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Unlocking supply chain agility and supply chain performance through the development of intangible supply chain analytical capabilities

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Unlocking supply chain agility and supply chain performance through the development of intangible supply chain analytical capabilities

Abstract

Purpose – Increasingly studies are reporting supply chain analytical capabilities as a key enabler of supply chain agility (SCAG) and supply chain performance (SCP). This study investigates the impact of environmental dynamism and competitive pressures in a supply chain analytics setting, and how intangible supply chain analytical capabilities (ISCAC) moderate the relationship between big data characteristics (BDC's) and SCAG in support of enhanced SCP.

Design/methodology/approach – The study draws on the literature on big data, supply chain analytical capabilities, and dynamic capability theory to empirically develop and test a supply chain analytical capabilities model in support of SCAG and SCP. ISCAC was the moderated construct and was tested using two sub-dimensions, supply chain organisational learning and supply chain data driven culture.

Findings – The results show that whilst environmental dynamism has a significant relationship on the three key BDC's, only the volume and velocity dimensions are significant in relation to competitive pressures. Furthermore, only the velocity element of BDC's has a significant positive impact on SCAG. In terms of moderation, the supply chain organisational learning dimension of ISCAC was shown to only moderate the velocity aspect of BDC's on SCAG, whereas for the supply chain data driven culture dimension of ISCAC, only the variety aspect was shown to moderate of BDC on SCAG. SCAG had a significant impact on SCP.

Originality/value – This study adds to the existing knowledge in the supply chain analytical capabilities domain by presenting a nuanced moderation model that includes external factors (environmental dynamism and competitive pressures), their relationships with BDC's and how ISCAC (namely, supply chain organisational learning and supply chain data driven culture) moderates and strengthens aspects of BDC's in support of SCAG and enhanced SCP.

Keywords: supply chain agility, big data analytics, intangible analytical capabilities, supply chain performance

1. Introduction

Supply chains are under increasing pressure with unprecedented global uncertainty due to volatile customer demands, rapidly changing technologies, global health pandemics, climate change, and extensive competition (Brintrup et al., 2020; Cadden et al., 2020a; Matthias et al., 2017). In this rapidly changing world, data has increasingly becoming a rich and valuable asset that has the potential to provide immense value to organisations and supply chains alike, if properly harnessed (Duan et al., 2020; Dubey et al., 2019a). Firms are increasingly understanding the importance of big data analytics (BDA) in supply chains, known from here as supply chain analytics, to respond to the external environment and competitive pressures.

The supply chain analytics approach is widely accepted as a composite term which includes the big data and the analytics perspective and is defined as "*data sets whose size is beyond the ability of typical database software tools to capture, store, manage and analyse*" supply chain data (Hofmann, 2017: p.5109). The analytics perspective has emerged from using the huge volume and variety of data available to generate holistic and accurate information to support management decision making. The application of advanced analytical techniques includes prescriptive and predictive analytics applications to uncover hidden customer patterns, trends, and correlations in the pursuit of competitive advantage (Dubey et al, 2019a; Gupta and George, 2016; Maheshwari et al, 2021; Wamba et al, 2019).

The three key big data characteristics (BDC's), volume, variety, and velocity, underpin the BDA value creation process, and these are central tenets of supply chain analytics studies (McAfee et al., 2012; Hofman et al, 2017). Volume includes all data that is available throughout the supply chain, irrespective of where it is collected. Variety refers to the types of data that is available in the supply chain, including forecasting information and customer demand changes, as well as new data sources, such as RFID or web-based data (Hofmann, 2017). Velocity refers to the speed at which information can be processed in the supply chain (Wamba et al, 2019; Maheshwari et al, 2021; Talwar et al, 2021).

The potential of supply chain analytics implementation is immense as it involves combining resources, enhanced planning and forecasting, coordination of systems, and increased data sharing, which makes the potential benefits of reduced costs, improved service levels and reduced lead times difficult to achieve (Duan et al., 2020; Dubey et al., 2019a; Kamble and Gunasekaran, 2020; Lee; 2018). Despite some firms implementing BDA successfully in their supply chains (Nguyen et al., 2018, Wang et al., 2016), achieving supply chain agility (SCAG) and improving supply chain performance (SCP) with supply chain analytics is a much more complex process than first assumed (Ghasemaghaei, 2020; Jha et al., 2020).

Scholars investigating supply chain analytics broadly agree that there are three main categories of supply chain analytics resources that are required to successfully create supply chain analytical capabilities (SCAC) in support of SCAG and SCP (Maheshwari et al, 2021; Tiwari et a, 2018). In supply chain analytical capability model development, scholars have consistently referred to three well-recognised seminal big data resources (BDR's), defined by Gupta and George, (2016) in their organisational big data analytical capability creation. These include tangible resources (for example, investing in BDA technologies, such as Hadoop), human resources (such as management and technical capability development), and intangible resources (such as organisational learning and a data-driven cultural capability development). For example, Wamba and Akter's (2019) SCAC typologies of management, talent and technology was underpinned by Gupta and George's (2016) work, and Cadden et al. (2020) also gave significant attention to this seminal work in their development of an artificial intelligence (AI) focused SCAC model of technology enablers, business enablers and cultural enablers.

However, limited attention has been given to the nuanced role of intangible supply chain analytics capabilities (ISCAC) and how they moderate the relationship in a big data environment in support of SCAG and SCP. Some early work in this area has demonstrated the promise of ISCAC in achieving competitive advantage and provides a useful platform for this study. For example, Cadden et al. (2020a; 2020b) reported the importance of socialisation mechanisms in developing a high SCP culture when implementing new practices. A data-focused supply chain culture can improve information flows and communication between partners, resulting in a more agile and integrated supply chain (Gupta and George, 2016; Yu et al., 2021). However, high performance supply chain cultures do not just emerge, they must be nurtured via a process of learning between supply chain participants (Cadden et al., 2020a; Cadden et al., 2020b; Cousins et al., 2006).

The tangible and human resources in themselves may be easily replicated or developed. For example, where a firm has financial resources, it can purchase a range of tangible resources such as Hadoop, Spark, RapidMiner, Apache Storm or Cloudera, and can also 'buy in' or headhunt technical or management 'human' resources. However, intangible resources capabilities such as information and knowledge created over time via a data driven learning culture are more difficult to replicate. It is unsurprising that scholars have failed to consider intangible resources when attempting to build SCAC as they are the most difficult set of supply chain analytical resources to identify and analyse (Brinch, 2018; Cadden et al, 2020; Gupta et al, 2019; Mikalef et al, 2019). The study adopts a dynamic capability theory (DCT) lens to investigate how firms engage and respond to turbulent and competitive environments to build a set of higher order intangible supply chain capabilities to create supply chain agility and performance. This study attempts to address the research gap through the following research aim and three research questions:

Research Aim: How does the development of ISCAC impact SCAG and SCP in turbulent environments?

Research Questions:

1. How does the external environment (competitive pressures (CP) and environmental dynamism (ED)) influence BDC's (volume, variety and velocity)?
2. What is the impact of BDC's on SCAG and SCP?
3. Does the development of ISCAC moderate the relationship between BDC's and SCAG and SCP?

This paper makes a number of contributions. Firstly, it applies dynamic capability theory (DCT) to scan the external environment and its relationship with BDC's in building a moderated ISCAC model in support of SCAG and SCP. Secondly, this study deconstructs BDC's into sub-dimensions (volume, variety, and velocity) to assess the role of each characteristic in achieving SCAG and SCP. Studies to date have tended to refer to BDA, without exploring the nuanced insights provided in this paper. Thirdly, two key ISCAC sub-dimensions, namely supply chain organisational learning (SCOL) and supply chain data driven culture (SCDDC) are developed offering a way forward to measure, build and embed these capabilities alongside the more measurable tangible and human SCAC resources.

This paper is structured as follows. A review of key literature related to BDA, SCAG and DCT is presented. The rationale for development of the hypotheses is outlined, followed by the research methodology. Then the results and analysis section are provided. Finally, a discussion of key findings, implications, and future research are presented.

2. Literature Review and Hypothesis Development

2.1 Theoretical Support

Our study is underpinned by DCT, which represents a company's ability to integrate, build, and reconfigure internal and external competences to respond to changes in business environment (Teece, 2007). Organisations can employ these higher-level capabilities as antecedents to organisational and strategic routines, by which managers alter their resource base to generate new value-creating strategies (Pisano, 1994). As an organisation develops its learning capability and integrates it into its decision-making process, it is better able to sense market changes and respond more rapidly.

Drawing on DCT, supply chain analytics can be conceptualised as a unique capability that improves SCAG to allow managers to reconfigure their resources, develop a better understanding of the market situation, and thus capitalise on environmental changes (Teece, 2007). As firm boundaries have become increasingly blurred in supply chains, the difficulty of maintaining a competitive advantage through firm-centric dynamic capabilities has increased. Therefore, it is important that multiple partners jointly develop and use dynamic supply chain capabilities to refresh and update their existing capabilities or form entirely new ones (Mikalef et al., 2020).

Supply chain analytics develops the integrative capabilities of the firm through communication and coordination of supply chain activities (Helfat and Raubitschek, 2018). These integrative capabilities facilitate shared information across supply chain actors, supporting better joint decision making and creating economies of scope across the supply chain. SCAG requires a rapid and effective reconfiguration of key resources so firms can meet changing customer demands and improve their competitiveness (Van Hoek et al., 2001, Blome et al., 2013). The integrative nature of BDA enhances the dynamic capabilities of the firm, by stimulating change internally to address external changes in the business environment, whilst reconfiguring their processes to improve operational performance (Wamba et al., 2020; Rojo et al., 2018).

2.2 Environmental Dynamism

An important aspect of DCT is ED (Girod and Whittington, 2017), which is characterised by changes in products/services, technology, and customer preferences, and it impacts a company's resource allocation strategy (Rojo et al., 2018). Prior research has highlighted that companies operating in volatile environments need to build dynamic capabilities to respond with innovative solutions to problems that are encountered to adapt to and satisfy customer requirements (Aslam et al., 2018, Girod and Whittington, 2017, Helfat and Raubitschek, 2018). It can be more difficult to attain superior performance in highly dynamic environments, and therefore timely information is required to make the right decisions.

In a turbulent environment, firms must capture and analyse large amounts of data to reveal new and unique insights into customers and suppliers which can give them an edge over their competitors (Johnson et al., 2017). Collecting data in a variety of formats and types, enables mangers to anticipate changing customer and supplier needs and take advantage of undiscovered market opportunities. The speed at which they convert this information into new product and service opportunities can be a competitive differentiator when dealing with uncertainties upstream and downstream in the supply chain (Matthias et al., 2017, Kamble and Gunasekaran, 2020). Given that ED plays an important role in developing dynamic capabilities, we argue that it is an important influence on the BDA characteristics. Thus, we posit:

H1 (a-c): ED is positively related to BDC's: volume, variety and velocity.

