Management Decision

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Big data analytics capability in supply chain agility

The moderating effect of organizational flexibility

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Abstract

Purpose – The purpose of this paper is to examine when and how organizations build big data analytics capability (BDAC) to improve supply chain agility (SCA) and gain competitive advantage.
Design/methodology/approach – The authors grounded the theoretical framework in two perspectives: the dynamic capabilities view and contingency theory. To test the research hypotheses, the authors gathered 173 usable responses using a pre-tested questionnaire.
Findings – The results suggest that BDAC has a positive and significant effect on SCA and competitive advantage. Further, the results support the hypothesis that organizational flexibility (OF) has a positive and significant moderation effect on the path joining BDAC and SCA. However, contrary to the belief, the authors found no support for the moderation effect of OF on the path joining BDAC and competitive advantage.
Originality/value – The study makes some useful contributions to the literature on BDAC, SCA, OF, and competitive advantage. Moreover, the results may further motivate future scholars to replicate the findings using longitudinal data.
Keywords Big data, Contingency theory, Dynamic capability view, Analytics capability,
Big data analytics capability
Paper type Research paper

1. Introduction

The most successful organizations create supply chains that can respond to sudden and unexpected changes in the market (Lee, 2004). Supply chain management has gained popularity among organizations as a source of competitive advantage (Lee, 2002). Managing supply chains is extremely challenging task due to the current business outsourcing, globalization, short product life cycle, and continuous advancement in information technology (IT) (Lee, 2002; Christopher and Towill, 2002). Fisher (1997) attempted to match supply chain strategies (i.e. efficient vs responsive) to the product characteristics (i.e. functional vs innovative products). Lee (2002) extended Fisher's work by proposing four strategies (i.e. efficient/responsive/risk hedging/agile), to accommodate different degrees of demand and supply uncertainty. Hence, according to the situation, the organization's supply chain agility (SCA) may directly affect its ability to produce and deliver innovative products to their customers at the right time, in the right place, in the right condition and at the right cost (Swafford *et al.*, 2006; Khan and Pillania, 2008). Lee (2002) further argues that agile supply chains utilize strategies aimed at being responsive and flexible to customer's needs, while the risks of supply shortages or disruptions are hedged by pooling inventory or other capacity resources.

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However, despite its immense popularity, SCA is still less understood (Braunscheidel and Suresh, 2009). The emerging literature has often used flexibility and agility interchangeably (Braunscheidel and Suresh, 2009). Liu *et al.* (2013) argues that amidst high environmental uncertainties, organizations are increasingly relying on IT capabilities to gain competitive advantage. Brusset (2016) further argues that supply chain managers are under extreme pressure to improve inventory turnover at minimal cost. Hence, in an effort to adapt the services and goods on offer to meet the customers' changing tastes and behaviors, supply chain managers are under pressure to build agility in their supply chains to match the intense competition in markets (Gligor *et al.*, 2016). However, an independent stream of research in recent years has led to the conceptualization of SCA as a distinct and different construct from flexibility (Christopher, 2000; Gligor and Holcomb, 2012a, b; Blome *et al.*, 2013; Brusset, 2016; Dubey, Altay, Gunasekaran, Blome, Papadopoulos and Childe, 2018). The literature focusing on SCA and its impact on organizational performance is limited (Gligor *et al.*, 2015) and has focused on the management practices needed to achieve the operational capabilities to enhance SCA from different managerial viewpoints, such as operations, strategy, information systems, marketing, and human resources (Brusset, 2016).

Choi *et al.* (2017) argue that big data has significant effects on operations management practices. Gunasekaran, Papadopoulos, Dubey, Fosso Wamba, Childe, Hazen and Akter (2017), Gunasekaran, Yusuf, Adeleye and Papadopoulos (2017) further argue that supply chain disruptions have negative effects and agile supply chain enablers were progressively used with the aid of big data and business analytics to achieve better competitive results. Srinivasan and Swink (2017) further argue that although big data analytics has been in use to understand customer intentions/behaviors, the use of analytics for supply chain operational decisions is less understood. Gunasekaran, Papadopoulos, Dubey, Fosso Wamba, Childe, Hazen and Akter (2017), Gunasekaran, Yusuf, Adeleye and Papadopoulos (2017) argue that big data and predictive analytics have positive effects on supply chain performance and organizational performance. Sambamurthy *et al.* (2003) argue that organizations are increasingly investing in IT capabilities. While some researchers have established the linkage between big data analytics capability (BDAC) and competitive advantage (Akter *et al.*, 2016; Ren *et al.*, 2017; Frisk and Bannister, 2017) and SCA and competitive advantage (Blome *et al.*, 2013; Gligor *et al.*, 2015), little empirical testing of big data analytics and SCA and competitive advantage exists (Sangari and Razmi, 2015; Gunasekaran, Papadopoulos, Dubey, Fosso Wamba, Childe, Hazen and Akter, 2017; Gunasekaran, Yusuf, Adeleye and Papadopoulos, 2017). Hence, we address our first research question:

RQ1. What are the distinct and joint effects of BDAC and SCA on competitive advantage?

Boyd *et al.* (2012) argue that direct effects are crucial, but they seem incapable of explaining real-world complexities. Hence, scholars have acknowledged that the performance effect of supply chain management practices hinges on the environmental context (Sousa and Voss, 2008). Eckstein *et al.* (2015) argue that such a view is often reflected in contingency theory (CT). The existing research focusing on IT capability and SCA has, however, largely neglected the influence of these contextual factors. In this paper we use a CT perspective to examine under what conditions the BDAC is effective.

