & Macdonald, J. R. (2017). Stages of supply chain disruption response: Direct, constraining, and mediating factors for impact mitigation. Decision Sciences, 48(5), 836-874.

Bode, C., & Wagner, S. M. (2015). Structural drivers of upstream supply chain complexity and the frequency of supply chain disruptions. Journal of Operations Management, 36, 215-228.

Bode, C., Wagner, S. M., Petersen, K. J., & Ellram, L. M. (2011). Understanding responses to supply chain disruptions: Insights from information processing and resource dependence perspectives. Academy of Management Journal, 54(4), 833-856.

Bowman, C., & Ambrosini, V. (2003). How the Resource-based and the Dynamic Capability Views of the Firm Inform Corporate-level Strategy. British Journal of Management, 14(4), 289–303.

Bozarth, C.C., Warsing, D.P., Flynn, B.B., Flynn, E.J., (2009). The impact of supply chain complexity on manufacturing plant performance. Journal of Operations Management. 27 (1), 78–93.

Brandon-Jones, A., & Knoppen, D. (2018). The role of strategic purchasing in dynamic capability development and deployment: A contingency perspective. International Journal of Operations & Production Management, 38(2), 446-473.

Brandon-Jones, E., Squire, B., & Van Rossenberg, Y. G. (2015). The impact of supply base complexity on disruptions and performance: the moderating effects of slack and visibility. International Journal of Production Research, 53(22), 6903-6918.
Brandon-Jones, E., Squire, B., Autry, C., & Petersen, K. (2014). A Contingent Resource-Based Perspective of SC Resilience and Robustness. Journal of Supply Chain Management, 50(3), 55-73.
Brusset, X., & Teller, C. (2017). SC capabilities, risks, and resilience. International Journal of Production Economics, 184, 59-68.

Byrne, D. (2002). Complexity theory and the social sciences: An introduction: Routledge.
Caridi, M., Crippa, L., Perego, A., Sianesi, A., & Tumino, A. (2010). Do virtuality and complexity affect supply chain visibility?. International Journal of Production Economics, 127(2), 372-383.
Chang, W. S., & Lin, Y. T. (2019). The effect of lead-time on supply chain resilience performance. Asia Pacific Management Review, 24(4), 298-309.
Chavez, R., Yu, W., Jacobs, M. A., & Feng, M. (2017). Data-driven supply chains, manufacturing capability and customer satisfaction. Production Planning & Control, 28(11-12), 906-918.
Chen, I. J., & Paulraj, A. (2004). Towards a theory of supply chain management: the constructs and measurements. Journal of operations management, 22(2), 119-150.

Chen, P.-T., Lin, C.-L., & Wu, W.-N. (2020). Big data management in healthcare: Adoption challenges and implications. International Journal of Information Management, 53, 102078.
Chen, Y., Chen, H., Gorkhali, A., Lu, Y., Ma, Y., & Li, L. (2016). Big data analytics and big data science: a survey. Journal of Management Analytics, 3(1), 1-42.
Cheng, J. H., Chen, M. C., & Huang, C. M. (2014). Assessing inter-organizational innovation performance through relational governance and dynamic capabilities in supply chains. Supply Chain Management: An International Journal. Vol. 19 No. 2, pp. 173-186.
Chin, W. W. 1998. “Commentary: Issues and Opinion on Structural Equation Modeling.” MIS Quarterly 22 (1): 7–16.

Choi, T. Y., Narayanan, S., Novak, D., Olhager, J., Sheu, J. B., & Wiengarten, F. (2021). Managing extended supply chains. Journal of business logistics, 42(2), 200-206.
Choi, T.Y., Krause, D.R., 2006. The supply base and its complexity: implications for transaction costs, risks, responsiveness, and innovation. Journal of Operations Management. 24 (5), 637–652.
Chopra, S., Sodhi, M.S. (2014). Reducing the risk of supply chain disruptions, MIT Sloan Management Review, Vol. 55 No. 3, pp. 73-80.
Chowdhury, P., Paul, S. K., Kaisar, S. & Moktadir, A. (2021). COVID-19 pandemic related supply chain studies: A systematic review. Transportation Research Part E, 148,
Chowdhury, M. M. H., Quaddus, M., & Agarwal, R. (2019). Supply chain resilience for performance: role of relational practices and network complexities. Supply Chain Management: An International Journal. 24 (5), 659-676.
Churchill, G. A. (1979). A Paradigm for Developing Better Measures of Marketing Constructs. Journal of Marketing Research, 16(1), 64.
Colicchia, C., Dallari, F., & Melacini, M. (2010). Increasing supply chain resilience in a global sourcing context. Production planning & control, 21(7), 680-694.
Collinson, S., & Jay, M. (2012). From Complexity to Simplicity: Unleash Your Organisation’s Potential. Palgrave Macmillan.
Craighead, C. W., Blackhurst, J., Rungtusanatham, M. J., & Handfield, R. B. (2007). The severity of supply chain disruptions: design characteristics and mitigation capabilities. Decision Sciences, 38(1), 131-156.

Day, J. M. (2014). Fostering emergent resilience: the complex adaptive supply network of disaster relief. International Journal of Production Research, 52(7), 1970-1988.