2.3 Competitive Pressures

Firms have turned to technology and integrated supply chain analytics in order to react to the opportunities and challenges brought about by globalisation and rapid technological change (Aslam et al., 2020). The impact of CP on supply chain analytics adoption has received limited attention in the literature (Chen et al., 2015). Chen et al. (2015) has found that external CP can positively affect the degree to which firms adopt supply chain analytics is likely influence firms to engage in similar practices. The ability to obtain large and diverse amounts of data from customers and suppliers, can enable a firm to reconfigure its operations and respond to CP in advance of them taking place (Johnson et al., 2017).

The power of prediction of such tools in supply chain analytics enables companies to pre-empt changes in the supply chain (Kamble and Gunasekaran, 2020, Mikalef et al., 2020). Increased CP in many markets has stimulated firms to invest in information technologies associated with supply chain analytics (Kamble and Gunasekaran, 2020). The successful adoption of supply chain analytics by firms is likely to trigger imitative practices being adopted by competitors. As a result, firms are likely to employ supply chain analytics tools to enable them to quickly react to CP to gain competitive advantage. Therefore, we posit that:

H2 (a-c): CP are positively related to the BDC's: volume, variety and velocity.

2.4 Big Data Analytics and Supply Chain Agility

Supply chain analytics can have a significant impact on SCAG by allowing firms to achieve competitive advantage through enhancing decision-making and increasing value-adding activities (Zhan and Tan 2020). Supply chain analytics also offers opportunities to collaborate with supply chain partners in order to respond to market changes in a rapid manner, thus allowing firms to enhance their competitive position (Blome et al*.*, 2013,Dubey et al*.*, 2018). Supply chain analytics have transformed businesses by serving as a cross-functional capability that has allowed managers to align strategies and make decisions in line with market demands (Zhan and Tan, 2020; Pisano et al. 2015). However, adhering to the logic of DCT firms need to adopt a proactive stance to reconfigure their resources and to respond to the opportunities that supply chain analytics offers (Lee 2004, Fayezi et al., 2017).

SCAG includes two dimensions: *change expectancy*, which refers to an organisation's ability to sense change and the effects of this change; and *change response*, which is based on the way in which an organisation responds to change (Fayezi et al., 2017; Fayezi et al., 2015). Supply chain analytics extracts useful information from massive data sets to identify useful insights and enable more targeted business decisions, in order to allow companies to excel in the current fast-paced and ever-changing market environment (Wang et al., 2016, Nguyen et al., 2018). SCAG involves the rapid and successful reconfiguration of key resources so firms can meet changing customers' demands (Van Hoek et al., 2001, Blome *et al.*, 2013).

Employing these characteristics can bring valuable insights into how the granularity of supply chain analytics enables dynamic capabilities and helps companies understand how to better leverage supply chain analytics in order to enhance their SCAG. For example, firms can use big data volume to explore the market and better understand trends, which will lead to an expansion of their knowledge base. By capturing varied forms of data through big data variety tools, rich and holistic supply chain information will be generated. Therefore, based on the arguments above, we posit:

H3 (a-c): BDC's: volume, variety and velocity, are positively related to SCAG

2.5 The Moderating Role of Intangible Supply Chain Big Data Analytical Capabilities

2.5.1 Big Data Resources (BDR's) and Big Data Analytical Capabilities (BDAC's)

The literature on big data has suggested three categories of organisational BDR's that are required to create BDAC's in support of organisational agility and performance improvements namely, tangible, human and intangible resources (Akhtar et al, 2018; Gupta and George, 2016). Firstly, tangible resources include investments in the latest technologies, such as Hadoop, No SQL, RFID, Blockchain and capturing and mining internal and external data.

Secondly, human BDR's include managerial and technical capabilities (Oh and Pinsonneault, 2007; Teece, 2014; Wamba et al, 2019). Big data managerial capabilities include firm knowledge, analytical acumen, trust, leadership skills and relationship skills that combine to provide information and insights for strategic decision-making. Although firms can acquire the analytical acumen element through recruiting new staff, this approach is inferior to the soft skills elements required to create bonds and knowledge across the organisation (Gupta and George, 2016). Big data technical skills are tangible BDR's that embrace the latest technologies in the field, such as machine learning, AI, prescriptive and predictive analytics.

Thirdly, there are intangible BDR's that include culture and organisational learning capabilities, and these are deemed the most important aspects of dynamic capabilities (Teece, 2014). Whilst ordinary capabilities, such as technical efficiency, operational processes and governance of the firm are in themselves valuable, it is the higher order dynamic capabilities, such as having the correct culture and being a learning organisation that ultimately shapes the ordinary capabilities and provides the agility, responsiveness, and innovation that firms require to be successful (Teece, 2014).

To harness the value of big data in the SC, these three categories of BDR's need to work in harmony to create BDAC's in support of competitive advantage. For example, an organisation with high levels of learning capabilities and a data driven culture will heavily rely on data derived from tangible and human resources to be able to capture, build, renew and reconfigure resources both within and outside into the supply chain (Zollo and Winter, 2002). However, many firms have not been achieving the anticipated benefits when attempting to develop BDAC's, and it has been suggested that this is due to firms focusing solely on tangible and human resources as a vehicle towards building BDAC'S, and largely ignoring the intangible resources (Gupta et al, 2016; Mikalef et al, 2019; Teece et al, 2015).

2.5.2 Intangible Supply Chain Analytical Capabilities

The application of supply chain analytics as an enabler to resolve a myriad of supply chain issues, from demand and supply management, coordination, and control issues have been receiving increasing attention (Brinch, 2018; Kache and Seuring, 2017; Wamba and Akter, 2019). Kache and Seuring (2017) employed the Delphi research technique and highlighted a range of opportunities from applying supply chain analytics, including supply chain visibility, demand management, risk management, data integration and traceability. Moreover, Wamba and Akter (2019) developed a SCAC model that comprised management, technology and talent capabilities, and found that SCAC's have an impact on supply chain agility and firm performance. Both studies strongly acknowledged the importance of ISCAC, namely supply chain organisational learning and a supply chain data driven culture as key capabilities required to achieve supply chain success.

2.5.3 Supply Chain Intangible Capabilities: Supply Chain Organisational Learning dimension (SCOL)

SCOL is well recognised as an important intangible capability aspect of SCAC creation (Wamba and Atker, 2019). SCOL is the level of interaction between, and communication of, various actors within and between the firms, which leads to the building of personal familiarity, improved communication, and problem solving (Cousins et al, 2008; Gupta and Govindarajan, 2000). In the organisational behaviour literature, organisational learning is often referred to as 'learning the ropes or socialisation' (Schein, 1996). Organisational learning is an inductive process and well understood as an essential antecedent to moulding person-fit and culture (Van Maanen and Schein, 1979). More recently, organisational learning capabilities along with organisational culture in a supply chain context have been gaining interest in the literature (Cadden et al., 2015; 2020). For example, Cadden et al. (2020b) demonstrated how informal and formal SCOL capabilities led to increased agility and performance outcomes for all supply chain partners.

Although authors have been highlighting the importance of SCOL in supply chain big data studies (Wamba and Akter, 2019), the role of SCOL has not yet been considered in the context of developing SCAC. Yet, SCOL encourages two-way information exchange, builds, and establishes relationship trust, and enables transparency of information and cost sharing in knowledge-based environments (Lawson et al., 2009; Brinch, 2018).

In this study SCOL capabilities are contextualised, developed, and measured trough a big data lens. The scales were adopted and developed from literature and supported primarily by the work of Cadden et al, (2020a); Cousins et al (2006); Gupta and George (2016) and Wamba and Akter, 2019). Measures include assessing how supply chain workshops and supply chain cross-functional teams enhance the SCOL capabilities of each partner to search, assimilate, analyse, and apply data analytics; and how effective supply chain reporting structures and supply chain data analytics communication mechanisms enhance the SCOL capabilities and application of data analytics by each partner. Therefore, we postulate:

H4: SCOL capabilities moderate the relationship between BDC's (volume, variety and velocity) and SCAG.

2.5.4 Supply Chain Intangible Capabilities: Supply Chain Data Driven Culture dimension (SCDDC)

Organisational culture has been variously described: (1) as language (Srivastava et al. 2018); (2) as emotion (Barsade and O'Neill 2014); (3) as ways of thinking (Harris 1994); (4) as organizational practices (Cadden, Marshall, and Cao 2013; Hofstede et al. 1990). Culture has become an important element of effective supply chain management (Cadden et al., 2020a). It has been found that an effective cultural fit between supply chain partners can support joint inventory management (Cadilhon et al., 2005), reduce quality and delivery problems (Pressey et al., 2007), and promote collaborative relationships between partners (Inemek and Matthyssens, 2013).

Organisational culture is also recognised as an important driver of achieving the benefits that digital technologies offer in supply chains (Gupta and George, 2016). Shamim et al. (2019) have argued that organizational culture can enhance a firm's ability to benefit from big data. A data-driven culture refers to the extent to which organisational members make decisions based on insights derived from data analysis (McAfee et al., 2012). Organisations with an effective data-driven culture can use data in an innovative way and develop supply chain processes that make it more straightforward to acquire the necessary information to manage their supply chains.

Wamba and Akter (2019) have investigated the role of supply chain analytics capabilities and agility in data rich environments. The study reported the importance of supply chain agility as an important mediator between supply chain analytics capabilities and supply chain agility. The study referred throughout to the importance of a big data driven culture in supporting SCAG. Further, Dubey et al., (2019b) highlighted the moderating role of organisational culture in big data environments in support of increased collaborative performance. Cadden et al. (2020a) reported that AI supply chain cultural enablers, especially a culture which is data driven and possesses high levels of two-way information sharing and openness along the supply chain, is key to supply chain agility and performance success. Therefore, we postulate:

H5: A SCDDC moderates the relationship between BDC's (volume, variety and velocity) and SCAG.

2.6 Supply chain agility and supply chain performance

Supply chain performance is an essential yet often overlooked measure in supply chain research, often due to the difficulty of operationalising a construct that goes beyond the boundaries of the firm (Cadden et al, 2020a). Yet, having the capabilities to measure and enhance SCP is an essential component of overall company success (Eckstein et al. (2015). Although, financial indicators, such as return on investment always attract attention (Cadden et al., 2020) they lack the integration and technical elements required for supply chain success (Cadden et al., 2015; Gunasekaran et al., 2004). The SCP construct needs to go beyond a financial measure to include other operational measures such as flexibility and delivery performance (Cadden et al., 2020; Gunasekaran et al., 2004; Zhan and Tan, 2020).