Insights derived via big data analysis can provide opportunities for operational improvements (Fosso Wamba *et al.*, 2015; Papadopoulos *et al.*, 2017; Lamba and Singh, 2017; Srinivasan and Swink, 2017; Choi *et al.*, 2017). However, organizations must also convert these valuable insights into actions. Galbraith (2014) argues that the final function to be accelerated by big data is the supply chain. Galbraith (2014, p. 9) further describes how P&G utilizes "decision spheres" where cross-functional teams meet. In case of any emergency plant maintenance, the supply chain managers leverage analytics capability to re-route their trucks and still meet their customers' demand. The role of organizational flexibility (OF) has

been widely discussed in operations management literature – the ability of an organization to deploy resources quickly and efficiently – as a means to respond to the changing market conditions (Upton, 1994; Swafford *et al.*, 2008; Srinivasan and Swink, 2017). Srinivasan and Swink (2017) argue that analytics capability can provide insights on what to change to match supply and demand; OF enables the organization to determine how to make the appropriate changes. However, such crucial effects have not been addressed by prior research theoretically or subjected to empirical testing. Thus, we specify our second research question as follows:

RQ2. What are the effects of OF on the relationships between big data analytics and SCA/competitive advantage?

We provide answers to our research questions, using data from 173 survey responses from experienced supply chain managers. To theoretically substantiate our empirical results, we have integrated the dynamic capabilities view (DCV) (Teece *et al.*, 1997) and CT, because neither perspective can, on its own, explain the direct impacts of BDAC on SCA and competitive advantage and the contextual conditions under which they are effective.

The paper is organized as follows. In Section 2 of the paper, we present the underpinning theories. In Section 3, we illustrate our theoretical framework and outline our research hypotheses accordingly. In Section 4, we present our research design, including discussion of instrument development, sampling design, and data collection. In Section 5, we present our statistical analyses and results. In Section 6, we provide discussion of our statistical results. In Section 7, we conclude our study with theoretical contribution and managerial implications, limitations and further research directions.

2. Underpinning theories

2.1 DCV

Following criticism of the resource-based view, which often fails to provide explanation of how and in what context the resources can provide competitive advantage to a firm (Eisenhardt and Martin, 2000), scholars have argued that the DCV provides explanation for the organization's competitive advantage in changing environments (Teece *et al.*, 1997; Sirmon *et al.*, 2010; Eisenhardt and Martin, 2000; Singh *et al.*, 2013). Teece *et al.* (1997, p. 516) defined dynamic capabilities as, "the firm's ability to integrate, build and reconfigure internal and external competencies to address rapidly changing environments." Teece *et al.* (1997) further argue that dynamic capabilities include the capabilities to sense and shape opportunities, to seize opportunities, and to maintain competitiveness through enhancing, combining, protecting and reconfiguring a firm's resources. Within the context of a highly uncertain environment, dynamic capabilities are simple, experiential, unstable processes that rely on rapidly created new insights that enable combination, transformation, or renewal of resources and competencies into capabilities which are essential for uncertain markets (Eisenhardt and Martin, 2000; Eckstein *et al.*, 2015). Based on these arguments scholars have considered big data analytics as a dynamic capability (Fosso Wamba *et al.*, 2017) that results from the organization's ability to reconfigure firm-level resources.

2.2 BDAC

There is increasing debate about the importance of big data analytics in supporting the strategic goals of an organization (Davenport, 2006; Manyika *et al.*, 2011; Prescott, 2014; Mishra *et al.*, 2016, 2017; Roden *et al.*, 2017; Ren *et al.*, 2017; Choi *et al.*, 2017; Fosso Wamba, 2017; Jabbour *et al.*, 2017), but there is as yet no consensus about how best to organize big data analytics efforts within the organization and what core analytics processes the organization should support (Galbraith, 2014). Following Manyika *et al.* (2011), we argue that big data are data whose volume, velocity, and variety make it difficult for an

organization to manage, analyze, and extract valuable insights using conventional and traditional methods. The term analytics refers to "the process that extracts valuable insights from data via creating and distributing reports, building and deploying statistical and data-mining models, exploring and visualizing data, sense-making and other related techniques" (Grossman and Siegel, 2014, p. 20). Hence, we can argue that BDAC is an organizational facility with tools, techniques, and processes that enable the organization to process, visualize, and analyze data, thereby producing insights that enable data-driven operational planning, decision making and execution (Srinivasan and Swink, 2017). In the context of supply chain management, BDAC enables to firms to examine alternatives related to supply and demand uncertainties (Waller and Fawcett, 2013; Hazen *et al.*, 2014; Wang *et al.*, 2016).

2.3 SCA

Lee (2004) argues that organizations are increasingly investing in building agility in supply chains to respond to sudden and unexpected changes in the market. Swafford *et al.* (2006) argue that SCA affects the ability of an organization to produce and deliver innovative products to their customers in a timely and cost-effective manner. Braunscheidel and Suresh (2009) noted that with intense competitive pressures as well as high levels of turbulence and uncertainty, organizations require agility in their supply chains. The agility in supply chains provides superior value as well as overcoming disruption risks and ensuring uninterrupted service to customers (Braunscheidel and Suresh, 2009; Blome *et al.*, 2013; Gligor *et al.*, 2016; Brusset, 2016). Christopher (2000) has noted that numbers of characteristics that a supply chain must possess to be agile are:

- Market sensitive – it closely monitor the changes in demand pattern.
- Virtual – information sharing among partners in supply chain is critical.
- Network-based – helps to build flexibility in supply chain network.
- Process integration – it has a high degree of process interconnectivity between the network members.

