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Dynamic capability Theory as A Lens to Investigate Big Data Analytics and Supply Chain Agility

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Abstract. The study draws on the dynamic capability perspective to explore how turbulent and competitive environments influence big data analytics capabilities which, in turn, impact supply chain (SC) agility. Survey data from 201 UK manufacturers is collected and analysed, and a moderation model is presented. The results show that in turbulent environments, characterized by high degrees of environmental dynamism, firms should leverage the volume, velocity and variety facets of big data which, in turn, enable sensing and creative search (dynamic) capabilities needed to adapt in such environments. In competitive environments however, where first mover advantage is crucial, firms should scale back on time consuming search capabilities (data variety). At the operational level, firms should exclusively leverage the velocity aspects of big data to enhance SC agility. Finally, while, previous studies have focused on analytical maturity as a prerequisite to big data implementation, this study finds that a reconfigured analytical orientation culture specifically on responsiveness, i.e. strategic alignment and predictive forecasting analytics, moderates the relationship between big data velocity and SC agility. The results of this study therefore fill a key gap in the SC management literature as the study demonstrates how environmental factors, both internal and external, influence big data and dynamic capability development in order to enhance SC agility.

Keywords: Big Data Analytics, SC Agility, Dynamic Capability

1 Introduction

Supply chain agility (SCA) is a strategic ability that assists organizations to rapidly sense and flexibly respond to such internal and external uncertainties and pressures [1;2] which, in turn, can result in enhanced customer value and competitive advantage [3]. Through the lens of dynamic capabilities, the ability to ‘sense’, ‘seize’ and ‘respond’ in a dynamic and competitive environment is critical to delivering competitive advantage [2;4]. Business organisations conduct data capturing, sharing, analysing and integration to create a learning SC and build the dynamic capabilities, and constantly stimulates innovation and change internally to address the dynamism and competitive in the external marketplace [5; 6]. Therefore, firms not only need to develop systems and processes to capture, store, share, analyse and integrate vast amounts of information available but also develop analytical-orientational culture within this dynamic environment to make

strategic decisions [4;7].

It has paved the way for a burgeoning research area within SCs known generally within the academic and industrial lexicon as Big Data Analytics (BDA). The result is an unprecedented interest and explosion of studies investigating the role of BDA in support of increased organisational value. Almost 400 papers (44%) of total papers in a Scopus search relating to SC and Big Data were published in recent years (between 2016 and 2018) [8]. Whilst BDA as a construct has variations in its reported definitions, generally definitions focus on the range of process and techniques that a firm possesses to collect and analyse this dynamic data (typically characterised as volume, variety and velocity) in support of competitive advantage [4;9]. Yet, interestingly a recent study reported that only 17% of enterprises have implemented BDA in one or more SC function [10] and found the ability to achieve SCA much more complex than assumed [11]. It is argued in this paper that a key reason firms are not realising the requisite SC success in respect of BDA in support of SC agility is due to ignoring the holistic and nuanced perspectives required. Sensing, seizing and reconfiguration capabilities are all interrelated dynamic capabilities that must be harnessed to adapt and transform internal SC processes to enhance SCA [12]. This study addresses this research gap through the following three research questions: (1) How does the external environment (external dynamism and competitive pressures) influence big data capabilities and data collection (Sensing and search capabilities)? (2) What types of BDA capabilities lead to enhanced SCA (Seizing capability)? (3) How can SCs be configured/reconfigured to enhance SCA (Configuration capability)?

A key contribution of this paper is the adoption of Dynamic Capability Theory (DCT) to scan the external environment to leverage the BDA capabilities in support of SC agility. A second contribution is this study aims to deconstruct BDA into sub dimensions (volume, variety and velocity) to assess the role of each characteristic in achieving SCA. Studies to date largely group BDA and therefore the results lose the nuanced insights that this paper will provide. Thirdly, this study develops a new and exciting construct (Analytical Orientation: AO) to assess how AO moderates a firm's relationship between BDA and SCA. Studies to date have largely ignored a firm's AO in leveraging BDA in support of SCA, yet many make fleeting and implied references to its importance. Finally, the paper provides a framework and insights for management on how to integrate and maximise the information available within the external environment in support of SCA.

