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Review

Big data analytics in logistics and supply chain management: Certain investigations for research and applications

Gang Wang [a], Angappa Gunasekaran [a,*], Eric W.T. Ngai [b], Thanos Papadopoulos [c]

[a] Department of Decision and Information Sciences, Charlton College of Business, University of Massachusetts Dartmouth, 285 Old Westport Road, North Dartmouth, MA 02747, USA
[b] Department of Management and Marketing, The Hong Kong Polytechnic University, Hung Hom, Kowloon, Hong Kong
[c] Kent Business School, University of Kent, Sail and Colour Loft, The Historic Dockyard, Chatham, Kent ME4 4TE, UK

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ABSTRACT

The amount of data produced and communicated over the Internet is significantly increasing, thereby creating challenges for the organizations that would like to reap the benefits from analyzing this massive influx of big data. This is because big data can provide unique insights into, inter alia, market trends, customer buying patterns, and maintenance cycles, as well as into ways of lowering costs and enabling more targeted business decisions. Realizing the importance of big data business analytics (BDBA), we review and classify the literature on the application of BDBA on logistics and supply chain management (LSCM) – that we define as supply chain analytics (SCA), based on the nature of analytics (descriptive, predictive, prescriptive) and the focus of the LSCM (strategy and operations). To assess the extent to which SCA is applied within LSCM, we propose a maturity framework of SCA, based on four capability levels, that is, functional, process-based, collaborative, agile SCA, and sustainable SCA. We highlight the role of SCA in LSCM and denote the use of methodologies and techniques to collect, disseminate, analyze, and use big data driven information. Furthermore, we stress the need for managers to understand BDBA and SCA as strategic assets that should be integrated across business activities to enable integrated enterprise business analytics. Finally, we outline the limitations of our study and future research directions.

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* Corresponding author.
E-mail address: agunasekaran@umassd.edu (A. Gunasekaran).

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1. Introduction

The widespread use of digital technologies has led to the emergence of big data business analytics (BDBA) as a critical business capability to provide companies with better means to obtain value from an increasingly massive amount of data and gain a powerful competitive advantage (Chen et al., 2012). BDBA incorporates two dimensions: big data (BD) and business analytics (BA). BD refers to the ability to process data with the following qualities: velocity, variety, and volume. Analytics involves the ability to gain insight from data by applying statistics, mathematics, econometrics, simulations, optimizations, or other techniques to help business organizations make better decisions (Accenture Global Operations Megatrends Study, 2014). BDBA has attracted significant attention from researchers and decision makers in organizations. It has been used in research to verify existing models or theories, and in industry to enable business organizations make better decisions (Muhtaroglu et al., 2013), particularly in logistics and supply chain management (LSCM) (Wamba et al., 2015).

Big data analytics in LSCM has received increasing attention because of its complexity and the prominent role of LSCM in improving the overall business performance. Based on the survey conducted by Accenture (2014), more than one-third of the respondents reported being engaged in serious conversations to deploy analytics in LSCM; and three out of ten already have an initiative in place to implement analytics. LSCM faces the most significant challenges that can potentially result in inefficiencies and wastage in supply chains, such as delayed shipments, rising fuel costs, inconsistent suppliers, and ever-increasing customer expectations, among others (Barnaghi et al., 2013). Companies highly expect to capitalize on BDBA in logistics and supply chain operations to improve the visibility, flexibility, and integration of global supply chains and logistics processes, effectively manage demand volatility, and handle cost fluctuations (Genpact, 2014). In the strategic phase of supply chain planning, BDBA plays a vital role. It has been applied to help companies make strategic decisions on sourcing, supply chain network design, as well as on product design and development. In the operational planning phase, BDBA has been used to assist management in making supply chain operation decisions, which often include demand planning, procurement, production, inventory, and logistics.