Hence, these characteristics help the organizations to meet customer demand by providing the right product at the right time, place, and price. Some notable examples include Dell, Wall-Mart and Amazon (Lee, 2004). Swafford *et al.* (2006) found that organizations' SCA is directly and positively impacted by flexibility in manufacturing and procurement/sourcing processes. Braunscheidel and Suresh (2009) observed, based on empirical results, that besides flexibility, internal cross-functional integration and external integration with key customers and suppliers are crucial for enhancing agility in supply chains. Eckstein *et al.* (2015) view SCA as a dynamic capability that not only helps to meet customers' demand but also helps to enhance the firm's profitability. Dubey, Altay, Gunasekaran, Blome, Papadopoulos and Childe (2018) further noted that supply chain visibility enhances SCA via bundling organizational resources (i.e. data connectivity and information sharing). Hence, we can argue that agility is a desired property of a supply chain that enables it to respond to short-term changes in demand and supply quickly and handle external disruptions smoothly.

2.4 OF

Volberda (1996, p. 361) defines OF, as "the degree to which an organization has a variety of managerial capabilities and the speed at which they can be activated, to increase the control capacity of the management and improve the controllability of the organization." Hence, we argue that OF is the organizational ability that enables organizations to operate in a

turbulent environment (Braunscheidel and Suresh, 2009; Sharma *et al.*, 2010; Srinivasan and Swink, 2017). Sanchez (1993) argues that in dynamic environments, an organization can gain competitive advantage by creating strategic flexibility. Sanchez (1995) further argues that flexibility is constrained not only by resources but also by the ways a firm uses the resources (see also Upton, 1994; Suarez *et al.*, 1996; Sanchez, 1997; Sanchez and Mahoney, 1997; Liu *et al.*, 2009).

2.5 Competitive advantage
Porter (1985) argues that firms can gain competitive advantage by identifying and implementing generic strategies and addresses the interplay between types of competitive advantage – cost and differentiation – and the scope of the firm's activities. Barney (1991, p. 102) defined competitive advantage, "a firm is said to have competitive advantage when it is implementing value creating strategy not simultaneously being implemented by any current or potential competitors." Peteraf (1993) argues that competitive advantage is the ability of an organization to maintain or sustain above-normal returns. However, Peteraf (1993) further argues that there are four cornerstones of competitive advantage: heterogeneity, *ex post* limits to competition, imperfect mobility and *ex ante* limits to competition. Barney (1991) argues that an organization can derive competitive advantage by creating bundles of strategic resources and/or capabilities. Reed and DeFillippi (1990) argue that competitive advantage can be derived from numerous sources. For instance, competencies are within the organization's control and can be exploited to generate competitive advantage for superior performance (Hinterhuber, 2013).

3. Theoretical framework and hypotheses development
The foundation of our theoretical model (see Figure 1) comprises two pillars: DCV and CT. Due to rapidly changing environments, the DCV has gained immense popularity among management scholars who seek to investigate how the bundling of firm resources and competencies can provide competitive advantage to a firm operating in a highly uncertain environment. Consistent with the previous arguments, information processing capability is seen a solution for uncertainty. The need for BDAC is further heightened by volatile and complex task environments, where high levels of uncertainty make effective planning and decision making difficult. Using the logic of fit, scholars have argued that organizational
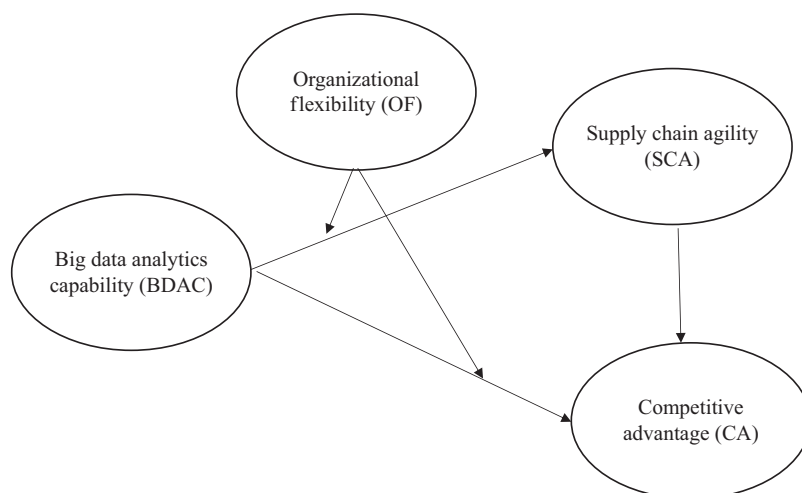

Figure 1.
Theoretical framework

flexibilities of several types are more valuable in highly uncertain environments (Swamidass and Newell, 1987; Pagell and Krause, 1999). Hence, we first draw direct links from BDAC to connect SCA and CA. Second, in order to examine the interaction effects of OF on the direct effects of BDAC on SCA and CA we draw links on the paths joining BDAC to SCA and CA. To further examine the direct effect of SCA on CA, we draw a link joining SCA and CA and propose four research hypotheses grounded in DCV and CT. These hypotheses do not exclude the possibility that other factors may influence the effect of BDAC on SCA/CA; we have controlled for these factors during our model testing and in our subsequent discussion.