Dev, N. K., Shankar, R., Gupta, R., & Dong, J. (2019). Multi-criteria evaluation of real-time key performance indicators of supply chain with consideration of big data architecture. Computers & Industrial Engineering, 128, 1076-1087.
Dittfeld, H., Scholten, K., & Van Donk, D. P. (2018). Burden or blessing in disguise: interactions in supply chain complexity. International Journal of Operations & Production Management.
Dolgui, A., Ivanov, D., Sokolov. B. (2018). Ripple Effect in the Supply Chain: An Analysis and Recent Literature. International Journal of Production Research 56 (1–2): 414–430.

Donaldson, L. 2001. The Contingency Theory of Organizations. Thousand Oaks, CA: Sage.

Dong, Y., Skowronski, K., Song, S., Venkataraman, S., & Zou, F. (2020). Supply base innovation and firm financial performance. Journal of Operations Management, 66(7-8), 768-796.

Dubey, R., Gunasekaran, A., Childe, S., Fosso Wamba, S., Roubaud, D., & Foropon, C. (2019). Empirical investigation of data analytics capability and organizational flexibility as complements to SC resilience. International Journal of Production Research, 1-19.

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", The International Journal of Logistics Management, 29(2), 485-512.

Fan, S., Lau, R. Y., & Zhao, J. L. (2015). Demystifying big data analytics for business intelligence through the lens of marketing mix. Big Data Research, 2(1), 28-32.

Fernandes, R., Gouveia, B., & Pinho, C. (2013). Integrated inventory valuation in multi-echelon production/distribution systems. International Journal of Production Research, 51(9), 2578-2592.

Fernández Campos, P., Trucco, P., & Huaccho Huatuco, L. (2019). Managing structural and dynamic complexity in supply chains: insights from four case studies. Production Planning & Control, 30(8), 611-623.

Ferraris, A., Mazzoleni, A., Devalle, A. and Couturier, J. (2019), "Big data analytics capabilities and knowledge management: impact on firm performance", Management Decision, Vol. 57 No. 8, pp. 1923-1936.

Finke, G. R., Singh, M., & Schönsleben, P. (2012). Production lead time variability simulation-insights from a case study. International Journal of Industrial Engineering, 19(5), 213 – 220.

Fornell, C., & Larcker, D. F. (1981). Structural equation models with unobservable variables and measurement error: Algebra and statistics.

George, G., Haas, M. R., & Pentland, A. (2014). Big Data and Management. Academy of Management Journal, 57(2), 321–326.

Giannoccaro, I., & Iftikhar, A. (2020). Mitigating ripple effect in supply networks: the effect of trust and topology on resilience. International Journal of Production Research, 1-18.

Giannoccaro, I., Nair, A., & Choi, T. (2018). The impact of control and complexity on supply network performance: An empirically informed investigation using NK simulation analysis. Decision Sciences, 49(4), 625-659.

Gölgeci, I., & Kuivalainen, O. (2019). Does social capital matter for supply chain resilience? The role of absorptive capacity and marketing-supply chain management alignment. Industrial Marketing Management.

Gölgeci, I., Ponomarov, S.Y. (2015). How does firm innovativeness enable supply chain resilience? The moderating role of supply uncertainty and interdependence. Technology Analysis and Strategic Management, 27 (3), 267-282.

Grötsch, V. M., Blome, C., & Schleper, M. C. (2013). Antecedents of proactive supply chain risk management–a contingency theory perspective. International Journal of Production Research, 51(10), 2842-2867.

Gu, V. C., Zhou, B., Cao, Q., & Adams, J. (2021). Exploring the relationship between supplier development, big data analytics capability, and firm performance. Annals of Operations Research, 1-22.

Gunasekaran, A., Yusuf, Y.Y., Adeleye, E.O. and Papadopoulos, T., (2018). Agile manufacturing practices: the role of big data and business analytics with multiple case studies. International Journal of Production Research, 56(1-2), pp.385-397.

Guo, C., & Li, X. (2014). A multi-echelon inventory system with supplier selection and order allocation under stochastic demand. International Journal of Production Economics, 151, 37-47.

Habermann, M., Blackhurst, J., & Metcalf, A. Y. (2015). Keep your friends close? Supply chain design and disruption risk. Decision Sciences, 46(3), 491-526.

Hair, J. F., Ringle, C. M., & Sarstedt, M. (2011). PLS-SEM: Indeed a silver bullet. Journal of Marketing theory and Practice, 19(2), 139-152.

Hair.Jr., J. F., Black., W. C., Babin., B. J., Anderson., R. E., & L.Tatham., R. (2006). Multivariant Data Analysis. New Jersey: Pearson International Edition.

Hamel G, and Välikangas L. The quest for resilience. Harv Bus Rev. 2003 Sep;81(9):52-63, 131.

Han, J. H., Wang, Y. and Naim, M. (2017). Reconceptualization of information technology flexibility for supply chain management: an empirical study. International Journal of Production Economics, 187, 196-215.

Hayes, A. F., & Scharkow, M. (2013). The relative trustworthiness of inferential tests of the indirect effect in statistical mediation analysis: Does method really matter?. Psychological science, 24(10), 1918-1927.

Heim, G., Peng, D. and Jayanthi, A. (2014), "Longitudinal analysis of inhibitors of manufacturer delivery performance", Decision Sciences, Vol. 45 No. 6, pp. 1117-1158.