This paper is structured as follows. First, a review of key literature related to BDA, SCA and DCT is presented. Next, the rationale for development of the hypothesis 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.

2.0 Literature Review and Hypothesis Development

2.1 Big Data Analytics

Firms are increasingly understanding the importance of Big data analytics (BDA) in responding to the external environment and competitive pressures; and the nuances that underpin the broad construct. The BDA approach is widely accepted as a composite term which includes big data perspective (BD) and the analytics perspective. The BD component comprises three key dimensions: volume, variety and velocity. The

analytics perspective builds on the data collection and storage element of Big Data and applies advanced analytic techniques, such as data mining, statistical analysis and predictive analytics, to interpret the huge amounts of data available in order to uncover hidden patterns, trends, correlations in support of strategic decision making. While resources in themselves may be easily replicated, it is believed that the information and knowledge created by BDA is not easy to replicate and will lead to sustained competitive advantage. BDA has thus risen to prominence due to the ability to gain meaningful insights from data and thereby help organisations make better decisions. The literature has also stated that BDA plays a key role in enhancing agility and business performance, (such as new product development, responding to sudden disruptions or change, customer service, sales and revenue, and market expansion), allowing businesses to excel in the current fast-paced and ever-changing market environment [10;13]. BDA creates novel ways of analysing and configuring SC processes [14;15], enhancing SC innovation and identifying new opportunities for SC collaboration [16]. The development of BDA capabilities within the organisation and SC has led to increased processing power, assimilation and reaction to market changes. However, BDA as an approach has not been without its criticisms. The perception that attempts to automate highly complex decisions ignore the human aspect and leads to relationship myopia and may impact holistic SC decision making [17].

2.2 Dynamic Capabilities View

Our study is underpinned by the dynamic capabilities view. The term dynamic capabilities originate from the resource-based theory [18] and represents a company's ability to integrate, build, and reconfigure internal and external competences to respond to changes in the business environment [5; 19]. Organisations use these higher levels capabilities as antecedents to organizational and strategic routines, by which managers alter their resource base to generate new value-creating strategies [20]. Chen et al. [21] summarised two reasons that organizations implement BDA to enable their dynamic capabilities. First, using BDA helps organizations establish knowledge creation routines particularly when market dynamism is high. Second, this view of BDA usage also reflects the key characteristics of dynamic capabilities suggested by the literature: commonalities in key features, coupled with idiosyncrasy in details [18]. Prior studies have investigated the performance effects of BDA at SC level. For example, Wamba et al. [2] found that BDA has positive effects on SC agility, SC adaptability and operational performance. Similarly, Dubey et al. [7] argue that companies that have successfully developed BDA capabilities have improved their SC performance. Having sophisticated planning tools and advanced IT-enabled control practices allows companies to move the value of data towards outcome values through increasing SC planning and performance capabilities [22]. These studies highlight the impact of BDA on SC agility, as well as the role of BDA-enabled dynamic capabilities. Our study draws on the dynamic capability view and seeks to further expand the conceptualisation of BDA as a dynamic capability. There is a scarcity of studies that decompose the BDA capability into sub-capabilities [2].

2.3 Environmental Dynamism

An important situational parameter in the DCT is environmental dynamism [23], which

represents the response of an organisation's competitive position created through organisational capabilities, to the changes in the business environment. Environmental dynamism is characterised by changes in products/services, technology, customer preferences and impacts a company's resource allocation strategy [6]. 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, in order to satisfy the market requirements [23;24;26]. Kovach et al., [27] asserted that it is more difficult to attain superior performance in highly dynamic environments and managers require timely information in order to make the right decisions. Given the unpredictable nature of environmental dynamism, the typical response for firms is to enhance their strategic sense making capacity, by acquiring and analysing information to develop cognitive maps which in turn enables them to effectively respond to external environmental variations. In a turbulent environment, firms must capture large amounts of data, that can potentially reveal new and unique insights which can give them an edge over their competitors [28]. The speed at which they convert this information into new products and services, can be the winning factor when dealing with upstream and downstream uncertainties [3]. Thus, we posit:

H1(a-c): Environmental dynamism tends to lead to firms having more BDA capabilities: volume, variety and velocity.