3.1 BDAC and SCA
Swafford *et al.* (2008) found that IT capability has positive effect on SCA. Srinivasan and Swink (2017) noted that supply chain visibility is a prerequisite for building data analytics capability and vice versa. Supply chain visibility and BDACs are complementary, in the sense that each supports the other (Gunasekaran, Yusuf, Adeleye and Papadopoulos, 2017; Gunasekaran, Papadopoulos, Dubey, Fosso Wamba, Childe, Hazen and Akter, 2017). Supply chain visibility is a desired organizational capability to mitigate risk resulting from supply chain disruptions (Jüttner and Maklan, 2011). Following Srinivasan and Swink's (2017) arguments that organizations investing in building supply chain visibility capability are likely to invest in BDAC, Dubey, Altay, Gunasekaran, Blome, Papadopoulos and Childe (2018) found a positive impact of supply chain visibility on SCA. Hence, we may argue that the use of data technology may help managers to sense the rapid changes in environments, so they can develop business continuity plans that may help to quickly respond to the changes. Thus:

> *H1.* Big data analytics has a positive impact on SCA.

3.2 BDAC and competitive advantage
Competitive advantage refers to any advantage that a firm has over their competitors (Porter, 1985). Chen *et al.* (2012) argue that big data presents an immense opportunity to achieve competitive advantage. LaValle *et al.* (2011) noted that top-performing organizations use analytics five times more than low performers. Raffoni *et al.* (2018) argue that big data analytics, if used cautiously, can help the organization to achieve better performance. Akter *et al.* (2016) argue that BDAC has a positive impact on organizational performance. Kache and Seuring (2017) argue that the use of big data analytics is still in its infancy stage, but despite challenges big data analytics appears to offer immense opportunities. Zhang *et al.* (2017) argue that organizations are increasingly exploiting big data to improve organizational competitiveness. Gunasekaran, Yusuf, Adeleye and Papadopoulos (2017), Gunasekaran, Papadopoulos, Dubey, Fosso Wamba, Childe, Hazen and Akter (2017) noted that the big data and predictive analytics capability have positive impact on supply chain and organizational performance. Hence, we hypothesize:

> *H2.* Data analytics has positive impact on organization's competitive advantage.

3.3 SCA and competitive advantage
The great companies create agile supply chains to respond to sudden and unexpected changes in markets. Brusset (2016) argues that SCA is desirable as in most industries, both demand and supply fluctuate rapidly. Lee (2004) argues that organizations like H&M, Mano and Zara use SCA to differentiate themselves from their competitors. Whitten *et al.* (2012) tested empirically, using a survey of 132 respondents, that SCA along with other capabilities (i.e. supply chain adaptability and supply chain alignment) has a positive impact on

supply chain performance and supply chain performance further positively affects organizational performance. Gligor *et al.* (2015) tested using a survey of 283 that SCA has a positive impact on financial performance under the mediating effects of customer effectiveness and cost efficiency. Thus, we test:

H3. SCA has a positive impact on competitive advantage.

3.4 Moderating effects of OF

The BDAC provides useful insights based on processing of the data gathered from multiple sources (Srinivasan and Swink, 2017; Choi *et al.*, 2017). Galbraith (1973, 1974) noted that organizations need flexibility to implement decisions quickly and efficiently, especially decisions that span various functions. OF has been noted as one of the key levers to reduce supply chain risk (Braunscheidel and Suresh, 2009). Hence, we posit that organizations can more effectively take advantage of new insights gained from BDAC when they possess high levels of OF. Organizations with better OF are more capable of coping with demand and supply uncertainties (Swafford *et al.*, 2006) and gain competitive advantage (Yusuf *et al.*, 2004, 2014). Consequently, those organizations have better capabilities to improve SCA than those organizations which rely on decisions based on limited data sets or mechanistic models of processing data. Thus:

H4. OF positively moderates the relationship between BDAC and: (a) SCA and (b) competitive advantage.

4. Research design

4.1 Sample and data collection

We analyzed data collected in 2015 through a survey of Automotive Components Manufacturers Association (ACMA of India), to test our theoretical model. ACMA and McKinsey administered this cross-sectional survey. The unit of analysis is the organization and the survey was developed for a single respondent. Our research team sent e-mail invitations to 745 supply chain managers drawn from the ACMA database. The sampling frame included senior supply chain managers from auto components manufacturing organizations located in various parts of India. For this study, senior supply chain managers in logistics, production, procurement, and information systems functions were targeted, as they are likely to have relevant information related to materials and information flow as well as supply chain innovation initiatives. With regard to the four supply chain types (Lee, 2002), it should be noted that all the respondents were in the auto components industry and could expect to be broadly comparable.

Overall, we received 173 complete and usable responses, representing an effective response rate of 23.22 percent (see Table I). In this study, we eliminated those respondents whose titles were not directly related to supply chain functions and had less experience. The resulting sample held senior managerial positions such as vice president, general manager, CXO (C-suite managers), director, head, senior manager and manager with more than 15 years of experience. We also included responses from analysts and planners. We provide the profile of the responding organizations in Table I and the profile of the respondents in Table AI.

In survey-based research, there is always a potential for biases. As we used a survey-based approach to gather data, we tested for non-response bias through comparison of early responses and late responses, following Armstrong and Overton's (1977) suggestions. The *t*-tests yielded no statistically significant differences between early and late responses, indicating that non-response bias is not a problem in our study.

Annual sales revenue	Number	Percentage
Under $10 million	25	14.45
$11-25 million	32	18.50
$26-50 million	32	18.50
$51-75 million	25	14.45
$76-100 million	14	8.09
$101-250 million	15	8.67
$251-500 million	20	11.56
Over $501 million	10	5.78
Total	173	
Number of employees		
0-50	7	4.05
51-100	13	7.51
101-200	35	20.23
201-500	35	20.23
501-1,000	47	27.17
1,001+	36	20.81
Total	173	

Table I.
Profile of the responding organizations

4.2 Measures

Following Malhotra and Grover's (1998) suggestions, we used established scales from literature in our study. This was feasible for measures of data analytics, OF, SCA, and competitive advantage. We made minor modifications in the wording of our questionnaire based on pre-tests to improve the performance of the questionnaire. All the scales were designed in five-point Likert format with anchors 1 = strongly disagree and 5 = strongly agree.