Hulland, J. (1999). Use of partial least squares (PLS) in strategic management research: A review of four recent studies. Strategic management journal, 20(2), 195-204.

Iftikhar, A., Purvis, L., & Giannoccaro, I. (2021). A meta-analytical review of antecedents and outcomes of firm resilience. Journal of Business Research, 135, 408-425.

Iftikhar, A., Ali, I., & Shah, A. (2021). The impact of big data analytics and firm's operational performance: mediating role of knowledge management process. In: 2nd Asia Pacific International Conference on Industrial Engineering and Operations Management, 14-16 September 2021, Surakarta, Indonesia.

Isik, F. (2010). An entropy-based approach for measuring complexity in supply chains. International journal of production research, 48(12), 3681-3696.

Ivanov, D. (2017). Simulation-based Ripple Effect Modelling in the Supply Chain. International Journal of Production Research 55 (7): 2083–2101.

Ivanov, D., Dolgui, A., Sokolov, B., Ivanova, M. (2017). Literature review on disruption recovery in the supply chain, International Journal of Production Research, 55(20), 6158 – 6174.

Ivert, L.K. and Jonsson, P. (2014), "When should advanced planning and scheduling systems be used in sales and operations planning?", International Journal of Operations and Production Management, 34 (10), pp. 1338-1362.

Jeble, S., Dubey, R., Childe, S. J., Papadopoulos, T., Roubaud, D., & Prakash, A. (2018). Impact of big data and predictive analytics capability on supply chain sustainability. The International Journal of Logistics Management.

Kaplan, R.S. and Norton, D.P. (2008). Mastering the management system. Harvard Business Review, January, pp. 1-17.

Kauffman, S. A. (1993). The origins of order: Self-organization and selection in evolution: Oxford University Press, USA.

Ketokivi, M. (2006). Elaborating the contingency theory of organizations: The case of manufacturing flexibility strategies. Production and Operations Management, 15(2), 215-228.

Kleindorfer, P. R., Saad, G. H. (2005). Managing Disruption Risks in Supply Chains. Production and Operations Management, 14 (1), 53-68.

Kock, N. (2015). Common Method Bias in PLS-SEM. International Journal of e-Collaboration, 11(4), 1–10.

Koufteros, X., Vonderembse, M., & Jayaram, J. (2005). Internal and external integration for product development: the contingency effects of uncertainty, equivocality, and platform strategy. Decision Sciences, 36(1), 97-133.

Lai, Y., Sun, H., & Ren, J. (2018). Understanding the determinants of big data analytics (BDA) adoption in logistics and supply chain management: An empirical investigation. The International Journal of Logistics Management, 29(2), 676-703.

Lamba, K., & Singh, S. P. (2017). Big data in operations and supply chain management: current trends and future perspectives. Production Planning & Control, 28(11-12), 877-890.

Latif, Z., Tunio, M. Z., Pathan, Z. H., Jianqiu, Z., Ximei, L., & Sadozai, S. K. (2018). A review of policies concerning development of big data industry in Pakistan: Subtitle: Development of big data industry in Pakistan. Paper presented at the 2018 international conference on computing, mathematics and engineering technologies (iCoMET).

Lempogo, F., Yeboah-Boateng, E. O., & Brown-Acquaye, W. L. (2021). Big Data Analytics in Developing Economies: Harnessing Insights and Creating Value. In Digital Technology Advancements in Knowledge Management (pp. 149-166): IGI Global.

Li, H., & Amini, M. (2012). A hybrid optimisation approach to configure a supply chain for new product diffusion: a case study of multiple-sourcing strategy. International Journal of Production Research, 50(11), 3152-3171.

Lu, G., & Shang, G. (2017). Impact of supply base structural complexity on financial performance: Roles of visible and not-so-visible characteristics. Journal of Operations Management, 53, 23-44.

Mandal, S., Bhattacharya, S., Korasiga, V., & Sarathy, R. (2018). The dominant influence of logistics capabilities on integration: Empirical evidence from SC resilience. International Journal of Disaster Resilience in the Built Environment, 8(4), 357-374.

Manhart, P., Summers, J. K., & Blackhurst, J. (2020). A meta-analytic review of supply chain risk management: Assessing buffering and bridging strategies and firm performance. Journal of Supply Chain Management.

Manuj, I., & Sahin, F. (2011). A model of supply chain and supply chain decision-making complexity. International journal of physical distribution & logistics management. Vol. 41 No. 5, pp. 511-549.

Marler, J. H., & Boudreau, J. W. (2017). An evidence-based review of HR Analytics. The International Journal of Human Resource Management, 28(1), 3-26.
Maroufkhani, P., Tseng, M. L., Iranmanesh, M., Ismail, W. K. W., & Khalid, H. (2020). Big data analytics adoption: Determinants and performances among small to medium-sized enterprises. International Journal of Information Management, 54, 102190.
Marr, B. (2016). Big Data in Practice: How 45 Successful Companies Used Big Data Analytics to Deliver Extraordinary Results, John Wiley & Sons.
Masson, R., Iosif, L., MacKerron, G. and Fernie, J. (2007), "Managing complexity in agile global fashion industry supply chains", The International Journal of Logistics Management, 18(2), pp. 238-254.