The link between supply chain agility and performance is well recognised in the current literature (Wamba and Atker, 2019; Eckstein et al., 2015; Gligor et al. 2016; Lee, 2002), and this is particularly evident in the areas of cost reduction and operational performance. Eckstein et al. (2015) have found that supply chain agility has allowed organisations to better balance supply and demand, which can reduce inventory and transportation costs. Gligor et al. (2016) have argued that supply chain agility can foster operating routines modification, enable organisational resource re-configuration and improve organizational sensing ability. For example, switching suppliers, identifying new suppliers and markets, or collaborating with suppliers to design new products can allow organisations to further reduce costs (Lee, 2002; Eckstein et al., 2015). Indeed, Wamba and Atker (2019) have argued that supply chain agility facilitates the development of organisational capabilities that enhance SCP which in turn contribute to sustained competitive advantage. Therefore, we postulate:

H6: SCAG is positively related to SCP.

TAKE IN FIGURE 1

3.0 Research Methodology

3.1 Sample and Data Collection

A survey was used to collect data from a random sample of senior and middle managers of UK manufacturers. They were deemed highly likely to be involved in both business analytics and supply chain management, based on a key informant approach (Bagozzi et al., 1991).

The survey covered: (a) respondent and company profile, (b) antecedents to the use of supply chain analytics, (c) the use of supply chain analytics, and (d) supply chain agility and SCP. The survey was scrutinized by subject experts and tested with five academic experts to ensure that there were no problems with the wording or measurements. This resulted in several questions being modified, as well as formatting and presentation modifications. The survey questionnaire was then distributed to managers electronically through an online survey tool.

Similar to other UK studies investigating supply chain relationships (Cadden et al., 2020), a national database of manufacturing industry companies, filtered by greater than 100 employees, was examined. The initial data resulted in 3228 companies. A random sample of 1000 companies were selected, and the survey forwarded based on job role (MD, CEO, IT Director, Supply Chain Director, Operations Director, Logistics Director or equivalent). Dillman's Total Design Method (1978) was utilised, i.e., the first survey included a personalized cover letter outlining the purpose and importance of the study along with reassurance of anonymity, and a specific instruction guide. Further, a management report summary of the study was offered to respondents. One week later a reminder email was forwarded, followed by reissuing of 3 and 7 weeks after initial contact for non-respondents. In total, 545 emails opened, we received 304 responses and 201 were usable responses, which represent a 36.8% response rate which was deemed appropriate, compared with other similar studies in the field (Malhotra and Grover, 1998; Wiengarten et al., 2013).

3.2 Respondents Profile

The respondent's profile highlights that 86% had more than 10 years industry experience. Of all participants, 15% were CEO or equivalent; 26% were logistics/supply chain directors; 14% were operations directors; and 35% were CIO/IT directors. In relation to the number of firm employees, 21.4% had 500 to 1000, 10% had over 1000, while 68% were under 500, which reflects SMEs being the predominant category in UK manufacturing. This correlates with the firm sales volume whereby a diverse spread was studied, 57%under £50mn, 23% between £50 to £100mn, and 15% between £100 to £250mn.

3.3 Common method and non-respondent bias

Following the recommendations of Tehseen et al. (2017), we employed several steps to minimize common method bias. First, we used three procedural remedies to improve scale items through: (a) defining them clearly and keeping the questions simple and specific, (b) labelling every point on the response scale to reduce item ambiguity (Krosnick, 1999), and (c) using positively and negatively worded measures to control for acquiescence and dis-acquiescence biases (Podsakoff et al., 2012). Second, we carried out two statistical approaches, including the partialling out of general factors suggested by Podsakoff and Todor (1985) and the partial correlation procedure (Lindell & Whitney, 2001) using manager's tenure as a marker variable, to assess common method bias. All the results indicated that there was no serious issue of common method bias in this study.

The presence of non-response bias was evaluated by conducting a t-test to compare early (n=102) and late (n=99) respondents on all measures. The t-test results did not find significant differences between the two respondent groups, suggesting an absence of non-response bias.

3.4 Measures

Scales for measuring the constructs were adopted from the pre-existing measurements present in the literature. All scales were measured by seven-point Likert scale (1=strongly disagree, 7=strongly agree for all except ED which was 1=extremely low, to 7, extremely high). ED was considered as a unidimensional construct, measured by using three items (Rojo et al., 2018; Ward and Duray, 2000). Competitive pressure was also considered as a unidimensional construct**,** measured by using four items (Chen et al., 2015, Liang et al., 2007); Big data analytics (BDA) has three dimensions, namely, Volume (VOL), Variety (VAR) and Velocity (VEL). Each dimension was measured by using four items (Johnson et al., 2017). The scale for measuring SCOL was informed from work of Cadden et al, (2020); Cousins et al., (2008); Gupta and George, (2016). SCOL was measured by four items; these items were developed from previous supply chain learning capabilities and extended to include big data analytical elements as per the central objectives of the study. SCDDC was informed using four items developed and extended from Gupta and George (2016). Supply chain agility (SCAG) was considered as a unidimensional construct, measured by using five items (Blome et al., 2013). SCP was measured using four items adopted from prior research (Cousins et al, 2008; Cadden et al, 2020b). Details of scales are given in Appendix 1.

3.5 Evaluation of the Measurement Model

In order to avoid measurement model misspecification, a confirmatory tetrad analysis (CTA-PLS) was conducted based on Gudergan et al. (2008) and Hair et al. (2013), which confirmed that the measurement model was a reflective model. The model was then evaluated and validated by considering the internal consistency (composite reliability), indicator reliability, convergent and discriminant validity (Hair et al., 2014). The scores of both composite reliability (CR) and Cronbach's α, summarised in Table 1, indicated that all constructs met the recommended threshold value of 0.7. Indicator reliability was satisfactory as all factor loadings were greater than 0.70 and each indicator's variance was above 0.50. Discriminant validity was satisfactory based on two tests: first, the Fornell-Larcker criterion, as shown in Table 2, was met as the square root of AVE value for each construct was greater than the correlation of the construct with any other construct analysed (Hair et al., 2013). Second, each reflective indicator loaded highest on the construct it was associated with.

TAKE IN TABLE 1

TAKE IN TABLE 2

The research model's predictive power was assessed by the amount of variance attributed to the latent variables (i.e., R^2) as shown in Figure 2. The R^2 values indicated that the full model explained 21% in SCP, 42% of the variance in SCAG, 38% in volume (VOL), 50% in variety (VAR), and 60% in velocity (VEL). According to Wetzels *et al.* (2009), the effect size suggested for R^2 in IT-related research is small=0.1, medium=0.25, and large=0.36. Thus, while SCAG's effect size is close to medium, the effect sizes of other variables were large.

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3.6 Hypotheses Testing and Moderation Analysis

Table 3 shows the results of hypothesis testing. H1 suggests that H2 has a significant positive relationship between ED to VOL (H1a), VAR (H1b), and VEL (H1c), and all 3 BDC's are supported; as ED has an effect of 0.42 ($p<0.001$) on VOL, 0.58 ($p<0.001$) on VAR, and 0.52 ($p<0.0001$) on VEL. H2 tests the relationship between CP to VOL (H2a), VAR (H2b), and VEL (H2c). H2a and H2c are supported since the effects of CP on VOL is 0.23 ($p<0.05$) and on VEL is 0.60 ($p<0.01$); However, H2b is rejected since the effects of CP on VAR is not significant. H3 hypothesizes that SA is positively affected by VOL (H3a), VAR (H3b), and VEL (H3c). Only H3c is supported as VEL has an effect of 0.49 ($p<0.01$) on SCAG. However, H3a and H3b are rejected as both VOL and VAR have no statistically significant effects on SCAG.

TAKE IN TABLE 3

H4 and H5 were moderated tests. The analysis was based on bootstrapping (5,000 samples) (Hair et al., 2014; Hayes, 2009). H4 postulates that SCOL moderates the relationship between VOL and SA (H4a), VAR and SA (H4b), and VEL and SCAG (H4c). Only H4c is supported as SCOL has an effect of 0.44 ($p<0.01$) on VEL. However, H4a and H4b are rejected as SCOL has no statistically significant effects on SA when moderated by VOL and VAR, respectively. H5 postulates that SCDDC moderates the relationship between VOL and SA (H5a), VAR and SA (H5b), and VEL and SA (H5c). Only H5b is confirmed as SCDDC moderates the link between VAR and SA, with the moderating effect of 0.52 ($p<0.01$) The moderating effects are represented in Figures 3 and 4. However, the rest of the moderating effects were rejected. H6 assumes Supply chain agility (SCAG) positively affect sustainable competitive advantage (SCAG), which is supported as SCAG has an effect of 0.25 ($p<0.01$) on SCP.

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4.0 Research Findings and Discussion

This study sought to explore the impact of BDA on SCAG by employing DCT. The study explores the effects of the external environment on BDC's, the sensing and response aspects of dynamic capabilities, and also explores the reconfiguration aspects (Teece 2007; Conboy et al., 2020) namely, the role of ISCACs such as SCOL and SCDDC in terms of enhancing SCAG (Gupta et al, 2016). In terms of the initial sensing aspects, this involved examining the effects of external environmental conditions such as ED and CP on the characteristics of big data (Jha et al., 2020; Wamba et al, 2020). In relation to the reconfiguration aspects of dynamic capabilities, this involved creating a supply chain learning (SCOL) and data-driven culture (SCDDC) that enables higher-order big data capabilities which can enhance SCAG (Conboy et al, 2020).

It is argued that these ISCACs may form co-specialized assets alongside big data to enhance SCAG and SCP (Teece, 2007; Conboy et al, 2020), and this could ultimately create higher-order capabilities (Winter et al, 2003; Teece, 2007). For example, SCOL and SCDDC could lead to greater supply chain synchronization and integration required for SCAG and foster the use of more advanced big data approaches such as predictive, prescriptive and real-time BDA applications (Securing and Kache, 2017). These big data techniques are quite advanced and require intangible SCOL practices that cannot be implemented using first order capabilities such as tangible IT related BDR's (Dubey and Gunasekaran, 2015; Dubey et al., 2019).

ISCACs have been underrepresented in existing big data-SCAG models or supply chain frameworks (Brinch et al., 2018; Dubey et al, 2019b; Wamba and Akter, 2019).

In relation to (H1a-c), which explored the impact of ED on three characteristics of big data, the results appear to show that in turbulent environments, characterized by high degrees of variability and changing customer tastes, ED is linked to all three facets of big data, which in turn form the firms' sensing (volume and velocity) and search (variety) dynamic capabilities (Teece, 2007; Mikalef et al., 2019). This finding extends existing research linking ED to BDA, which only found partial support for such a relationship (Wamba et al., 2020). Moreover, the results respond to calls for additional insights in a supply chain analytics context by segregating big data into separate characteristics, with the results suggesting that the scale, scope and velocity of big data is essential for firms operating in turbulent environments (Dubey et al., 2019a; Wamba et al, 2020).

In relation to H1a, there is a positive link between ED and big data volume (0.42***). It can be argued that in turbulent environments, firms are under pressure to analyze an extensive history of data, not only to help understand the environment, but also to identify patterns in the data which can be later used to facilitate forecasting in uncertain settings sharing the logic of sensing dynamic capabilities (Pandza and Thorpe, 2009; Yu et al., 2019; Brintrup et al., 2020).

