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Does Supply Chain Analytics Enhance Supply Chain Innovation and Robustness Capability?

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Background and purpose: Little are known about the nature of the interaction between supply chain analytics, supply chain innovation and robustness capability. The purpose of this paper is to examine the effectiveness of supply chain analytics in enhancing firms supply chain innovation and robustness capability in the Arabian context.
Design/Methods: Using knowledge-based view and survey data from line managers in supply and logistics departments, the present study uses variance-based structural equation modeling (PLS-SEM) to diagnose the association between supply chain analytics, supply chain innovation and robustness capability.
Findings: Results suggest that supply chain analytics exerted significant impact on supply chain innovation and not on robustness capability. It appears that supply chain innovation exerted a significant impact on robustness capability, in doing so, supply chain innovation mediates the link supply chain analytics and robustness capability.
Conclusion: The outcome of this study points to the importance of supply chain analytics as a functional tool for supply chain and/or logistic routes stability and success. The paper concludes supply chain analytics can help managers have access timely and useful data for greater innovation; and that supply chain innovation is reliant not only on data, but also on firms' analytic capabilities.

Keywords: *Big data, supply chain analytics, supply chain innovation, robustness capability*

1 Introduction

In the last decade, scholars and practitioners uncover that Big data analytics has significant business value for the success of their enterprises amid fierce competition (Chen et al., 2013). Big data analytics (BDA) refers to technology enabled capability to process large volume, high velocity, variability and varieties of data to extract meaningful and valuable insights that can help firms gain competitive advantage (Fosso et al., 2017). Thus, incorporating BDA into business process can help firms to use data to gain business insights known as supply chain analytics in supply chain management (Jeble et al., 2018; Zhu et al., 2018). Prior researches revealed that BDA is an important tool that can boost firm performance (Akter et al., 2016; Côrte-Real et al., 2016; Ramanathan et al., 2017).

Other scholars embraced BDA to predict market trends and consumer demands (Miah et al., 2016), marketing efficiency (Xu et al., 2016), decision-making process (Abubakar, Elrehail, Alatailat, & Elçi, 2017; Marijn et al., 2017). The availability of modern data analytic techniques allows firms to have the know-how and use supply chain analytics, which in turn boost the strategic and operational performance (Wang et al., 2016). Traditional supply chain managers usually analyze routes and/or warehouse data to gain insights (Galbraith, 2014), because effective decision in supply chain is contingent on the availability of timely and quality route and/or warehouse data (Fosso et al., 2018). Quality data and ability to process the data can abate disruption and also reduce uncertainty (Papadopoulos et al. (2017). Thus, this can be extended via supply chain analytics.

Firms can improve innovation in their supply chain with competitive weapons namely; timely and quality data (Fernando et al., 2018). Despite these claims in the liter-

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ature, the impact of supply chain analytics (SCA) has on supply chain management (SCM) is still an uncharted area (Lai et al., 2018). For instance, research linking supply chain analytics to supply chain innovation and robustness capability are scarce to come by. According to the authors' knowledge so far, Kwak, Seo, and Mason (2018) is the only research paper that linked supply chain innovation with robustness capability. Moreover, Waller and Fawcett (2013) encouraged scholars to link business and predictive analytics with logistics and supply chain management citing business opportunities for firms. This paper responds to this call. The extent discussions highlight the need for additional insights from logistics management perspectives, theoretically, this paper draws on knowledge-based view to diagnose the nexus between supply chain analytics, supply chain innovation and robustness capability in an Arabian setting. In doing so, the paper set out to catechize theory developed for and tested in Western settings. The purpose of this study is to examine the relationship between supply chain analytics, supply chain innovation and robustness capability, specifically how supply chain analytics boosts innovation and robustness. Accordingly, this study attempts to answer these research questions:

RQ1. How does supply chain analytics enhance supply chain innovation?

RQ2. How does supply chain analytics enhance robustness capability?

RQ2. How does supply chain innovation enhance robustness capability?