2.4 Competitive Pressures

Globalisation and rapid technological change have created opportunities and challenges that led to new competitive pressures. To respond to these, firms have turned toward technology and integrated BDA throughout their SCs [25]. Firms are under pressure from their customers, suppliers and competitors to improve resource efficiency and achieve competitive advantage [29]. Very few studies have looked at the impact of competitive pressures on organisational BDA adoption [21]. Chen et al. [21] posits that external competitive pressures may positively affect the degree to which firms adopt BDA in their SCs. For instance, the use of BDA by SC actors (customers and suppliers), will likely influence the firm to engage in similar practices [30]. Over the last ten years, companies have been taking advantage of new economics of data and the heightened global nature of rivalry among market incumbents has stimulated management to heavily invest in information technologies [3]. The successful adoption of BDA by competitors will trigger imitative practices throughout organisations. As a result, in order to gain competitive advantage, firms are likely to employ BDA tools to enable them to quickly react to market changes. Therefore, we posit that:

H2 (a-c): Competitive pressures tends to lead to firms having more BDA capabilities: volume, variety and velocity.

2.5 Big Data Analytics and Supply Chain Agility

BDA has a huge operational and strategic impact on SC agility by allowing firms that adopt it to achieve a competitive advantage through enhancing decision-making and increasing value-adding activities [31;32]. BDA extracts useful information from massive data sets to identify useful insights such as market trends, customer buying patterns and how to enable more targeted business decisions, in order to allow companies to excel in

the current fast-paced and ever-changing market environment [10]. BDA also offers opportunities to effectively collaborate with SC partners in order to respond to market changes in a rapid manner, thereby allowing businesses to gain competitiveness [33]. Pisano et al. [20] pointed out that BDA transformed business by serving as a cross-functional capability that allows managers to align strategies and make decisions in accordance with market demands. Zhan and Tan [32] stated that BDA provides a roadmap to firms and managers by generating practical SC strategies, facilitating collaboration between departments, and generating fact-based operational decisions. SC agility has been recognised as the rapid and successful reconfiguration of key resources so firms can meet changing customers' demands and as a necessary ingredient for improving competitiveness [33;34]. While there is a rich body of literature on SC agility [1;33;35] the majority of research has focused on the factors relating to speed, flexibility and adaptability, which contribute to change response. However, in order for an organization to respond to changes effectively, organizations need to adopt a proactive stance to be able to reconfigure their resources and to respond to changes quickly and effectively [1]. Because of a dynamic and volatile business environment, SC agility needs simple, experiential and flexible processes to rapidly make decisions and create new knowledge in order to yield unpredictable outcomes [18;35].

H3(a-c): BDA capabilities: volume, variety and velocity, are positively related to SC agility.

2.6 The Moderating Role of Analytical-orientation Culture

Most organisations have adopted various advanced BDA techniques to process and analyse data quickly and accurately, in order to extract valuable insights from data and to develop the agility to cope with constantly changing market conditions and to explore business opportunities. The results of BDA mean different things to different people and many organisations face enormous challenges when deriving quality insights from BDA results [21]. McAfee et al. [36] identified five challenges for organizations in becoming data-driven: leadership, talent management, technology, decision-making, and company culture. Clearly, analytics is not simply a technical matter. In this study, we follow Davenport [37] and Ransbotham et al. [38] proposed that firms need to develop an analytical orientation to combine critical data results as well as adapt cultural norms to guide management decisions and actions. In this sense, analytical orientation allows companies to maximize decision-making processes by developing an organization's capacity to conduct analysis and act, providing better results by generating value and efficiency in decision making.

H4: The firm analytical orientation culture moderates the relationship between BDA and SC agility.

3.0 Research Method

3.1 Sample and Data Collection

In order to test the above hypotheses, primary data was collected from a sample of UK manufacturers using a questionnaire survey. To capture the responses to the measurements of all constructs, the questionnaire survey was generated using a seven-point Likert scale. Akin to other UK studies investigating SC relationships [39], a national database of manufacturing industry companies, filtered by greater than 100 employees, were examined. A random sample of 1000 companies were selected, and the survey forwarded based on job roles. We received 304 responses and 201 were usable responses, which represent a 36.8% response rate which was deemed appropriate and exceeds the level of 20% reported by Malhotra & Grover [40]. Several steps were undertaken to minimize common method bias, following the recommendations of Tehseen et al. [41]. 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.

