Humanities and Social Sciences Letters
2019 Vol. 7, No. 4, pp. 209-224
ISSN(e): 2312-4318
ISSN(p): 2312-5659
DOI: 10.18488/journal.73.2019.74.209.224

TRIAD OF BIG DATA SUPPLY CHAIN ANALYTICS, SUPPLY CHAIN INTEGRATION AND SUPPLY CHAIN PERFORMANCE: EVIDENCES FROM OIL AND GAS SECTOR

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Article History
Received: 12 August 2019
Revised: 16 September 2019
Accepted: 22 October 2019
Published: 4 December 2019

Keywords
Big data
Supply chain analytics
Covariance based-structural
Equation modelling
Oil & Gas marketing companies.

ABSTRACT

The objective of the paper is to examine the impact of big data supply chain analytics on supply chain performance. Second, study also examines the role of supply chain integration in the association between big data supply chain analytics and supply chain performance. The data were collected from 166 experts working in Oil and Gas Marketing companies. The experts were selected through expert sampling, a sub case of purposive sampling. We employed covariance based structural equation modeling to estimate the modelled relationships. The results of measurement model indicated the reliability, validity and fitness of measurement models. The findings of the study revealed a significant direct impact of big data supply chain analytics upon the five major dimensions of supply chain i.e., plan, supplier management, procurement management, make, and inventory management. Whereas the results did not show any effect of BDSCA on transportation management. Likewise, findings also revealed that distribution and network designing part of supply chain could be radically improved with the application of BDSCA. The study concludes that despite sea-potential of BDSCA in supply chain management field, the research work in this area is yet in infancy stage. Primarily, the research work aiming to know the level of BDSCA orientation and its application strategy requires immediate attention of the researchers and practitioners.

Contribution/Originality: The study contributes to the literature on BDSCA-supply chain performance association in two ways. First it provides empirical evidences on the association of BDSCA and supply chain performance. Second, it clarifies the role of supply chain integration in the association between BDSCA and supply chain performance.

1. INTRODUCTION

The emergence of blockchain technology has created revolution in the field of big data. Primarily, Block chain-generated Big Data is secure, because of its unique network architecture. It is also well organized, rich in detail, and comprehensive (Bibri, 2019). Due to these reasons, *interalia*, block chain technology-driven big data analytics (BDA) are appearing as a critical business capability (Casino *et al.*, 2018). Presently, due to the central role of supply chain management, block-chain has driven big data supply chain analytics (BDSCA) has assumed pivotal role in the firm's performance. It improves company's supply chain capabilities by getting benefits from large amounts of data (Chen *et al.*, 2012). Before proceeding further, it is important to define BDSCA. It is combination of big data (BD) and supply chain analytics (BDSCA), where former represents the availability of data in high velocity, high variety, and large volume. Analytics explains the capability of a firm to analyze the various patterns of a large amount of data by applying econometrical, mathematical, optimizations, and/or analytical techniques for improving the business decision making (Accenture Global Operations Megatrends Study, 2014). It is also being considered instrumental in improving the agility, adaptability, and alignment of supply chains (Muhtaroglu *et al.*, 2013; Wamba *et al.*, 2015) . Due to its pivotal role, BDSCA is captivating attention of researchers and practitioners. According to AGOMS (2014) survey, around 35% of the respondent's firms were in the process of deploying supply chain analytics and three out of ten firms already in the final phases of implementing BDSCA. These companies expect to overcome the SCM challenges like delayed shipments, increasing fuel costs, varying supplier's behaviors, and ever-rising customers' expectations with the help of BDSCA (Barnaghi *et al.*, 2013; Mubarik *et al.*, 2016). Likewise, companies are adopting BDSCA to improve the integration, flexibility, visibility, and flexibility of their supply chain processes by effectively managing demand and costs variations (Genpact, 2014).

In short, in the operational planning phase, BDSCA can assist upper-management in decisions making about supply chain operations, which frequently comprises demand planning, procurement, production, inventory, and logistics (Waller and Fawcett, 2013). Besides its role in operational tasks, BDSCA can play an apex role in strategic supply chain decision making. For example, it is expected that strategic decisions on supply chain planning, sourcing, network designing, and development can be significantly improved with the help of BDSCA. It is worth mentioning that, despite emergence of research in the field of BDSCA, overall research work is still in its initial stages and yet there is much to explore the role of BDSCA by studying more literature in the various filaments of SCM, i.e. supply chain strategy and operations (Wamba *et al.*, 2015; Mubarak *et al.*, 2019). Further within supply chain strategy, it is essential to know how BDSCA restructures supply chain agility, adaptability, sustainability, and collaboration. Likewise, it is also pivotal to examine whether BDSCA driven processes and functions are meaningful in context of supply chain operations, or it is onerous. The primary focus of the extant studies on BDSCA remained on analyzing various definitions perspectives of BDSCA or exploring the opportunities for supply chain research (Waller and Fawcett, 2013). Researchers (Waller and Fawcett, 2013; Wamba *et al.*, 2015; Mubarak *et al.*, 2019) argue that BDSCA is still in its infancy and require the attention of researchers to explore BDSCA. This research study is to address the concerns in the application of BDSCA by examining its impact on supply chain performance directly and through supply chain integration. Doing so study contributes to literature on BDSCA-supply chain performance in two ways. First it provide empirical evidence association of BDSCA and supply chain performance. Second, it includes the supply chain integration in BDSCA-supply chain performance dyad and study its role in the association between BDSCA and supply chain performance.