2 Literature review and hypotheses

The management of the flow of goods and services e.g., the movement and storage of raw materials, of work-in-process inventory, and of finished goods from point of origin to point of consumption is known as supply chain management (SCM). Whereas, logistics delineate the movement, storage, and flow of goods, services and information within the overall supply chain. Henceforth, logistics is an important component of SCM, as applicable to outsourcing (i.e., delegating parts of business operations to a specialist outside of the organization to manage) and offshoring (i.e., moving parts of business operations to another part of the world, firms can outsource without having to offshore). The common themes linking SCM with outsourcing and offshoring are desires for cost savings, demand for efficiency, increased turn-around time, sustainability etc. Resource-based theory (RBT) purports that firms' resources and competencies are the main drivers of competitive advantage (Barney, 1991). Firms' resources can be categorized into tangible (e.g., physical, monetary and human resources) and intangible (e.g., skills, knowledge and technical know-how).

Competence is used interchangeably with capability, resources build up firms' capabilities which in turn lead to competitive advantage (Grant, 1991). Resource-based theory has been linked with increased capability, innovation and performance (Verona, 1999) in situations where competitors are unable imitate, lack the knowledge, and specialization is scarce. Unlike RBT, knowledge-based theory (KBT) purports that firms excel as a result effective use of knowledge and not just possession. Possession of unique knowledge is not enough, rather firm's ability to capture, process and disseminate this knowledge to yield competitive differentiation is more important (Blome, Schoenherr & Eckstein, 2014; Grant, 1996). The present study is interested in supply chain analytics, which encompass iterative exploration of past knowledge, technologies and practices to gain insight. Thus, supply chain analytics can provide for inimitable resources, logically innovative and robustness capabilities.

2.1 Supply chain analytics and supply chain innovation

The rise in outsourcing and offshore productions comes with benefits such as cost advantage and access large markets, but also presents challenges for the supply chain ecosystem such as exchange rate and transportation risks, political and environmental uncertainty. Traditional supply chain managers usually respond to these challenges using SC risk management methods (Christopher and Lee, 2004). For instance, an analysis of the supply chain, this can only be achieved with the availability of timely data and information. This is the juncture at which Big data and supply chain management (SCM) intersected. Prior studies documented that BDA can improve supply chain performance by improving visibility, resilience and robustness, and organizational performance (Brandon-Jones, Squire, Autry, & Petersen, 2014; Schoenherr and Speier-Pero, 2015; Waller and Fawcett, 2013). The use of quantitative tools (i.e., statistical and machine-learning techniques), past and present data for predictive modeling to find meaningful information and improve operational performance in supply chain ecosystems is known as supply chain analytics (Gunasekaran et al., 2017). Whence, supply chain analytics is can viewed as a mixture of IT-enabled resources, data management and supply chain planning (Chae, Olson & Sheu, 2014).

In line with KBT, supply chain decisions are analytical and data-driven supported by information technology and data science techniques to improve supply chain planning and management. At best, supply chain analytics is mainly aimed at improving operational capability and reducing risk, but somehow may serve as innovation enhancer. Innovation is essential for organizational sustainability (Gao, Xu, Ruan & Lu, 2017). In supply chain, innovation is a complex process involving the identifications of new ways and methods and turning opportunities into new ideas and the latter practice in the supply chain management (Lee, Lee & Schniederjans, 2011). Supply chain analytics is a complex process in which past and present data are processed with quantitative tools and techniques. Effective acquisition, transformation and storage of data; transforming the data into meaningful information that supports evidence-based decision-making. This process can unveil unknown information and knowledge, that can help managers in planning, monitoring, and forecasting; and time series comparisons. Such information can identify error spots and strategies to reduce delivery time, error rates and cost, and improve operational capability and efficiency. KBT the main theoretical anchor posit that processed knowledge is a source of competitive advantage. As noted earlier BDA denotes processing business data to gain competitive advantage, whereas, supply chain analytics denotes processing supply chain related data to procure meaningful and valuable insights that maybe useful for innovation or use as inputs for innovations. Thus, the following hypothesis is proposed:

H1: *Supply chain analytics will enhance supply chain innovation*

2.2 Supply chain analytics and robustness capability

Physical strength denotes robustness. However, in supply chain management and logistic literatures, robustness denotes certain features such as capability to withstand varied shocks, man-made errors and variability in business environment (Wieland & Wallenburg, 2012). Robustness plays an important role during disruption, because well-equipped supply chain and logistics networks with risk awareness can alleviate or eliminate the occurrence of risk (Kwak et al., 2018). In other words, robust supply chain and logistics networks should be able to endure, confront and control disruptions. Robustness can buy time for a firm to identify and implement control mechanism necessary for risk mitigation or elimination (Kwak et al., 2018). Interestingly, identification of risk mitigation and/or control mechanism is contingent on timely and reliable data. Researchers (e.g., Kache & Seuring, 2017; Sahay & Ranjan, 2008) noted that firms rely on data analytics to reduce cost, uncertainty and enhanced decision-making. Supply chain analytics concept signifies the extraction, transformation, cleaning and integration data generated and captured by supply chain systems into meaningful patterns for decision-makers (Tiwari, Wee & Daryanto, 2018). In line with KBT, the acquisition, transformation and extraction of meaningful information using supply chain analytics can inform decision-makers about the possibility of such risks; allow them to develop strategies to respond to varied shocks, enhance firm's pliability against changing environment and intense competition, and also increases supply chain and logistics networks efficiency. Thus, the following hypothesis is proposed:

H2: *Supply chain analytics will enhance robustness capability*

2.3 Supply chain innovation and robustness capability

Supply chain innovation transpires in the form of new and advanced supply chain techniques and investments (Wagner, 2008). Research has shown that supply chain innovation can minimize risks and also foster resource and method reconfiguration to improve resilience (Ambulkar, Blackhurst, & Grae, 2015). Supply chain innovation needs changes of processes and rules, which may cause unexpected fluctuation in logistics operations. Whence, risk is often the price of innovation on one hand, and robustness is price of innovation on the other hand. For example, real-time supply chain and logistic channels tracking systems can increase firm's resilience against internal and external disruptions and potentials risks. Additionally, innovative vehicles, packages, agile and responsive processes appear to be an auxiliary mechanism by which supply chain and logistic firms use for risk management capabilities, logically enhancing resilience and robustness capacity (Waters, 2007). Supply chain innovation plays a very important role in providing opportunities for fortifying the capabilities of the firm's risk management (Kwak et al., 2018). Supply chain innovation needs continuous changes in supply processes, methods and arrangements, these changes offer considerable latitude for planning, monitoring, forecasting and replenishment, resulting in accurate, concrete and fast decision-making in the event of crises, thereby strengthening robustness and resilience of firms against (un)expected shocks. Consequently, higher accuracy and error-proofing supply chains can be facilitated by innovation (Kwak et al., 2018). Moreover, implementation of an innovative process can create an awareness of vulnerabilities and knowledge sharing with supply chain entities, which in turn enables a continuous process innovation to effectively reduce risk occurrence (Matook, Lasch & Tamaschke, 2009) and strategies to overcome and avoid adverse effects, technically, enhancing firm's robustness. Thus, the following hypothesis is proposed:

H3: *Supply chain innovation will enhance robustness capability*

3 Methods

3.1 Sample and procedure

Simple random sampling technique was utilized to obtain data from firms in United Arab Emirates. A survey was developed in English and subsequently back-translated to Arabic by two linguistic experts and several adjustments and modification were made. The respondents consist of line managers, they were briefed about the purpose and intent of the research and were subsequently told that the information they provided will not share with third parties. The participants voluntary participated in survey and were told that they can discontinued at any time. Nationwide, four hundred firms were targeted in the United Arab Emirates. The survey packets were randomly distributed to the line managers in supply and logistics departments because they have accurate knowledge on the supply chains of their firm. Prior suppl chain analytics (i.e., Wieland & Wallenburg, 2012; Zhu et al., 2018); supply chain innovation, risk management capabilities (i.e., Kwak et al., 2018) studies deployed the same strategy deployed in the present study. To increase response rate, the respondents were asked to complete the survey at their convenient time. We also assured them of confidentiality to reduce social desirability and common method bias. At the end, 245 survey forms were obtained, and 32 forms were discarded due to missing values, leaving the researchers with 213 valid forms.