3.2 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 [42] and Hair et al. [43]. The result of the CTA-PLS confirmed that the measurement model was a reflective model, which was then evaluated and validated by considering the internal consistency (composite reliability), indicator reliability, convergent validity and discriminant validity [43]. The evaluation results are summarized in Table 1 and Table 2. Discriminant validity was also satisfactory based on two tests.

The research model's predictive power was assessed by the amount of variance attributed to the latent variables (i.e., R^2) (Figure 1). The R^2 values indicated that the full model explained 35% of the variance in SCA, 38% in volume (VOL), 50% in variety (VAR), and 60% in velocity (VEL). According to Wetzels *et al.* [44], the effect size suggested for R^2 in IT-related research is small=0.1, medium=0.25, and large=0.36. Thus, while SCA's effect size was very close to large, the effect sizes of other variables were large.

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			
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)	VARI1	0.90	0.81	0.95	0.94	0.84
	VARI2	0.88	0.77			
	VARI3	0.95	0.90			
	VARI4	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 (SCA)	SCA1	0.90	0.81	0.94	0.92	0.81
	SCA2	0.90	0.81			
	SCA3	0.91	0.83			
	SCA4	0.88	0.77			
Analytical Socialisation Mechanisms (ASM)	ASM1	0.87	0.76	0.94	0.91	0.79
	ASM 2	0.91	0.83			
	ASM 3	0.88	0.77			
	ASM 4	0.89	0.79			

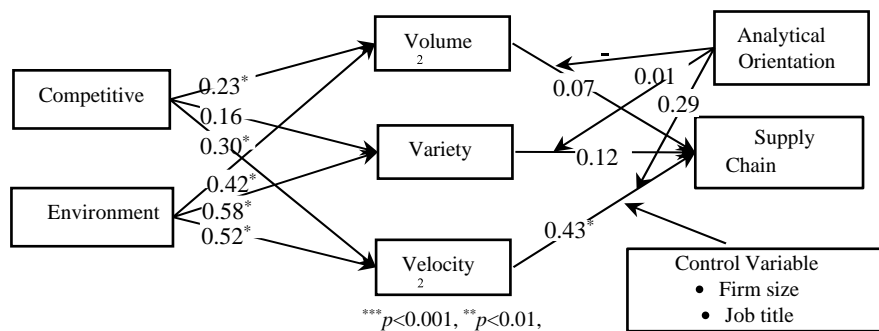


Fig 1. Hypothesis test results

3.3 Hypotheses Testing and Moderation Analysis

Table 3 shows the results of hypothesis testing. H1 suggests that environmental dynamism (ED) relates to VOL (H1a), VAR (H1b), and VEL (H1c) positively. H1 is supported as ED has a statistically significant 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 assumes that competitive pressure (CP) is positively related to VOL (H2a), VAR (H2b), and VEL (H2c). H2a and H2c are supported since NP's effects on VOL is 0.23 ($p < 0.05$) and on VEL is 0.30 ($p < 0.01$); however, H2b is rejected since CP's effects on VAR is not significant. H3 hypothesizes that SCA is positively affected by VOL (H3a), VAR (H3b), and VEL (H3c). H3c is supported as VEL has a statistically significant effect of 0.43 ($p < 0.01$) on SCA. However, H3a and H3b are rejected as both VOL and VAR have no statistically significant effects on SCA. H4 postulates that analytical orientation level (AO) moderates the relationship between VOL and SCA, VAR and SCA, and VEL and SCA. In order to test these moderation effects, the function of "Create Moderating Effect" (a two-stage method) provided by SmartPLS3 was used, with VEL as a predictor variable and AO as a moderator variable. The analysis

was based on bootstrapping (5,000 samples) [43; 45], which indicated that H4c is supported as AO moderates the relationship between VEL and SCA, with the moderating effect of 0.29 ($p < 0.05$). However, H4a and H4b are rejected as the AO does not moderate the relationship between either VOL and SCA or VAR and SCA.