2. LITERATURE REVIEW

2.1. Big Data Supply Chain Analytics and Supply Chain Planning

Planning is the first pillar of supply chain management (Luo *et al.*, 2018). This pillar plays pivotal role in providing the basis of an effective supply chain. Primary, production planning, and design are the important function perfumed in planning pillar. Without Product quality and reliability neither competitiveness can increase nor profitability. Therefore, companies always look for product differentiation based on low cost and high quality (Srinivasan *et al.*, 2012). Apart from high quality and low-cost paradox, the pressure to launch the product in given time (time to market) demands that process of product design and development must follow the timeliness and efficiency (Mubarik *et al.*, 2019). Consequently, finding and removing bottlenecks in procedures/processes and dividing workload equitably across resources are essential for organizations. Here, BDSCA can help organizations by identifying the bottlenecks (expected bottlenecks) in advance by analyzing the data patterns. Likewise, it can help organization to produce high-quality products at lowest possible cost by optimizing quality-product tradeoffs. It also empowers firms to outshine their competitors by effectively capitalizing on market opportunities (Nakatani and Chuang, 2011). Mostly in practice, organizations tend to apply the BDSCA capabilities in two streams. These are product design and product improvements to make it differentiated products (Siva, 2012). It assists organizations in taking right decision to gain competitive advantage. Nowadays, firms are eager to implement excellence and reliability projection in order to achieve quality criterion and make better decisions (Nakatani and Chuang, 2011). In addition, BDSCA also leverages organizations to effectively manage and control the progress of design and development tasks by allowing flexibility in resource deployment (Song *et al.*, 2014). Furthermore, keeping track of the actual results and comparing them with the targeted goals improves the efficiency of design and development cycles (Li *et al.*, 2014). Against this backdrop, we draw the first hypothesis of these study, as follows:

Hypothesis 1: Big data supply chain analytics improves supply chain design planning.

2.2. Big Data Supply Chain Analytics and Supply Chain Sourcing

The source is the second pillar of the supply chain which primarily deals with procurement of material by selecting the suppliers and then maintain relationship with them for ensuring uninterrupted flow of supplies. It has two essential functions as explained below.

2.2.1. Supplier Management

Supplier selection and relationship management are collectively termed as supplier management. Supplier sourcing is a series of collective activities that emphasis on selection of suppliers using comprehensive criteria than maintaining supplier relationship management by scrutinizing spending costs and obtaining merchandise and services on economical basis. It supports firms to reduce cost of operations, improve financial condition and enhance suppliers' performance as well (Apte *et al.*, 2011). The essence of strategic sourcing is management of commodity, which encompasses performance enhancement and cost savings. Supply chain analytics (SCA) can help to accomplish these goals as follows: primarily, it analyzes the spending profile of organization, procurement process, and forthcoming demand in order to authenticate the alignment of sourcing strategies with strategic level objectives (Scott *et al.*, 2013); furthermore, SCA assists the establishment of ideal sourcing approaches by appraising suppliers' involvement and supply market trends . To frame sourcing strategies, Supply chain analytics (SCA) applies analytics and assessment tools such as risk assessment and cost modeling in order to delineate apposite contract terms, generate optimum tendering procedures and limitations, and choose contractors on the base of their best value offerings (Apte *et al.*, 2011; Shen and Willems, 2012; Jain *et al.*, 2013). Alternatively, Suppliers valuation and assortment is a significant facet of strategic sourcing. Supply Chain Analytics (SCA) can empower firms to standardize industry's best practices, apply customized metrics and establish performance targets (Choi, 2013; Chai and Ngai, 2015). At the time of appraising vendors' performance multi standard-based decision making approaches (Ho *et al.*, 2010; Ekici, 2013) have been extensively used (such as AHP).The edge of AHP is that it breaks big complex problems into a series of separate sub-problems with perspective of evaluating purposes such as lead time, optimized cost and flexibility, among many others.