3.2 Measures

Supply chain / business analytics is measured with triplet first order construct adapted from (Wang & Byrd, 2017) namely: (a) *effective use of data aggregation tools* (3-items) – Respondents were asked to rate the effectiveness by which their organization uses the supply chain data analytic tools to provide better services; (b) *effective use of data analysis tools* (4-items) - Respondents were asked to rate the effectiveness by which their organization uses the supply chain data analytic tools to provide better services and (c) *effective use of data interpretation tools* (3-items) - Respondents were asked to rate the effectiveness by which their organization uses the supply chain data analytic tools to provide better services using a 5-point scale 1-poorly developed and 5-well developed.

Supply chain innovation is measured with 6 scale items adapted from (Seo et al., 2014, Kwak et al., 2018) study. Respondents were asked to rate how much the pursue number of innovation activities using a 5-point scale 1-Strongly disagree and 5- Strongly agree.

Robustness capability is measured with 4 scale items adapted from (Kwak et al., 2018; Wieland & Wallenburg, 2012). Respondents were asked to rate at which they possess certain capabilities using a 5-point scale 1-Strongly disagree and 5- Strongly agree. The scale items are presented in the Appendix section.

4 Data analysis and findings

4.1 Demographic data

About 12.6% of the firms under investigation have less than 50 employees, 17.3% of the firms have between 51 to 100 employees and 69.6% have more than 100 employees; 31.3% of the sampled firms have between 1 – 5 years in operation, 23.4% have between 6 to 10 years and the rest have been operating for more than 10 years. In regard to the type of manufacturing / production / procurement process employed by the firms under investigation, 22.4% uses job shop method, 17.3% uses batch, 27.1% uses repetitive assembly and the rest uses continuous flow method. As for sector, 15.9% are in apparel and textile products sector, 13.1% are in automotive / spare parts sector, 15.9% are in vegetable / perishable goods sector, 20.6% are in supermarkets and households' product sector, 16.4% are in construction and building materials sector, 12.6% are in electric and electronics products sector, and the rest are in chemicals and allied products sector. The detailed information is presented in Table 1.

SEM is a statistical technique that can be used to assess the factor structure of a set of observed variables, in addition to this, SEM allow scholars to test for construct validity (i.e., convergent and discriminant validities) as noted by Bagozzi and Heatherton (1994). Modern scholars have embraced SEM because it is useful for evaluation, weighing of scale instruments and testing the significance and associations of variables in the measurement model. In this paper, partial least squares structural equation modeling (PLS-SEM) was used to analyze and test the proposed model because of the sample size and complexity of the model (Hair et al., 2013). Smart PLS 3.0 software was used to evaluate the researched variables reliability and convergent validity. The factor loadings (outer model) of each item exceeded the benchmark of .70. See Figure 1. Cronbach's alpha (α), composite reliability (CR) and average variance extracted (AVE) exceeded 70, .70 and 0.5, respectively (Hair et al., 2013). See Table 2. Table 3 shows that the square root of AVE values (diagonal values) for each construct is greater than its correlation coefficients with other constructs, which satisfies Fornell and Larcker's (1981) criterion. These outcomes convey evidence of convergent and divergent validity.