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	0.15 ^{ns}	Rejected
H2c	CP -> VEL	0.30**	Supported
H3b	VAR -> SCA	0.12 ^{ns}	Rejected
H3c	VEL -> SCA	0.43**	Supported
H4a	VOL \times AO -> SCA	-0.15 ^{ns}	Rejected
H4b	VAR \times AO -> SCA	0.01 ^{ns}	Rejected
H4c	VEL \times AO -> SCA	0.29*	Supported

4.0 Research Findings and Discussion

In relation to subset one i.e. Hypotheses H1a-H1c, which explored the impact of environmental dynamism (ED) on BDA capabilities (i.e. volume, variety and velocity), the results are clear. In turbulent environments, characterized by high degrees of variability and changing customer tastes, ED significantly influences BDA capabilities and thus the initial data collected, which is ultimately leveraged for decision-making. Interestingly, ED is linked to all three BDA capabilities (i.e. volume, variety and velocity). In other words, the results support DC theory, as all three facets of BD are significant and form both the firms' sensing (volume and velocity) and search (variety) DCs [19;46;47]. This finding contradicts previous research linking ED to BDA, which only found partial support for such a relationship (see 2). In relation to H1a specifically, the positive link to BD volume is surprising. It can be argued that in turbulent environments, products can become outdated quickly and there is a need for as much information as possible in relation to the external environment [19;48]. In relation to H1b, there is a positive relationship between ED and variety. It's argued that in turbulent environments, changing customer tastes and the need for new products require both flexibility and exploration in the SC [24]. This observation also aligns with DCT, particularly the creative search capability (see 46). For example, in relation to data variety, data may be acquired from many different sources in the SC to facilitate innovation and visibility in dynamic environments [19; 46]. In other words, BD variety enables creative search DCs which help set the scene for the subsequent seizing and transformation aspects of DCs [19; 46;47;49]. The idea is to facilitate greater SC visibility and to capture new opportunities and innovations (incremental or radical) needed for changing customer demand [24;47;49]. Finally, the results of H1c demonstrate that ED is positively related to data

velocity (H1c). This suggests that swiftness in terms of accessing real-time data to facilitate rapid customization, greater SC responsiveness, and the introduction of new products, is crucial for adapting and responding to dynamic and ever-changing environments. In other words, velocity is linked to the response aspects of DCT and SCA due to the need to quickly sense and react to environmental threats [19; 46; 47].

In relation to H2a to H2c. The results demonstrate that Competitive Pressures (CP) are significantly related to (H2c) data velocity (0.30**) while also positively related to data volume (H2a) (0.23*). Conversely, CPs were not found to be related to data variety (H2c). Hence H2a and H2c are supported, while H2b is rejected. The positive results are related to DCT, in particular sensing capabilities as opposed to creative search DCs (see 46). Sensing capabilities help develop subsequent response and transformation capabilities by initially analyzing the competitive landscape and selecting the appropriate response [15; 46]. 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 and seek large amounts of customer data/market intelligence which can be accessed and processed quickly. In such settings, firms sense that a first mover advantage characterized by agility and responsiveness are market winners.

Hypotheses H3a to H3c, consider the seizing aspects of DCs and how BD capabilities can be leveraged to enhance SCA. A second key contribution of this study is that it not only explores if BDA can be leveraged to enhance SCA, but also identifies which BDA capabilities are specifically related to SCA. Hence, this study facilitates transparency in terms of uncovering the micro-foundational relationships between DCs, BDA and SCA by allowing management to narrow down the BDA antecedents of both DCs and SCA. Moreover, the path from the external environment (sensing DCs) is now linked to the internal environment, providing a clear link between BDA strategy, and secondly, how can the data be seized to enhance SCA. The results of H3a to H3c find that data volume and data variety are not linked to SCA, while BD velocity was found to have a significant relationship with SCA (0.43**). Hence, hypotheses H3a and H3b are rejected while hypothesis H3c is supported.