Masson, R., Iosif, L., MacKerron, G., & Fernie, J. (2007). Managing complexity in agile global fashion industry supply chains. The International Journal of Logistics Management, 18(2), 238-254.
Matsuo, H. (2015). Implications of the Tohoku earthquake for Toyota′ s coordination mechanism: Supply chain disruption of automotive semiconductors. International Journal of Production Economics, 161, 217-227.
McAfee, A., Brynjolfsson, E., Davenport, T. H., Patil, D. J., & Barton, D. (2012). Big data: the management revolution. Harvard business review, 90(10), 60-68.

McMillan, E. (2008). Complexity, management and the dynamics of change: Challenges for practice: Routledge.
Melnyk, S. A., Closs, D. J., Griffis, S. E., Zobel, C. W., & Macdonald, J. R. (2014). Understanding supply chain resilience. Supply Chain Management Review, 18(1), 34-41.
Mikalef, P., Krogstie, J., Pappas, I. O., & 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.
Moktadir, M. A., Ali, S. M., Paul, S. K., & Shukla, N. (2019). Barriers to big data analytics in manufacturing supply chains: A case study from Bangladesh. Computers & Industrial Engineering, 128, 1063-1075.

Moretto, A., Ronchi, S., & Patrucco, A. S. (2017). Increasing the effectiveness of procurement decisions: The value of big data in the procurement process. International Journal of RF Technologies, 8(3), 79-103.
Mubarik, M. S., Naghavi, N., Mubarik, M., Kusi-Sarpong, S., Khan, S. A., Zaman, S. I., & Kazmi, S. H. A. (2021). Resilience and cleaner production in industry 4.0: Role of supply chain mapping and visibility. Journal of Cleaner Production, 292, 126058.
Nguyen, T., Li, Z., Spiegler, V., Ieromonachou, P., & Lin, Y. (2018). Big data analytics in supply chain management: A state-of-the-art literature review. Computers & Operations Research, 98, 254-264.
Opresnik, D., & Taisch, M. (2015). The value of big data in servitization. International journal of production economics, 165, 174-184.

Papadopoulos, T., Gunasekaran, A., Dubey, R., & Fosso Wamba, S. (2017). Big data and analytics in operations and supply chain management: managerial aspects and practical challenges. Production Planning & Control, 28(11-12), 873-876.
Pavlou, P. A., Liang, H., & Xue, Y. (2007). Understanding and mitigating uncertainty in online exchange relationships: A principal-agent perspective. MIS quarterly, 105-136.
Peng, D. X., & Lai, F. (2012). Using partial least squares in operations management research: A practical guideline and summary of past research. Journal of Operations Management, 30(6), 467-480.
Pettit, T. J., Croxton, K. L., & Fiksel, J. (2013). Ensuring SC resilience: development and implementation of an assessment tool. Journal of business logistics, 34(1), 46-76.
Podsakoff, P. M., & Organ, D. W. (1986). Self-reports in organizational research: Problems and prospects. Journal of management, 12(4), 531-544.
Podsakoff, P. M., MacKenzie, S. B., Lee, J. Y., & Podsakoff, N. P. (2003). Common method biases in behavioral research: a critical review of the literature and recommended remedies. Journal of applied psychology, 88(5), 879.
Ponomarov, S., & Holcomb, M. (2009). Understanding the concept of SC resilience. The International Journal of Logistics Management, 20(1), 124-143.
Prahalad, C.K. and Krishnan, M.S. (2002). The dynamic synchronization of strategy and information technology. Sloan Manage. Rev., 43 (4).

Prasad, S., Zakaria, R., & Altay, N. (2018). Big data in humanitarian supply chain networks: A resource dependence perspective. Annals of Operations Research, 270(1), 383-413.

Preacher, K. J., & Hayes, A. F. (2008). Asymptotic and resampling strategies for assessing and comparing indirect effects in multiple mediator models. Behavior research methods, 40(3), 879-891.

Queiroz, M. M., Ivanov, D., Dolgui, A., & Wamba, S. F. (2020). Impacts of epidemic outbreaks on supply chains: mapping a research agenda amid the COVID-19 pandemic through a structured literature review. Annals of operations research, 1-38.

Ramanathan, R., Philpott, E., Duan, Y., & Cao, G. (2017). Adoption of business analytics and impact on performance: a qualitative study in retail. Production Planning & Control, 28(11-12), 985-998.

Reinartz, W., Haenlein, M., & Henseler, J. (2009). An empirical comparison of the efficacy of covariance-based and variance-based SEM. International Journal of Research in Marketing, 26(4), 332–344.

Romano, P., & Formentini, M. (2012). Designing and implementing open book accounting in buyer–supplier dyads: A framework for supplier selection and motivation. International Journal of Production Economics, 137(1), 68-83.

Salvador, F., Forza, C., & Rungtusanatham, M. (2002). Modularity, product variety, production volume, and component sourcing: theorizing beyond generic prescriptions. Journal of Operations Management, 20(5), 549-575.

Sanders, N. R. (2014). Big data driven supply chain management: A framework for implementing analytics and turning information into intelligence. Pearson Education.

Sanders, N. R., & Ganeshan, R. (2018). Big data in supply chain management. Production and Operations Management, 27(10), 1745-1748.