Current studies on the application of BDBA within LSCM – that we define in this study as supply chain analytics (SCA) – have focused mainly on analyzing definitions and different perspectives (Wamba et al., 2015), or identifying opportunities for supply chain research and education (Waller and Fawcett, 2013). However, these scholars emphasize that BDBA is still in its infancy and there are yet studies to explore BDBA in LSCM. To address the concerns of these scholars and extend their studies, we (i) review the literature related to the application of BDBA in LSCM (that we define as: SCA) through a framework for classifying the literature. In particular we draw on a taxonomy of SCA that classifies analytics into predictive, prescriptive, and descriptive categories, which is currently missing from the literature (Trkman et al., 2010; Demirkan and Delen, 2013; Souza, 2014); (ii) synthesize the findings of the literature review and propose a maturity framework of SCA based on five capability levels, that is, functional, process-based, collaborative, agile SCA, and sustainable SCA; (iii) highlight the role of SCA for LSCM, and stress the importance for companies to acknowledge SCA as a strategic asset to be understood and integrated holistically to enable the creation of business analytics capabilities; and (iv) identify future research directions.

The main contributions of this paper are (i) to present a review of the literature on SCA, based on the nature of analytics (descriptive, predictive, prescriptive) and the focus of the LSCM (strategy or operations); (ii) assess the capabilities of SCA through proposing a maturity framework based on our review of the literature; (iii) highlight the role of SCA in achieving organizations' success; and (iv) acknowledge the importance of SCA as strategic asset to be applied holistically for creating business analytics capabilities.

2. Framework and methodology used for the review of the literature on applications of BDBA within LSCM

2.1. Framework for the classification of the literature

Scholars have attempted to classify the literature on BDBA within LSCM by paying attention to different definitions and perspectives, and aimed to identify opportunities for further research. For instance, Wamba et al. (2015) have highlighted the role of value creation from BD in real-time access and sharing of information across national governmental agencies that allows improved decision-making and subsequently emergency service response, as well as transparency and accountability across the governmental agencies. However, their main focus is on defining BD based on attributes such as volume, velocity, variety, value, and veracity. In this paper we are not focusing on solely on different definitions of BDBA; rather, we draw on the taxonomy of analytics under three main categories: descriptive, predictive and prescriptive analytics (Trkman et al., 2010; Demirkan and Delen, 2013; Souza, 2014):

(a) Descriptive analytics takes place either at standardized periods or whenever needed using techniques such as online analytical processing (OLAP) or drill down, and aims at identifying problems and opportunities within existing processes and functions.
(b) Predictive analytics involves the use of mathematical algorithms and programming to discover explanatory and predictive patterns within data. The aim of this type of analytics is to accurately project what will happen in the future and provide reasons as to why it may happen. Predictive analytics is enabled by the use of techniques such as data/text/web mining, and forecasting (Demirkan and Delen, 2013).
(c) Prescriptive analytics involves the use of data and

mathematical algorithms to determine and assess alternative decisions that involve objectives and requirements characterized by high volume and complexity, with the aim to improve business performance. Prescriptive analytics include multi-criteria decision-making, optimization, and simulation.

Predictive and prescriptive analytics play a vital role in helping companies make effective decisions on the strategic direction of the organization (Demirkan and Delen, 2013). They can be applied to address problems related to the changes in organizational culture, sourcing decisions, supply chain configuration, and design and development of products or services. Descriptive analytics answer questions related to "what happened and/or what is happening". These decisions may also involve performance analysis by employing models, techniques, and tools to help companies make quick, efficient, and effective decisions.

Given the aforementioned advanced analytical methodologies and techniques, we focus on the application of BDBA in LSCM (SCA) that provides organizations and supply chains with the capabilities for handling variability and uncertainty, thus achieving supply chain integration and coordination. These methodologies and techniques have a significant influence on the effectiveness and efficiency of SCA performance because they determine whether it is successful to gain useful information and make correct decisions through analyzing huge amounts of data, structured and unstructured at strategic, tactical, and operational levels. Since most of the papers deal with a mix of analytics (predictive, prescriptive and descriptive analytics) for LSCM strategy and operations, we have identified methodologies and techniques classified within these categories. We primarily focus on reviewing articles in peer-review, major journals in order to ensure the quality of research, following Esposito and Evangelista (2014), Chen et al. (2014), and Gunasekaran et al. (2015). The papers presented in each category are not necessarily mutually exclusive.