Finally, hypotheses H4a to H4c consider the moderating role of analytical orientation to help deconstruct the relationship between BDA and SCA. More specifically, in order to analyse data quickly and efficiently, the final stage may require the reconfiguration of SC culture and the creation of co-specialized assets [15]. According to DCT theory [15; 19], this may be achieved by reconfiguring the SC and creating an analytical orientation in order to better facilitate data velocity (or variety and volume). The results demonstrate however, that the moderating effect of SC analytical orientation in the relationship between BDA and SCA is only significant for data velocity (H4c). This highlights that specific analytical enablers, i.e. strategic alignment, top management support and predictive modelling skills will facilitate SCA, but only in relation to velocity capabilities. This positive relationship with data velocity may be explained by DCT, as BD structures can be reconfigured and aligned to create co-specialized assets to enhance SCA [15; 19]. More specifically, reconfiguring the SC to support an analytical orientation helps enhance data flow in the SC which, in turn, facilitates real-time data and the ability to respond to opportunities and threats (responsiveness) [49]. Finally, data volume (H4a) and variety (H4b) are not related to SCA, even when a firm possesses a strong SC analytical orientation. 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 [15;19].

5.0 Research Implications

5.1 Implication for theory

BDA has the potential to reduce many of the complexities inherent within agile SCs [2; 11]. Conversely, in the literature, the capabilities which link to this outcome are not clear. Accordingly, this study employed a DC lens [19; 46] in a SC setting to explore three novel research questions which aimed to examine; (1) How the external environment influences BD capabilities and data collection (Sensing and search capabilities), (2) What types of BDA capabilities lead to enhanced SCA (Seizing capability) and (3) How SC culture can be reconfigured to enhance SCA (Reconfiguration capability). Our results find strong support for the DCT across all three research questions. While previous research has only considered the “seizing aspects” of BD [12] this study employs a holistic DC perspective, which focuses on both the initial “sensing” and subsequent “reconfiguration” aspects of BD alongside the seizing aspects i.e. the entire path.

The results show that in turbulent environments, ED is linked to all three BDA capabilities (volume, variety and velocity) as they enable *both* sensing and creative search DCs [19;46]. These capabilities in turn form sensing capabilities (volume and velocity) and search capabilities (variety) which help firms not only adapt in turbulent environments, but also pinpoint the most appropriate data for strategic decision-making relevant to the firm. As shown in this study, this is particularly important in relation to SCA [19;46]. This research therefore expands on previous studies, which found ED was only partially linked to BDA and SCA (See referenced 2) by finding a wholly positive association with all three BD capabilities (i.e. the development of sensing and search capabilities) and, secondly, by offering a transparent breakdown of which BDA capabilities can help firms adapt in turbulent environments..

6.0 Conclusions, limitations and the way forward

Previous research suggests that there is a need for new theoretical approaches to holistically capture the dynamic nature of big data in the field of SCM [12;48]. Accordingly, this study sought to explore the impact of BDA on SCA by employing a DC lens at the SC level. More specifically, the contribution of this study is to not only examine the “response” aspects of DC and SCA in the domain of BDA, but also to explore the initial sensing and subsequent reconfiguration aspects of DCs (see 15;19;46), which have been largely overlooked in the BDA-SC literature [12;48]. In terms of contributions, this study has achieved its aims and objectives by identifying how firms operating in dynamic and competitive environments can harness BDA to enhance SC agility. More specifically, the study contributes to the literature by employing a DC lens in a BD and SC setting. Accordingly, the results demonstrate that ED and CP play a key role in BD capability development and data collection as they enable the sensing and search DCs which allow firms to adapt in turbulent and competitive environments. Subsequently, it’s shown that data velocity is a key dynamic response capability (Seizing capability) needed to enhance

SCA. Finally, BD can act an enabler of SC reconfiguration and the development of co-specialized assets (DCs) which is needed to facilitate a better analytical environment for SCA (Reconfiguration capability). This study is restricted in number of ways and therefore offers many opportunities for future research. Firstly, this study only considered turbulent and competitive environments, additional outcome variables could be explored in the domain of BDA such as SC resilience, SC flexibility and SC innovation (incremental and radical). In relation to the BDA-SCA relationship specifically, studies could also examine, using factor analysis, additional enablers of the BDA-SCA relationships using the 3V framework outlined in this study. In conclusion, this study filled a major oversight in the literature in relation to how firms can implement BD to enhance SCA in turbulent and competitive environments. The study also considered how the external environment intertwines with BDA to play a key role in shaping DC capabilities and how these capabilities can be leveraged internally to enhance SCA.

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