Since each sub-problem is divided into a single objective decision making problem, which can be resolved quite quickly (Ho *et al.*, 2012; Subramanian and Ramanathan, 2012; Rajesh and Malliga, 2013). Moreover, SCA has the ability to envisage disruptions and variations which can occur in supply chain. This helps to identify the supply chain risks and provides platform through collaboration enterprise networking to mitigate these SC risks (Souza, 2014). If a vendor fails to provide demanded products on time of requirement it can put adverse impact on a company. When the suppliers delay the product deliveries on regular intervals supply chain of a firm is disturbed. It compels companies to maintain high inventories thus resulting in high inventory costs. In order to circumvent disorder in supply chain, suppliers should be selected meticulously, partnering with them to enhance their performance and keep an eye on abnormal happenings like natural adversities, in order to mitigate any disruption promptly (Chai and Ngai, 2015) and secondly, 'safeguarding' business from financial damage and having the capability to change suppliers. This discussion leads us to draw the following hypothesis:

Hypothesis 3: Big data supply chain analytics improves supplier management.

2.2.2. Procurement

A huge of information in the acquisition is produced from different sources or potentially applications through expenditure, supplier performance evaluation, and arbitration, regardless of whether inside or outside. These information sources encourage the utilization of advanced analytics. The consolidated utilization of outer operational and macroeconomic information improves supply chain productivity. SCA furnishes procurement managers with predictable, objective-based analytics for a wider assortment of real choices and business issues, such as material accessibility and quality problems (Souza, 2014). The applicability of SCA in procurement is embodied in these aspects: (a) handling supply risks and (b) dealing supplier's performance.

SCA enables associations to recognize dangers that must be maintained a strategic distance from risks that must be engaged by distinguishing patterns and occasions through observing freely accessible social-media and news channels affiliated with vendors or particular sourcing markets. Hence, firms can persistently acquire the latest information about sourcing markets and suppliers and rapidly react to changes or supply hazards even with emergency courses of action. Researchers center around utilizing nonexclusive models or philosophies to measure supply risks or assess the effect of supply risks on performance of supply chain (Kabak and Burmaoğlu, 2013; Mishra *et al.*, 2013; Zeotmulder, 2014). Various scholars have established, among other things, optimization techniques, and mathematical models in order to manage suppliers' relation with supply chain disruptions (Khan, 2013). Furthermore, SCA is a powerful instrument in order to assist firms in measuring and managing performance of their respective suppliers for superior sourcing (Oruezabala and Rico, 2012). SCA has ability to analyze and evaluate suppliers' performance on the basis of various dimensions such as delivery assurance, timeliness, quality, quantity, and spending analysis through collecting all types of comprehensive information about suppliers across global firms, hence helping firms make well informed and better choices (Walker and Brammer, 2012; Yeniyurt *et al.*, 2013). This leads us to draw fourth hypothesis of the study.

Hypothesis 4: Big data supply chain analytics improves procurement efficiency.

2.3. Supply Chain Production Planning and Big Data Supply Chain Analytics

SCA tells manufacturers to understand various dimensions of production costs and their impact on the bottom line. With the implementation of SCA, managers can be insightful regarding levels of production and any forthcoming improvements required to better allocate resources for different production lines. Nevertheless, SCA is also used to identify raw-material wastage and the procedures and techniques to reduce or even eradicate this wastage (Agrawal and Sharma, 2012). Hence, application of SCA can be useful for operations scheduling and aggregate planning at operational as well tactical levels (Mirzapour *et al.*, 2011; Souza, 2014). SCA helps to decide on corporate planning, among other things, matching demand and delivery, inventory management, and budget estimation. The numerous alternate production plans can be made after estimation of sales and required resources (Liu *et al.*, 2011; Li *et al.*, 2013). Moreover, operations and scheduling related problems can be sorted and formulated as mixed-integer linear programming problems through SCA (Wang and Lei, 2012;2015). In routing problems, SCA can be helpful in, e.g. forming the arrangement of processes and the work places that helps to attain the objectives (Chen and Blue, 2010; Wei *et al.*, 2011; Leung and Chen, 2013). In this context, we hypothesize following:

Hypothesis 2: Big data supply chain analytics improves supply chain production planning.

2.4. Supply Chain Distribution and Big Data Supply Chain Analytics

Supply chain distribution entails two important functions namely inventory management and transportation management.