2.2. Methodology for the review of the literature

The literature review was inspired by the general guidelines for conducting literature reviews by Rowley and Slack (2004). These guidelines likewise were used in a recent paper by Chen et al. (2014).

(a) The material based on ScienceDirect, Emerald Insight, Inderscience, and Taylor & Francis was collected. Particular databases were selected based on their inclusion of a comprehensive coverage of journals, including highly ranked academic journals. On the basis of the focus of our paper on big data analytics, logistics, and supply chain management as well as methods, metrics, and techniques, the following keywords were used: BD, sourcing, procurement, production, logistics, and supply chain management, inventory, sustainability as well as techniques, metrics, business analytics. The keywords were used both separately and in combination (using "and"/"or"). The papers that used the aforementioned keywords and/or their combination in the title, abstract, and full text were identified. The present literature review covers the years 2004–2014 because BDBA has matured over the previous years. The following steps were followed.
(b) The bibliography and classifications were built based on the framework outlined in Section 2.1.
(c) Each article was reviewed briefly for its SCA and application areas.
(d) Managerial implications, limitations, and future research directions were discussed.

The methodologies and techniques found during the literature review indicated their high adaptability to specific situations in both manufacturing and service environments (Denk et al., 2012; Beske et al., 2014). Chen et al. (2014) mentioned that all co-authors collaborated and interacted on all the aspects/steps of the literature review and classifications. They read the title, abstract, and full text, and acted as reviewers. In cases when disagreements on whether particular articles could be included and classified, further discussions took place until agreement was reached. Esposito and Evangelista (2014) discussed that only peer-reviewed articles were included to control for higher quality of articles. The final sample contained 101 papers, whose bibliographic details are provided at the reference section to control the transparency of the review. The authors studied and analyzed the articles in depth, and the results of this analysis are provided in the following sections.

3. Review of the literature on BDBA for LSCM

3.1. Big data analytics

Big data analytics implies two perspectives: big data (BD) and business analytics (BA). BD refers to high-volume, high-velocity, and high-variety sets of dynamic data that exceed the processing capabilities of traditional data management approaches (Russom, 2011; Chen and Zhang, 2014). BA is the study of the skills, technologies, and practices used to evaluate organization-wide strategies and operations continuously to obtain insights and guide the business planning of an organization. Such evaluation ranges from strategic management to product development to customer service through evidence-based data, statistical and operations analysis, predictive modeling, forecasting, and optimization techniques (Russom, 2011; Chen et al., 2012).

BDBA offers new opportunities for competitive advantage by extracting significant value from massive amounts of data. In particular, BDBA can help organizations make better decisions and improve their strategy, operations efficiency, and financial performance. Such improvements can be realized by a deeper understanding of business dynamics, intensifying customer engagement, optimizing daily operations, and capitalizing on new sources of revenue (Russom, 2011).

For business organizations to be truly competitive in a dynamic business environment, BDBA as a strategic advantage of business organizations has become a rapidly growing and influential practice in recent years. An important BDBA application is its use in strategic management, that is, the strategy formulation and strategic alignment between organizational and supply chain strategies. Organizational strategy is important because it provides the overall direction for the entire organization, and guides the operations and supply chain strategies of an organization. Thus, the operations and supply chain strategies must be consistent with the organizational strategies. BDBA can complement strategic management by introducing advanced predictive insights into the strategy execution processes. Furthermore, BDBA has been widely applied in supply chain operations, such as demand planning, procurement, production, inventory, and logistics; an improvement in supply chains can considerably contribute to the overall supply chain performance of business organizations. In this paper, we explore and investigate BDBA in logistics and supply chains, that is, supply chain analytics (SCA).