Schoenherr, T., & Speier-Pero, C. (2015). Data Science, Predictive Analytics, and Big Data in Supply Chain Management: Current State and Future Potential. Journal of Business Logistics, 36(1), 120–132.

Senge, P., 2006. The Fifth Discipline: The Art and Practice of the Learning Organization. Doubleday, New York, NY.

Serdarasan, S. (2013), "A review of supply chain complexity drivers", Computers and Industrial Engineering, Vol. 66, pp. 533-540.

Shamout, M.D. (2020), "Supply chain data analytics and supply chain agility: a fuzzy sets (fsQCA) approach", International Journal of Organizational Analysis, 28(5), 1055-1067.

Sheffi, Y & Rice, J (2005). A SC view of resilient enterprise. MIT Sloan Management Review, 47(1), 41-48.

Simchi-Levi, D., Snyder, L., & Watson, M. (2002). Strategies for uncertain times. Supply Chain Management Review, 6(1), 11-12.

Simon, H.A., 1962. The architecture of complexity. Proc. Am. Philos. Soc. 106 (6), 467–482.

Singh, N.P. and Singh, S. (2019), "Building supply chain risk resilience: Role of big data analytics in supply chain disruption mitigation", Benchmarking: An International Journal, 26(7), pp. 2318-2342.

Sirmon, D. G., & Hitt, M. A. (2009). Contingencies within dynamic managerial capabilities: Interdependent effects of resource investment and deployment on firm performance. Strategic management journal, 30(13), 1375-1394.

Sivadasan, S., Efstathiou, J., Frizelle, G., Shirazi, R. and Calinescu, A. (2002), "An information-theoretic methodology for measuring the operational complexity of supplier-customer systems", International Journal of Operations & Production Management, 22(1), 80-102.

Song, J. S., Zhang, H., Hou, Y., & Wang, M. (2010). The effect of lead time and demand uncertainties in (r, q) inventory systems. Operations Research, 58(1), 68-80.

Souza, G. C. (2014). Supply chain analytics. Business Horizons, 57(5), 595-605.

Srinivasan, R., and M. Swink. (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.

Stone, J., & Rahimifard, S. (2018). Resilience in agri-food SCs: a critical analysis of the literature and synthesis of a novel framework. Supply Chain Management, 23(3), 207-238.

Tang, C., & Tomlin, B. (2008). The power of flexibility for mitigating supply chain risks. International journal of production economics, 116(1), 12-27.

Teece, D. J., Pisano, G., & Shuen, A. (1997). Dynamic capabilities and strategic management. Strategic management journal, 18(7), 509-533.

Tenenhaus, M., Vinzi, V. E., Chatelin, Y. M., & Lauro, C. (2005). PLS path modeling. Computational statistics & data analysis, 48(1), 159-205.

Tiwari, S., Wee, H.-M., & Daryanto, Y. (2018). Big data analytics in supply chain management between 2010 and 2016: Insights to industries. Computers & Industrial Engineering, 115, 319-330.

Tukamuhabwa, B.R., Stevenson, M., Busby, J., Zorzini, M. (2015). Supply chain resilience: definition, review and theoretical foundations for further study. International Journal of Production Research, 53 (18), 5592-5623.

Turner, N., Aitken, J., & Bozarth, C. (2018). A framework for understanding managerial responses to supply chain complexity. International Journal of Operations & Production Management. 38(6), pp. 1433-1466.

Vachon, S., & Klassen, R. D. (2002). An exploratory investigation of the effects of supply chain complexity on delivery performance. IEEE Transactions on Engineering Management, 49(3), 218-230.

Vanpoucke, E., Vereecke, A., & Wetzels, M. (2014). Developing supplier integration capabilities for sustainable competitive advantage: A dynamic capabilities approach. Journal of Operations Management, 32(7-8), 446-461.

Vlajic, J. V., van Lokven, S. W., Haijema, R., & van Der Vorst, J. G. (2013). Using vulnerability performance indicators to attain food supply chain robustness. Production Planning & Control, 24(8-9), 785-799.

Wagner, S. M., & Bode, C. (2006). An empirical investigation into supply chain vulnerability. Journal of purchasing and supply management, 12(6), 301-312.

Waller, M. A., & Fawcett, S. E. (2013). Data science, predictive analytics, and big data: a revolution that will transform supply chain design and management. Journal of Business Logistics, 34(2), 77-84.

Wamba, S. F., Akter, S., Edwards, A., Chopin, G., & Gnanzou, D. (2015). How 'big data'can make big impact: Findings from a systematic review and a longitudinal case study. International Journal of Production Economics, 165, 234-246.

Wamba, S. F., Dubey, R., Gunasekaran, A., & Akter, S. (2020). The performance effects of big data analytics and supply chain ambidexterity: The moderating effect of environmental dynamism. International Journal of Production Economics, 222, 107498.

Wamba, S. F., Gunasekaran, A., Dubey, R., & Ngai, E. W. (2018). Big data analytics in operations and supply chain management. Annals of Operations Research, 270(1-2), 1-4.

Wang, G., Gunasekaran, A., Ngai, E. W., & Papadopoulos, T. (2016). Big data analytics in logistics and supply chain management: Certain investigations for research and applications. International Journal of Production Economics, 176, 98-110.

