The role of big data and predictive analytics in developing a resilient supply chain network in the South African mining industry against extreme weather events

Highlights

- Emerging technologies such as big data and predictive analytics (BDPA) can reduce the negative impacts of extreme weather events.
- BDPA is most effective when there is a strong alignment between BDPA strategy and BDPA initiatives.
- Supply chain visibility improves the resilience of the supply chain network.
- Community resilience and resource resilience are crucial in developing supply chain resilience under extreme weather conditions.
- Managing operations and supply chains in a socially responsible way are vital when facing extreme weather events.

Abstract

Most parts of the world have suffered the negative impacts from extreme weather events, in whatever form they may take. To mitigate such impacts, attention in the operations management literature has focused on how firms build resilience in their supply chains, in order to quickly respond to such events and also to return, as soon as possible, to a business-as-usual state. Prior studies have examined the process of building a supply chain (SC) in different countries, industries and in response to various disruptions, such as the COVID-19 pandemic, whilst, at the same time, calling for further research in different contexts. We respond to these calls by exploring SC resilience ability in the South African mining industry under extreme weather events. We situated our study in the dynamic capability view (DCV) view of the firm. We examined the direct effect of big data and predictive analytics (BDPA) capabilities on SC visibility and the final effects on community and rresource resilience. We adopted a sequential mixed methods research design, collecting data from interviews with 10 industry practitioners and from 219 respondents to an online survey. We built and tested our theoretical model using partial least squares structured equation modelling (PLS-SEM). Notable theoretical contributions of our study are that big data enables a more efficient supply chain monitoring system, which, in turn, improves SC visibility. BDPA capability improves a company's ability to make the best use of its available resources. It improves the South African mining industry's

dynamic capability, allowing them to adjust their strategies in response to diverse adverse weather conditions. Furthermore, BDPA capability's ability to improve SC visibility is enhanced when there is strong alignment between BDPA strategy and initiatives. Finally, having a high level of SC visibility helps develop community and resource resilience, which are necessary to ensure that firms in the industry fulfil their responsibilities in relation to social sustainability.

Keywords: big data and predictive analytics, supply chain visibility, resilience, mining operations, South Africa, extreme weather events

1. Introduction

Over the past decades, more than sixty extreme weather events were reported all over the world[1]. According to National Geographic, extreme weather events are typically tornadoes, hurricanes, blizzards, dust storms, floods, hailstorms, and ice storms[2]. Such events are generally followed by severe problems. For example, excessive rainfall can cause floods and landslides; hurricanes and tornadoes may damage infrastructures and other physical resources; and ice storms can lead to avalanches and blizzards (Bag et al., 2020a). These extreme weather events are a result of climate change, which is amplifying their frequency and impact (USGCRP, 2018). Such climate change is primarily the result of human actions. For instance, poor city planning, devastation of wetlands, unsustainable mining activities, bad production practices, and associated logistics activities are all major reasons for climate change (Kusimi & Kusimi, 2021). In South Africa, for example, which is the country focus of our empirical study; mining operations are increasingly becoming a threat to the country's water resources. In addition, environmental scientists fear that the failure of some dams and nearby mine setups will lead to water contamination (Aleke & Nhamo, 2016; Odell et al., 2018).

Worldwide, various strategic environmental protection initiatives have been taken to protect the earth's ecology. We note that to cope with the risks from extreme weather and develop the resilience of nations and societies to disasters, the Sendai Framework[3] was introduced. The Sendai framework replaced the Hyogo framework[4] and aims to reduce the worldwide mortality rate arising from disasters between 2020 and 2030. The framework emphasizes the implementation of measures that cover three dimensions of disaster risks: 1) it

[1] https://www.weather.gov/mob/events (accessed 30 October 2021)
[2] https://www.nationalgeographic.org/activity/extreme-weather-on-earth/ (accessed 30 October 2021)
[3] https://www.undrr.org/implementing-sendai-framework/what-sendai-framework (accessed October 2021)
[4] https://www.undrr.org/implementing-sendai-framework/what-sendai-framework (accessed October 2021)

is important to identify the risks related to the disaster; 2) improve the disaster risk governance; and 3) make investments for building resilience, improving preparedness and enhancing the capability to quickly respond to and recover from any disasters[5].

According to a WEF report (2018), extreme weather events and natural disasters can result in supply chain disruption and adversely affect the economy of the country. In the past, it was difficult to accurately monitor climate changes; however, in this fourth industrial revolution, advanced information and communication technologies make it easier to track the changes, implement responses and accurately monitor results (Yu et al., 2018). One such powerful technology is big data and predictive analytics (BDPA) (Gupta & George, 2016; Bag et al., 2020b; Choi et al., 2022); which can be a valuable tool for managing operational risks that are generated from extreme weather events (Araz et al., 2020).

The potential role of BDPA in mitigating the negative impacts of extreme weather conditions can also be viewed through the prisms of supply chain (SC) visibility and SC resilience. Williams et al. (2013) indicated that demand visibility, supply visibility, and market visibility are important dimensions of SC visibility. Brandon-Jones et al. (2014) described SC resilience as an outcome of SC visibility and as a system's capacity to restore to its former state after being disrupted in a reasonable amount of time. Christopher and Lee (2004) posited that SC visibility is a key capability to mitigate supply chain risks. Brandon-Jones et al. (2014) tested this proposition through empirical study, finding that SC resilience is an output metric that is influenced by SC visibility. They highlighted that connectivity and information sharing amongst supply chain partners are key resources that aid in developing SC visibility (capability), leading to enhanced SC resilience (performance). Dubey et al. (2017) further examined the SC resilience model by incorporating the factors of trust and behavioural uncertainty). Furthermore, Dubey et al. (2020) confirmed through empirical study that connectivity and information sharing improve SC visibility, which in turn leads to sustainable improvements in SC performance. So, whilst the connection between SC visibility and SC resilience, with associated elements, such as connectivity and information sharing, is well acknowledged in the literature (Kalaiarasan et al., 2022), the relationships between BDPA, SC visibility and SC resilience have not yet been empirically explored. We address this gap in the context of their roles in responding to extreme weather events.

In terms of our empirical focus on the mining industry, prior studies have examined SC resilience in the agriculture, food, and construction industries. However, there is a dearth of

[5] https://www.undrr.org/implementing-sendai-framework/what-sendai-framework (accessed 30 October 2021)

studies exploring such resilience ability in mining industries, such as those in South Africa, and also, under extreme weather events. Arza et al. (2020) highlighted that there is great scope for measuring and enhancing social welfare using BDPA. Given that mining companies operations have a large potential impact on the societies in which they operate in, it is a moot point whether BDPA capabilities are able to build certain types of SC resilience, i.e., community resilience and resource resilience. Community resilience is defined as the manifestation of the population wellness embedded with mental and behavioral health to improve the quality of life (Norris et al., 2008). Resource resilience refers to a firm's ability to address both the relevant ecosystem and the corresponding human and management systems (Lengnick-Hall et al., 2011; Chowdhury & Quaddus, 2017; Parker & Ameen, 2018). Moreover, in the context of harnessing the power of big data, previous research has also highlighted the relevance of analytics capability–business strategy alignment, which is defined as the degree to which analytics strategies are aligned with the organization's overall business plan (Akter et al., 2016). Hence, it will be worthwhile to examine the influence of BDPA capabilities and SC visibility under the moderating effect of alignment between BDPA strategy and BDPA initiatives. Therefore, this study seeks to answer the following two research questions (RQs):

RQ1: What are the effects of big data predictive analytics capability (BDAC) and supply chain visibility (SCV) on resilience?

RQ2: What is the effect of alignment on the path joining big data predictive analytics capability (BDAC) and supply chain visibility (SCV)?

To the best of our knowledge, this is one of the pioneer studies exploring the development of resilient supply chain networks in the mining industry, in response to extreme weather events. We build upon recent work on the topics of SC resilience and visibility published in this journal and respond to the calls for further research in specific papers (see, Dixit et al., 2020; Doetzer, 2020; Li & Zobel, 2020; and Queiroz et al., 2022). For example, Queiroz et al. (2022) explored the antecedents of SC resilience in U.K. firms responding to the COVID-19 pandemic and called for further work on this topic, including in different country contexts.

Our research is grounded on the premise of using big data and predictive analytics (BDPA) to develop resilient SC networks; which is validated by management decision-makers and the community. We articulate our study through research model development and an exploratory research design. This involves a Phase 1 study, at time one (T1), followed by a rigorous test of the model empirically from the data collected from the employees of the South African mining industry at time two (T2) and time three (T3) (Phase 2 study). Our study also measures community resilience and resource resilience at time four (T4), through additional data collected to test for the effect of supply chain network resilience.