In relation to H1b, there is a positive relationship between ED and variety (0.58***). It is argued that in turbulent environments, changing customer tastes and the need for new products requires both flexibility and exploration (Aslam et al., 2018; Dubey et al., 2019b). This observation aligns with DCT, particularly in relation to creative search capabilities (Pandza and Thorpe, 2009). For example, in relation to data variety, data may be acquired from many different sources in the supply chain to facilitate innovation and visibility in dynamic environments (Teece, 2007; Pandza and Thorpe, 2009). It could be argued that access to various sources of data is crucial in turbulent environments, as ED forces organisations to assimilate and use new information from an array of internal and external sources, create new product configurations and move readily to new markets (Teece, 2007; Conboy et al, 2020). The idea is to facilitate greater supply chain visibility and to capture new opportunities and innovations, either incremental or radical, needed for changing customer demand (Aslam et al., 2018; Dubey et al., 2018; Mikalef et al., 2019).

Finally, the results of H1c demonstrate that ED is positively related to data velocity (0.52***). This suggests that swiftness in terms of accessing real-time data to facilitate rapid customisation, greater supply chain responsiveness, and the introduction new products, is crucial for adapting and responding to dynamic and ever-changing environments. In other words, velocity is linked to the response aspect of DCT and SCAG, due to the need to quickly sense and react to environmental threats (Teece, 2007; Pandza and Thorpe, 2009; Mikalef et al., 2019). This aligns with the findings of Hofmann, (2017) who found that when it comes to reducing the bullwhip effect in the supply chain, data velocity, as opposed to data volume and variety, was the most critical "lever" for mitigating demand shocks and the bullwhip effect. Therefore, in the context of this research, it can be argued that ED is positively related to data velocity, because it plays a key role in mobilizing BDA for real-time decision making and forecasting, which in turn underpins seizing and response capabilities (Dubey et al., 2019b; Conboy et al., 2020).

In relation to H2(a-c), the results highlight that competitive pressures are significantly related to data velocity (H2c) (0.30**), while also positively related to data volume (H2a) (0.23*).

Conversely, CP were not found to be related to data variety (H2b). The positive results are related to sensing dynamic capabilities, as opposed to creative search dynamic capabilities (see Pandza and Thorpe, 2009). In this case, a possible explanation for the positive linkages between CP and volume and velocity is that in highly competitive environments many firms may seek a first mover advantage in terms of products, process and services (Lee, 2004; Vázquez-Bustelo et al., 2007). This is enabled by the velocity of data, which can improve responsiveness and reduce lead-times, ultimately enhancing customer value in competitive environments (Hofmann, 2017; Dubey et al., 2019b).

Conversely, collecting a diversity of data from different sources (variety) may be time consuming particularly in competitive settings and therefore may be more suited to stable and complex environments (Siggelkow and Rivkin, 2005). The lack of relationship between CPs and data variety represents an important contribution to the literature, as previous studies have not empirically considered how CPs are related to the types of big data collected (Dubey et al 2019c; Jha et al., 2020).

Lastly, CPs were shown to be related positively to data volume. It can be argued that firms may collect a large amount of historical data to analyze customer demand patterns (Hofmann et al., 2017; Brintrup et al., 2020). Conversely, it is also possible that data volume is positively linked to BDA at this stage because firms are pressured by rivals into blindly collecting a large volume of data, without considering the quality of such data (Richey et al., 2016). This is consistent with institutional theory (Myer and Rowan, 1974) and the effects of isomorphic pressures (Dimaggio and Powell, 1983), thus raising new implications for the rationale behind the adoption of big data in SCs. (Dubey et al., 2019c; Jha et al., 2020)

Hypotheses H3(a-c), consider the seizing aspects of dynamic capabilities and how the characteristics of big data can be leveraged to enhance SCAG. The results show that data volume and variety were not linked to SCAG, while big data velocity was found to have a significant relationship with SCAG (0.43**). This finding aligns with the results of Hofmann (2017) and Brintrup et al. (2020), which assert that only data velocity is linked to reducing the bullwhip effect and predicting supplier disruptions and late orders. The tacit understanding is that volume and variety do not facilitate real-time data needed to quickly respond to demand shocks (Hofmann, 2017). Moreover, Conboy et al., (2020) argue that the ability to mobilise BDR's to facilitate decision-making and address new opportunities, represents an important seizing dynamic capability in the realm of big data. In line with DCT, data velocity enables the dynamic capability response capability by facilitating real-time decision-making to enable SCAG (Teece, 2007).

Hypotheses H4(a-c) consider the moderating role of SCOL to help understand the relationship between BDA and SCAG (Cadden et al., 2020b). More specifically, fostering a supply chain learning climate can constitute an important co-specialised asset (Teece, 2007), giving supply chain members the expertise to implement higher-order BDA capabilities i.e., predictive, prescriptive, and real-time analytics applications needed for SCAG (Conboy et al 2020). For instance, this may be accomplished by developing big data analytical skills i.e. joint BDA workshops with suppliers (Dubey et al., 2019b; Jha et al., 2020), facilitating cross functional supply chain teams which mentor suppliers in the use of big data (Dubey et al., 2019b) and lastly, achieving strategic alignment and integration in the supply chain using cross channel formal and informal communication mechanisms (Lee, 2004; Cadden et al., 2020b).

The results show that the moderating effect of SCOL in the relationship between BDA and SCAG is only significant for data velocity (H4c) i.e. (0.44**). The positive relationship with data velocity may be explained by DCT, as both formal and informal learning mechanisms with suppliers can lay the foundations for integrated big data structures by creating co-specialised assets which collectively create higher order capabilities (Winter, 2003: Teece, 2007). In line with both Foss (1996) and Rothaermel and Hess (2007), higher order capabilities are formed across "networks" or "clusters". These insights complement research that focused on tangible or human capabilities such as physical, IT or technical capabilities in big data (Gupta et al., 2016 Gunasekaran et al, 2017; Wamba et al, 2020), but did not fully investigate the intangible 'higher order' aspects of BDR's. It is believed that these higher order dynamic capabilities such as that of organizational learning and how this can facilitate even the development of first and second order big data capabilities (Winter, 2003). Finally, Data volume (H4a) i.e. (0.05ns) and variety (H4b) i.e. (-0.32ns) were not related to SCAG, even when a firm implements supporting SCOL. Hence, a key finding is that data volume and data variety are only relevant for developing sensing and search capabilities, where strategic flexibility and the ability to adapt to external conditions are key (Teece, 2007; Conboy et al., 2020).

Hypothesis H5 (a-c) considers the moderating role of SCDDC in the relationship between BDA and SCAG. The results suggest that data-driven culture is linked to data variety (H5b) (0.53**) as opposed to data velocity (H5a) (-0.18ns) and data volume (H5c) (-0.1ns). As data variety is not linked to SCAG, data-driven culture is not a moderator in the relationship between big data and SCAG. The results therefore support the work of Cadden et al., (2020c) who found that although data-driven cultures are linked to the technical implementation of big data, they are not related to business level enablers of big data. A contribution of this study is that the results suggest that the SCOL aspects of big data play a greater role than the purely technical data-driven aspects of big data culture in terms of enhancing SCAG, perhaps because suppliers first have to learn how to leverage big data before they can even build basic zero-level big data capabilities (Winter, 2003). This represents a useful finding as many previous studies allude or focus on the data-driven cultural aspects of big data in SCAG (Hofmann et al., 2017; Brintrup et al., 2020), without necessarily investigating how this culture may be developed through SCOL capabilities (Cadden et al., 2020b).

Lastly, Hypothesis H6 explored the relationship between SCAG and SCP, finding a significant and positive relationship (0.25**). This supports previous research linking SCAG to SCP (Wamba and Akter, 2019) and compliments SCAG research in terms of cost efficiency, inventory turnover, and delivery speed (Eikstein et al., 2015: Inman and Green, 2021).

5.0 Research Implications

5.1 Implications for theory

Our results find strong support for the DCT across our research hypotheses. The results show that in turbulent environments, ED is linked to all three characteristics of big data as they enable both sensing and creative search dynamic capabilities (Teece, 2007; Pandza and Thorpe, 2009). These dynamic capabilities are needed to identify external threats and opportunities by helping firms to adapt to their environment whilst also setting the scene for the seizing (response) and transformation dynamic capabilities needed to enhance SCAG (Teece, 2007; Yu, 2019). Therefore, this study expands on previous studies, which found ED was only partially linked to BDA and SCAG (Wamba et al., 2020) by finding a positive association between big data and the characteristics of volume, variety and velocity.

DCT (Teece, 2007) may explain why firms target the volume and velocity of data, as opposed to data variety, which involves the development of time-consuming search capabilities (Siggelkow and Rivkin, 2005; Richey et al., 2016; Dubey et al., 2019b). Hence, from a theoretical standpoint, our results add value by exploring how the external environment influences big data collection and how sensing capabilities linked to the competitive environment are used to inform seizing and reconfiguration dynamic capabilities. The results suggest that big data velocity is the single big data characteristic which allows firms to adapt in both turbulent and competitive environments, whilst also enabling operational responsiveness to enhance SCAG (Hofman et al., 2017; Brintrup et al., 2020). Interestingly, our results align with Siggelkow and Rivkin's (2005) organizational design model by finding that search diversity in BDA may be suitable in stable yet complex environments, although rapid improvement (velocity) is needed in turbulent and simple environments.

Finally, the study finds support for higher order (intangible) capabilities alongside the sensing and seizing aspects of DCT (Teece, 2007; Conboy et al 2020). A key contribution of this paper is that it demonstrates that firms who implement SCOL in a supply network (Foss, 1996), are in a better position to reap the benefits of big data velocity's effect on SCAG (Cadden et al., 2020b; Conboy et al., 2020). Previous research has largely focused on tangible second and first order dynamic capabilities (see Gunarsekaran et al 2017; Wamba et al, 2020). Yet, it is recognised that a combination of tangible, human and intangible capabilities are required to build SCAC's (Wamba et al, 2019). Our results suggest SCOL is pivotal in terms of overcoming big data integration barriers and developing supplier BDAC's to enhance SCAG. As big data integration is a key challenge for firm implementing big data in their supply chain (Kache and Seuring, 2017) our research makes an important contribution to DCT, supply chain management and big data literature.

5.2 Implications for practice

From a practitioner perspective, this study raises many important considerations. SCAC's can reduce the complexities of large volumes and types of date and create SCAG by facilitating real-time decision making by helping firms make more informed and responsive decisions operating in turbulent and competitive environments. This leads to greater SCP benefits in terms of lead-times and cost reductions. Managers should focus attention on the intangible capabilities to provide value creation when developing SCAC's. This involves having the infrastructure to capture data quickly from the external environment, analyzing this data and when triangulated with the higher levels of internal knowledge and learning orientation that a data driven firm espouses, this will result in enhanced SCA and SCP. Joint supplier workshops, cross supply chain analytical teams and formal and informal reporting are techniques to build SCOL and create a supply chain culture of learning and performance improvement.