Wang, Y., Kung, L., & Byrd, T. A. (2018). Big data analytics: Understanding its capabilities and potential benefits for healthcare organizations. Technological Forecasting and Social Change, 126, 3-13.

Wetzels, M., Odekerken-Schröder, G., & Van Oppen, C. (2009). Using PLS path modelling for assessing hierarchical construct models: Guidelines and empirical illustration. MIS quarterly, 177-195.

Wiedmer, R., Rogers, Z. S., Polyviou, M., Mena, C., & Chae, S. (2021). The dark and bright sides of complexity: A dual perspective on supply network resilience. Journal of business logistics, 42(3), 336-359.

Wilkins, J. (2013). Big data and its impact on manufacturing [online]. Available http://www.dpaonthenet.net/article/65238/Big-data-and-its-impact-on-manufacturing.aspx (Accessed 20 February 2020).

Winter, S. G. (2003). Understanding dynamic capabilities. Strategic management journal, 24(10), 991-995.

Wong, C. W., Lai, K. H., & Bernroider, E. W. (2015). The performance of contingencies of supply chain information integration: The roles of product and market complexity. International Journal of Production Economics, 165, 1-11.

Wu, Y., Frizelle, G., & Efstathiou, J. (2007). A study on the cost of operational complexity in customer–supplier systems. International Journal of Production Economics, 106(1), 217-229.

Wu, Z., & Choi, T. Y. (2005). Supplier–supplier relationships in the buyer–supplier triad: Building theories from eight case studies. Journal of Operations management, 24(1), 27-52.

Yu, W., Jacobs, M. A., Chavez, R., & Yang, J. (2019). Dynamism, disruption orientation, and resilience in the supply chain and the impacts on financial performance: A dynamic capabilities perspective. International Journal of Production Economics, 218, 352–362.

Zhan, Y., & Tan, K. H. (2020). An analytic infrastructure for harvesting big data to enhance supply chain performance. European Journal of Operational Research, 281(3), 559-574.

Zollo, M., & Winter, S. G. (2002). Deliberate learning and the evolution of dynamic capabilities. Organization science, 13(3), 339-351.

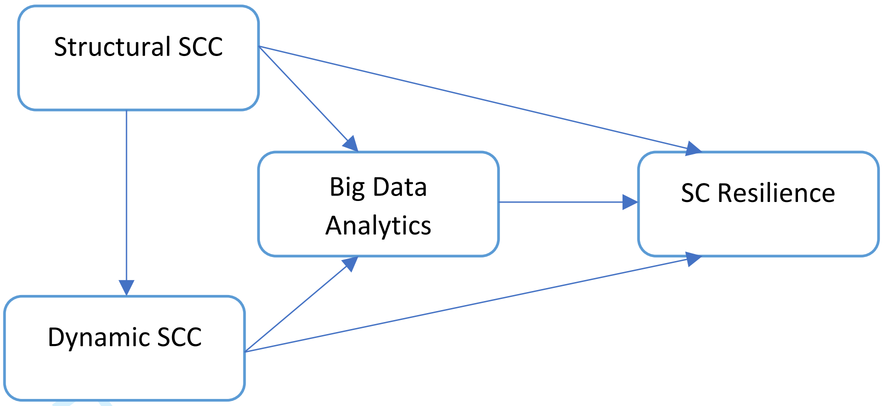

Figure 1: Conceptual Model

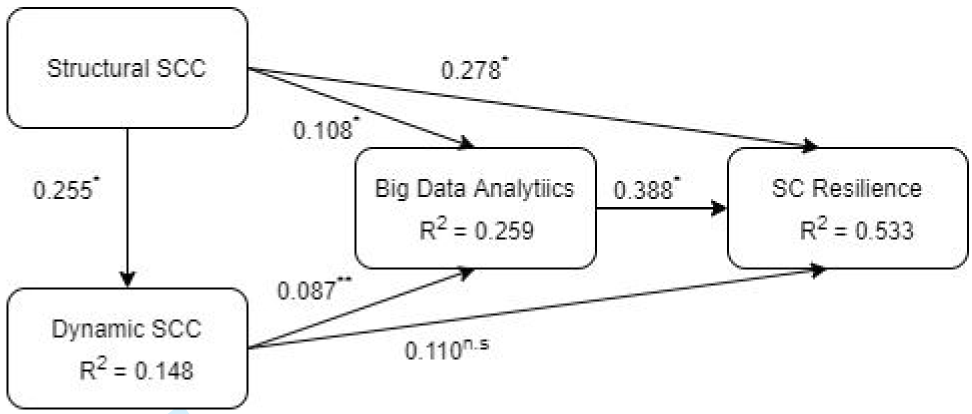

Figure 2: Structural model results, ** $p < 0.10$, * $p < 0.05$, N.S – Not Significant.