The remainder of our paper is organized as follows. In Section 2, we review the literature on BDPA, extreme weather events, BDPA in extreme weather events, and DCV, providing the theoretical and empirical underpinning for our investigation of the relationships between BDPA, SC resilience and SC visibility. In Section 3, we present our exploratory mixed methods research design. We detail the method and results of the first phase of the design, which involved the collection of qualitative data through interviews with 10 SC managers working in the mining industry in South Africa. We present the main themes induced from the data, which are management capabilities, BDPA alignment, enhancing SC visibility and building resilience, and we discuss the significance of these findings by referring to relevant literature. Next, in Section 4, we present our theoretical model, showing the proposed relationships between BDPA capabilities, SC visibility, and community and resources resilience and develop our hypotheses to test our model. In Section 5, we provide details of the second phase of the research design, including the quantitative data collected from an online survey of employees of mines/mineral processing plants in South Africa (n = 219). We document our measurement process and specific measures used, the sampling and data collection protocols adopted, the results of tests for non-response and common method biases and tests for differences using the control variables of firm size and age and industry sub-type. Our data analysis, including the measurement model, the structural model testing and result of the endogeneity test are presented in Section 6. In Section 7, we discuss the theoretical and practical implications of our findings. Finally, in Section 8, we draw our main study conclusion, and reveal that resource and community resilience in the South African mining industry supply chains is vital for the sustainability of the sector in response to extreme weather events caused by changing climatic conditions. We also acknowledge the limitations of our study and discuss the future research directions.

2. Literature review

Firstly, we review literature on two main topics, namely: big data and predictive analytics (BDPA) and extreme weather events. We then bring these two topics together to conclude our review. Finally, we review studies related to the dynamic capabilities view (DCV), which is used in the development of our theoretical model.

2.1 Big data and predictive analytics (BDPA)

The use of big data has transformed business practices, as it can provide more accurate information for making decisions, and big data-enabled statistical tools drive better analysis of results (Bradlow et al., 2017). Big data analytics is becoming increasingly important in the development of strategy, which is required for creating long-term competitive advantage. The success of big data analytics is dependent on the realization of business value, which provides a competitive advantage to the organization. Predictive analysis based on big data places a strong emphasis on return on investment and the ability to create value. Big data is used as an input to generate insight and knowledge that can be used to make decisions. Business organizations need stronger managing, sharing, and integrating capabilities of big data, in various formats, to develop predictive analysis models (Grover et al., 2018). Big data analytics assists in creating business intelligence and is continuously evolving the way business are done. The world has changed dramatically in the last century as a result of the global revolution in operations management, increased energy demands from growing populations and leading to technological advancements for enhanced economic and social outcomes. These modifications generate a large amount of data, which assists in the development of a business intelligence support system (Araz et al., 2020). Big corporations recognize the value of big data in today's globalized world. Big data analytics is a time-consuming process that necessitates human expertise as well as tangible and intangible resources.

Big data and predictive analytics, combined with resource-based theory, provide a foundation for managing technology resources at the firm level. The resource-based theory makes it easier to determine the link between a firm's resources and its performance (Gupta & George, 2016). Predictive analysis models, based on big data, enable researchers to investigate operational risk management concerning various man-made and natural disasters that disrupt the world's social and economic routines.

There is a requirement for a predictive monitoring system that is supported by big data analytics. Organizations require a monitoring system, real-time emerging data, and predictive analysis to optimize strategic planning and execution (Araz et al., 2020). Big data analytics-enabled management capabilities play a key role in identifying long-term competitive advantages that rely on effective decision-making. Big data technological capabilities emphasize the importance of a versatile platform for collecting data and on ensuring a smooth flow of information throughout the organization's various departments. Big data needs to come from a reputable and trustworthy source. Technological flexibility is required based on the needs of the organization to develop an efficient predictive model (Akter et al., 2016). Big data and predictive analysis (BDPA) could be used as part of organizational capabilities to improve visibility and coordination among supply chain actors. The two most important aspects of BDPA that have a significant impact on supply chain management are coordination and visibility (Dubey et al., 2018a). BDPA accelerates the organization's learning and sharpens managerial skills. It enables firms to aggregate all the information from available resources and to develop a predictive model to guide future strategies and planning (Mikalef et al., 2021).

2.2 Extreme weather events

In the present highly connected world, extreme weather conditions make industrial processes more intricate and complex. Extreme weather damages business performance by reducing production capacity and disrupting supply chains (Bierkandt et al., 2014). Climate change has an impact by increasing the frequency of extreme weather, changing rainfall patterns, and causing rising sea levels (Papadopoulos & Balta, 2022). Mining companies around the world are experiencing a variety of consequences as a result of environmental impacts (Nakano, 2021). Global warming, in particular, is hastening climate change, which is dangerous for the mining industry in the long term. Climate change has put the mining industry at risk in the twenty-first century and risks are grave in the future.

Extreme weather events caused by climate change include cyclones, flooding, hailstorms, droughts, fog, and mist (Aleke & Nhamo, 2016). Extreme weather harms both public and private sector supply chains and recently, after the Covid-19 pandemic, the focus on resilience has drawn the attention of researchers. The concept of resilient supply chain management was developed to address the effects of extreme weather. The resilient supply chain is vital in responding to and recovering from natural and man-made disasters. Both the public and private sectors are working together to create resilient supply chains. Ignoring the topic can lead to management's failure to adopt appropriate and well-executed resilient supply chain management strategies (Stewart et al., 2009).

In today's globally interconnected world, the importance of a resilient supply chain is increasing, being a response to disruptions caused by extreme weather. The resilient supply chain is a proactive risk management strategy for dealing with disruptions (Scholten et al., 2014). Sudmeier et al. (2013) created a framework to assess vulnerability and resilience, as well as producing guidance tools for determining landslide risk in eastern and central Nepal. The framework uses quantitative analysis to measure resilience. Skills training, community leadership, water quality, and health care are all important factors in the framework for building resilience. It is necessary to understand and raise awareness about adaptation to cope with the effects of extreme weather (Kovács & Pato, 2014). In the mining industry, a climate framework is a critical tool for integrating the value supply chain and dealing with cyclones. It organizes and integrates information from the dynamic process of implementing coal mine supply chain strategies. In a complex climate environment, such a framework enables management to make appropriate decisions (Lim-Camacho et al., 2021). Literature has indicated that the mining industry should not ignore the current issues generated due to climate change and should gear up for future events. Therefore, it is important that policymakers should consider all the supply chain players, including the communities in which they operate, when developing a resilience framework.

2.3 Big data and predictive analytics (BDPA) in extreme weather events

Big data analytics is useful to deal with risk and uncertainty in humanitarian supply chains. Business organizations rely heavily on big data analytics to predict future events. Literature has indicated that some top management of companies is focusing on managing the supply chain in a disaster situation using big data and predictive analysis (Dubey et al., 2018a). Big data improves the flow of integrated data and the precision of predictive analysis (Bag et al., 2020a). Big data and predictive analytics (BDPA) strengthen an organization's capability to enhance the coordination and visibility of the supply chain. Because visibility is a key factor in the supply chain, big data helps to improve coordination among channel members by creating efficient and effective predictive models. Big data and predictive analysis are critical for shaping the supply chain's future. The role of BDPA varies due to the complex organizational culture and high level of uncertainty. BDPA enhances management's ability to improve the supply chain disaster relief efforts (Dubey et al., 2018a). Extreme weather has a massive impact on supply chains. Analytics is critical in developing appropriate supply chain mechanisms to deal with extreme weather events. Weather forecasts should be continuously monitored to mitigate supply chain management disruptions and to take timely proactive corrective actions, in order to continue to meet customer demands (Doll et al., 2014).

2.4 Dynamic capability view

Dynamic capability view (DCV) investigates how organizations combine, develop, and rearrange their internal and external organization-specific proficiencies into novel proficiencies that align with their uncertain business surroundings (Teece et al., 1997). The fundamental assumption of DCV is that organizations having higher dynamic capabilities (DC) will demonstrate superior performance and vice-versa. DCV is a popular theory that explains the attitude of organizations towards the utilization of DC in building a competitive advantage

(CA). The theory explains how organizations react to changes in the business environment. If we look at the capabilities of an organization, then we find a group of advanced-level knowledge gained, patterned and repetitive actions that can give an edge to the organization. The building blocks of DCV start from "zero-level" which are basically organizational capabilities. This is followed by "first-order" capabilities, which are also known as DCs' (Winter, 2003). Ordinary capabilities (zero-order) entail the execution of managerial, operative, and overseeing the control-related functions that are required for job completion. DCs' are advanced activities that allow a firm to direct its regular operations toward high-reward undertakings. Knowledge, firm's resources, and the past history of firm's help to contribute to capability building (Teece, 2014). The organizational capabilities explain how basic trading is done, by selling the same product and service without varying supply and demand, to the same set of buyers. DCs' allows the company to participate, develop, and reconfigure inside and outside resource sets to stay ahead of the competition in ever-changing business settings (Teece, 2014).

The mechanisms of how DC works are important, and the building of capabilities is essential to sense and recognize new prospects. After it is done, the organization can seize these prospects by making the necessary investment to enhance organizational capabilities. Lastly, the organization re-arranges its lower-level capabilities to form new capabilities that are a good fit for its business environment. This can result in a sustained CA compared to its market competitors (Teece & Pisano, 2003; Teece, 2007; Han et al., 2020).

Strong DCs', on their own, is doubtful to provide a CA. It must be accompanied by rare resources and a strong strategy (Teece, 2014).