2.4.1. Inventory

Firms are constantly gathering massive databases within ERP systems using internet driven software applications and devices. Data created in ERP systems contain the desired service level, past demand patterns their fulfillment times (lead times), and costs. This data helps organization to forecast and plan for sudden changes in the demand patterns. Nevertheless, since the dawn of new millennium, the demand fluctuations are becoming highly disruptive, making it difficult for the conventional software to make an accurate forecast. Big data coupled with block chain technologies have the ability to increase the forecasting efficacy manifold. BDSCA have the ability to compete the challenges, such as diverse firms' requirements and supply and demand variations (Sage, 2013). BDSCA can help companies in designing latest inventory optimization process instrumental in overcoming the contemporary inventory management challenges. For example, SCA usage in Vendor Managed Inventory (VMI) structures permits gathering, processing, and reporting on inventory records and patterns. This data can further be used for decisions to reduce the costs and increase effectiveness related to inventory holding (Borade *et al.*, 2013). BDSCA significantly improves the forecast accuracy of inventory requirements and in responding to varying buyer demands, using statistical predicting procedures (Downing *et al.*, 2014) and in addition to decreasing reasonably inventory costs (Wei *et al.*, 2011). Furthermore, SCA is applied to cater difficulties that happen within multi-echelon supply systems (Wang and Lei, 2012;2015). It regulates the suitable inventory echelons while undertaking factors such as demand unevenness at the network nodes as well as performance (e.g., delays, lead time and service level) (Gumus *et al.*, 2010; Guo and Li, 2014). SCA helps to get a complete sight at inventory altitudes across the supply chain while considering the influence of inventories at any specific echelon on other echelons. Decisions associated with safety stock optimization can be taken with the help of SCA (Fernandes *et al.*, 2013; Guerrero *et al.*, 2013). We hypothesize as follows:

Hypothesis 5: Big data supply chain analytics improves procurement efficiency.

2.4.2. Transportation Management

Downing *et al.* (2014) stated that as per the Council of Supply Chain Management Specialists, logistic worldwide play pivotal role to produce huge volumes of data as transporters and logistics providers with addition manage carriers for logistic operations. The Planning purposes of logistic can be achieved with the help of big data-driven by EDI transactions, RFID tags and Mobile Devices (Swaminathan, 2012). Moreover, this facilitates with delivery of goods (Merchandises) from the point Supply (e.g. warehouses or production houses) to the point of demand (as retail or wholesale site) through midway distribution centers. Transportation scheduling issues can be outlined as flow of network issues where everyone represents a distribution method with various competencies and frames of time (Ozdamar and Demir, 2012). Logistics data is produced from diverse sources in supply networks such as costs of shipment, estimates on stock capacity at suppliers' plants, demand estimates in network capacity, and demand points (Najafi and Farahani, 2013). Predictive analytics instruments are indispensable to formulate flexibility in the logistics operations due to disruptions and uncertainty in demand. The enhancement of equipment and team routing both are very critical in logistics planning. The vehicle steering issue tries to improve the order of visited nodes in a way, for instance for a parcel distribution lorry, for returns gathering lorry or for both (Drexl, 2012; Ozdamar and Demir, 2012). The ideal plan considers the gap between each pair of hubs, left turns, possible traffic volume, and different restrictions put on the routes, for example, pickup and delivery time frames (Vidal *et al.*, 2013). Although in worldwide logistics networks, the planning of transportation and distribution operations can be confused by several vehicles and their capabilities, limitations of tour length, Pickup and delivery time frame with comparison to others. Analytics approaches and methods are employed to enhance the routing goods, vehicles and employees in order to maintain stability between margins and costs of transportation, awareness to safety and maintenance (Minis and Tatarakis, 2011). One of the major issues which firms face while managing the transportation is traceability (Mubarik *et al.*, 2019). Application of the SCA not only helps track the goods under transit but it also helps to communicate in real time. It helps to execute the cost effective solutions like cross-docking and milk run distribution in an effective way (Li and Liu, 2019; Moktadir *et al.*, 2019). Further, firms have an increased pressure to reduce the time to market (Li and Liu, 2019) which can be well catered by SCA. We draw the last hypothesis of the study:

Hypothesis 6: Big data supply chain analytics improves transportation efficiency.

2.5. The Role of Supply Chain Integration

Supply chain integration brings supply chain players together by improving communication, and flow of information. Improved flow of information, communication and better understanding of the counterparts are some of the key traits of supply chain integrations. The presence of these elements at the three interfaces of a business entails real supply chain integration. These interfaces are internal focused, suppliers focused and customer focused. Internal integration represents the integration of various departments of organizations to perform business transactions. It also takes into account the integration of supply chain department with rest of the departments of the departments of the organization. The supplier integration represents the improved flow of communication, collaboration and connectedness with major suppliers. Likewise, the customer integration represents the effective flow of communication, products, services, and funds with the customers. It also takes into account the level understanding, cooperation, trust and loyalty between organization and its customers. Putting together, supply chain integration reflects an effective communication, higher degree of trust and collaborativeness, timely sharing of right information and concern for other parties at the level of suppliers, customers and intra-organization. Both practitioners and theorists agree that supply chain integration acts as lynchpin between the various development aim to improve the supply chain and supply chain performance itself. Specifically, supply chain integration acts as a mediator in the relationship between big data supply chain analytics and supply chain performance (Mubarik *et al.*, 2018). They argue that incorporation of modern technologies like big data in the supply chain significantly improves the integration of supply chain bringing various players together and sharing the real tie information. It further improves the performance of various functions of supply chain. Similarly, Gunasekaran *et al.* (2017) and Mubarik *et al.* (2019) argue that big data analytics in supply chain results in higher integration of supply chain. They further argue that supply chain integration can have a significant momentous effect on the planning function of supply chain. Adding to Gunasekaran *et al.* (2017), Mubarik *et al.* (2018) argue that adopting BDSCA not only improves the supply chain integration but it also have direct impact on the supply chain performance. They further explain that supply chain integration affect all four pillars functions of supply chain i.e. plan, source, make, and deliver. Against this backdrop we hypotheses followings:

Hypothesis 7: Supply chain integration mediates the relationship between Big Data Supply Chain Analytics and supply chain planning.

Hypothesis 8: Supply chain integration mediates the relationship between Big Data Supply Chain Analytics and supplier management.

Hypothesis 9: Supply chain integration mediates the relationship between Big Data Supply Chain Analytics and procurement management.

Hypothesis 10: Supply chain integration mediates the relationship between Big Data Supply chain Analytics and production management.

Hypothesis 11: Supply chain integration mediates the relationship between Big Data Supply Chain Analytics and transportation management.

Hypothesis 12: Supply chain integration mediates the relationship between Big Data Supply Chain Analytics and inventory management.

The above hypothesis are graphical explained in the conceptual frameworks exhibited in Figure 1 and Figure 2.

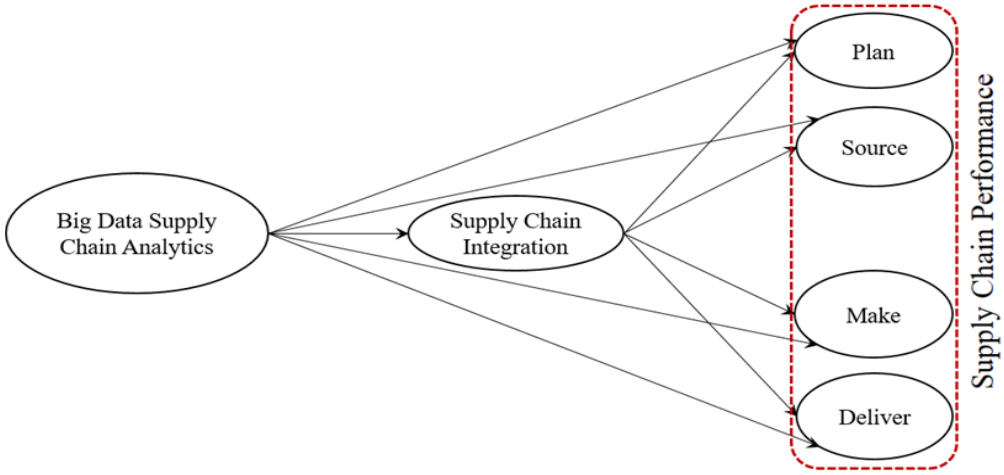

Figure-1. Conceptual framework.
Source: Author's conceptualization derived from literature.

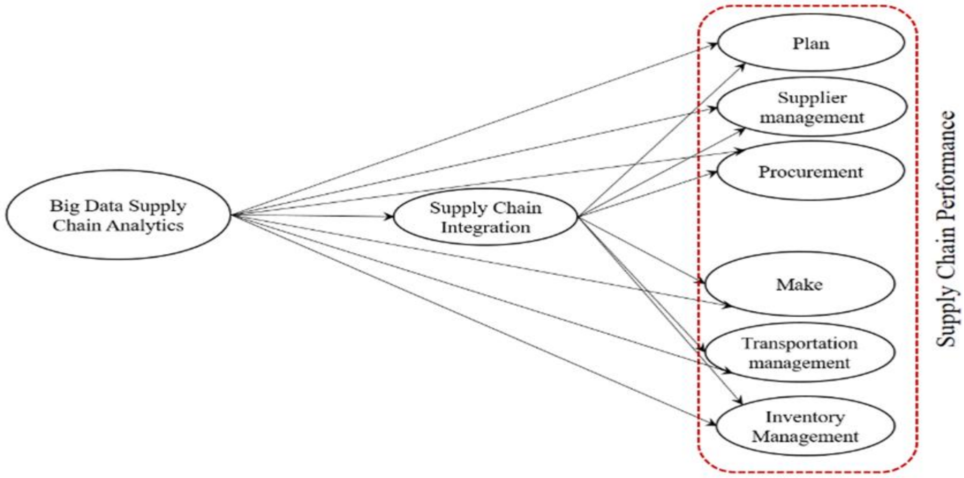

Figure-2. Expanded conceptual framework.
Source: Author's conceptualization derived from literature.