3.2. Review of the literature on SCA

This section reviews the existing literature in terms of the application of SCA and the critical role it plays in effectively developing supply chain *strategies* and efficiently managing supply chain operations at tactical and operational levels. The first part of this section focuses on how SCA is applied to strategic decisions. Our results from the literature review suggest that when the focus is on logistics and supply chain strategy, SCA is applied insourcing, supply chain network design, and product design and development at the strategic level. SCA can assist managers and decision makers in understanding changing marketing conditions, identifying and assessing supply chain risks, and leveraging supply chain capabilities to formulate cutting-edge, implementable supply chain strategies, thus improving supply chain flexibility and profitability. The second part of this section focuses on how SCA is applied to tactical and operational levels. For tactical/operational level decisions, SCA involves analyzing and measuring supply chain performance on demand planning, procurement, production, inventory, and logistics. Hence, SCA is useful for improving organizations operations efficiency, measure supply chain performance, reduce process variability, and implement the best possible supply chain strategies at the tactical and operational level. These improvements are achieved through seamless interconnected operations between supply chain processes from the suppliers of raw materials to end customers. The results of the literature review are extrapolated in Table 1, whereas each one of the application areas classified under strategy ('Strategic sourcing', 'Supply chain network design', and 'Product design & development') and operations ('Demand planning', 'Procurement', 'Production', 'Inventory', and 'Logistics') are further discussed in the following section.

3.2.1. Logistics and supply chain strategy

3.2.1.1. Strategic sourcing. Strategic sourcing is collaborative, focusing on supplier relationship management by analyzing organizational spend costs and acquiring commodities and services on a cost-effective basis. Strategic sourcing helps companies optimize financial performance, minimize operations cost, and improve their suppliers' performance (Talluri and Narasimhan, 2004). At the core of strategic sourcing is commodity management, which involves identifying and implementing both cost savings and performance-enhancing opportunities.

SCA can help achieve these objectives as follows: firstly, SCA analyzes organizational spend profiles, procurement processes and future demand to ensure that sourcing strategies are aligned to the organizations strategic goals and objectives (Bartels, 2006; Scott et al., 2013); secondly, SCA facilitates the development of optimal sourcing strategies by evaluating supply market trends and suppliers' inputs and economics. To formulate sourcing strategies, SCA uses analytics and assessment tools including, for instance, cost modeling and risk assessment, to define appropriate contracting terms, create optimal bid processes and parameters, and select suppliers on the basis of their optimal value offerings (Apte et al., 2011; Shen and Willems, 2012; Jain et al., 2013).

Another important aspect of strategic sourcing is suppliers' evaluation and selection (Romano, 2012). SCA can enable organizations to benchmark industry best practices, set performance targets, and implement customized metrics (Chai and Ngai, 2015; Choi, 2013). When trying to evaluate suppliers' performance, multi-criteria decision-making techniques (Ho et al., 2010; Ekici, 2013) have been widely used (e.g., analytic hierarchic process (AHP)). AHP decomposes complex problems into separate small-size sub-problems in terms of different evaluation objectives such as cost optimization, timely delivery, and flexibility, among others. Each sub-problem is a single objective decision making problem that can be solved quite easily (Vaidya and Kumar, 2006; Ho, 2008; Ho et al., 2012; Subramanian and Ramanathan, 2012; Rajesha and Malligab, 2013). Furthermore, SCA is used to predict supply disruptions by supply chain mapping and enterprise social networking to identify the sources of supply uncertainties and manage ongoing collaborative relationship with suppliers (Souza, 2014). Failure by a supplier to supply goods or services on time, in the right quantity and with the required quality can have a major impact on a company. For suppliers who regularly miss deliveries, organizations will often hold a higher quantity of products in inventory, tying up additional working capital. Avoiding supply disruption means firstly carefully selecting suppliers with good reputations, working with them to maintain their performance, and monitoring events, like natural disasters, to avoid or quickly mitigate any disruption (Chai and Ngai, 2015); and secondly, 'protecting' an organization from financial loss and having the ability to switch suppliers.

3.2.1.2. Supply chain network design. Network design studies how the supply chain could be configured physically and as far as the infrastructure is concerned. It is related to decisions on the number, location, and size of manufacturing plants and distribution centers and/or warehouses that serve as intermediary stocking and the shipping points between the existing plants and retailers (Mohammadi et al., 2009). Supply chain network design problems can be classified into two categories in terms of available information on demand: those with known demand and those with demand fluctuations or uncertainties. In particular, network design with uncertain demand is well suited to capture changes on demand patterns, product mix, production processes, sourcing strategies, or operating costs (Hsu and Li, 2011; Lin and Wang, 2011; Benyoucef et al., 2013; Bouzembrak et al., 2013; Soleimani et al., 2014).