In addition, we identified three control variables, which may influence the exogenous and endogenous variables and may cause unwanted sources of variance. First, firm size, following Cao and Zhang's (2011) arguments that smaller firms have fewer resources for the implementation of supply chain management practices, and Wagner and Neshat (2012) who noted that larger organizations are more vulnerable to supply chain disruptions. The number of employees (logarithmic) measured the size of the firm (Gligor *et al.*, 2015). Second, we included industry dynamism in order to level out the effects of uncertainty across industry segments. Aldrich (1979) argues that dynamism reflects the unpredictability and volatility, of the changes in the industry that heightens the uncertainty of the organizations' predictions. We measured industry dynamism on a five-point Likert format anchored as, 1 = slow and 5 = rapid, with items reflecting the industry rates of change for product/service introduction, operating processes, customer tastes/preferences, and research and development (Brandon-Jones *et al.*, 2014). Third, we controlled for the age of the organization. Gligor *et al.* (2015) argue that the age of the organization can influence the implementation of supply chain practice and therefore, impact upon competitive advantage. The firm age is calculated as the number of years since the firm foundation (logarithmic) (see, Srinivasan and Swink, 2017). Table II shows the summary of the items used for measures.

5. Data analyses and results

We used WarpPLS 5.0 software to test our model. The software employs the partial least squares (PLS) structural equation modeling method or in short form PLS SEM (Kock, 2014, 2015). PLS is a prediction-oriented tool which allows researchers to assess the predictive validity of the exogenous variables (Peng and Lai, 2012). Scholars argue that PLS is better suited for explaining complex relationships as it avoids two serious problems: inadmissible solutions and factor indeterminacy (see, Peng and Lai, 2012;

Construct	Reference	Item	Description
Big data analytics capability (BDAC)	Akter *et al.* (2016), Srinivasan and Swink (2017)	BDAC1	We use advanced tools (like optimization/regression/simulation) for data analysis
		BDAC2	We use data gathered from multiple sources (like company reports, tweets, Instagram, YouTube) for data analysis
		BDAC3	We use data visualization techniques to assist decision makers in understanding complex information extracted from large data
		BDAC4	Our dashboards display information, which is useful for carrying out necessary diagnosis
		BDAC5	We have connected dashboard applications or information with the manager's communication devices
Organizational flexibility (OF)	Sethi and Sethi (1990), Upton (1994)	OF1	We can quickly change organizational structure to respond to demand and supply uncertainties
		OF2	Our organization can cost effectively respond to sudden changes in the market
		OF3	Our organization is more flexible than our competitors in changing our organizational structure
Supply chain agility (SCA)	Gligor *et al.* (2015)	SCA1	Our organization can quickly detect changes in our environment
		SCA2	Our organization can quickly identify opportunities in its environment
		SCA3	Our organization can quickly sense threats in its environment
		SCA4	Our organization continuously collects information from suppliers
		SCA5	Our organization continuously collects information from customers
		SCA6	We make quick decisions to deal with changes in environment
		SCA7	When needed we can adjust our supply chain operations to the extent necessary to execute our decisions
		SCA8	Our organization can increase its short-term capacity as needed
		SCA9	We can adjust the specification of orders as requested by our customers
Competitive advantage (CA)	Tracey *et al.* (1999), Vorhies and Morgan (2005)	CA1	Our customers are satisfied with our product quality
		CA2	We deliver value to our customer
		CA3	We deliver at the right time what our customers want
		CA4	Our market share growth is significant in comparison to our customers
		CA5	We are able to acquire new customers
		CA6	We have reached our financial goals
Industry dynamism (ID)	Brandon-Jones *et al.* (2014)	ID1	Our product and services become outdated
		ID2	Our organization continuously introduces new products and services
		ID3	Our organization introduces new operating processes
		ID4	The customers taste and preferences in our industry changes fast
Age of the organization (OA)	Gligor *et al.* (2015)	OA	Logarithmic value of number of years
Organization size (OS)	Gligor *et al.* (2015)	OS	Logarithmic value of number of employees

Table II.
Measures

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Henseler *et al.*, 2014; Moshtari, 2016; Pratono, 2016; Akter *et al.*, 2017; Martí-Ballester and Simon, 2017; Dubey, Gunasekaran, Childe and Papadopoulos, 2018). In our study, we aim to examine the prediction or explanatory power of BDAC. The relationships between two variables – BDAC and SCA – are not examined in literature. With no theoretical foundation that explains the relationships between these two variables, PLS becomes the most suitable technique for data analysis (Peng and Lai, 2012). We carried out our model estimation based on Peng and Lai's (2012) suggestions in two stages: examining the reliability and validity of the measurement model and then analyzing the structural model.

5.1 Measurement model

A series of procedures were used to determine convergent and discriminant validity for the constructs used in our model (see Figure 1). In support of convergent validity, we noted that factor loadings were significant except for a few items which we dropped from our study. Next, we found that the average variance extracted (AVE) of each construct was greater than 0.7. As shown in Table AII, the loadings are in an acceptable range and they are significant at the 0.01 level (Fornell and Larcker, 1981). The discriminant validity was assessed via AVE comparisons (see Table III). The square roots of the AVEs were greater than all of the inter-construct correlations; it is a strong evidence of sufficient discriminant validity.