3. METHODOLOGY

3.1. Population and Sampling

The focus of the study was Oil & Gas Marketing Companies of Pakistan. The respondents of the study were experts which were selected through purposive sampling. The primary reason to choose the experts was the requirement to understand the both conventional supply chain and big data analytics in supply chain. Adopting expert sampling, a sub case of purposive sampling, we e developed the criteria to select the experts Table 1. Experts were taken from three major departments operation, supply chain and information technology. All the experts had minimum of one year experience while working on completely or partially big data driven supply chains.

Table-1. Experts sampling.

Department	Average experience	Numbers
Operation	02 years	58
Information technology	04 years	40
Supply chain management	4.5 years	63
Total		166

3.2. Data Collection Instrument

The data were collected with the help of close-ended questionnaire. All the constructs were adopted from the previous studies. The constructs of supply chain performance were adopted from Bressolles and Lang (2019) and Lapide (2000). The constructs of Big Data supply chain was adopted from the studies Hazen *et al.* (2012) and Liang *et al.* (2007). Table 2 exhibits details about constructs, items and their sources.

Table-2. Constructs and their sources.

Department	Sub-Constructs	Number of items	Source(s)
Supply chain performance	Plan	8	Lapide (2000); Bressolles and Lang (2019)
	Supplier management	8	
	Procurement	8	
	Make	13	
	Transportation management	12	
	Inventory management	12	
Supply chain integration	-	13	Kaliani *et al.* (2016)
Big data supply chain	BDPA acceptance	3	Hazen *et al.* (2012)
	BDPA routination	6	Hazen *et al.* (2012)
	BDP assimilation	5	Hazen *et al.* (2012) Liang *et al.* (2007)

Source: Authors' Compilation. The sources of constructs mentioned against each.

3.3. Analytical Method

We employed Covariance based-structural equation modelling (CB-SEM) for the analysis of the model. The choice to employ this method was based upon its ability to confirm the theory. Likewise, CB-SEM also provides the fitness indices to ascertain the incremental, parsimonial and absolute fitness of the model. It helps to overcome the common method bias issue. The results of the CB-SEM are divided into two parts. The results of the first part are used to check the reliability and validity of the measurement models. Likewise, the results of the fitness indices are also taken to ascertain the fitness of individual measurement models. The results of second step are used to test the hypotheses as well as the fitness and of overall path model.

4. RESULTS AND DISCUSSIONS

4.1. Respondents Demography

The questionnaire was administered to total of 166 selected experts. Among which 163 responded the questionnaire which were found to fit for final estimation. The demographic details of the responded appears in Table 3.

Table-3. Respondents' demography.

Designation	Number	Percentage
General Manager	4	2%
Deputy General Manager	29	17%
Senior Manager	46	28%
Manager	54	33%
Deputy Manager	33	20%
Experience		
1 year	36	21%
2 year	65	39%
3 year	39	23%
4 year	19	11%
5 year	7	4%

4.2. Measurement Models

Three aspects of a measurement model are tested before proceeding toward the path analysis. These are reliability tests, validity tests and fitness indices. All the measurement models are reliable as shown by the results of factor loading, CB alpha and CR. According to Hair *et al.* (2017) a measurement model or construct is considered reliable if the values of factor loading, CB alpha and CR are greater than the threshold values of 0.70. Gleaning through Table 4 we can see that values of all the items are greater than the 0.70, ascertaining the reliability of all constructs. Further validity of the constructs are checked through AVE. The values of AVE should be greater than 0.50 for ascertaining the convergent validity of the constructs/measurement models. Results in Table 4 show that all the constructs have AVE values greater than 0.50. The fitness of the models was examined by adopting a threefold approach. We computed the values of CFI, GFI, RMSEA and chi-square to *df* for examining the fitness of all measurement models. The threshold values of these indices are given in the footnote of Table 4. The findings show that all the measurement models have CFI and GFI above threshold value, and RMSEA and Chi-square to df ratio well within the limits specified. It ascertains the fitness of all measurement models thus allowing to proceed for hypotheses testing.

Table-4. Reliability and validity of measurement model.