However, the amount of data involved with supply chain network design is massive, which contains aggregate demands for products at each retailer, plant capacities, shipping costs per unit between each pair of locations, and the fixed operations cost at each potential location. SCA can deal with supply chain network design problems under both situations, where network design with known demand is formulated as a mixed-integer linear program (Nagurney, 2010; Lee et al., 2010; Tiwari et al., 2012; Jindal and Sangwan, 2014), while uncertain network design can be transformed into robust network design by using robust optimization techniques (Klibi et al., 2010; Mir Saman et al., 2011; Hasani et al., 2012, 2014; Baghaliana et al., 2013). Decision variables used in SCA include continuous variables, which represent shipping quantities between locations, and binary variables that indicate whether each facility should be opened or closed. SCA utilizes different types of objective functions to measure supply chain performance. The majority of the papers attempt to determine supply chain network configuration by minimizing the sum of various cost components as a single objective (Klibi et al., 2010; Mir Saman et al., 2011; Hasani et al., 2012, 2014; Baghaliana et al., 2013).

Solution algorithms used in SCA include algorithms and heuristics. The first category includes general-purpose techniques such as branch-and-bound, branch-and-cut, column generation, and decomposition methods. These algorithms combined with Lagrangian relaxation or heuristic procedures to obtain bounds (Melo et al., 2009; Benyoucef et al., 2013). However, when the size of supply chain network becomes large, the techniques used are heuristics, including for instance Lagrangian relaxation, linear programming based heuristics, and meta-heuristics (Melo et al., 2009; Bouzembrak et al., 2013).

3.2.1.3. Product design and development. To be competitive, capture market share, and improve profitability, companies have to ensure that their products are of high quality and reliability. Hence, companies would need to strengthen their capabilities to make differentiated, low-cost products (Luchs and Swan, 2011; Srinivasan et al., 2012). Apart from the critical but extremely difficult

Table 1
Review of the literature on SCA.

Focus	Applications	Supply Chain Analytics (SCA)		
		Descriptive	**Predictive**	**Prescriptive**
Logistics and supply chain strategy (strategy)	Strategic sourcing		Shen and Willems (2012), Chai et al. (2013), Choi (2013), Souza (2014).	Talluri and Narasimhan, (2004), Vaidya and Kumar (2006), Ho (2008), Ho et al. (2010), Apte et al. (2011), Ho et al. (2012), Romano (2012), Subramanian and Ramanathan (2012), Scott et al. (2013), Jain et al. (2013), Chai et al. (2013), Ekici (2013), Rajesha and Malligab (2013), Chai and Ngai (2015), Souza (2014).
	Supply chain network design		Hsu and Li (2011), Lin and Wang (2011).	Melo et al. (2009), Mohammadi et al. (2009), Klibi et al. (2010), Lee et al. (2010), Nagurney (2010), Mir Saman et al. (2011), Hasani et al. (2012), Tiwari et al. (2012), Baghaliana et al. (2013), Benyoucef et al. (2013), Bouzembrak et al. (2013), Hasani et al. (2014), Jindal and Sangwan (2014), Soleimani et al. (2014).
	Product design and development		Bae and Kim (2011), Luchs and Swan (2011), Son et al. (2011), Song et al. (2014).	Luchs and Swan (2011), Nakatani and Chuang (2011), Siva (2012), Srinivasan et al. (2012), Li et al. (2014), Ma and Kim (2014), Salicr and Civit (2014).
Logistics and supply chain operations (operations)	Demand planning	Choudhury et al. (2008), Jonsson and Gustavsson (2008), Chen and Blue (2010).	Lu and Wang (2010), Sodhi and Tang (2011).	Feng et al. (2008), Gallucci and McCarthy (2009), Chen et al. (2010), Haberleitner et al. (2010), Cheikhrouhou et al. (2011), Beutel and Minner (2012), Li et al. (2012), Lim et al. (2014).
	Procurement	Mishra et al. (2013)		Kabak and Burmaoglu (2013).
	Production	Jodlbauer (2008), Noyes et al. (2014).	Wang and Liang (2005).	Chen and Vairaktarakis (2005), Sawik (2009), Chen (2010), Liu et al. (2011), Mirzapour et al. (2011), Heo et al. (2012), Sharma and Agrawal (2012), Wang and Lei (2012), Leung and Chen (2013), Li et al. (2013), Wang and Lei (2015), Wang et al. (2015).
	Inventory	Jonsson and Mattsson (2008).	Hayya et al. (2006), Babai et al. (2009), Chhaochhria and Graves (2013), Downing et al. (2014).	Gumus et al. (2010), Wei et al. (2011), He and Zhao (2012), Borade et al. (2013), Fernandes et al. (2013), Guerrero et al. (2013), Guo and Li (2014).
	Logistics			Dong and Chen, (2005), Jharkharia and Shankar (2007), Novoa and Storer (2009), Grewal et al. (2008), Li et al. (2010), Lei et al. (2011); Minis and Tatarakis (2011), Najafi et al. (2013), Vidal et al. (2013).