Nonetheless, strong DCs are required when organizations face considerable uncertainty (Teece et al., 2016). Literature has indicated that organizations are facing a high level of uncertainty due to extreme weather events induced by climate changes. It is essential that an organization must sense and make plans to overcome the challenges before others (competitors) come to know about them. Once the organization develops capabilities to utilize BDPA technologies, it will gain a higher level of visibility in the SC that will aid in implementing resilience building strategies and completing the actions. Only in accordance with the needs of the business environment and the firm's strategy may BDPA technology be pursued. The level of BDPA competence that executives choose to establish and maintain in their company is determined by their strategy and positioning. Firms with high DCs' (here BDPA capabilities), on the other hand, will be better at recognizing upcoming progress, as well as achieving SC visibility with less efficiency sacrifice and making better use of whatever visibility they have. This is because they will be better at sensing, seizing, and transforming by its very nature (Teece et al., 2016).

To summarize, whilst previous literature report findings relating to the relationships between two or more of our study variables i.e., BDPA, supply chain resilience and visibility, however, none of them present them all together in a testable framework. Furthermore, whilst prior studies have highlighted how BDPA can mitigate generic risk and uncertainty in relation to future events, this study adds to knowledge by focusing on the specific event of an extreme weather occurrence. Lastly, we take the wealth of prior research on DCV, to examine how the alignment between BDPA strategy and capabilities acts as a moderator in our theoretical framework.

3. Methodology

3.1 Research design

Our study design comprised two consecutive phases. In phase one, qualitative semi-structured in-depth interviews were initiated, via an online platform, to understand the critical factors influencing a firm's community and resource resilience. The interviews also sought data on how supply chain resilience can be achieved through BDPA and through the firm's general dynamic capability. In phase two we used multivariate analysis of survey data to test our research framework and hypotheses, to examine the relationships between BDPA, community resilience, and resource resilience. Therefore, our study used a mixed methods approach to build on the qualitative findings with the interview data (Östlund et al., 2011; Yeng et al., 2018). This is because there was no established guiding theory of the relationships between all our study constructs and our research design is suited for exploring a phenomenon in such situations (Creswell et al., 2033).

3.2 Phase 1 study

3.2.1 Method

To answer the two RQs on the "what" and "how", this first phase aimed to identify the most essential influencing antecedents of firms' community and resource resilience and to advance deep understanding about the role of BDPA and the effects of firms' supply chain visibility on SC network resilience (community and resources resilience). This was in the context of the South African mining industries under extreme weather events. The semi-structured online interviews were conducted in December 2020 (T1) with 10 managers from different firms in the sector. Our sampling strategy was informed by Bag et al. (2021), which reports a study of a similar nature. In our case, we selected plant managers from the mineral processing industry having more than 10 years of working experience. After 10 interviews, it was deemed that theoretical saturation had been reached and no more interviews were conducted as new themes were emerging.

The interview protocol is comprised of three steps. Step one collected demographic information on the respondent's background, his/her role in their mining firm, and their overall experiences in this industry. In step two, data were collected on the topics of big data and predictive analytics and their firm's supply chain visibility, in the context of preparedness, responsiveness, and recovery (i.e., pre, during, and post-extreme weather events management) to achieve supply chain resilience. Finally, in step 3, their opinions about the effect of supply chain resilience on community and resource resilience were collected. The process for data coding and analysis is described in Figure 1.

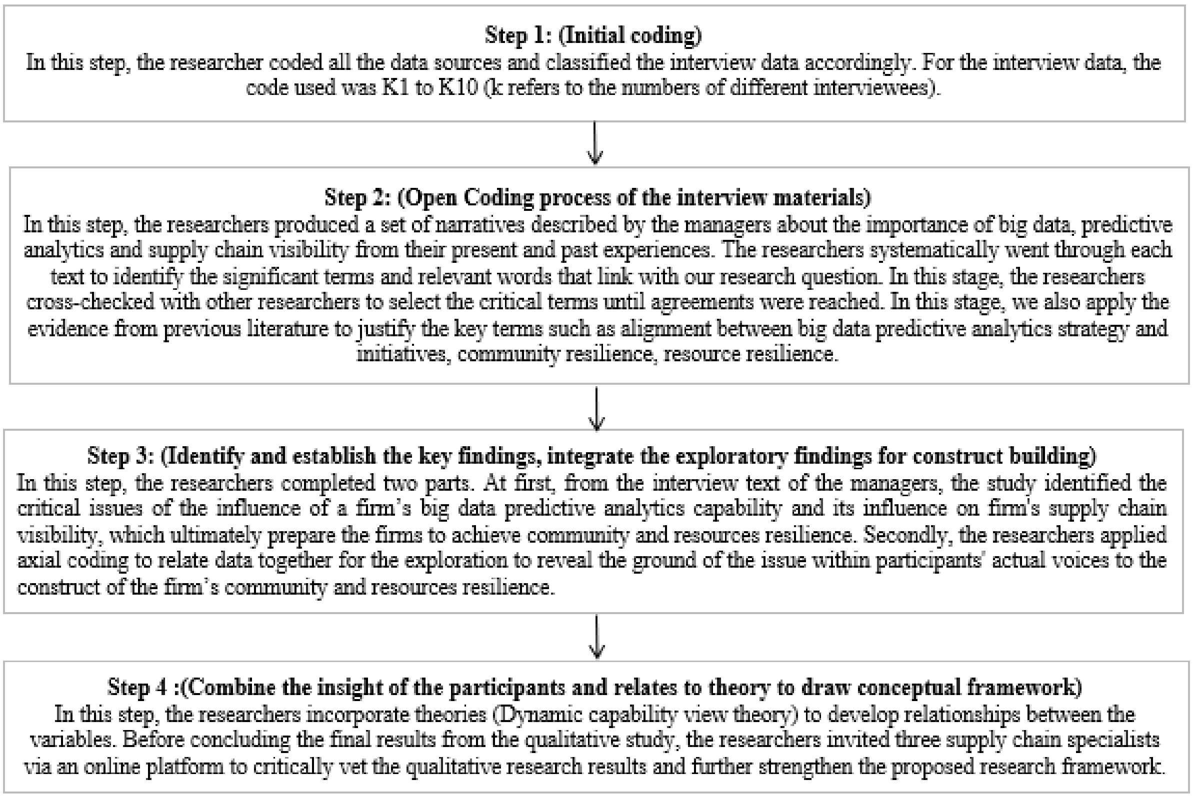

Figure. 1. Data analysis process in phase one study

3.2.2 Results and discussion

Common words that our open coding process (See step 2 in Figure 1) identified were, in descending frequency of mention: management, data, predictive, response, dynamic, supply, big, resources, capabilities, decisions, data-driven, resilience, disasters and future. The data revealed two antecedents of supply chain network resilience, namely: BDPA capabilities and supply chain visibility. It further showed both community resilience and resources resilience as two outcomes. Also, that a firm's alignment between BDPA strategy and initiatives may moderate the effect of a firm's BDPA capabilities on supply chain visibility. The more positive the alignment between the two, the higher the influence of BDPA capabilities on supply chain visibility. Themes in the data were: management capabilities, BDPA alignment, enhancing SC visibility and building resilience. In the remainder of this section, we cover each of these in turn.

In the literature, BDPA capabilities refer to manager's belief that firms must have sophisticated management capability, analytical tools, data processing, for exploring meaningful insights and the bundling of strategic resources to gain competitive advantage (Brandon-Jones et al., 2014; Wamba et al., 2015; Gupta & George, 2016; Akter et al., 2016; Wamba et al., 2017). According to Sirmon et al. (2011), firms need to develop capabilities on the basis of the existing internal and external environmental conditions in order to achieve and sustain competitive advantage. In the context of BDPA, a platform with high technical, managerial, data-driven decision-making culture and organizational learning would provide a firm with the capabilities to sense, coordinate, learn, integrate, and reconfigure, such that it can safeguard the mining firms. As articulated by K7: "*Machine learning, algorithms, predictive analytics, and other big data tools, are highly valuable tools for preparing organizations in anticipation of any future disasters. We have implemented data-driven response plan, measurements, and metrics. These tools can also help in making good decisions after any disasters.*"

A number of interviewees highlighted that the alignment between BDPA strategy and BDPA initiatives can provide a platform for the firm to enhance its dynamic capability. For example:

> "*Our country is rich in natural resources, and we should leverage advanced 4IR technologies like big data and predictive analytics to make key decisions in business. Since the application of these advanced technologies can improve efficiency in the extraction of ores, processing of ore and improving productivity; therefore, we have launched a big data platform couple of years back to drive operational excellence.*" (K3).

This ability to build upon aspects of BDPA is consistent with prior literature (see, Akter et al., 2016).

A common theme amongst interviewees was the mechanisms to enhance visibility by which firm's build resilience to supply chain disruptions, with the roles of codes of practices, operational guidelines, management plans and systems highlighted. A typical response was described by K1:

> *"We developed a code of practice on emergency preparedness and response measures to lower any risks associated with emergencies. We ensure that health and safety are not affected by any disasters. We have a disaster management model that provides guidelines for prevention, preparedness, response, and recovery."*

This finding adds to literature which suggests that a firm's SC visibility is an effective way to SC network resilience, in anticipation of extreme weather events, to facilitate quick response during extreme weather events and to enable fast recovery after extreme weather events. Using clear mechanisms, firms can manage the corresponding risks and recover from supply chain disruption (National Research Council, 2007; Ambulkar et al., 2015). Resilience allows firms to manage SC disruption, deal with unforeseen situations and continue to deliver their services, in order to optimize their resources whilst providing community resilience (Sheffi & Rice, 2005; Thun & Hoenig, 2011; Pettit et al., 2013).