Construct	Sub-construct	Items	λ	AVE	CR	CB α	CFI	GFI	RMSEA	$\chi2$ /df
Plan		P1	0.78	0.67	0.78	0.91	0.91	0.9	0.06	3.15
		P2	0.77							
		P3	0.84							
		P4	0.71							
		P5	0.89							
		P6	0.95							
		P7	0.89							
		P8	0.73							
Source	Supplier management	SS1	0.71	0.78	0.85	0.89	0.92	0.9□	0.055	3.75
		SS2	0.79							
		SS3	0.81							
		SS4	0.69							
		SS5	0.83							
		SS6	0.7							
		SS7	0.77							
		SS8	0.75							
	Procurement	SP1	0.81							
		SP2	0.79							
		SP3	0.77							
		SP4	0.75							
		SP5	0.68							
		SP6	0.89							
		SP7	0.88							
		SP8	0.82							
Make		M1	0.91	0.6	0.81	0.84	0.94	0.92	0.073	4.15
		M2	0.77							
		M3	0.71							
		M4	0.83							
		M5	0.78							
		M6	0.74							
		M7	0.76							
		M8	0.79							
		M9	0.83							
		M10	0.79							
		M11	0.77							
		M12	0.7							
		M13	0.73							
Deliver	Transportation	DT1	0.81	0.61	0.88	0.87	0.89	0.88	0.067	3.91

		DT2	0.79							
		DT3	0.81							
		DT4	0.77							
		DT5	0.71							
		DT6	0.73							
		DT7	0.76							
		DT8	0.71							
		DT9	0.7							
		DT10	0.79							
		DT11	0.86							
		DT12	0.84							
	Inventory management	DI1	0.88							
		DI2	0.77							
		DI3	0.73							
		DI4	0.71							
		DI5	0.69							
		DI6	0.68							
		DI7	0.93							
		DI8	0.89							
		DI9	0.82							
		DI10	0.73							
		DI11	0.84							
		DI12	0.75							
Supply chain integration		SC1	0.68	0.61	0.83	0.91	0.91	0.89	0.05	3.5
		SC2	0.81							
		SC3	0.89							
		SC4	0.93							
		SC5	0.77							
		SC6	0.78							
		SC7	0.72							
		SC8	0.74							
		SC9	0.73							
		SC10	0.79							
		SC11	0.73							
		SC12	0.77							
		SC13	0.76							
Big data supply chain analytics	BDPA acceptance	BDA1	0.89	0.63	0.81	0.93	0.92	0.9	0.065	4.25
		BDA2	0.87							
		BDA3	0.81							
	BDPA routinization	BDR1	0.78							
		BDR2	0.91							
		BDR3	0.81							
		BDR4	0.72							
		BDR5	0.73							
		BDR6	0.7							
		BDR7	0.77							
	BDPA assimilation	BDS1	0.81							
		BDS2	0.78							
		BDS3	0.79							
		BDS4	0.81							
		BDS5	0.72							

a. λ shows factor loading. The acceptable threshold value of factor loading is 0.50 (Hair *et al.*, 2017).
b. AVE stands for average variance extracted. The acceptable threshold value of AVE is 0.50 (Hair *et al.*, 2017).
c. CR stands for composite reliability. The acceptable threshold value of CR is 0.70 (Hair *et al.*, 2017).
d. CB alpha stands for Cronbach alpha. According to Peterson (1994) the acceptable value of CB alpha is 0.70.
e. CFI, GFI, RMSEA, $\chi 2$ /df are fitness indices used to ascertain the fitness of measurement models. For model fitness CFI and GFI >0.85; RMSEA<0.08; $\chi 2$ /df <8.

4.3. Path Analysis

The results of path analysis appear in Table 5. The results show that BDSCA exerts a directly significantly impact on plan (β=0.53, p=0.000), supplier management (β=0.28, p=0.000), procurement management (β=0.57, p=0.005), Make (β=0.34, p=0.000), and inventory management (β=0.35, p=0.000). Whereas it does not have any significant impact upon transportation management (β=0.09, p=0.071). It shows that among first six hypotheses, fifth hypothesis did not prove to be justified. The direct impact of BDSCA on various dimensions of supply chain is quite apprehensible as explained by Tseng and Liao (2015). According to Tseng and Liao (2015) the incorporation of Big data in supply chain management helps firm to not only review their historical performance in various aspects like supply chain planning, supplier performance, inventory costs and accuracies, and production losses etc. but it also provides the suitable solution to overcome or reduce the intensity of such problems. Likewise, BDSCA significantly improves the flow of information by instantly providing the real-time information to the various stakeholder. It helps to take better and accurate decisions. These all facts indicate that BDSCA significantly improves the various threads of supply chain. The findings upon the role of supply chain integration in the relationship between BDSCA and supply chain performance are exhibited in Table 5 hypothesis 7 to hypothesis 12. The results reveal that SCI plays a significant mediating role in the association between BDSCA and plan (β=0.41, p=0.000), supplier management (β=0.22, p=0.001), procurement management (β=0.41, p=0.000), Make (β=0.26, p=0.005), transportation management (β=0.15, p=0.005) and inventory management (β=0.44, p=0.000). These results concur with the extant literature. For example, Mubarik *et al.* (2019) argue that any development in the supply chain capacity , especially related to analytics, helps to improve the supply chain integration. The up gradation of the data recording system , communication tools, and decision making tools through BDSCA greatly help the professional to understand the other parties in the supply chain (Mubarik *et al.*, 2012).