5.2 Common method bias (CMB)

Ketokivi and Schroeder (2004) argue that data gathered using a survey-based instrument from a single source has potential biases. Podsakoff *et al.* (2003) argue that in the case of self-reported data, there is potential for CMBs resulting from multiple sources such as consistency motif and social desirability. Hence, we designed our survey to minimize the CMB effect using different scale formats and anchors for independent, moderating, and dependent variables. In addition, we performed several statistical analyses to assess the extent of CMB. First, following Podsakoff and Organ (1986) we performed a conservative version of Harman's one-factor test. The results from this test showed that the single factor explains 43.69 percent (approx.), of total variance, demonstrating that CMB is not a significant concern. Second, we tested for CMB using the marker technique (Lindell and Whitney, 2001). We used an unrelated variable to partial out the correlations caused by CMB. We also calculated the significant value of the correlations based on Lindell and Whitney's (2001) equations. We noted no significant differences between adjusted and unadjusted correlations. Based on these results we consider that the potential effects of common method variance are negligible.

Guide and Ketokivi (2015) noted that causality is an important issue that should be examined prior to hypothesis testing. Following Kock's (2015) suggestions, we calculated the nonlinear bivariate causality direction ratio (NLBCDR). The NLBCDR refers to "an interesting property of nonlinear algorithms […] that bivariate nonlinear coefficients of

	BDAC	OF	CA	SCA	ID
BDAC	0.76				
OF	0.24	0.95			
CA	0.24	0.56	0.95		
SCA	0.61	0.37	0.41	0.93	
ID	0.08	0.01	0.17	0.20	0.88

Table III.
Correlations among major constructs

Notes: BDAC, big data analytics capability; OF, organizational flexibility; SCA, supply chain agility; CA, competitive advantage; ID, industry dynamism. ✔ (AVE) are in italic

association vary depending upon the hypothesized direction of the causality. That, is they tend to be stronger in one direction than the other, which means that the residual (or error) is greater when the hypothesized direction of causality is in one way or the other. Hence, the NLBCDR index is a measure of the extent to which bivariate nonlinear coefficients of association provide support for the hypothesized directions of the causal links in the model" (Kock, 2015, pp. 52-53). The desired acceptable value is greater than 0.7. In our model NLBCDR = 0.818, which is greater than the cut-off value. Hence, based on these results we can argue that endogeneity is not a serious concern in our study. We further tested the model fit and quality indices (see Table AIII).

5.3 Hypothesis testing

Figure 2 presents the estimates obtained via PLS SEM analysis. The model explains a significant amount of variance for SCA ($R^2 = 0.29$) and competitive advantage ($R^2 = 0.69$). We have reported the PLS path coefficients and the corresponding p-values for the model in Table IV (*H1-H3*) and Table V (*H4a* and *H4b*). The links BDAC → SCA ($\beta = 0.32$, $p < 0.01$),
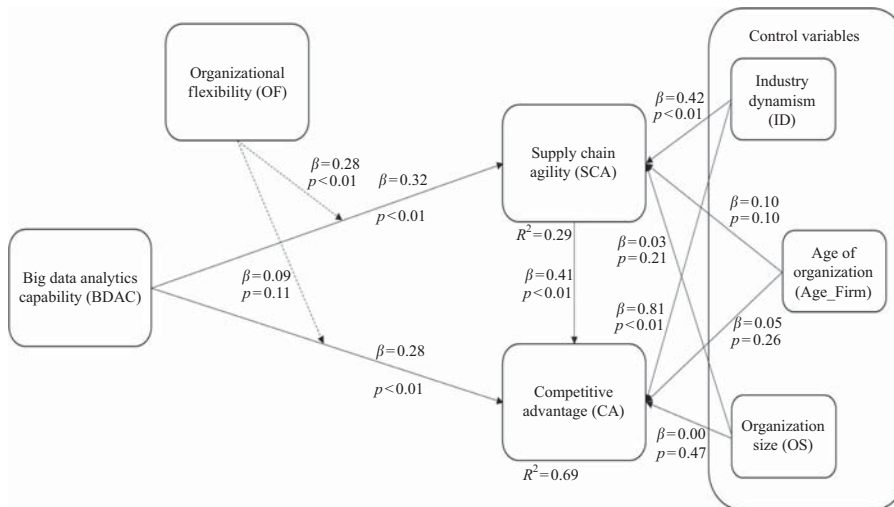
Figure 2.
Causal model

Hypothesis	Effect of	Effect on	β	p	Result
H1	BDAC	SCA	0.32	***	Supported
H2	BDAC	CA	0.28	***	Supported
H3	SCA	CA	0.41	***	Supported
Control variables					
	ID	CA	0.81	***	Significant
	OA	CA	0.05	*	Not significant
	OS	CA	0.00	*	Not significant
	ID	SCA	0.42	***	Significant
	OA	SCA	0.1	*	Not significant
	OS	SCA	0.03	*	Not significant

Notes: BDAC, big data analytics capability; SCA, supply chain agility; CA, competitive advantage; ID, industry dynamism; OA, age of the organization; OS, organizational size. *$p > 0.1$; ***$p < 0.01$

Table IV.
Structural estimates
(*H1-H3*)

BDAC→CA ($\beta = 0.28$, $p < 0.01$), and SCA→CA ($\beta = 0.41$, $p < 0.01$) are positively related. Thus, we can argue, based on β values and their corresponding p-values, that $H1$-$H3$ were supported. The control variables organization age and organizational size (OS) do not have significant effect in this model (see Table IV). However, industry dynamism has a significant effect on SCA and CA.