In particular, having supply chain resilience may help to construct community resilience and resource resilience (Stewart et al. 2009; Papadopoulos et al. 2017). Through the firm's supply chain resilience, it can positively influence the capability of the respective communities to adapt to the consequences of natural disasters and facilitate the restoration of a community's economic and social networks. The importance of focusing on community resilience is reflected in the following response from one of the interviewees.

> "*Society and community members are an integral part of our business. Hence, we always stand beside them in good and bad times. Our leaders' plant new trees every year as part of the forest management program. We are also investing huge financial resources for saving existing dams and stopping any kind of pollution happening from mining operations"* (K6).

Furthermore, resource resilience's importance was highlighted. For example, one interviewee stated: "*Resources resilience is vital for the sustainability in the mining industry. We have spent a significant amount of time and resources on the training and skills development of our laborers. We have also invested heavily managing grazing lands by planting new trees, digging new bore wells, maintaining the cleanliness of surrounding lands and water systems"* (K8).

4. Theoretical model and hypothesis development

4.1 Theoretical model

By incorporating the DCV (Teece & Pisano, 2003), big data literature (Gupta & George, 2016; Grover et al., 2018; Mikalef et al., 2021), and the findings from our qualitative study (phase 1 study), we developed our theoretical framework (see Figure 2). Our model includes BDPA and the firm's SC visibility factors related to the mining industry, and outcome variables such as community resilience and resources resilience. The moderating role of alignment between BDPA strategy and BDPA initiatives is proposed to be important and hence it is included as a variable in the model for further investigation. Relationships among the variables were empirically tested as described in subsequent sections.

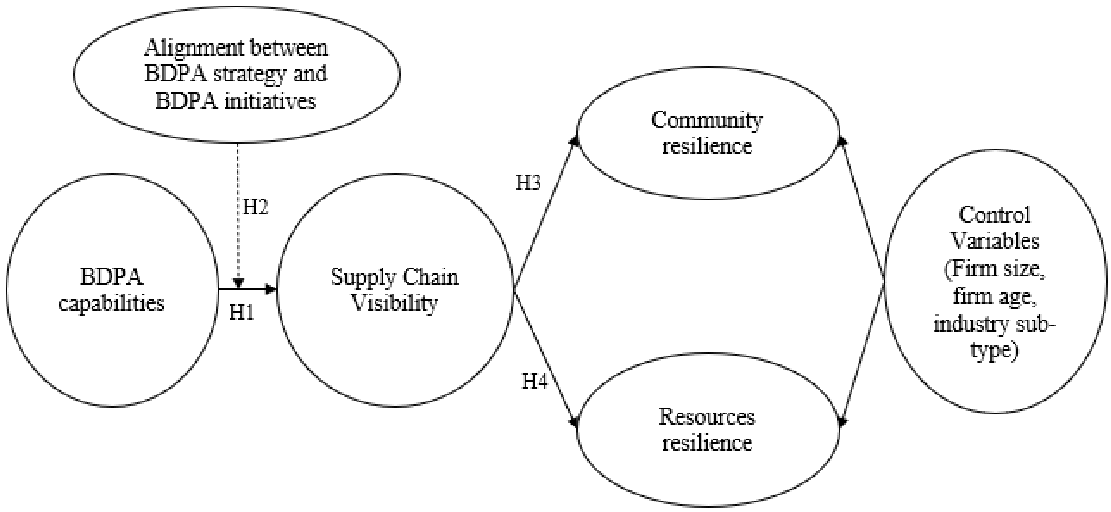

Figure 2. Theoretical framework showing relationship between BDPA capabilities, SC visibility, and community and resources resilience

Grover et al. (2018) highlighted that resources such as assets, human skills, and investments can lead to the development of BDPA capabilities which enhances specific target and generate functional/symbolic value (Grover et al., 2018). In our study, we adopt an evolutionary fitness view (Helfat & Peteraf, 2009) where BDPA capabilities help to reposition an organization under extreme weather events (Dubey et al., 2018a). We propose that BDPA capabilities build SC visibility in an organization (Mikalef et al., 2021). This will lead to improvement in SC network resilience, i.e., community resilience, and resource resilience (Papadopoulos et al., 2017). Lastly, we theorize that the effect of BDPA capabilities on SC visibility will be magnified under strong alignment between BDPA strategy and BDPA initiatives (Akhter et al., 2016).

4.2 Hypotheses development

Supply chain management has become more reliant on BDPA (Schoenherr & Speier-Pero, 2015). According to Kamble & Gunasekaran (2020), performance measures and metrics are essential indicators for managing diverse supply chains. They used a resource-based view to describe how big data enhances predictive analysis capability (Kamble & Gunasekaran, 2020). However, this view has been criticised for failing to provide clarity in terms of the required supply chain resources and capabilities. The quality of information system resources and capabilities has a big impact on how well a company performs (Brandon-Jones et al., 2014). An organization's ability to use technology successfully to optimize resources leads to SC visibility, which is dependent on its information system capabilities (Brandon-Jones et al., 2014). Big data could be a valuable resource in determining the supply chain's future requirements, improving monitoring and tracking capabilities, leading to more efficient and sustainable supply chain management. (Kamble & Gunasekaran, 2020). Zhan & Tan (2020) found that an analytic infrastructure enhanced by big data capabilities provides managers and organizations with a roadmap for developing actionable supply chain networks. The information extracted from big data helps to develop supply chain management's future competencies. A big data-enabled integrated supply chain system assists the firm in overcoming challenges. Big data analytics capabilities improve the dynamic capabilities of supply chain networks by reducing response times (Zhan & Tan, 2020). Using organizational information processing theory, Yu et al. (2021) demonstrated the usefulness of big data analytics capabilities in supply chain management. With big data, particularly combined with analytical tools and processes, increases the performance with which information is processed within an organization and accelerates decision-making processes. The ability to make quick and informed decisions has a big impact on supply chain management (Wantao et al., 2021). Hence, we posit the following:

H1: There is a positive relationship between big data and predictive analytics capabilities (BDPAC) and supply chain (SC) visibility.

The complexity involved in processing large amounts of unstructured data is increasing as supply chains become more globalized. The visibility of the supply chain is determined by internal and external informational data, which leads to resilient supply chain management (Doetzer, 2020). The resilience supply chain depends upon the visibility of the network; and the visibility of the supply chain increases via information sharing and transparency among channel participants. Smooth information sharing mitigates threats associated with high levels of uncertainty, resulting in less of a need for reduced inventory safety stock. It turns the system into a demand-driven one, rather than a supply-driven (Christopher & Lee, 2004). Visibility into the supply chain improves responsiveness, decision-making, and operational and supply chain performance. It also improves supply chain robustness and resiliency (Dubey et al., 2017). According to resource-based perspectives, bundling resources and capabilities can be used to gain a competitive advantage. Information sharing and supply chain connectivity are complementary tools that can be combined to generate effective supply chain visibility (Dubey et al., 2017). Supply chain visibility is improved by bundling available resources, which has an impact on sustainable performance (Dubey et al., 2020). The sharing of information concerning sales, order status, inventory, manufacturing, scheduling, and demand forecasting is important. The supply chain visibility is enhanced through accurate and timely information sharing (Dubey et al., 2020). When unfavourable activity is observed, visibility in the supply chain enables contingency planning and the use of tools to take corrective action. For example, if the inventory shipment plan changes due to weather conditions, a contingency plan should be in place to take appropriate action (Christopher & Lee, 2004). Visibility is a critical aspect of supply chain management that helps businesses decrease risk, mitigate threats, and improve organizational performance (Dubey et al., 2017). The visibility of the supply chain is improved by the technological integration of information sharing.

Big data plays a crucial role in the world of information. It accelerates the processing of information, which, in turn, improves supply chain management's predictive analysis capability and leads to enhanced supply chain visibility (Doetzer, 2020). Big data analytics capabilities improve information processing in supply chain management, enabling managers to make faster decisions. Besides, they can also predict natural disasters that may occur in the future, which assists management in developing a proactive supply chain resilience strategy to mitigate for the negative impact of such events. Big data analytics supports management in maximizing available resources. Therefore, big data is critical for data management, which provides supply chain managers with an edge and a competitive advantage. In line with the study of Akter et al. (2016), we argue that alignment between BDPA strategy and BDPA initiatives acts as a moderating variable between BDPA capabilities and SC visibility. Hence, our second hypothesis is as follows:

H2: Alignment between BDPA strategy and BDPA initiatives has a moderating effect on the path between big data and predictive analytics capabilities (BDPAC) and SC visibility.

Efficient supply chain management requires the optimal allocation of diverse resources, such as safety stock, optimizing network structures, contracting with many suppliers, and implementing a supplier development program (Li et al., 2020). SC resilience is the ability to restore normality to operations that have been affected by disruptive circumstances (Brandon-Jones et al. 2014). Multinational firms like Toyota were able to restore supply chain normal conditions in 29 sites within 3-4 days after a severe earthquake in Kobe in 1995, which demonstrated Toyota's supply chain resilience (Brandon-Jones et al. 2014). Resilient supply chain management enables management to plan for any unexpected disruptions, respond to them, and recover from them, while maintaining the desired level of sustainability in operations. Visibility in the supply chain results in enhanced resilience (Brandon-Jones et al. 2014). The partnership between channel partners is critical for effective and efficient resilience. It assists in the development of channel partner credibility and cooperation, resulting in more resilient supply chains. Appropriate integration of trust, cooperation, and visibility could greatly increase supply chain management resilience. (Dubey et al., 2017). Literature indicates that supply chain network resilience is achieved through community resilience. The concept of community resilience focuses on a community's ability to adapt after a disturbance. Building community resilience is an important part of disaster preparedness strategy (Ryan et al., 2021). Economic resources and social systems must be integrated and developed for a community to be resilient (Norris et al., 2008; Stewart et al., 2009). Bringing this prior literature together, we hypothesize that

H3: There is a positive relationship between SC visibility and community resilience.