Table 1: Studies exploring the impact of SC Complexity and firm outcomes

Publication	SC Complexity Elements	Type of SC Complexity	Country/Region	Methodology	Impact on firm outcome (Firm Performance/Resilience/Disruptions)
Salvador et al. (2002)	Number of products and parts	Structural complexity	6 EU countries	Multiple case study	Negative influence on operational performance.
Vachon and Klassen (2002)	Number of suppliers & products	Structural complexity	Data collected from 19 countries	Survey	Negative influence on delivery performance (throughput time & lead time).
	Production scheduling changes, demand volatility, & late supplier deliveries.	Dynamic complexity			
Craighead et al. (2007)	Number of nodes, no. of forward flows and no. of backward flows.	Structural complexity	USA	Multiple case study	Complexity increases the severity of SC disruptions.
Bozarth et al. (2009)	Number of customers, no. of products & parts, no. of suppliers.	Structural complexity	7 countries - U.S., Japan, South Korea, Germany, Austria, Finland and Sweden.	Survey	Negative influence on manufacturing plant performance.
	Manufacturing schedule instability, unreliable supplier lead times, short product lifecycle.	Dynamic complexity			
Blackhurst et al. (2011)	Number of nodes in the SC, no. of parts, types of parts	Structural complexity	USA, South Korea, China	Multiple case study	Negative influence on supply resilience.
Vanpoucke et al. (2014)	Number of suppliers, percentage of international suppliers in the supply base.	Structural complexity	20 countries in America, Europe and Asia	Survey	Negative influence on market and financial performance.
Bode and Wagner (2015)	Number of first tier suppliers, no. of countries represented in the supply base.	Structural complexity	Germany, Austria and Switzerland.	Survey	Complexity increases the frequency of disruptions.
Brandon-Jones et al. (2015)	Number of supply chain players, varying level of technical capabilities by the suppliers.	Structural complexity	UK	Survey	Complexity increases the frequency of disruptions and reduce plant performance.
	Dependence on time delivery from suppliers, Shorter lead-time from suppliers.	Dynamic complexity			
Birkie et al. (2017)	Number of products, customers, brands; no. of suppliers and facilities.	Structural complexity	NA	Secondary data	Positively influence recovery performance after disruptions.
Bode and Macdonald (2017)	Number of SC players, detailed SC network spanning several scales.	Structural complexity	EU	Survey	Negative influence on firm's disruption response speed.
Campos et al. (2018)	Numerousness and variety within the SC.	Structural complexity	EU	Multiple case study	Complexity improves firm performance.
	Frequent changes to the SC elements or to their interconnections.	Dynamic complexity			
Giannoccaro et al. (2018)	Number of suppliers	Structural complexity	NA	Simulation, NK fitness landscape.	Negative influence on supply network performance.

	Degree of supply interactions	Dynamic complexity			
Chowdhury et al. (2019)	Number of buyers, suppliers, facilities; detailed SC network.	Structural complexity	Bangladesh	Survey	Complexity positively influences SC performance and resilience
Birkie and Trucco (2020)	Number of products, customers, brands; no. of suppliers and facilities.	Structural complexity	NA	Secondary data	Complexity positively influences recovery performance.
Dong et al. (2020)	Number of suppliers, no. of countries in the supply base, detailed SC network.	Structural complexity	USA	Secondary data	Negative influence on the firm's financial performance.
Wiedmer et al. (2021)	Number of suppliers, no. of logistics partners, no. of parts and components	Structural complexity	Japan, Germany and USA	Secondary data	Positive influence on disruption recovery; Negative influence on disruption impact.

Table 2: Antecedents and outcomes of BDA adoption

Publication	Country/Region	Methodology/Approach	Antecedents of BDA	Outcomes of BDA
Chen et al. (2016)	USA	Survey	Grounded in technology-organization-environment (TOE) framework, technological factors directly influence, while organizational & environmental factors indirectly influence BDA adoption.	BDA positively influences business growth.
Schoenherr and Speier-Pero (2015)	USA	Survey	Various motivators and barriers in adopting BDA identified in SCM.	Improved SC efficiency, enhanced demand planning, increased visibility, faster response in dynamic environment.
Ramanathan et al. (2017)	UK	Qualitative	Various technological, organizational and environmental determinants for BDA adoption.	Poositive impact on business performance.
Chavez et al. (2017)	China	Survey	N/A	Positively influence on various manufacturing capability dimensions (quality, delivery, flexibility & cost).
Papadopoulos et al. (2017)	Nepal	Content Analysis	N/A	Enhanced sustainability.
Dev et al. (2019)	India	Fuzzy ANP, Simulation, TOPSIS	N/A	Improved key performance indicators in dynamic environments.
Dubey et al. (2018a)	India	Survey	N/A	Enhanced SC agility and competitive advantage.
Dubey et al. (2018b)	India	Survey	N/A	Positive influence on inter-organizational compatibility & resource complementarity.
Mandal (2018)	India	Survey	N/A	Positive influence on SC resilience dimensions.
Lai et al. (2018)	China	Survey	Perceived benefits and top management support positively influence BDA adoption; environmental factors positively moderate BDA adoption.	N/A
Dubey et al. (2019)	India	Survey	N/A	Positively influences SC resilience and competitive advantage.
Wu et al. (2019)	USA	Empirical data	N/A	Positively influence on process innovation which further improves firm productivity.
Singh and Singh (2019)	USA - EU	Survey	N/A	Positive influence on firm's knowledge management ability and enhanced resilience.
Moktadir et al. (2019)	Bangladesh	Delphi based AHP	Investment, technology, and organizational related barriers identified in adopting BDA.	N/A
Maroufkhani et al. (2020)	Iran	Survey	Technological, organizational and environmental factors significantly affect BDA adoption.	Positive influence on market and financial performance of SMEs.