Next, our hypothesis $H4$ was tested for the moderation effect of OF on the path connecting data analytics capability and supply chain resilience ($H4a$) and data analytics capability and competitive advantage ($H4b$). $H4a$ ($\beta = 0.28$, $p < 0.01$) was found to be supported (see Table IV). However, $H4b$ ($\beta = 0.09$, $p > 0.1$) was not supported.

Next, we examined the explanatory power of our proposed theoretical model. For this, we examined the explanatory power (R^2) of the endogenous construct. The R^2 for SCA is 0.29 which is moderately strong and for CA is 0.69 which is strong (Chin, 1998) (see Figure 2). We further examined the f^2 value of the BDAC using Cohen's f^2 formula. Consequently, the effect size of BDAC on SCA is 0.002 and on CA is 0.003 (see Table VI) which were greater than the cut-off value of zero. Next, we examined the model's capability to predict. Stone-Geiser's Q^2 values for the endogenous constructs were SCA (0.3) and CA (0.66) (see Table VI) for BDAC which is greater than zero, indicating acceptable predictive relevance (Peng and Lai, 2012).

6. Discussion

Our results provide a better understanding of the impact of BDAC on SCA and competitive advantage, answering the calls for research (Brusset, 2016; Gunasekaran, Yusuf, Adeleye and Papadopoulos, 2017; Gunasekaran, Papadopoulos, Dubey, Fosso Wamba, Childe, Hazen and Akter, 2017; Dubey, Altay, Gunasekaran, Blome, Papadopoulos and Childe, 2018). Our results contribute to building and refining theories of BDAC, SCA, OF, and competitive advantage and provide empirically grounded normative suggestions to management practitioners. The results provide improve our understanding about the relationship between BDAC, SCA, and competitive advantage. Our study is the first to offer a rigorous empirical test of the distinct effects of BDAC on SCA and competitive advantage, which was called for in previous research (Gunasekaran, Yusuf, Adeleye and Papadopoulos, 2017; Gunasekaran, Papadopoulos, Dubey, Fosso Wamba, Childe, Hazen and Akter, 2017). We found that age of the firm (OA) and OS have no significant effect on SCA and competitive advantage. We interpret these observations as evidence the auto components

Hypothesis	Effect of	Effect on	β	p	Result
$H4a$	BDAC×OF	SCA	0.28	***	Supported
$H4b$	BDAC×OF	CA	0.09	*	Not supported

Table V.
Structural estimates ($H4a$ and $H4b$)

Notes: BDAC, data analytics capability; SCA, supply chain agility; CA, competitive advantage; OF, organizational flexibility. *$p > 0.1$; ***$p < 0.01$

Construct	R^2	Q^2	f^2 in relation to	
			SCA	CA
BDAC	–	–	0.002	0.003
OF	–	–		
SCA	0.29	0.30		
CA	0.69	0.66		

Table VI.
R^2, prediction and effect size

sector is increasingly using big data analytics to improve SCA and gain competitive advantage in the face of rapid change, and the size and age of the firm play little role in the BDAC-SCA-competitive advantage relationship. However, industry dynamism has positive effects on SCA and competitive advantage. We interpret these observations to suggest that dynamic elements such as the rate with which new products or services are introduced, operating processes, customer tastes/preferences, and research and development may have a major role to play in the big data analytics-SCA-competitive advantage relationship. While this may be contrary to our expectations, the role of industry dynamism may be further explored in the context of the big data analytics-SCA-competitive advantage relationship.

Our hypotheses that under high OF the relationship between BDAC and SCA/competitive advantage will be strengthened were partially supported. Specifically, our results support our belief that OF positively moderates the link joining BDAC and SCA. However, our expectation that OF would positively moderate the link from BDAC to competitive advantage, this was not supported. These results may be due to the inclusion of OF as a key contextual factor in our theoretical model. Hence, we suggest further research is needed to examine whether OF has a role to play on the impact of BDAC and competitive advantage.

7. Conclusions
7.1 Implications for theory
Brusset (2016) found empirically that visibility may not have a significant effect on SCA. Contrary to Brusset's (2016) findings, Dubey, Altay, Gunasekaran, Blome, Papadopoulos and Childe (2018) observed that supply chain visibility has a positive and significant effect on SCA. Srinivasan and Swink (2017) argue that visibility is created via external relations, which may help decision makers to sense changes in customer and competitors markets, including demands, pricing and promotional actions, and product inventories. Hence, the organizations that develop demand and supply visibility are also better positioned to develop and deploy systems and processes supporting analytics capability. Building upon this tautology, we posited that organizations that seek to enhance supply chain visibility would invest in building BDAC, which will help them handle large data derived from various sources to extract useful insights. Building on Srinivasan and Swink's (2017) arguments, we tested the direct impact of BDAC on SCA. Our study is the first to provide an empirical test of the distinct effects of BDAC on SCA and competitive advantage. The information derived via BDAC provides firms with real-time information regarding changes in future product demand due to changes in downstream inventories, promotions, and sales. Moreover, supplier-sourced data provide information regarding supply shortages and excess inventories resulting from changes in upstream inventories, capacities, and the status of orders and shipments. We have thus answered the research calls of prior literature (see Gunasekaran, Yusuf, Adeleye and Papadopoulos, 2017; Gunasekaran, Papadopoulos, Dubey, Fosso Wamba, Childe, Hazen and Akter, 2017; Dubey, Altay, Gunasekaran, Blome, Papadopoulos and Childe, 2018). Moreover, our study is the first to empirically investigate the moderating effect of OF on the paths connecting BDAC and SCA/competitive advantage. Thus, we contribute to the literature by addressing the need for more holistic understanding of distinct relationships among contingencies (i.e. OF), response alternatives (i.e. BDAC) and multiple performance outcomes (i.e. SCA and competitive advantage). In doing so, we contribute to our understanding of the specific contextual factors under which BDAC can effectively improve SCA. Hence, by integrating the perspectives of the DCV and CT, we provide a solid theoretical grounding for our empirical investigation of CT as a complement to DCV, given its shortcomings in recognizing the complexity involved while bundling resources and capabilities (Eckstein et al., 2015).