Resource integration is critical to dealing with the after-effects of natural disasters. Economic, social, human, environmental, and physical resources should all be combined to generate resilience resources (Dixit et al. 2020). Resource resilience improves a community's ability to respond to supernatural events promptly (Sudmeier et al., 2013). SC resilience improves the awareness, adaptation, and response capabilities of the organization (Ryan et al., 2021). The resilience capacity of an effective and efficient supply chain system is built on a collaborative plan. The operation of a resilient supply chain is dependent on strong intermediary relationships. The supply chain system's channel participants should aggregate their resources to achieve a shared goal (De Sá et al., 2020). The resource-based view shows how supply chain management contributes to achieving competitive advantage, by combining inimitable, precious, and rare resources and competencies (Dubey et al., 2017). Operational information and status reports, such as predictions, inventory, work-in-progress, production and shipment information, and backlogs, require supply chain visibility. All channel partners should be able to easily access this information. For future supply chain planning, the accuracy and timeliness of the information is beneficial to all parties (Christopher & Lee, 2004). Supply chain visibility enables channel partners to make timely changes to the supply chain before or after a disruption (Christopher and Lee, 2004). Analysing the link between the concepts of visibility and resource resilience, our final hypothesis is indicated as follow:

H4: There is a positive relationship between supply chain visibility and resource resilience

5. Phase 2 study: Quantitative investigation

5.1 Measurement and measures

To measure our study constructs, we adopted well-established scales from the literature (i.e., Malhotra & Grover, 1998; Zhu et al., 2008). Specifically, we measured big data and predictive analytics capabilities (BDPAC), supply chain visibility (SCV), alignment between BDPA strategy and BDPA initiatives (ABDPI), community resilience (CRES), and resources resilience (RESRE). All the measures were first pretested by the managers and academics in the field of big data analytics and supply chain management. Then, minor modifications to the wording of some of the items were made in order to enhance the scale operationalization and performance (Churchill, 1979). Table A1 in the appendix lists all the items for the constructs. With the exception of the control variables, such as firm's size and age, and industry subtype, all scales were assessed using a 7-point rating scale: 1 = strongly disagree and 7 = strongly agree.

5.2 Sampling and data collection

We used a survey instrument to collect data for empirically testing the proposed theoretical framework through the associated hypotheses. We pretested the instrument with five senior supply chain faculty members and ten industry experts. The feedback collected from these two groups helped improve the survey instrument before final distribution to the employees of mines and mineral processing plants in the Republic of South Africa.

We selected the samples from the list of mines and mineral processing companies in the Republic of South Africa (with a directory no: D1/2016, named "Operating mines and quarries and mineral processing plants in the Republic of South Africa, 2016, Directorate: Mineral Economics". In the first stage of data collection (T2: January 2022), 650 online survey questionnaires (one survey for each mine) were distributed, and we received 57 responses. After follow-ups, we received 162 responses (T3: February 2022). Eventually, we received 219 responses, resulting in a 33% response rate. A detailed profile of the survey respondents is provided in Table 1.

Table 1. Demographic profile of the respondents

Demographic details	Description	Numbers	Percentage
Age Group	20-30	14	6.39%
	31-40	21	9.59%
	41-50	72	32.88%
	51-60	108	49.32%
	Above 60	4	1.83%
Educational Qualifications	Postgraduate	72	32.88%
	Graduate	123	56.16%
	Diploma	15	6.85%
	Matric	9	4.11%
Designation	Board Member	0	0.00%
	CEO/President/Owner/ Managing Director	0	0.00%
	CFO/Treasurer/Controller	0	0.00%
	CIO/Technology Director	2	0.91%
	Chief Procurement Officer	6	2.74%
	Senior VP/VP	4	1.83%
	Head of Business Unit or Department	141	64.38%
	Plant Manager	47	21.46%
	Data Analyst	8	3.65%
	Data Scientist	2	0.91%
	Consultant	9	4.11%
	Researcher	0	0.00%
	Others	0	0.00%
No of Employees in your Organization	Less than 10	0	0.00%
	50-300	0	0.00%
	300-500	0	0.00%
	500-1000	60	27.40%
	More than 1000	159	72.60%
Age of the Organization (Years)	Above 15	219	100.00%
	10 to 14	0	0.00%
	5 to 9	0	0.00%
	Less than 5	0	0.00%
Nature of Business Activities	Mines and Quarries	166	75.80%
	Mineral processing	53	24.20%
Firm Size	Small	0	0.00%

	Medium	27	12.33%
	Large	192	87.67%

5.3 Non-response bias test

We assessed non-response bias through a comparison of the data of early wave and late wave (T2 & T3) respondents (Armstrong and Overton, 1977; Chen et al., 2004). The results from t-tests analysis on all items was not significant (i.e., p=0.0879), hence non-response bias was not deemed to be present in the dataset.

5.4 Common method bias test

As common method bias (CMB) in data generated from cross-sectional studies is a great concern in social science research (Podsakoff & Organ, 1986), we applied two methods to control for it. These were: 1) design of the study's procedures and/or 2) statistical measurement (Podsakoff et al., 2003). To address the design procedures, we used multiple strategies, including obtaining the measures of the exogenous and endogenous variables from different sources, separating the measurement items of the exogenous and endogenous variables, collecting data at different locations, ensuring respondent anonymity, structuring the items of the survey questions simply, clearly, and concisely for the respondents and finally avoiding double-barrelled questions (Jarvis et al., 2003; Reio, 2010; Podsakoff et al., 2012).

For statistical measurement control, we operationalized Harman's single-factor test (Harman, 1976). The results from the test showed that 38.79% of the variance was explained by a single factor. We also tested the values of tolerance and variance inflation factors (VIF) for assessing multi-collinearity (See Table 2). This showed no multi-collinearity issues among the variables (Sheather, 2009). We also tested for CMB through the application of confirmatory factor analysis (CFA), by loading all the measurement items under one factor to perform the CFA analysis (Malhotra et al., 2006). The overall fit in regards to single factor proved poor (χ^2/df = 9.82; RMSEA= 0.397; NNFI=0.096; CFI= 0.164 and RMSR=0.576). Finally, we applied a marker variable (which is an unrelated variable) to partial out the correlations and check the significance level, as suggested by Lindell & Whitney (2001). The results from this procedure showed that the significance of the correlations did not substantially change. All these tests suggest there is no issues resulting from CMB in our collected data set.

Table 2. The results of multi-collinearity analysis

Variables	Tolerance	VIF
BDPAC	0.913	1.098
ABDPI	0.846	1.572

SCV	0.604	1.869

Note: Big data and predictive analytics capabilities (BDPAC), Alignment between BDPA strategy and BDPA initiatives (ABDPI), Supply chain visibility (SCV)

5.5 Control variables

Finally, we used firm size, age, and industry sub-type as control variables. First, we controlled for the size of mine and minerals plants, which were measured by using the number of employees in the plants. This is because large mines and mineral processing plants must have access to a greater number of resources compared with small and medium firms (Wu et al., 2014; Sun et al., 2020). Second, we controlled for the firm's overall age of the firm in the mining industry. An older firm has more experience and is more likely to have greater exposure to the community and resource resilience and capacity to recover from any type of supply chain disruption (Lin & Ho, 2009). Last, but not least, we controlled for industry type, in order to check whether these variables would influence community resilience and firms' resources resilience (Wiengarten et al., 2012; Sun et al., 2020). Our results found no statistically significant differences based on the firm size, age, and industry sub-type towards community resilience and firm resources resilience.

6. Data analysis

We applied PLS-SEM to estimate a hierarchical, reflective, and formative construct, in order to avoid the limitations of CBSEM in such empirical studies (Chin 2010; Akter et al., 2017; Sarstedt et al. 2017). Due to the soft modelling assumptions, the application of PLS-SEM helps to avoid positively biased model fit indices for large-complex models like ours (Chin & Newsted 1999; Hair et al., 2012; Akter et al., 2017), with 11 latent constructs (including 9 first-order, 2 second-order and 2 outcome constructs) and 60 items. Furthermore, we used PLS-SEM as it is explanatory in nature and predicts the main outcome variables, with smaller sample sizes, i.e., n = 219 in our case, for complex relationships (Wright et al., 2012; Roldán & Sánchez-Franco, 2012; Henseler et al., 2014). For testing the moderation effect of ABDPI in between BDPAC and SCV, we applied PROCESS macro, as suggested by Hayes et al. (2017). We also applied the interaction effect of ABDPI, via simple slopes comparison, as suggested by Soper (2013).