tradeoff decisions between cost and quality, time-to-market pressures require the product design and development to guarantee the efficiency and timeliness of releasing new revenue-producing products (Bloch, 2011). Thus, identifying process bottlenecks and properly distributed workload across available resources are critical for companies. SCA can help companies produce high-quality, competitively priced products by optimizing product tradeoffs, increasing sales revenue. It also enables companies to outperform their competitors by making the most of these market opportunities (Tsai et al., 2011; Nakatani and Chuang, 2011). In practice, companies have used the SCA capabilities in two dimensions: design and improvements on competitively differentiated products (Bae and Kim, 2011; Siva, 2012).

SCA helps companies make appropriate decisions to give their products a competitive edge. To meet the quality criterion and make efficient decisions to assess product reliability, companies are willing to use quality and reliability prediction standards to determine clearly what is required of the part and the reliability of the materials used in the part (Nakatani and Chuang, 2011). Data concerning the expected performance of the supplied components under given operating conditions are required. Given the time pressures on product design and development, easily accessible data enables a rapid design and development process. Companies also monitor and analyze the substances in the supplied components, using real-time data from internal processes and suppliers (Son et al., 2011). Thus, it is easier to determine whether components from suppliers comply with quality standards, government regulations, and the requirements of customers and performance, such that the delays caused by non-compliance issues or suspended shipments are avoided (Son et al., 2011; Paulson, 2014). Finally, SCA evaluates potential tradeoffs by performing what-if scenario analysis to assess the effects of product design and development costs, thereby achieving the most economical design that meets the quality and reliability criteria (Ma and Kim, 2014).

SCA can also be used to help companies make the correct decisions in less time. To meet the quality and cost objectives, SCA helps automate the comparison of actual performance criteria to target goals, and this allows companies to assess quickly how close they are to achieving their goals (Salicr and Civit, 2014). SCA also provides a better understanding of the influence of different factors so that companies can easily achieve their goals in less time. In addition, the information obtained from SCA enables companies to manage the progress of design and development work better and to flexibly adjust the available resources as needed (Song et al., 2014). Moreover, comparing the actual results with the target goals can contribute to continuous improvements during the design and development cycles and ensure a more rapid achievement of the goals (Li et al., 2014).

3.2.2. Logistics and supply chain operations

3.2.2.1. Demand planning. A key aspect in supply chain management is managing processes and operations to meet demand and deal with variations in both demand and processes. However, process variation and demand variability may become an obstacle in achieving a match between process capacity and demand. Effective capacity planning requires accurate demand forecasting, the ability to translate forecasts into capacity requirements, and supply chain operations capable of meeting anticipated demand. Hence, demand planning is crucial to supply chain operations planning (Chen and Blue, 2010).