Table 1: Respondent profile

Variables	Frequency	Percentage
Number of employees		
Less than 50	27	12.6%
51 - 100	37	17.3%
Above 100	149	69.6%
Total	**213**	**100%**
Firms age		
1 - 5 years	67	31.3%
6 - 10 years	50	23.4%
10 years and above	96	44.9%
Total	**213**	**100%**
Manufacturing / production / procurement process		
Job shop	48	22.4%
Batch	37	17.3%
Repetitive assembly	58	27.1%
Continuous flow	70	32.7%
Total	**213**	**100%**
Sector / Industry		
Apparel and other textile products	34	15.9%
Automotive / spare parts	28	13.1%
Vegetables / perishable goods	34	15.9%
Supermarkets and households' products	44	20.6%
Construction and building Materials	35	16.4%
Electric and electronics products	27	12.6%
Chemicals and allied products	11	5.1%
Total	**213**	**100%**

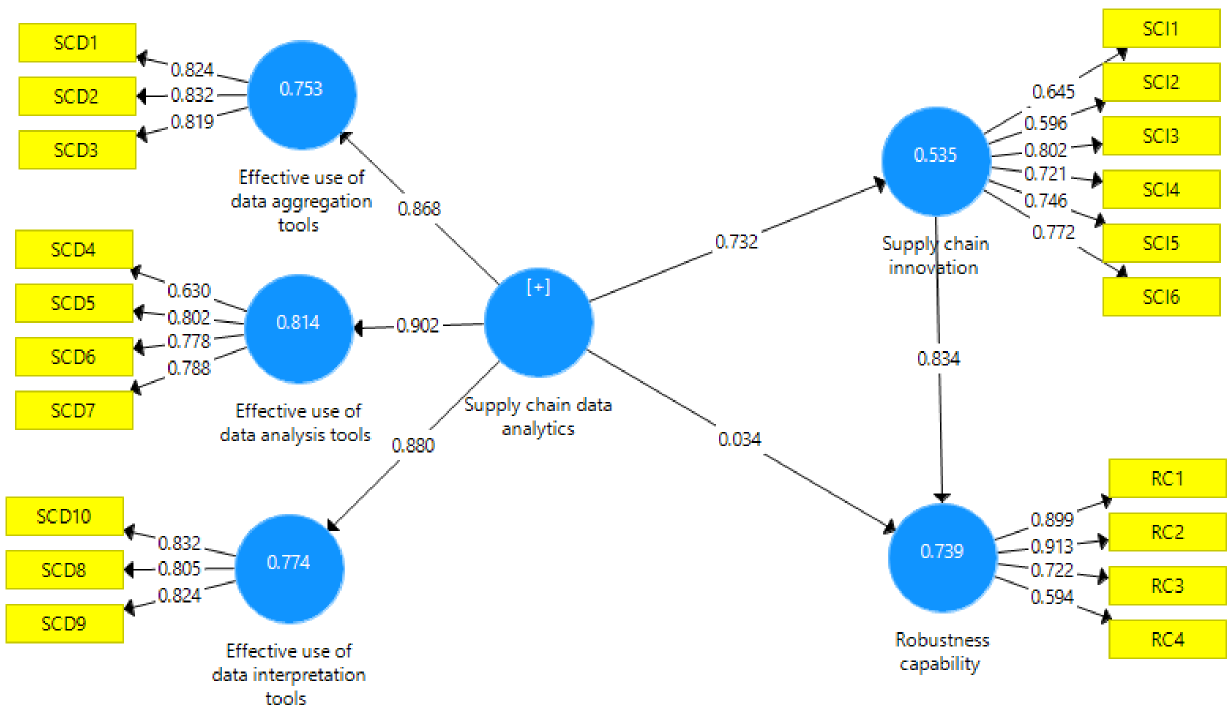

Figure 1: Scale items factor loadings (outer links) and directs effects (inner links). Please refer to the Appendix for explanation of the scale items.