6.1 The measurement model

We used the psychometric measurement properties for examining reliability and validity (see Table 3). The key properties being: loadings of manifest variables, Cronbach's alphas, omega score, composite reliabilities (CRs), average variance extracted (AVEs), maximum shared variance (MSV) and average shared squared variance (ASV). The results confirmed the scale reliability and validity (convergent validity and discriminant validity) of the dataset (Chin, 2010; Green & Yang, 2015; Deng & Chan, 2017; Viladrich et al., 2017; Hair et al. 2017; Akter et al., 2017). The resultant measurement model successfully met the required thresholds (See Table 3). All the loadings under each item are above 0.60 and, hence, the reliability of the scale is confirmed (Hair et al. 2017). In addition, the measurement model confirmed convergent validity, due to the AVE values under each construct being above 0.50. The results validate discriminant validity, as MSV values under each construct are less than AVE, and ASV is also less than AVE (Hair et al., 2017). The square root of the AVE values is higher than inter-construct correlations, which demonstrates discriminant validity (Fornell & Larcker, 1981). Please refer to Table 4.

Table 3. Psychometric properties for constructs at first-order level

Constructs	**Sub-constructs Items**	**Loadings**	**Alpha (α)**	**Omega (ω)**	**CR**	**AVE**	**MSV**	**ASV**
BDPAC	TS1	0.748	0.850	0.863	0.886	0.556	0.349	0.262
	TS2	0.758						
	TS3	0.708						
	TS4	0.745						
	TS5	0.736						
	TS6	0.812						
	MS1	0.841	0.867	0.870	0.886	0.566	0.346	0.276
	MS2	0.701						
	MS3	0.725						
	MS4	0.708						
	MS5	0.735						
	MS6	0.794						
	DDM1	0.871	0.849	0.858	0.881	0.598	0.387	0.286
	DDM2	0.741						
	DDM3	0.762						
	DDM4	0.701						
	DDM5	0.783						
	OL1	0.817	0.840	0.851	0.862	0.611	0.396	0.290
	OL2	0.796						
	OL3	0.807						
	OL4	0.703						
SCV	SCVS1	0.862	0.840	0.852	0.862	0.676	0.321	0.280
	SCVS2	0.813						
	SCVS3	0.791						
	SCVL1	0.703	0.803	0.814	0.860	0.553	0.357	0.290
	SCVL2	0.801						
	SCVL3	0.742						
	SCVL4	0.746						
	SCVL5	0.725						
	SCVC1	0.758	0.819	0.828	0.894	0.547	0.340	0.271

	SCVC2	0.703						
	SCVC3	0.714						
	SCVC4	0.709						
	SCVC5	0.763						
	SCVC6	0.731						
	SCVC7	0.795						
	SCVI1	0.816	0.841	0.856	0.869	0.571	0.394	0.324
	SCVI2	0.806						
	SCVI3	0.702						
	SCVI4	0.709						
	SCVI5	0.739						
ABDPI	ABDPI1	0.809	0.846	0.859	0.871	0.630	0.308	0.249
	ABDPI2	0.709						
	ABDPI3	0.846						
	ABDPI4	0.806						
CRES	CRES1	0.702	0.807	0.816	0.886	0.527	0.384	0.309
	CRES2	0.817						
	CRES3	0.702						
	CRES4	0.701						
	CRES5	0.717						
	CRES6	0.705						
	CRES7	0.732						
RESRE	RESRE1	0.768	0.852	0.841	0.835	0.628	0.329	0.271
	RESRE2	0.846						
	RESRE3	0.762						

Notes: Big data and predictive analytics capabilities (BDPAC) [Technical skills –TS; Managerial skill-MS; Data driven decision making culture-DDDM; Organisational learning-OL]; Supply chain visibility (SCV) [Visibility for sensing -SCVS; Visibility for learning –SCVL; Visibility for coordinating-SCVC; Visibility for integrating-SCVI]; Alignment between BDPA strategy and BDPA initiatives (ABDPI); Community resilience (CRES), Resources resilience (RESRE). CR = Composite Reliability, CA = Cronbach's Alpha, Average Variance Extracted (AVEs), Maximum Shared Variance (MSV), average shared squared variance (ASV).

Table 4. Mean, standard deviation (SD), and correlations of the latent variables for the first order constructs

Constructs	Mean	SD	TS	MS	DDDM	OL	SCVS	SCVL	SCVC	SCVI	ABDPI	CRES	RESRE
TS	4.897	1.007	**0.745**										
MS	4.758	1.008	0.397	**0.752**									
DDDM	4.789	1.002	0.426	0.295	**0.773**								
OL	5.021	1.106	0.369	0.268	0.249	**0.781**							
SCVS	4.863	1.008	0.343	0.372	0.216	0.369	**0.822**						
SCVL	5.170	1.005	0.426	0.343	0.293	0.314	0.297	**0.743**					
SCVC	4.905	1.004	0.318	0.325	0.405	0.328	0.304	0.401	**0.739**				
SCVI	4.872	1.003	0.297	0.410	0.394	0.347	0.354	0.416	0.329	**0.755**			
ABDPI	5.638	1.001	0.421	0.395	0.327	0.329	0.316	0.429	0.257	0.403	**0.793**		
CRES	5.091	1.006	0.301	0.408	0.427	0.348	0.379	0.417	0.236	0.417	0.349	**0.725**	
RESRE	4.689	1.003	0.376	0.314	0.461	0.401	0.399	0.403	0.348	0.302	0.326	0.407	**0.792**

Notes: Square root of AVE on the diagonal.

Big data and predictive analytics capabilities (BDPAC) [Technical skills –TS; Managerial skill-MS; Data driven decision making culture-DDDM; Organisational learning-OL]; Supply chain visibility (SCV) [Visibility for sensing -SCVS; Visibility for learning –SCVL; Visibility for coordinating-SCVC; Visibility for integrating-

SCVI]; Alignment between BDPA strategy and BDPA initiatives (ABDPI); Community resilience (CRES), Resources resilience (RESRE).

We also tested the degree of explained variance of the second-order BDPAC and SCV constructs which are explained by their first-order dimensions i.e., BDPAC is explained by TS (30%), MS (25%), DDDM (20%), and OL (26%). The findings ensure that all the paths are significant at $p < 0.001$. We analyse the implications of these results in the discussion section.

Table 5. Assessment of reflective-formative model

Second-order formative constructs	**Relationships with first-order dimensions**	**β**	**t-stat**
BDPAC	TS	0.317	3.087
	MS	0.285	3.176
	DDDM	0.251	2.749
	OL	0.179	2.053
SCV	SCVS	0.367	4.067
	SCVL	0.286	3.029
	SCVC	0.234	3.014
	SCVI	0.198	2.176

Notes: Big data and predictive analytics capabilities (BDPAC) [Technical skills –TS; Managerial skill-MS; Data driven decision making culture-DDDM; Organisational learning-OL]; Supply chain visibility (SCV) [Visibility for sensing -SCVS; Visibility for learning –SCVL; Visibility for coordinating-SCVC; Visibility for integrating-SCVI]

Overall, the measurement model provides adequate evidence of reliability and validity, providing a solid foundation on which to undertake a further empirical assessment of the hypothesized relationships of the structural model.

6.2 Structural model testing

To test the structural relationship, we applied PLS-SEM analysis with a bootstrapping option, as recommended by Pavlou & Gefen (2005). The results of the path analysis are shown in Figure 3. BDAPC explains 37.28% of the variance of the firm's SC visibility, which in turn explains 41.43% and 39.42% of the variance in community and resource resilience respectively. Tests revealed that all the direct relationships were positively significant and, hence, hypotheses H1, H3 and H4 are supported (See Table 4). The results also show that the proposed structural model adequately fits, with goodness of fit (GoF) value (>0.387) and standardized root mean square residual (SRMSR) (<0.060) and Q^2 (>0.561). Thus, the model meets the model fit criteria, predictive relevance (Q^2) and unobserved heterogeneity (Tenenhaus et al. 2005; Esposito Vinzi et al. 2010; Henseler et al. 2016).