6.0 Conclusions

This study offers several important contributions to the supply chain domain. The results suggest that external environmental conditions shape the type of big data sought by organizations. Interestingly, in environments with CP the effect is different, and the variety of data is not relevant. It is argued that this could be related to the idea that firms seek quick gains such as first mover advantage in competitive environments, while the exploration of data sources is more suited to complex markets (Siggelkow and Rivkin, 2005).

It has been shown that the velocity of big data is the catalyst for not only adapting in turbulent and competitive environments, but also in terms of seizing the benefits of big data in relation to SCAG. This is an important finding as data velocity appears to be the key element in the supply chain linking the external environment with the internal environment and SCAG and SCP. Our results provide additional insights through a DCT lens and underlines the importance of intangible capabilities (SCOL and SCDDC) in achieving SCA and SCP (Winter, 2003, Conboy et al 2020).

6.1 Limitations and future research

There are a number of limitations and opportunities for future research. Firstly, this study only considered turbulent and competitive environments, however, complex environments, characterized by high levels of R&D and exploration may lead to different results, particularly in relation to big data variety capabilities and data collection (Siggelkow and Rivkin, 2005). Moreover, in relation to turbulent environments, additional outcome variables could be explored in the domain of BDA such as supply chain resilience, flexibility and innovation. Secondly, this study was limited in that only three aspects of big data capabilities were examined, namely volume, variety and velocity. Accordingly, additional subdivisions of SCAC could also be explored, particularly the veracity of data, may be linked to SCAG through the use of high quality data for producing more accurate forecasts and simulations and making more fast-paced and reliable decisions (Wamba et al., 2015; Richey et al., 2016).

An issue that requires further investigation relates to the effects of ED and CP on the motivation behind the adoption of big data. As highlighted in this paper, both ED and CP were linked to the volume of data, and this raises the question whether firms are implementing big data in the anticipation of quick results, without considering the quality and accuracy of the data or, alternatively, if firms are collecting large volumes of data to use as training datasets for pattern analysis using big data and AI in supply chains (Brintrup et al., 2020). Hence, further research is required in the area of institutional theory and the effects of CP on big data collection (Dubey et al., 2019c; Cadden et al 2020a; Jha et al., 2020).

Lastly, as shown in this paper, SCOL was a moderator in the relationship between big data and SCAG, and further investigation is required to identify other SCOL elements which may enhance these relationships and overcome supply chain integration issues This could involve the development of a supplier learning curriculum which seeks to improve the governance and quality of data which would be required for more rapid decision making and accurate forecasting.

TAKE IN APPENDIX 1

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Table 1. Convergent Validity and Internal Consistency Reliability

Construct	Indicator	Loading	Indicator Reliability	Composite Reliability	Cronbach's α	*AVE*
Environmental Dynamism (ED)	ED1	0.87	0.76	0.91	0.85	0.77
	ED2	0.89	0.79			
	ED3	0.88	0.77			
Competitive Pressures (CP)	CP1	0.83	0.69	0.86	0.75	0.67
	CP2	0.83	0.69			
	CP3	0.80	0.64			
SC Data-Driven Culture (SCDDC)	SCDDC1	0.87	0.76	0.89	0.81	0.73
	SCDDC2	0.84	0.71			
	SCDDC3	0.85	0.72			
	SCDDC3	0.83	0.70			
Volume (VOL)	VOL1	0.72	0.52	0.92	0.89	0.74
	VOL2	0.89	0.79			
	VOL3	0.90	0.81			
	VOL4	0.92	0.85			
Variety (VAR)	VAR1	0.90	0.81	0.95	0.94	0.84
	VAR2	0.88	0.77			
	VAR3	0.95	0.90			
	VAR4	0.93	0.86			
Velocity (VEL)	VEL1	0.92	0.85	0.95	0.94	0.84
	VEL2	0.93	0.86			
	VEL3	0.93	0.86			
	VEL4	0.88	0.77			
Supply Chain Agility (SCAG)	SCAG1	0.90	0.81	0.94	0.92	0.81
	SCAG2	0.90	0.81			
	SCAG3	0.91	0.83			
	SCAG4	0.88	0.77			
Supply Chain Organisational Learning (SCOL)	SCOL1	0.87	0.76	0.94	0.91	0.79
	SCOL 2	0.91	0.83			
	SCOL 3	0.88	0.77			
	SCOL 4	0.89	0.79			
Supply Chain Performance (SCP)	SCP1	0.93	0.94	0.97	0.96	0.88
	SCP2	0.93	0.87			
	SCP3	0.94	0.88			
	SCP4	0.95	0.90			

Note. Indicators (or items) ED1 to SCOL 4 are mentioned in Appendix 1; *AVE*=Average Variance Extracted

Table 2. Descriptive Statistics, Correlations, and Average Variance Extracted

Construct	Mean	S.D.	1	2	3	4	5	6	7	8	9
1 ED	6.03	0.82	**0.88**								
2 CP	5.98	0.76	0.75**	**0.82**							
3 SCDDC	5.85	0.83	0.72**	0.67**	**0.85**						
4 VOL	5.30	1.04	0.60**	0.55**	0.54**	**0.86**					
5 VAR	5.59	0.94	0.70**	0.59**	0.59**	0.68**	**0.92**				
6 VEL	5.79	0.87	0.75**	0.69**	0.69**	0.70**	0.71**	**0.92**			
7 SA	6.12	0.72	0.41**	0.41**	0.37**	0.41**	0.45**	0.52**	**0.92**		
8 SCOL	5.283	0.82	0.71**	0.74**	0.68**	0.53**	0.61**	0.67**	0.43**	**0.85**	
9 SCP	5.09	1.16	0.54**	0.43**	0.57**	0.63**	0.55**	0.60**	0.33**	0.48**	**0.94**

Note. ED= Environmental Dynamism; SCOL=Supply Chain Organisational Learning; CP=Competitive Pressure; SCDDC=SC data-driven culture; SA= Supply Chain Agility; VAR=Variety; VEL=Velocity; VOL=Volume; SCP=Supply chain Performance; SD=Standard deviation; bold scores diagonally indicate square root of AVE; ** p<0.01

Table 3. Summary Results of Hypotheses Testing

Hypothesis	Hypothesized Path	Direct effect	Empirical evidence
H1a	ED -> VOL	0.42^{***}	Supported
H1b	ED -> VAR	0.58^{***}	Supported
H1c	ED -> VEL	0.52^{***}	Supported
H2a	CP -> VOL	0.23^{*}	Supported
H2b	CP -> VAR	0.16^{ns}	Rejected
H2c	CP -> VEL	0.60^{**}	Supported
H3b	VAR -> SCAG	0.15^{ns}	Rejected
H3c	VEL -> SA	0.49^{**}	Supported
H4a	VOL × SCOL -> SCAG	0.05^{ns}	Rejected
H4b	VAR × SCOL -> SCAG	-0.32^{ns}	Rejected
H4c	VEL × SCOL -> SCAG	0.44^{**}	Supported
H5a	VOL × SCDDC -> SCAG	-0.10^{ns}	Rejected
H5b	VAR × SCDDC -> SCAG	0.52^{**}	Supported
H5c	VEL × SCDDC -> SCAG	-0.18^{ns}	Rejected
H6	SCAG -> SCP	0.25^{**}	Supported