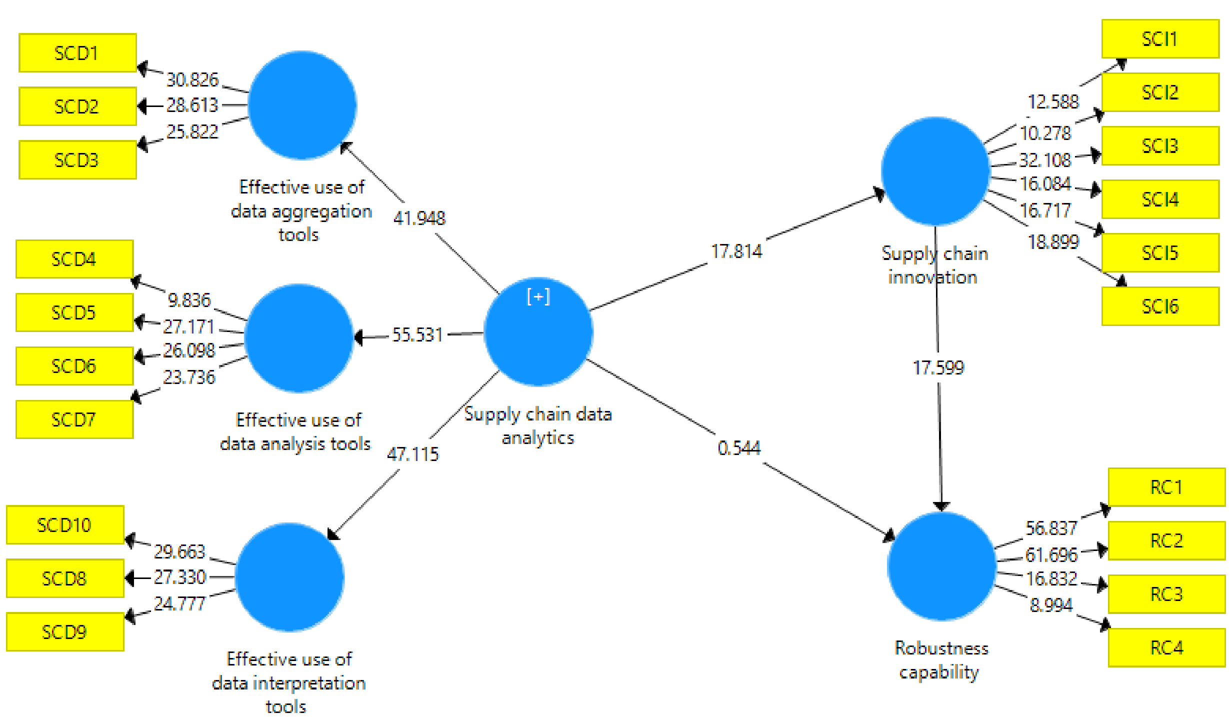

Figure 2: T-values of the coefficients in Figure 1.

Table 2: Reliability and convergent validity

Variables	α	Rho	CR	AVE
Effective use of data aggregation tools	0.77	0.77	0.87	0.68
Effective use of data analysis tools	0.74	0.76	0.84	0.57
Effective use of data interpretation tools	0.76	0.76	0.86	0.67
Supply chain data analytics	0.89	0.89	0.91	0.49
Supply chain innovation	0.81	0.83	0.86	0.51
Robustness capability	0.79	0.83	0.87	0.63
Average variance extracted	.735	.743	.729	.731

Table 3: Discriminant validity

Variables	1	2	3
Fornell-Larcker Criterion			
Supply chain analytics	.703		
Supply chain innovation	.732	.717	
Robustness capability	.645	.860	.793

Figure 1 depicts the direct effects (beta estimates) in inner links; the factor loadings are illustrated in the outer model links and the R square estimates for each effect is illustrated on the blue circles. The beta estimates significance level is illustrated in Figure 2 (inner model) and the significance of the factor loadings are illustrated in the outer model. These results demonstrate that supply chain analytics has a significant impact on supply chain innovation (β = .73, ρ = .000) and but not robustness capability (β = .03, ρ = .586). Supply chain innovation has a significant impact on robustness capability (β = .83, ρ = .000). Although, this study did not hypothesize the mediating role of supply chain innovation on the relationship between supply chain analytics and robustness capability. This paper specifically used bootstrapping analysis with a resample of (n = 5,000) as recommended by (Hair et al., 2013). Prior studies have utilized similar approach (i.e., Abubakar et al., 2018; Behravesh et al., 2019; Jahmani et al., 2018). The present outcome highlights that supply chain innovation mediates the link between supply chain analytics and robustness capability (β = .61, ρ = .000) with the following intervals (Bias=.004; 2.5% = .53; 97.5% = .69