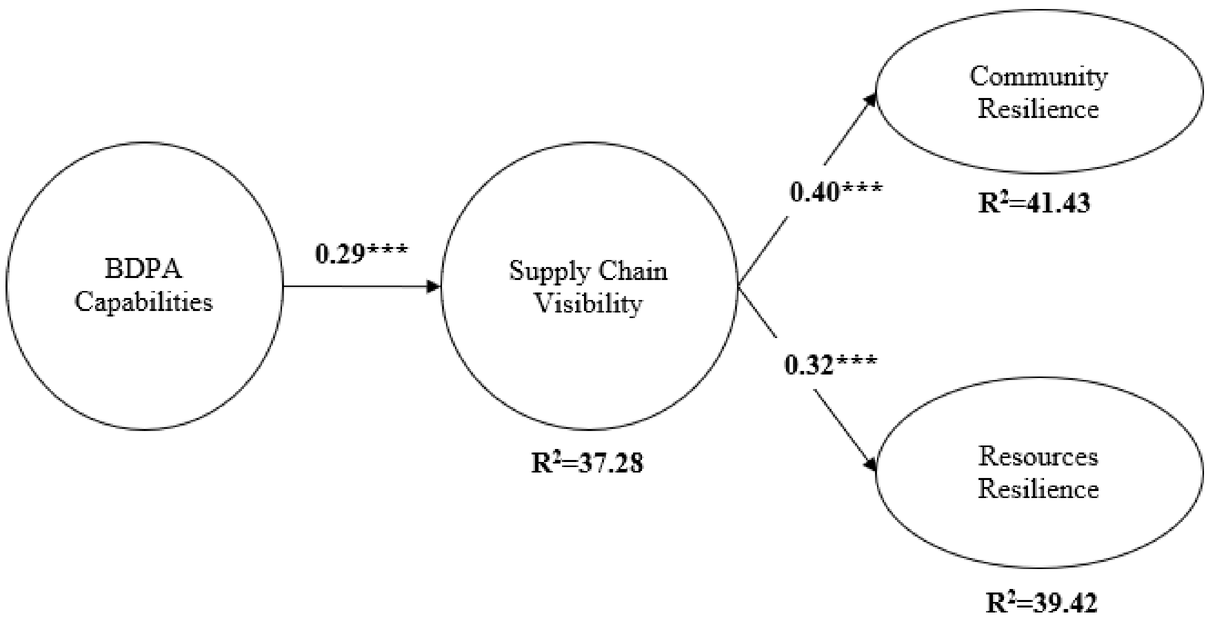

Fig. 3. Tested model

Table 4. Results of hypothesis testing

No.	Hypothesis	Path coefficients	t-Statistics	Results
H1	BDPAC-→ SCV	0.2948	2.498**	Supported
H3	SCV→ CRES	0.4021	9.546***	Supported
H4	SCV→ RESRE	0.3221	8.657*	Supported

Notes: *significant at the 0.05, **significant at the 0.01, ***significant at the 0.001 level.
Big data and predictive analytics capabilities (BDPAC), Supply chain visibility (SCV), Alignment between BDPA strategy and BDPA initiatives (ABDPI); Community resilience (CRES), Resources resilience (RESRE).

To assess whether alignment between BDPA strategy and initiatives (ABDPI) moderates the relationship between BDPA capabilities (BDPAC) and SC visibility (SCV) (Hypothesis 2), we performed ordinary least squares regression via the conditional PROCESS macro for SPSS (Hayes, 2017). We applied two independent variables and analysed their relevant interaction terms to the model, coefficients, standard errors, and a 95% confidence interval were calculated to examine the moderating effect of ABDPI between BDPAC and SCV. The results of interaction terms are shown in Table 5, which shows the moderation effect of ABDPI is significant in the relationships between BDPAC and SCV.

Table 5 Hayes' moderated regression analysis results

Predictor	Beta	SE	t-statistic	p-value	LLCI	ULCI	Assessment

BDPAC* SCV	0.157	0.063	2.608	0.014	0.032	0.294	Supported

Notes: SE = standard error; LLCI and ULCI = lower and upper levels for the confidence interval.
Big data and predictive analytics capabilities (BDPAC), Supply chain visibility (SCV)

Finally, the moderating effect of ABDPI on the relationship between BDPAC and SCV is shown in Figure 4. Simple slopes comparison between high (+1 standard deviation (SD)) and low (-1 SD) ABDPI were performed by Interaction, as suggested by Soper (2013). The results show that a high alignment between BDPA strategy and BDPA initiatives has a significant moderating effect on the path of big data and predictive analytics capabilities and firm's supply chain visibility and that such a relationship is significant and positive (simple slope = 0.018, $p<0.001$).

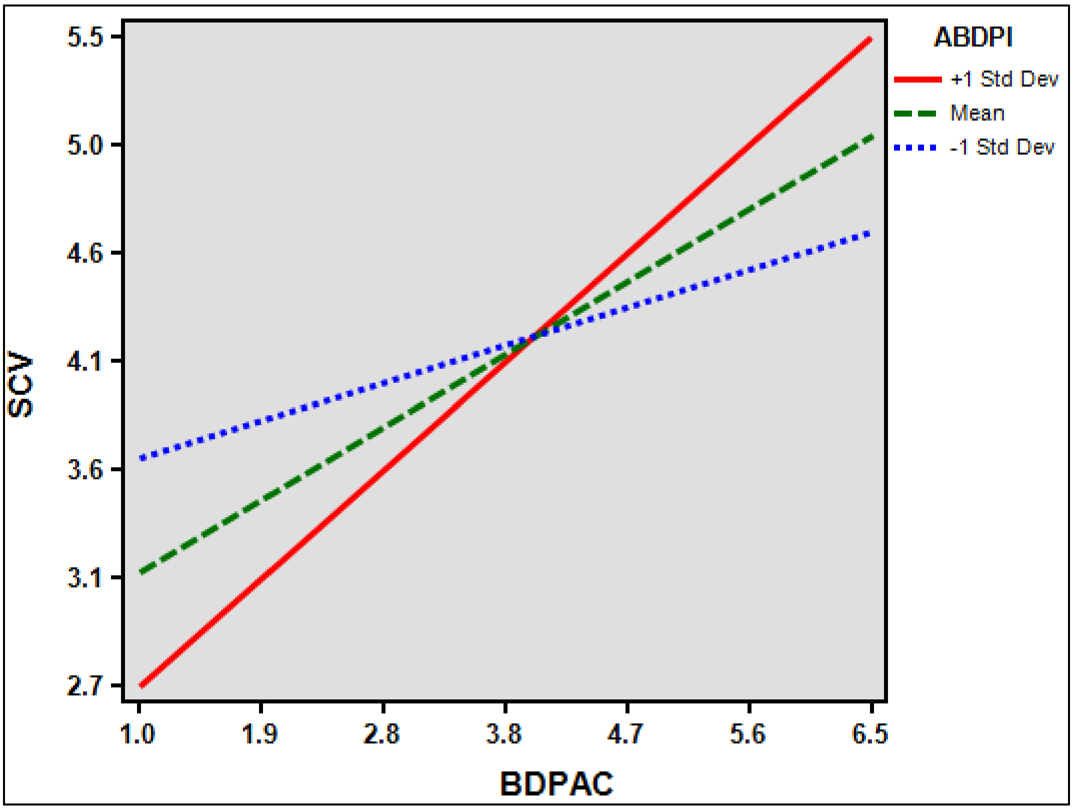

Fig. 4.The interaction of big data and predictive analytics capabilities (BDPAC) and alignment between BDPA strategy and BDPA initiatives (ABDPI) in predicting supply chain visibility (SCV)

We also conducted a robustness test (Kiefer et al., 2000; Brandon-Jones et al., 2014; De Luca et al., 2021) to see if there was a lagged effect of supply chain visibility (SCV) on community resilience (CRES) and resources resilience (RESRE). We measured SCV, CRES and RESRE, at time four (T4) by collecting additional data on CRES and RESRE, to test the effect of firms' supply chain resilience (SCRES). After one month, we obtained data from 48 employees of mining companies and 43 community members who reside in the worker colony close to the mines and mineral processing units. These samples were different from the initial samples. We found that the time-lagged perceived CRES and RESRE measures had a significant and positive correlation with employees' perceived CRES and RESRE in the original data collection (CRESr = 0.781; RESREr = 0.702).

Furthermore, the results of multiple regression analysis showed that SCV has a positive influence on lagged perceived CRES and RESRE performance (CRES-$\beta 1 = 0.308$, $p < 0.001$; RESRE-$\beta 2=0.207$, $p<0.001$). This provides further empirical validation of the measurement scales and supports our findings on the relationships among supply chain visibility, community resilience, and resource resilience. They suggest that community members working in the mines and mineral firms recognise the importance of community resilience, which, in turn, is significantly influenced by a firms' supply chain visibility. Alongside the finding that supply chain visibility also affects a firm's resource resilience, these results suggest that investing resources into building big data and predictive analytics capability may drive superior supply chain visibility performance.

6.3 Endogeneity test

An endogenous effect of CRES and RESRE on SCV could produce an inconsistent outcome. Hence, we performed a two-stage least squares regression analysis, embedded with instrumental variables (Scholten et al. 2014; Liu et al., 2016; Gligor, 2018; Prajogo et al., 2021). We measured "firm's preparedness" using the item: "we have implemented data-driven preparedness plan by translating strategic agreements into operational matters". This instrumental construct is related to a firm's SCV but not directly connected with CRES and RESRE. The results from regression analysis in the model 1 revealed that a firm's big data and predictive analytics capabilities (independent variable) has a positive and significant influence on SCV (mediating variable) (0.417 at $p < 0.01$). This supports the earlier findings of our research. In model 2, we saved and applied the predicted values of SCV. The estimation value of the effect of SCV (dependent variable) and RESRE (dependent variable) show significant and positive (0.286 at $p < 0.01$; 0.382 at $p < 0.01$).

We then performed the analysis of model 3, in order to examine the role of "firm's preparedness" in predicting SCV and the regression results showed that it has a significant and positive influence on SCV (0.173 at $p < 0.05$). Next, we saved the predicted values of SCV from model 3 and applied them in model 4. The results revealed that the firm's SCV significantly influences CRES (0.279 at $p < 0.01$) and RESRE (0.364 at $p < 0.01$). Finally, we compared the regression results of models 3 and 4, finding that the inclusion of the instrumental variable did not change the R^2 values in a significant amount of the two models (0.193 and 0.187, respectively). Overall, the results from the two-stage least squares regression analysis indicates no serious issues in the data relating to endogeneity.