Table-5. Hypotheses testing.

	Hypothesis	β	p-value	Decision
H1	BDSCA → Plan	0.53	0.000	Rejected H0
H2	BDSCA → Supplier management	0.28	0.000	Rejected H0
H3	BDSCA → Procurement management	0.57	0.005	Rejected H0
H4	BDSCA → Make	0.34	0.000	Rejected H0
H5	BDSCA → Transportation management	0.09	0.071	Fail to Reject
H6	BDSCA → Inventory management	0.35	0.000	Rejected H0
H7	BDSCA → SCI → Plan	0.41	0.000	Rejected H0
H8	BDSCA → SCI → Supplier management	0.22	0.001	Rejected H0
H9	BDSCA → SCI → Procurement management	0.41	0.000	Rejected H0
H10	BDSCA → SCI →Make	0.26	0.005	Rejected H0
H11	BDSCA → SCI →Transportation management	0.15	0.005	Rejected H0
H12	BDSCA → SCI →Inventory management	0.44	0.000	Rejected H0
	R square	*0.63*		
	GFI	*0.91*		
	CFI	*0.90*		
	RMSEA	*0.064*		
	Chi-square/df	*4.15*		

Note: p value≤ 0.05 shows rejection of null hypothesis at 5 percent.
GFI, CFI, RMSEA, and chi-square/df test the fitness of overall path model.

These also enable professional to communicate clearly and accurately, due to real time provision of the information's. Specifically, BDSCA helps to improve the communication with three stakeholder customer, employees, and suppliers.

5. CONCLUSION AND IMPLICATIONS

The study examined the impact of BDSCA on supply chain performance as well as the role of supply chain integration in the relationship of BDSCA and Supply chain performance. The supply chain performance was operationalized by adopting the six major constructs from Lapide (2000) and Bressolles and Lang (2019). By employing CB-SE on the data collected from 166 experts, the study concludes a positive direct effect of BDSCA on major dimensions of supply chain performance. Likewise, we also conclude a significant partial mediating role of supply chain integration in the association of BDSCA and supply chain performance. The results concur with the extent literature and call immediate attention of practitioners to look as to why the pace of BDSCA implementation is slow despite of its glaring significant impact on SC performance. Generally our findings state that BDSCA is very helpful for organizations to measure their supply chain performance several areas in supply chain management and also assist them in enabling their ability to establish a benchmark to evaluate value-added operations. Moreover, BDSCA provides facilitation to the organizations to monitor the metrics on an ongoing basis, to identify root causes, poor performance troubleshoots, enable to make better business decisions and provide remarkable benefits by improved business processes. One of the major challenges to the firm is seamless flow of information and real-time integration with supply chain partners. Using big data supply chain analytics not only improves the flow of information across channel but it dramatically enhances the supply chain visibility. Thus, resulting in better supply chain integration and improved competence. Likewise, having several outsourced partners, it becomes increasingly difficult for a firm to maintain appropriate relationships with their outsourced partners. Number of times due to ineffective collaboration, supply chain downtime occurs. Using big data supply chain analytics and connecting outsourced partners with it not only helps company to improve its collaboration with existing partners but it also helps to source the right partners. Another challenge that companies face is demand forecasting. Despite experienced managers and sophisticated software, it remains onerous to forecast the demand of customers. The use of big data, which has a high velocity and volume of data, by applying analytics, is making the task efficient.

As findings demonstrate a profound improvement in supply chain performance due to BDSCA, the question arises as to why the organizations are reluctant to adopt it. Second question also arises about the risk associated with these development. Since the scope of this study is limited to empirically test the association of BDSCA and supply chain performance, we did not go into the aspects like challenges to implement BDSCA etc. Hence, a detail study identifying and weighing the risks and challenge in the way of BDSCA is essential in this regard. Further, two domains demand immediate attention. The first is to know about the level of orientation about BDSCA among firms and second is its application strategy. These two aspects need immediate attention from both researchers and practitioners. One of the limitations of the study may be the use of selective databases for a particular period. It may have resulted in ignoring some of the important studies. Therefore, we suggest future researchers to take more databases and greater time period to validate the results of this study.

Funding: This Research Work is entirely encouraged by Research and Management Center Universiti Tun Hussein Onn Malaysia (Rmc-UTHM), and FRGS Grants vote number K073 under Ministry of Higher Education, Malaysia (MOHE).
Competing Interests: The authors declare that they have no competing interests.
Acknowledgement: Both authors contributed equally to the conception and design of the study.

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