5 Discussion

The objectives of this paper are to fill the voids in the extant literature by providing empirical justification for the effects of supply chain analytics on supply chain innovation and robustness capability. *First*, this paper found that firms that uses supply chain analytics were more likely to develop supply chain innovation capabilities. The result is in line with Fernando et al. (2018) claims, that Big Data analytics is a strong determinant for supply chain innovative capability. From KBT perspective, this finding suggest supply chain innovation is contingent upon acquiring, transforming, storing information and quantitative analyzing such data. This assertion is also consistent with Gunasekaran et al. (2017) claims, that Big data and predictive analytics are strong determinants for organizational performance and competitive intelligence. *Second*, contrary to the existing claims; data analysis revealed that supply chain analytics did not influence robustness capability. Implying firms that use supply chain analytics were less likely to develop robustness capability. Prior study (e.g., Zhu et al., 2018) draws on information processing theory to link supply chain analytics with operational supply chain transparency (i.e., monitoring of operational activities and managing supply chain risks). Similarly, Papadopoulos et al. (2017) found that predictive analytics provides firms with information which allows them to mitigate and respond to threats, thereby allowing the firms to create a resilience capability and strategies. This paper aim was to extend this claim by using KBT and robustness capability as a response variable. Surprisingly, this claim was not supported, the cultural (e.g., Arabian) and service climate might be the reason. For instance, Hofstede (2011) highlighted uncertainty avoidance as the degree to which the members of a society feel uncomfortable with uncertainty and ambiguity. It is possible that Arabian firms specifically, UAE firms are less inclined to uncertainty avoidance as oppose to Western firms. About 52.4% of the firms are mostly customer-oriented firms, more specifically apparel and other textile products (15.9%); vegetables / perishable goods (15.9%) and supermarkets and households' products (20.6%). Thus, the nature of service climate for these kinds of firms may have affected their perception of robustness. More research is needed to affirm the present outcome.

Third, this paper found that firms that possess high supply chain innovation capabilities are more likely to develop robustness capability. The result is in line with Wang and Byrd (2017) work, that draws on RBT to link Big data analytics with firm absorptive capacity. García-Sánchez et al. (2018) further demonstrated that organizational desire for innovation can nurture its absorptive capacity. Similarly, our finding shows that as firms' capabilities in innovation increases, in response the firms robustness capability increases through chances in processes and rules. The present study has documented the link between supply chain innovation and robustness capability. Fourth, this paper found that supply chain innovation mediates the link between supply chain analytics and robustness capability. Specifically, supply chain analytics nurture supply chain innovation capabilities through data aggregation, data analysis, and data interpretation; all of which enhances effective decision-making. Effective decision-making has been shown to mitigate risks and serve as a shock observer (Matook et al., 2009). Innovation capabilities serve as a reminder of firm's vulnerabilities through which robustness can emerge as firm strive to bypass disruptions (Kwak et al., 2018). In sum, the current study documents the link between supply chain analytics and supply chain innovation capability, and between supply chain innovation capability and robustness capability using KBT.

5.1 Implication for theory and practice

Successful innovations, technology or innovative breakthrough and/or competitive advantage require a great deal of information from various stakeholders. This primarily because rapid change in market trends, fierce competition, continuous and non-stop technological breakthrough. These factors do not only increase environmental complexity and uncertainty, but also puts pressure on firms to acquire, analyze, interpret the information or intelligence and/or make decision in a timely manner (Dehghani et al., 2018). In docile markets, managers are tasked with retrieving huge amount of digital information depending on the speed with which each of the key elements' changes. For instance, Xu et al. (2016) argued found that using BDA enabled smartphone manufacturers mine what consumers want in social media e.g., waterproof, solar panel, battery life etc. In doing so, the manufacturers were able to respond to and meet consumers demand in their future products.