7. Discussion

According to Jha et al. (2020), big data analytics skills improve the decision-making processes in the management of supply chains, with the flow of timely and accurate information crucial. Big data technologies allow managers to see how they can best utilize their available resources (Jha et al., 2020). Shamim et al. (2019) investigated the importance of big data-driven decision-making capabilities in business organizations utilizing dynamic capability view (DCV). Brandon-Jones et al. (2014) determined visibility in the supply chain is an important factor in reducing risk. Supply chain visibility enables managers to track product movement and identify any disruptions, in order to mitigate negative impacts of risk. SC visibility is enhanced by good network connections between actors and efficient and effective communication channels, which enables the flow of information. The speed, nature, and quality of information determine the efficiency of SC visibility. End-to-end visibility in supply chains enables transparency and offers accurate information to actors in the chain when it is needed. This all builds confidence amongst the different actors (Christopher & Lee, 2004). It is in this context that we explored the applications of big data in framing predictive analysis and enhancing SC visibility. Building on the literature and using our finding that there is a positive relationship between BDPAC and SC visibility, we theorise that big data enables a more efficient supply chain monitoring system, which improves SC visibility. Big data capability improves a company's ability to make the best use of its available resources. It improves the South African mining industry's dynamic capability, allowing them to adjust their strategies in response to diverse adverse weather conditions. The SC visibility is improved by an efficient and effective dynamic strategy.

Big data analytics enables in the improvement of supply chain management network architecture (Dolgui et al., 2020). As a consequence of disruptive technology, the supply chain dynamic needs to deal with both positive and negative changes. The supply chain's dynamic capability leads to efficient and effective supply chain visibility, which is essential for supply chain resilience management (Dolgui et al., 2020). Dubey et al. (2020) concluded that the ability to share information is a crucial aspect of SC visibility. However, SC visibility is dependent on information and shared data, being greatly influenced by information sharing and supply chain connectivity. The technology infrastructure, which is critical for information sharing among channel partners, determines SC visibility. The quality, speed, and character of the data determine the efficacy of data exchange. Torres et al. (2018) identified the linkage between business intelligence and analytics and firm performance by applying strategic management theory. They revealed that business intelligence and analytics improve an organization's dynamic capabilities.

Based on Torres et al. (2018), we analysed the connection between SC visibility and quick responses, particularly in the event of extreme weather. Businesses must raise awareness of the effects of extreme weather. Enterprises must establish long-term and trusting relationships with their suppliers to cope with the consequences of extreme weather (Kovács & Pató, 2014). To help with this process our results highlight the importance of BDPA for helping organizations to prepare for extreme weather conditions. The dynamic aspect of supply chain management is emphasized by big data predictive analysis, which has a substantial impact on SC visibility. Also, context is important, as demonstrated by our finding that BDPA strategy and initiatives have a high/low moderating effect on the path of BDPAC and SC visibility.

Due to disruptive extreme weather events, SC resilience becomes crucial for enterprises. Big data analytics can promote effective supply chain visibility and resilience (Wong et al., 2020). Wong et al. (2020) established a theoretical model to assess the impact of supply chain disruptions on the resilience of the supply chain. Linnenluecke et al. (2012) created a framework to better understand organizational adaptability, resilience, and environmental discontinuity in extreme weather situations. The framework can be used to guide management in minimizing the impacts of extreme weather conditions. The resource-based view enables the management to understand the value of investing in supply chain management, in order to improve resilience and robustness (Gupta & George, 2016). Brandon-Jones et al. (2014) determined that the process of establishing resilient supply chain management can be better understood using a resource-based approach. It allows supply chain management to understand when and how to build resilience to preserve a competitive edge. The resource-based view claims that combining strategic resources and capabilities can give a company a competitive advantage. Supply chain management resources are typically irreplaceable, scarce, valuable, and non-replaceable (Brandon-Jones et al., 2014). Suppliers are the most important aspect of supply chain complexity when it comes to determining the link between supply chain visibility and supply chain resilience and robustness. Using our finding that there is a positive relationship between SC visibility and community resilience, we broaden our understanding of the resources that need utilising, highlighting the critical role of stakeholders in the development of such SC resilience. Furthermore, the dynamic capability (supply chain visibility) helps the channel partners to develop community resilience which is an essential requirement for supply chain visibility.

Brandon-Jones et al. (2014) suggested that SC visibility is important in dealing with the complexities of supply chain management. However, SC visibility sees maximum returns to robustness and resilience when a supply chain is highly complex. The complexity within the supply chain increases when it moves towards dealing with a global network of suppliers. Resilience enables the management to respond quickly if any disruptions occur. Resilience enhances visibility in supply chain management (Brandon-Jones et al., 2014). Dubey et al. (2020) proposed a theoretical model to conceptualize information sharing and connectivity as a bundle of resources that improve SC visibility as a contingent capability to influence long-term performance. Contingent capability facilitates the bundling of resources, resulting in increased SC visibility and a positive impact on environmental and social performance (Dubey et al., 2020). Despoudi et al. (2021) used contingency theory to conclude that high levels of environmental turbulence lead to higher levels of uncertainty in supply chain management. Weather, economic, regulatory, market, competition, and political turbulence were identified as six factors of environmental turbulence; though individual factors that could impact on SC resilience were not considered. Resources resilience is necessary to optimize supply chain resources and improve supply chain network resilience. Our finding shows that there is a positive relationship between SC visibility and resource resilience which enables us to develop the theory further. To be specific, by positing that SC visibility is a dynamic capability, it can be used to improve resource resilience.

7.1 Theoretical implications

DCV is based on the idea that valuable, scarce, non-imitable, and non-substitutable resources can be combined to create higher-order capabilities, also known as DCs'. Although BDPA capabilities are valuable, they are not uncommon, unique, or non-interchangeable. Any company can invest money, train workers, and expand its BDPA skills. Furthermore, DCV does not identify which are DCs. Finally, DCV theory claims that if resources are available and strategy and objectives are aligned, a corporation can accomplish CA. DCs' (BDPA capabilities) enable sensing (SC visibility) abilities to capture new chances (build community resilience and resources resilience) and develop sustainability advantage, according to the current study findings.

7.2 Practical implications

Extreme weather occurrences are becoming more often, causing business uncertainty have created concerns about how quickly operational capabilities deteriorate and stop providing competitive advantages. Organizations are concerned about supply chain interruptions as a result of these extreme weather events and therefore, need to create DCs'. They need to develop BDPA capabilities to enhance visibility and further build resilience in order to transform the business into a competitive vigor. Nonetheless, managers are putting more emphasis on operational resilience, but they are ignoring resource and community resilience. Our findings offer mining companies in South Africa guidance on not only how to develop resilience for their supply chains but also, importantly, how to build the resilience of the communities affected by their operations and the resources required, for achieving sustainable development. We show that managers of mining operations need to exploit opportunities of the fourth industrial revolution, by building BDPA capabilities, in order to deal with extreme weather events. Managers need to understand that the antecedents of BDPA capabilities are technical skills, managerial skills, culture, and organizational learning. They have to develop and strengthen these elements when building their BDPA capabilities, which, once in place, will allow managers to focus on developing DC's to put in place risk mitigation plans, and other risk responses, so that the supply chain can deal with the shocks of future disasters caused by extreme weather events.

Managers must also develop effective BDPA driven strategies for quickly responding and recovering from the negative consequences of extreme weather events. It is important that managers align the BDPA strategies with BDPA initiatives, in order to enhance the firm's dynamic capabilities, which, in turn, will result in new competencies to deal with a changing environment. Lastly, those responsible for the operations of the mines and mineral processing plants must be socially responsible, and they should not be myopic in focusing only on the development of SC resilience. They should also aim to develop network resilience by considering the community and resources. Unless they think about developing SC network resilience, there will be a deterioration of social sustainability performance by firms in the sector, which will be severely detrimental to the well-being of future generations.

8. Conclusion, limitations and future research directions.

Our study explored the role of BDPA capabilities and dynamic capabilities (SC visibility) in developing the resilience of South African mining industries under extreme weather events.

Our research showed how BDPA capabilities are helpful in developing dynamic capabilities i.e., supply chain visibility, and it identified the importance of developing supply chain network resilience in the South African mining industries. We highlight that resource resilience and community resilience is vital for the sustainability of the mining industry, in response to changing climatic conditions.

Our study does have its limitations. Firstly, data were only collected from South Africa. In the future, we recommend extending the empirical study and collecting data from a multi-country perspective. Also, we focused on collecting data from the key actors in the supply chain and it would be useful to collect data from those directly affected by the actions of the supply chain, such as community members.

Other potential future research directions are as follows. First, it would be useful to investigate the effect of institutional pressures on critical tangible and intangible resources that are used in preparing, responding and recovering from extreme weather events, under the moderating effect of BDPA-driven culture, among mining companies. Another potentially fruitful avenue of future research is to examine the absorptive capacity and rate of innovation among mining companies. This could help explain how mining companies effectively respond to disasters caused by extreme weather events. In terms of disaster responses, an exploration of the behaviours of supply chain partners, i.e., collaborative or opportunistic, and how these influence the development and adoption of BDPA driven disaster management systems would be illuminating. Finally, future studies could investigate the ethical code of practices that could guide African mining companies, where BDPA-driven disaster management systems are put in place.

Appendix: See Table A1

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