Wamba et al. (2020)	USA	Survey	N/A	Positive influence on SC Ambidexterity and Organizational Performance.
Chen et al. (2020)	Taiwan	Qualitative	Identifies barriers in healthcare sector to adopt big data systems, and devise a strategy to overcome these barriers.	N/A

Table 3: Descriptive statistics of participants

Profile	Number	Percentage
Industry Sector		
Manufacturing	92	55%
Others	16	10%
Service	58	35%
Gender		
Male	156	94%
Female	10	6%
Designation		
Manager	128	77%
Senior Manager	24	14%
General Manager	8	5%
Director	6	4%
Experience		
3 - 5	55	33%
6 - 8	29	17%
9 - 11	30	18%
>11	52	31%
Firm Size		
Below 500 employees	53	32%
500 - 1000 employees	41	25%
> 1000 employees	72	43%
Annual Sales		
Less than $1 million	19	11%
$1 - 50 million	49	30%
$51 - 500 million	45	27%
$501 million - $1 billion	22	13%
Greater than $1 billion	31	19%

Table 4: Indicator reliability – Outer loading factors

Latent Constructs	Loadings	t - value	p - value
Big Data Analytics			
1. We use advanced tools and analytical techniques (e.g. simulation, optimisation, regression) to take decision.	0.726	13.9	< 0.001
2. We use information extracted from various sources of data to make decision.	0.76	16.225	< 0.001
3. We use data visualisation technique (e.g. dashboards) to assist users or decision-maker in understanding complex information.	0.827	20.173	< 0.001
4. Our dashboards display information which is useful for carrying out necessary diagnosis.	0.817	19.952	< 0.001
5. We have connected dashboard applications or information with the manager's communication devices.	0.748	15.757	< 0.001
SC Resilience			
1. Our firm is able to adequately respond to unexpected disruptions by quickly restoring its product flow.	0.782	15.774	< 0.001
2. Our firm is well prepared to deal with financial outcomes of potential supply chain disruptions.	0.801	14.673	< 0.001
3. Our firm has the ability to maintain a desired level of control over structure and function at the time of disruption.	0.785	12.395	< 0.001
4. We deploy alternative plans associated with identified risks.	0.742	15.199	< 0.001
Structural SC Complexity			
1. Our firm serve large number of customer base.	0.904	39.976	< 0.001
2. Our firm has large number of first tier suppliers.	0.845	19.288	< 0.001
Dynamic SC Complexity			
1. We seek short lead times in the design of our supply chains	0.634	4.566	< 0.001
2. Our company strives to shorten supplier lead time, to avoid inventory & stockout	0.833	11.344	< 0.001
3. We can depend upon on time delivery from our suppliers	0.743	8.905	< 0.001

Table 5: Measurement model summary

Constructs	**CR**	**AVE**
Big Data Analytics	0.883	0.603
Dynamic SC Complexity	0.783	0.549
SC Resilience	0.86	0.605
Structural SC Complexity	0.867	0.766

CR - Composite Reliability; AVE - Average Variance Extracted

Table 6: Fornell-Larcker Criterion

Constructs	Big Data Analytics	Dynamic SC Complexity	SC Resilience	Structural SC Complexity
Big Data Analytics	**0.776**			
Dynamic SC Complexity	0.298	**0.741**		
SC Resilience	0.511	0.302	**0.778**	
Structural SC Complexity	0.338	0.249	0.439	**0.875**

Table 7: VIF Analysis Results

Constructs	Item	VIF
Big Data Analytics	BD-1	1.585
	BD-2	1.627
	BD-3	3.156
	BD-4	3.318
	BD-5	1.736
SC Resilience	SCRE-1	1.621
	SCRE-2	1.727
	SCRE-3	1.638
	SCRE-4	1.385
Structural SC Complexity	NC-1	1.401
	NC-2	1.401
Dynamic SC Complexity	NC-3	1.182
	NC-4	1.247
	NC-5	1.184

Table 8: Hypotheses results

Hypothesis	Path Coefficient	*t* - statistics	*p* -values	Lower bound 95% CI[a]	Upper bound 95% CI[a]	Decision
Direct Effect Results						
H1. SSCC -> SCRE	0.278	2.883	0.004*	0.093	0.471	Supported
H2. SSCC -> DSCC	0.255	2.777	0.006*	0.060	0.421	Supported
H3. DSCC -> SCRE	0.110	1.185	0.236[n.s]	-0.074	0.284	Not Supported
H4. BDA -> SCRE	0.388	4.833	0.000*	0.216	0.530	Supported
Indirect Effects (Mediation) Results						
H5. SSCC -> BDA -> SCRE	0.108	2.825	0.005*	0.050	0.174	Supported (**Partial Mediation**)
H6. DSCC -> BDA -> SCRE	0.087	1.908	0.078**	0.018	0.178	Supported (**Full Mediation**)

Note – BDA – Big Data Analytics, SSCC – Structural Supply Chain Complexity, DSCC – Dynamic Supply Chain Complexity, SCRE – Supply Chain Resilience. * Significant at $\alpha < 0.05$, ** $\alpha < 0.10$ (2-tailed test), n.s – not significant, a – bias-corrected.