Gao et al. (2017) added that in supply chain and logistic industry, data analytics approaches allow firms to consider the need of all stakeholders along the supply chain and channel, thereby creating a sustainable innovation cycle. This paper confirmed this claim; thus, this makes supply chain analytics a form of digital information source important for supply chain managers. By highlighting the importance of supply chain analytics, this study has offered guidance to the supply and logistics managers on how to leverage the power of data for innovation and robustness. Second, this paper offers some interesting insights that by making investments, collecting hordes of data, and having access to world class technology can foster innovation and robustness capability in supply chain. Similar arguments were echoed by (Jeble et al., 2018).

This put forth that organizations that have strong supply chain innovation has a higher level of robustness capability. The finding is consistent with prior studies that argued that risk management capability can be enriched by the adoption of new technologies and innovative supply chain practices (Grant, 1991). Similarly, firms supply chain innovation is likely to enhance firm's resilience capability (Kwak et al., 2018). Wang et al. (2016) added that predictive analytics allow firm bypass supply disruptions and demand uncertainty, thus, supply chain analytics can enhance network capacity. This study extends this claim to the domain of robustness capability.

The outcomes of this paper indicate that supply chain analytics can be an effective aid to survival in competitive markets (Likoum et al., 2018), particularly by enhancing innovation and robustness capability. In essence, this paper shows that merging the field of information systems, supply chain and logistics, innovation and strategic management can be fruitful, because firms can acquire capabilities to innovate and rapidly adjust to external demands (e.g., optimize business processes, supply routes and channels). Henceforth, this paper suggests that value creation process can be acquired by supply and logistics firms if they invest in BDA activities like supply chain analytics. This implies that supply chain analytics can foster greater competitive performance through innovation, which in turns creates agile and robust business process. Future studies can embrace predictive models such as artificial intelligence techniques (i.e., neural network) as suggested by (Abubakar et al., 2018; 2019).

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Appendix

Supply chain analytics

Effective use of data aggregation tools

SCD1: “Collect data from external sources and from various supply chain channels and systems throughout your organization”
SCD2: “Make supply chains records consistent, visible and easily accessible for further analysis”
SCD3: “Store transaction or channel data into appropriate databases”

Effective use of data analysis tools

SCD4: “Identify important business insights and trends to improve the supply chain value”
SCD5: “Predict patterns of each channel in response to each supply chain need”
SCD6: “Analyze data in near-real or real time that allows responses to unexpected events”
SCD7: “Analyze social media data to understand current trends from a large population”

Effective use of data interpretation tools

SCD8: “Provide systemic and comprehensive reporting to help recognize feasible opportunities for supply chains channels and service
improvement”
SCD9: “Support data visualization that enables users to easily interpret results”
SCD10: “Provide near-real or real time information on public operations and services within organization and across other supply chain systems / organizations”

Supply chain innovation (SCI)

SCI1: “We pursue a cutting-edge system that can integrate supply chain information”
SCI2: “We pursue technology for real-time tracking of our supply chain and channels”
SCI3: “We pursue innovative vehicles, packages or other physical assets”
SCI4: “We pursue continuous innovation in core global supply chain processes”
SCI5: “We pursue agile and responsive processes against changes in our supply chain”
SCI6: “We pursue creative supply chain methods and/or service”

Robustness capability (RC) - Our supply chain and logistics networks

RC1: “Our supply chain and logistics networks can remain effective and sustain even when internal/external disruptions occur”
RC2: “Our supply chain and logistics networks can avoid or minimize risk occurrence by anticipating and preparing for them”
RC3: “Our supply chain and logistics networks can absorb a significant level of negative impacts from recurrent risks”
RC4: “Our supply chain and logistics networks can have sufficient time to consider most effective reactions”