Figure 1: Research Framework

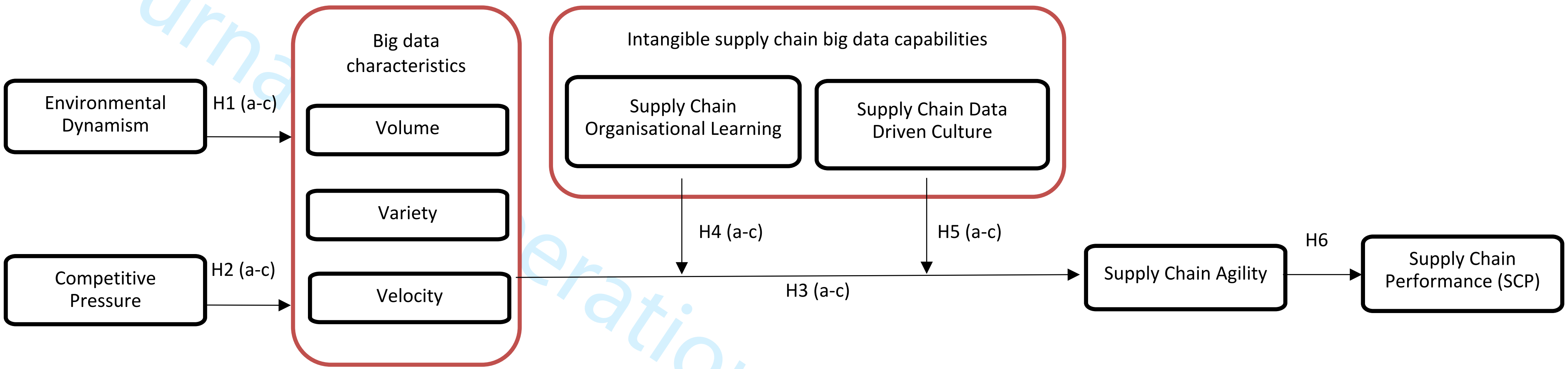


Figure 2. Hypothesis test results

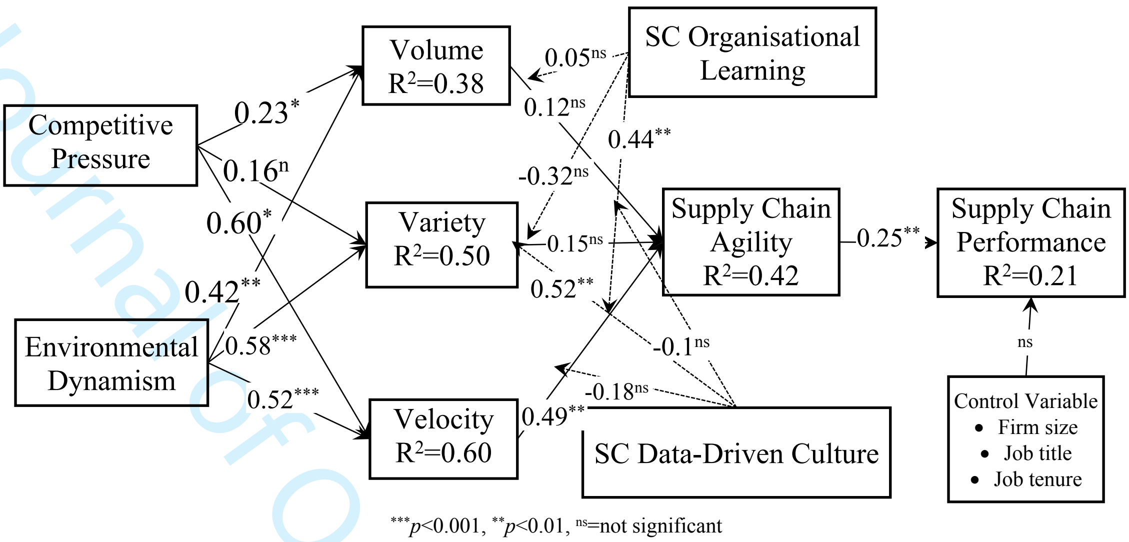


Figure 3. The moderation effect of SCOL on the relationship between VEL and SA

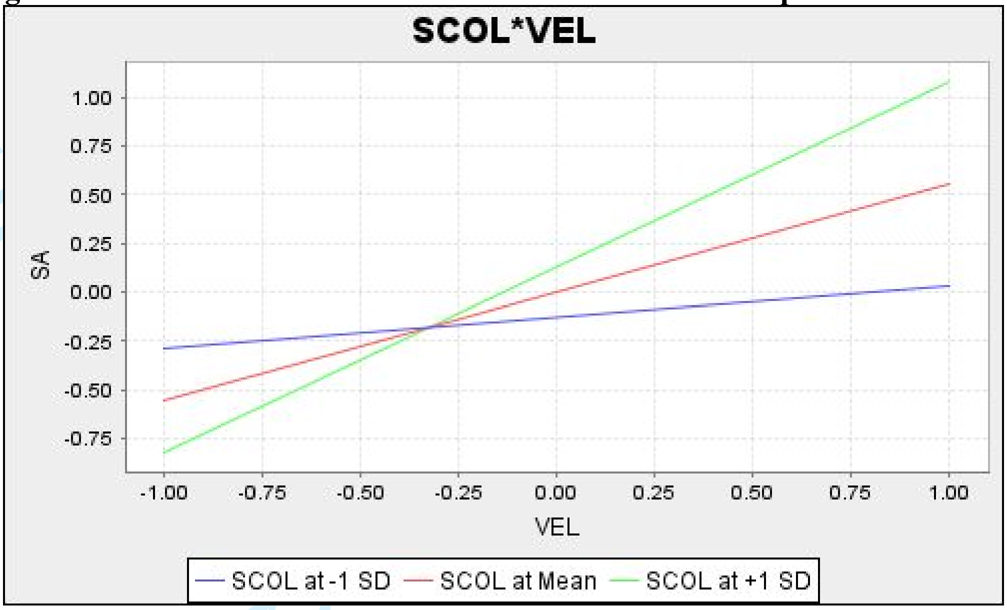
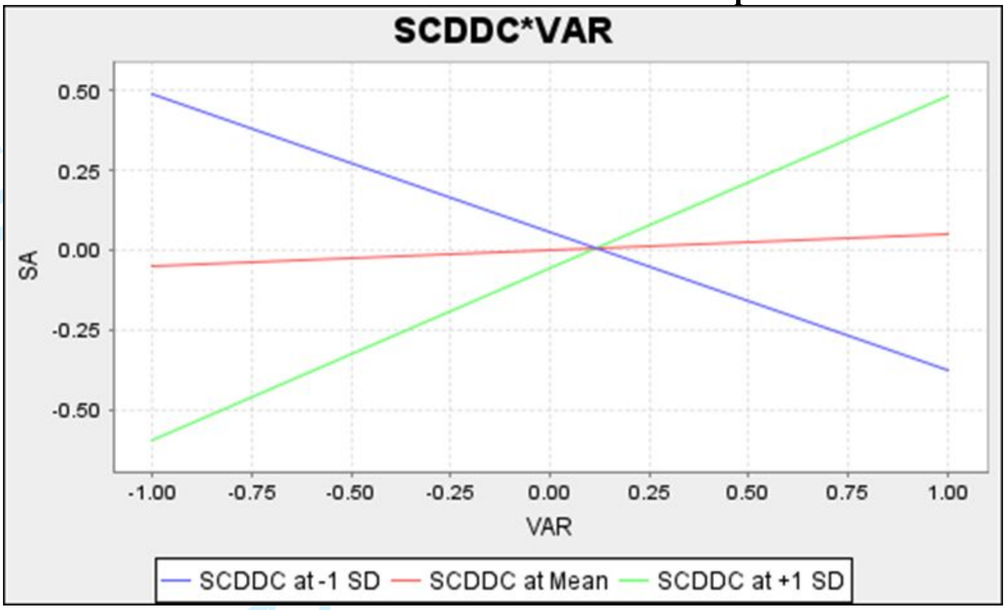


Figure 4. The moderation effect of SCDDC on the relationship between VAR and SA



Appendix 1. Constructs and Indicators of the Study

External Factors		
Constructs	**Indicators**	**References** (Adapted and developed from)
Environmental Dynamism (ED)	Environmental Dynamism measures the rate of change (volatility) in your organisations supply chains competitive environment relative to change in other industries. In your supply chain, what is: ED1. The rate at which products and services become outdated. ED2. The rate of innovation of new products and services. ED3. The rate of change in taste and the preference of customers in your industry	(Rojo et al., 2018, Ward and Duray, 2000)
Competitive pressure (CP)	NP1-Our competitors have implemented data analytics to collect, manage, and analyse data to extract useful insights NP2-Our suppliers have implemented data analytics to collect, manage, and analyse data to extract useful insights NP3-Our customers have implemented data analytics to collect, manage, and analyse data to extract useful insights	(Chen et al., 2015, Liang et al., 2007)
Big Data Characteristics		
Constructs	**Indicators**	**References**
Volume (VOL)	VOL1-My company analyses large amounts of data VOL2-The quantity of data we explore is substantial VOL3-We use a great deal of data VOL4-We scrutinise copious volumes of data	(Johnson et al., 2017)
Variety (VAR)	VAR1-We use several different sources of data to gain insights VAR2-My company analyses many types of data VAR3-We have many databases from which we can run data VAR4-We examine data from a multitude of sources	(Johnson et al., 2017)
Velocity (VEL)	VEL1-We analyse data as soon as we receive it VEL2-The time period between us getting and analyzing data is short VEL3-My company is lightning fast in exploring our data VEL4-My company analyses data speedily	(Johnson et al., 2017)
Supply Chain Agility		
Constructs	**Indicators**	**References**
Supply Chain agility (SCAG)	SCA1-We are able to adapt our services and/or products sufficiently fast to new customer requirements. SCA2-We are able to react sufficiently fast to new market developments. SCA3-We are able to react to significant increases and decreases in demand as fast as required by the market. SCA4-We are always able to adjust our product portfolio as fast as required by the market. SCA5-We are able to react adequately fast to supply-side changes, e.g, compensate for spontaneous supplier outages, delivery failures, market shortages	(Blome et al., 2013)
Intangible Supply Chain Capabilities		
Constructs	**Indicators**	**References**
Supply Chain Organisational Learning (SCOL)	SCOL1- We hold SC workshops focusing on data analytics to enhance the understanding and knowledge of each SC partner SCOL2- We hold SC cross functional teams focusing on data analytics to enhance the understanding and knowledge of each SC partner SCOL3- We have effective SC data analytics reporting structures to enhance the understanding and knowledge of each SC partner SCOL4 - We have effective SC data analytics communication guidelines to enhance the understanding and knowledge of each SC partner	Cadden et al., 2020; Cousins et al., 2006; Yu et al., 2021; Gupta and George, 2016)
Supply Chain Data Driven Culture (SCDDC)	SCDDC1- We consider supply chain data a tangible asset SCDDC2- We base our supply chain decisions on data rather than on instinct	Gupta and George (2016)

	SCDDC3- We are willing to override our own intuition when supply chain data contradicts our viewpoints SCAC4- We continuously assess and improve the business rules in response to insights extracted from supply chain data	
Performance Factors		
Constructs	**Indicators**	**References**
Supply Chain Performance (SCP)	SCP1- In the past 3 years, on time delivery has improved due to our supply chain relationships SCP2- In the past 3 years, conformance to product specifications have improved due to our supply chain relationships SCP3- In the past 3 years, our flexibility to respond to changing customer demands has improved due to our supply chain relationships SCP4- In the past 3 years, increasing number of successful cost reduction initiatives have resulted due to our supply chain relationships	Ahmad and Schroeder, 2003; Cadden et al., 2020; Gunasekaran et al., 2004; Zhan and Tan, 2020

Manuscript ID IJOPM-06-2021-0383 entitled "Big data analytics and supply chain agility: the moderating role of socialisation mechanisms" which you submitted to the International Journal of Operations and Production Management, has been reviewed.

Responses to Editor and Reviewer Comments

Editor Comment: We however believe that most of the review comments can be addressed, and we therefore invite you to revise and resubmit your manuscript. Please aim to address as many of the reviewer concerns as possible to the best of your ability. If you are not able to address a concern, please acknowledge this in the paper and note it as a potential limitation. If you disagree with a concern, please provide a rebuttal, ideally with evidence and references, for your position.

Authors Response to Editor Comments: We have been very thorough in addressing the useful comments from the reviewers. We feel the revised submission is significantly stronger and makes a much more valuable contribution to the operations management literature.

Editor Comment: As you undertake the revision, please make sure to address in particular the concern that many of the hypotheses are intuitive. Can a more interesting model be built, by the integration of other moderators?

Authors Response to Editor Comments: The paper has been significantly revised throughout. A much more interesting and developed model has been presented (see Figure 1 within manuscript)

Editors Comments: The review team also seemed to be concerned about consistent vagueness in the paper, the lack of differentiation to prior work (thus not demonstrating well the additional insight created by this paper)

Authors Response to Editor Comments: This paper has redeveloped aims and objectives and the revised model results in addressing a significant research gap (see structured abstract for summary and page 3 for research gap/paper contributions and the key research aim and objectives)

Response to Reviewer 1 Comments

Reviewer 1 Comments: The writing needs a lot of refinement. Some sentences look incomplete, and many others are hard to understand. Lack of continuity in the ideas is also an issue. Many times, I had to re-read sentences or paragraphs to (mentally) correct the grammar and punctuation and extract some sense out of it, not always succeeding. It is very frustrating to review something that was so carelessly put together.

Authors Response to Reviewer 1 Comments: The paper has been significantly improved throughout, both in terms of content, writing style and format.

Reviewer 1 Comments: The level of redundancy in the literature background is astonishing. Subsections repeat the same ideas, sometimes presented under different labels, and very little information is added to the reader as the text progresses (sometimes the same sentence is repeated twice, with the exact same wording, in the same paragraph). The background gives almost no background. The authors are concerned in giving definitions to well-known concepts (e.g., SCA, environmental dynamism) and bypass all the literature that is directly related to their work, i.e., how others have tested the role of business analytics (or big data analytics) on the agility of SCs, moderated or not by social interactions. I was left with no evidence that the hypotheses are worth being tested.

Authors Response to Reviewer 1 Comments: Much more consideration and inclusion of relevant literature has been included to carefully articulate the research objectives and gap being investigated. The hypothesis section has been significantly developed to support the proposed new model (see especially section 2). Two leading scholars in operations management and big data analytics were added to the research team to build a stronger model and research gap and assist with the paper development.