7.2 Implications for practice

By empirically testing our theoretical model we provide established evidence (to surpass anecdotal evidence) that organizations in our sample do indeed benefit from BDAC to sense market changes, including demands, pricing and promotional schemes of their competitors, and product inventories. Moreover, our results strengthen the notion that managers who can exploit the innovative technology in attempts to build capability at supply chain level can expect their organizations to gain competitive edge over their competitors (Davenport, 2006; Akter *et al.*, 2016; Srinivasan and Swink, 2017). However, before building BDAC, a thorough understanding of OF is critical. OF stems from knowledge and abilities to change organizational structures and resource allocations quickly and efficiently. Our results suggest that OF serves as a complementary capability to BDAC in consistently improving SCA in highly uncertain environments. Even though research provides evidence to show management practitioners that BDAC does indeed pay off, practitioners require a better understanding of how they can develop this critical dynamic capability. This issue is of critical importance, as BDAC requires a significant investment of resources and effort. Hence, without appropriate understanding of the resources and the competences needed to build BDAC, practitioners may not achieve the desired outcome via BDAC.

7.3 Limitations and further research opportunities

Like any other studies, the results of our study are subject to several limitations that must be taken into consideration while interpreting these results. First, we tested our theoretical model using data gathered at one point in time. Following Guide and Ketokivi (2015), we can argue that cross-sectional data are one of the major causes of CMB and causality. While we have performed several statistical analyses which may provide evidence that CMB and causality were not a major concern in our study, a longitudinal design would help to reduce the possibility of CMB that undermines the validity of studies with data from a single source at a single point in time.

Second, we used the perspectives of DCV and CT. However, future studies may use other theory or theories to provide better explanation. Scholars may investigate other organizational capabilities or assets considered as complements to BDAC. Moreover, other theoretical perspectives including knowledge based view, absorptive capacity, organizational learning, organizational culture and top management commitment might provide useful extensions to our study.

Third, we believe that survey-based research has its own limitations. Hence, future researchers may be able to address some unanswered questions via case based methods.

Finally, the demographic of our research sample may limit the generalizability of our findings. Thus, the research findings should be applied to other contexts with caution. We acknowledge that any study using a survey-based approach often faces a generalizability issue. It is very difficult to obtain a sample that could claim to be truly representative of the whole population. Still, future research should be conducted over a period with samples from more industries, countries, and informants with diverse backgrounds.

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Appendix 1

Variables	Category	Respondents	%
Gender	Male	163	94.22
	Female	10	5.78
Age	> 50	110	63.58
	40-50	50	28.90
	30-39	13	7.51
	< 30	Nil	Nil
Education level	Doctorate	6	3.47
	Postgraduate degree in management	60	34.68
	Postgraduate degree in engineering	70	40.46
	Postgraduate degree in science	12	6.94
	Bachelor's degree	23	13.29
	Associate degree	2	1.16

Table AI.
Profile of the
respondents

Appendix 2

Construct	Items	Factor loadings	Variance	Error	SCR	AVE
BDAC	BDAC1	0.75	0.57	0.43	0.80	0.58
	BDAC2	0.66	0.44	0.56		
	BDAC3	0.86	0.74	0.26		
OF	OF1	0.95	0.90	0.10	0.97	0.91
	OF2	0.95	0.91	0.09		
	OF3	0.96	0.92	0.08		
CA	CA2	0.96	0.92	0.08	0.98	0.91
	CA3	0.97	0.94	0.06		
	CA4	0.94	0.87	0.13		
	CA5	0.94	0.89	0.11		
	CA6	0.95	0.91	0.09		
SCA	SCA2	0.95	0.91	0.09	0.97	0.86
	SCA3	0.93	0.87	0.13		
	SCA4	0.93	0.87	0.13		
	SCA5	0.95	0.90	0.10		
	SCA6	0.90	0.81	0.19		
	SCA7	0.88	0.78	0.22		
ID	ID1	0.78	0.61	0.39	0.93	0.77
	ID2	0.96	0.92	0.08		
	ID3	0.96	0.92	0.08		
	ID4	0.81	0.65	0.35		

Table AII.
Loadings of the
indicator variables,
SCR and AVE

Notes: BDAC, big data analytics capability; OF, organizational flexibility; CA, competitive advantage; SCA, supply chain agility; ID, industry dynamism; (BDAC1, CA1, SCA1, SCA8, SCA9, SCA10 were dropped from our analysis due to weak loadings)

Appendix 3

Model fit and quality indices	Value from analysis	Acceptable if	Reference
APC	0.183, $p = 0.003$	$p < 0.05$	Rosenthal and Rosnow (1991)
ARS	0.489, $p < 0.001$	$p < 0.05$	
AVIF	1.134, $p < 0.001$	$p < 0.05$	Kock (2015)
Tenenhaus GoF	0.693	Large if $\geqslant 0.36$	Tenenhaus *et al.* (2005)

Table AIII.
Model fit and
quality indices

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