Reviewer 1 Comments The survey is presented in Appendix I. In my view, the survey is flawed, and any analysis derived from the data gathered from it is worthless. Take the constructs VOL, VAR and VEL, for instance. Each contains 4 questions which, in my view, are exactly the same, with slight changes in wording, e.g., my company analyses large amounts of data and the quantity of data we explore is substantial. The same appears in other constructs (SCA and SM). Some of the items cannot be, in my view, responded using the 5-point Likert scale (1=strongly disagree to 5=strongly agree) proposed by the authors, e.g., ED1. The rate at which products and services become outdated, and ED2. The rate of innovation of new products and services, to name a few. I really do not know how the respondents managed such a survey but I am quite sure the responses are not reliable, regardless of all statistical verifications.

Authors Response to Reviewer 1 Comments: We have developed and extended the model under study by adding additional constructs that were collected at the data collection stage but weren't included in the initial paper (see figure 1). A more robust and considered critical literature review led to this model development. However, we strongly disagree with the reviewers that certain constructs within the model that remain from version one is flawed. The reviewer highlights several specific constructs. For example: Big Data Characteristics: volume, variety and velocity; SCA and Environmental Dynamism). All constructs were adopted from validated constructs and have been published in many international journals.

For example:

Big Data Characteristics: volume, variety and velocity were adopted from:

- Johnson, J.S., Friend, S.B. and Lee, H.S. (2017), "*Big data facilitation, utilization, and monetization: exploring the 3Vs in a new product development process*", Journal of Product Innovation Management, 34(5), 640-658.
- Ghasemaghaei, M. and Calic, G., (2020), "*Assessing the impact of big data on firm innovation performance: Big data is not always better data*", Journal of Business Research, 108, pp.147-162.
- Ghasemaghaei, M., & Calic, G. (2019b), "*Does big data enhance firm innovation competency? The mediating role of data-driven insights*", Journal of Business Research, 104, 69–84.

Supply Chain Agility was adopted from**:**

- Blome, C., Schoenherr, T. and Rexhausen, D. (2013) "*Antecedents and enablers of supply chain agility and its effect on performance: a dynamic capabilities perspective*", International Journal of Production Research, 51(4), 1295-1318.

Environmental Dynamism was adopted from:

- Ward, P.T. and Duray, R. (2000) "Manufacturing strategy in context: environment, competitive strategy and manufacturing strategy", Journal of Operations Management, 18(2), 123-138.
- Rojo, A., Stevenson, M., Lloréns Montes, F.J. and Perez-Arostegui, M.N. (2018) "Supply chain flexibility in dynamic environments: The role of operational absorptive capacity and organisational learning", International Journal of Operations and Production Management, 38(3), 636-666.

- Dubey, R., Gunasekeran, A., Childe, S.J., Bryde, D.J., Giannikis, M., Foropan, C., Rouband, D. and Hazen, B.T. (2019a) "Big data analytics and artificial intelligence pathway to operational performance under the effects of entrepreneurial orientation and environmental dynamism: A study of manufacturing organisations", International Journal of Production Economics, 107599.

In the measurement scales of ED, the full item question should have been listed. A generic description was provided as per previous papers, such as Rojo et al (2018) above, as the terms are well defined in the literature and the authors felt is simplified the measurement table.

The authors understand this perhaps caused unnecessary confusion to the reviewer.

For example: The authors added item 1: ED1. The rate at which products and services become outdated rather than the full introduction was included in the scale that was provided to the respondents and it was the only scale with a very low-very high scale rather than strongly agree to strongly disagree). This has been clarified in the revision, i.e.:

Environmental Dynamism measures the rate of change (volatility) in your organisations supply chains competitive environment relative to change in other industries. Measured in a 1-7 scale (extremely low, to extremely high)

In our supply chain, what is:

ED1. The rate at which products and services become outdated.

ED2. The rate of innovation of new products and services.

ED3. The rate of change in taste and the preference of customers

Reviewer 1 Comments: I made several remarks along the text, which goes attached to this review. I went over the results and discussion but did not make any remarks (for the reasons given above). I hope they will help the authors, although I am sure the help will be needed. I do not recommend trying to fix a research based on such a problematic data collection instrument.

Authors Response to Reviewer 1 Comments: The comments within the manuscript provided added detail to the same comments within these reviewer comments. We feel we have now adequately addressed all of these issues comprehensively. In essence, all the pages the reviewer refers to have been rewritten and repositions to articulate the research gap and key research objectives.

Reviewer 2 Comments: In the abstract, the explained purpose is not providing sufficient input to be able to understand the findings presented. Authors will have to revisit the abstract and revise it such that it can be understood standalone.

Authors Response to Reviewer 2 Comments: A revised title and structured abstract has been entirely rewritten given the revised model specification.

Responses to Reviewer 2 Comments:

Reviewer 2 Comments: The motivation for answering RQ1 and RQ2 is not captured in the introduction. Authors have focused on motivating for RQ3. It is important to explain why answering RQ1 and RQ2 is critical. For instance, how is competitive pressure expected to influence big data capabilities. To address this limitation, authors can individually introduce the research questions after its corresponding motivation content rather than stating them altogether.

Authors Response to Reviewer 2 Comments: The idea proposed by the reviewer is a useful idea. There are several ways to present one's research objectives. We have completely rewritten the introduction, and research objectives and we have adopted an approach that is similar to other key authors in this field. For example:

- Wamba, S.F. and Akter, S. (2019) "Understanding supply chain analytics capabilities & agility for data-rich environments", *International Journal of Operations & Production Management*, 39(6), 887-912
- Maheshwari, S., Gautam, P. and Jaggi, C.K., 2021. Role of big data analytics in supply chain management: current trends and future perspectives. *International Journal of Production Research*, *59*(6), pp.1875-1900.

See page 3 for our research aim and questions.

Reviewer 2 Comments: It is not clear why big data capabilities and data collection are treated separately in RQ 1. Will sensing and storing data not be an integrated part of big data capabilities?

Authors Response to Reviewer 2 Comments: We accept the terminology was confusing in the original version as we referred to big data characteristics as big data capabilities. Much developed writing and justification is included in the significant revision to support the respecified model. Therefore, this comment is now somewhat redundant. However, it is important to highlight our overarching research aim as indicated in my previous response is:

"*How does the development of ISCAC impact SCAG and SCP in turbulent environments?*"

Therefore, we agree that the sensing and storing of data is certainly a major part of big data capability development. Big data capability development is holistic. Within our paper we outline the 3 key big data capability development building blocks: tangible, human and intangible resources and the interrelationships between these. Our paper focuses on the influence of the intangible capabilities in providing enhanced SCA and SCP.

Our paper's purpose is summarised within the structured abstract:

We articulated the 3 research questions, which have been revised in this version to support the delivery of the research aim. The introduction session provides further insights into the research study and rational for the gaps and approach taken.

Reviewer 2 Comments: Towards the end of the introduction, authors anchor their core contributions on the process adopted to conduct the research (e.g. adoption of dynamic capabilities; deconstruct BDA into sub-dimensions and its linkage to SCA, etc.). But the core contributions should be what was identified/revealed by adopting that process to conduct the research. This has to be rewritten.

Authors Response to Reviewer 2 Comments: The contributions have been completely rewritten, supported by your valuable feedback, but also due to the respecified model revealing added and different insights and contributions (see page 3, last paragraph).

Reviewer 2 Comments: The initial two paragraphs in section 2 are too generic to the research questions answered in this study. Authors can consider removing it to add content elsewhere in the manuscript. Also, the initial paragraph for section 2 can give a high-level view of the section is organized and why it is done that way.

Authors Response to Reviewer 2 Comments: The entre front end of this revision is new and was in part guided by this valuable feedback comment.

Reviewer 2 Comments: Section 2.1 is vague, what is the author attempting to achieve through this sub-section is not clear. The argument towards the end in the last but one paragraph in this sub-section lacks relevance because published research has approached BDA from dynamic capabilities perspective multiple times and none of them have argued for its standalone sufficiency.

Authors Response to Reviewer 2 Comments: This section has been largely restructured and the writing has been developed and refined.

Reviewer 2 Comments: Authors state that they would like to further expand the conceptualization of BDA as a dynamic capability, but it is not clear how, especially in the light of what has been already published at the intersection of BDA and dynamic capabilities.

Authors Response to Reviewer 2 Comments: The paper is concerned with investigating the role of ISCAC as a key moderator to ensuring increased SCA and SCP. DCT is the lens that was used as ISCAC are recognised as higher order dynamic capabilities and important enables in achieving increased agility and performance, as supported by previous work in this space (such papers are listed throughout the paper in support of the justification for this research study). For example, section 2.5 is a new section supporting the revised model.

Reviewer 2 Comments: Authors are mixing big data characteristics and capabilities. Volume, velocity and variety are the characteristics of big data, not sure why they are being approached as capabilities. In other words, these characteristics are prerequisites to qualify as big data and not the capabilities achieved by deploying big data. This severely constraints the potential contribution that the empirical model can make.

Authors Response to Reviewer 2 Comments; The authors totally agree that the terminology used in the original version was entirely misleading. As noted earlier, the paper has reported on a developed and extended research model and volume, velocity and variety are correctly identified as characteristics. As noted earlier, the research team was supplemented by two international researchers in the area of big data analytics and supply chain management to provide active support in developing the revised version.

Reviewer 2 Comments: First three hypotheses are quite intuitive. The efforts invested to test them can only be justified by getting into the nuances. Authors can discuss how competitive pressure (CP) and environmental dynamism (ED) individually impact the three different characteristics of big data. I am not convinced that all the characteristics are positively impacted by CP and ED. For instance, high CP can push firms to reduce their data variety to be able to arrive at quick results. High ED can make firms reduce the volume of big data as they can get outdated quickly. Authors can attempt to capture such nuances; blanket hypotheses are less value adding.

Authors Response to Reviewer 2 Comments: In our literature review in the context of supply chain analytics and through a DCT lens, we found that volume, variety and velocity were widely recognised, but under studied. Our review also suggested that both environmental dynamism and competitive pressures appears to have a significant impact on each of the 3 big data characteristics. This is unsurprising to us as big data comprises all 3 characteristics (volume, variety and velocity). In our study, supply chains require high levels of reliability and validity in their data. To reduce the data variety to arrive at quick results in isolation may lead to unreliable or inaccurate trends or analysis. Similarly, we found that high levels of environmental dynamism actually result in increased data volume as customer tastes continue to change due to societal and environmental impacts and this results in increased innovations. It is the combination of the 3 characteristics that increase the reliability and validity in support of triangulated data. It is the tangible (technological tools and investment), human (technical and management skills) and intangible capabilities (organisational learning and a data driven culture) working together that lead to value creation and agility. For example, large amounts of various data sets are sensed and captured from the external environment. The tangible (technological tools: AI, Machine learning, Hadoop) and human capabilities (technical skills) work together to swiftly analyse the data, and the intangible capabilities (learning and data driven culture) translate this knowledge into increased agility and performance. Our much-revised discussion section (section 4) and implications section (section 5) highlights the key findings and contributions further.

Reviewer 2 Comments: When was the data collected? Is there an explanation for why the average environmental dynamism is so high?

Authors Response to Reviewer 2 Comments: The data was collected in 2020. The sector under study was manufacturing during a period of significant disruption with both COVID and Brexit, therefore the market was extremely volatile and many manufacturing organisations had to evaluate their supply chains, their markets, their products and services to survive. For example, some manufacturing firms have moved to supplying health equipment and services to support the global pandemic. Other manufacturers saw a slump in their demand and had to reconsider their operations. In addition, if we consider the items within ED which is really assessing the rate of change; with a societal drive towards sustainability and a green agenda due to climate change, many firms are repositioning product development and innovation at the top of their strategic agendas and this is resulting in increased rates of new products and services.

Reviewer 2 Comments: If all the items were measured on 5-point Likert scale, it is not clear why the mean presented in Table 2 are higher than 5.

Authors Response to Reviewer 2 Comments: This was a typo as it was a 1-7 scale.

Reviewer 2 Comments: A table summarizing the demographics of the respondents can be included (e.g. position, manufacturing sector, etc.)

Authors Response to Reviewer 2 Comments: Due to space limitations, we didn't include the below. It can be included if felt an important addition.

Characteristics	**Number**	**%**
Industry		
Automotive and aerospace	57	29%

Chemical and pharmaceutical	36	18%
Electrical/electronic	21	10%
Food and beverage	37	19%
Mechanical	23	11%
Textile good	27	13%
Total	**201**	**100%**
Position		
CEO/President/Owner/Managing director	37	18%
Operations/Production/Supply Chain manager	67	34%
General manager	39	20%
IT manager or equivalent	54	27%
Other	4	1%
Total	**201**	**100%**
Organization size (employees)		
Less than 50	34	17
50 to 100	32	16
101 to 249	45	23
250 to 499	21	10
500 to 999	46	23
1000+	23	11
Total	**201**	**100**

Reviewer 2 Comments: As mentioned in comment 9, hypothesizing the individual impact on three different characteristics will assist in explaining the results which are presented individually. For instance, it is difficult to comprehend the reason why for one characteristic of big data, the relationship is significant and not for other.

Authors Response to Reviewer 2 Comments: The hypotheses of the 3V's are investigated individually. These are listed as such in the hypothesis, the model, the results and in the discussion. Some of the results were significant and others weren't. The discussion section provides insights as to why these results may be as such.

Reviewer 2 Comments: Why is H3a excluded from Table 3?

Authors Response to Reviewer 2 Comments: This was simply a formatting issue. Now resolved

Reviewer 2 Comments: The initial point in implication for practice is more of an implication for theory.

Authors Response to Reviewer 2 Comments: This point has been amended.

Reviewer 2 Comments: Limitations and avenues for future research can be separate subsection.

Authors Response to Reviewer 2 Comments: These have been restructured as such.

Reviewer 2 Comments: Overall, the paper has chosen an important field for investigation, but the execution has significant scope for improvement. I hope the above-listed comments/suggestions help in bridging the gap.

Authors Response to Reviewer 2 Comments: Many thanks. The comments were instrumental in redeveloping this paper into a much stronger, coherent, and insightful paper.

<u>**Response to Reviewer 3 Comments**</u>

Reviewer 3 Comments: The abstract is not very clear and informative

Response to Reviewer 3 Comments: The abstract has been completely rewritten

Reviewer 3 Comments: The introduction presents properly the relevance of the topic, but the shift from the use of BDA for reducing uncertainty and the need to include in the investigation socialization mechanisms is pretty sharp.

Response to Reviewer 3 Comments: The introduction has been completely restructured and rewritten and is much better in its articulation and flow of the research study and key objectives (see introduction, section 1).

Reviewer 3 Comments: It is also not very clear why the authors decided to use dynamic capability theory.

Response to Reviewer 3 Comments: DCT is commonly used in BDA and supply chain studies. For example:

- Blome, C., Schoenherr, T. and Rexhausen, D. (2013) "Antecedents and enablers of supply chain agility and its effect on performance: a dynamic capabilities perspective", International Journal of Production Research, 51(4), 1295-1318
- Rameshwar, D., A. Nezih, G. Angappa, B. Constantin, P. Thanos and C. S. J. (2018). "Supply chain agility, adaptability and alignment: Empirical evidence from the Indian auto components industry." International Journal of Operations & Production Management 38(1): 129-148.
- Wamba SF, Gunasekaran A, Akter S, Ren SJ, Dubey R, Childe SJ. (2017) "Big data analytics and firm performance: Effects of dynamic capabilities. Journal of Business Research". 70 (1), 356-65.
- Wamba, S.F. and Akter, S. (2019) "Understanding supply chain analytics capabilities & agility for data-rich environments", *International Journal of Operations & Production Management*, 39(6), 887-912;

Drawing on the previous literature and aligning this to which theoretical lens we feel best achieves these objectives, we have positioned the application of DCT with more clarity. For example, see section 2, paragraph 1 and 2.

Reviewer 3 Comments: In the anticipation of the contribution, some elements not mentioned yet are made explicit (eg., the focus on volume, variety and velocity), reducing the comprehension for the reader.

Response to Reviewer 3 Comments: The abstract and introduction have been completely rewritten to ensure these sections are much more coherent (see pages 1-3).

Reviewer 3 Comments: Literature review on big data is limited and in my view it is not allowing to understand which are the main existing gaps and why there is the need to cover these. Moreover, I believe authors need to reinforce literature specifically focused on the use of BDA in the supply chain domain.

Response to Reviewer 3 Comments: The paper has been significantly rewritten and improved throughout. Specifically, the research questions and the revised model have much better justification and positioning, through a nuanced critical review of the extant literature.

Reviewer 3 Comments: It is also not very clear why the dynamic capability perspective was adopted in the paper.

Response to Reviewer 3 Comments: See earlier comment which asked this also.

Reviewer 3 Comments: Literature about big data is considering different definitions and those with just 3Vs is quite limited. The authors should address why they selected this one and not another more expansive.

Response to Reviewer 3 Comments: Yes, we acknowledge that there are many different definitions within the literature of big data and big data characteristics has been presented with a range of sub dimensions, primarily 3V's, 4V' and 5V's. We chose to adopt 3V's (volume, variety and velocity) as three V's are widely adopted in the extant literature, such as:

- Assunção MD, Calheiros RN, Bianchi S, Netto MA, Buyya R. Big Data computing and clouds: Trends and future directions. Journal of parallel and distributed computing. 2015 May 1;79:3-15.
- Brunekreef, H and Pournadar, M (2018), "Supply Chain Big Data, How big data is shaping the supply chains of the future", KPMG
- Ghasemaghaei, M. and Calic, G., (2020), "*Assessing the impact of big data on firm innovation performance: Big data is not always better data*", Journal of Business Research, 108, pp.147-162.
- Ghasemaghaei, M., & Calic, G. (2019b), "*Does big data enhance firm innovation competency? The mediating role of data-driven insights*", Journal of Business Research, 104, 69–84.

- Hofmann, E. (2017) "Big data and supply chain decisions: the impact of volume, variety and velocity properties on the bullwhip effect", International Journal of Production Research, 55(17), 5108-5126;
- Johnson, J.S., Friend, S.B. and Lee, H.S. (2017), "*Big data facilitation, utilization, and monetization: exploring the 3Vs in a new product development process*", Journal of Product Innovation Management, 34(5), 640-658.
- McAfee, A., Brynjolfsson, E., Davenport, T.H., Patil, D.J. and Barton, D., (2012). "Big data: the management revolution". Harvard business review, 90(10), pp.60-68.

Reviewer 3 Comments: I would invite the authors to present why the methodology selected and the sample used are appropriate for the purpose of the study. Moreover, try to address why the final sample is representative of the overall population.

Try to better explain which kind of differences were introduced in the questionnaire through the support of the experts.

Response to Reviewer 3 Comments:

Our research seeks to examine the complex relationships among a number of constructs to provide generalizable conclusions based on survey data. We have used a quantitative analysis based on positivism, which is deemed appropriate. To test our hypotheses, we collected data from managers who are familiar with both business analytics and supply chain management. We have used a key informant approach and sent our survey to middle and senior managers, including managing directors, CEOs, IT directors, supply chain directors, Operations directors, Logistic directors or equivalent. We believe our sample is appropriate for achieving our research objectives. Our sample was randomly selected from a national database of manufacturing companies to represent the overall population. Considering company size may affect the hypothesized relations, it is used as a control variable. in addition to formatting and presentation modifications, feedback from expert review helped us to make the survey questions more focused, coherent and shorter.

Reviewer 3 Comments: Try to motivate why you used Smart PLS and how this is an appropriate method for the goal of the analysis. The dataset seems limited for the framework under investigation.

Response to Reviewer 3 Comments: PLS path modelling is recommended to be more suitable for research situations where theory is less developed (Gefen et al., 2011; Hair et al., 2013; Wetzels et al., 2009) and/or the research model is large and complex (Akter et al., 2017; Chin et al., 2008). While supply chain agility and its impact are well examined, volume, variety and velocity as constructs are relatively new. In particular, the relationships between supply chain agility and volume, variety and velocity are proposed for the first time in our research. Additionally, our research model consists of relationships among 12 constructs (including control variables). Thus, we selected PLS to empirically test our research model.

Akter, S., Fosso Wamba, S., Dewan, S., 2017. Why PLS-SEM is suitable for complex modelling? An empirical illustration in big data analytics quality. Prod. Plann. Contr. 28 (11–12), 1011–1021.

Chin, W.W., Peterson, R.A., Brown, S.P., 2008. Structural equation modeling in marketing: some practical reminders. J. Market. Theor. Pract. 16 (4), 287–298.

Gefen, D., Rigdon, E.E., Straub, D., 2011. An update and extension to SEM guidelines for administrative and social science research. MIS Q. 35 (2), iii–A7.

Hair, J.F., Ringle, C.M., Sarstedt, M., 2013. Partial least squares structural equation modeling: rigorous applications, better results and higher acceptance. Long. Range Plan. 46 (1), 1–12.

Wetzels, M., Odekerken-Schr¨oder, G., van Oppen, C., 2009. Using PLS path modeling for assessing hierarchical construct models: guidelines and empirical illustration. MIS Q. 33 (1), 177–195.

Reviewer 3 Comments: Results are quite descriptive without a proper discussion of the main motivations for the results and in comparison with existing literature. In order to really exploit the value of the paper, a stronger presentation and discussion of the results would be necessary.

Response to Reviewer 3 Comments: The revised model and associated results have been presented. A developed discussion has been presented.

Reviewer 3 Comments: Conclusions and limitations are very limited: especially the contribution of the paper should be better presented and the future avenues for research

Response to Reviewer 3 Comments: These sections have been developed.