Demand planning analyzes different customer segments in terms of channels, brands, and product down to the SKU level, and develops models used to shape demand and create revenue plans, which is the foundation for collaborative planning and forecasting with major supply chain partners (Jonsson and Gustavsson, 2008; Chen and Blue, 2010; Haberleitner et al., 2010). Demand planning is bi-directional allocation and aggregation, integration with brand, product and/or SKU level forecasting at various hierarchical levels through information sharing among partners and increasing supply chain visibility by allowing supply chain partners to access real-time sales and inventory information (Choudhury et al., 2008; Gallucci and McCarthy, 2009). Hence, demand planning is not just forecasting, but involves sales and operations planning.

Demand forecasting on independent demand items requires predictive analytics using time-series approaches (Cheikhrouhou et al., 2011; Li et al., 2012). Among the time-series methods is the exponential smoothing, which is widely used for both short-term and intermediate-range forecasting since it can incorporate both trend and seasonality. Another important method is the auto-regressive model, which achieves demand forecast in one period by using a weighted sum of demand realizations in previous periods. Moreover, intermediate-range forecasting can also be realized from associative forecasting methods, particularly in service industries or in manufacturing the non-discrete items (Lu and Wang, 2010; Beutel and Minner, 2012). Using forecasts of demand, sales, and optimization techniques, sales and operations planning (S&OP) provides an integrative cross-functional management capability for marketing, production, and inventory management to manage operational components and ensure customer commitments (Feng et al., 2008; Chen et al., 2010; Sodhi and Tang, 2011; Lim et al., 2014).

3.2.2.2. Procurement. A large amount of data in procurement is generated from various sources and/or applications through spending, supplier performance assessments, and negotiation, whether internal or external. These data sources facilitate the use of advance analytics. In the case of DHL for instance, the combined use of external operational and macroeconomic data enhances its supply chain operations efficiency. SCA provides procurement decision makers with consistent, data based analysis for a wide variety of major decisions and business issues, e.g., quality problems and material availability (Souza, 2014). In the literature, the application of SCA in procurement is illustrated in the following aspects: (a) managing supply risks and (b) managing suppliers performance.

SCA gives organizations the ability to distinguish between risks that must be avoided, and risks that must be taken by identifying trends and events through monitoring publicly available news or social media channels associated with suppliers or specific sourcing markets. Thus, organizations can continuously obtain updated information on suppliers and sourcing markets and quickly respond to changes or supply risks even with contingency plans. Scholars focus on using generic models or methodologies to model supply risks or evaluate the impact of supply risk on supply chain performance (Kabak and Burmaoglu, 2013; Mishra et al., 2013; Zeotmulder, 2014). Other scholars develop, inter alia, mathematical models and optimization based approaches to supplier relationship management with supply disruptions (Case, 2013; Khan, 2013).

SCA is also a powerful tool for helping organizations measure, analyze, and manage their suppliers' performance for better sourcing (Oruezabala and Rico, 2012). Through comprehensively collecting and consolidating all forms of supplier data across global organizations, SCA can quickly evaluate and analyze suppliers' performance such as quality, delivery guarantee and timeliness, and spend analysis, thus helping procurement organizations make informed decisions (Walker and Brammer, 2012; Yeniyurt et al., 2013).

3.2.2.3. Production. Supply chain analytics can enable manufacturers to understand the different production costs involved and how they influence the bottom line. The application of SCA can provide useful insights regarding the production capacity levels and inform managers/decision makers whether improvements are needed to maximize productivity (Jodlbauer, 2008; Heo et al., 2012; Noyes et al., 2014). SCA can also help manufacturers of multiple products adjust production to ensure that the right mix of resources is allocated to the right production lines. Further, SCA is used by production analysts to identify material waste and manufacturing techniques and processes that can reduce or even eliminate material waste (Sharma and Agrawal, 2012). Thus, SCA can be applied to production planning at both the tactical and operational level for aggregate planning and operations scheduling (Souza, 2014).

To enable aggregate planning SCA permits decision-making related to, inter alia, matching demand and supply, inventory management, and budget forecasting. After sales forecasts and resource requirements, the various alternate production plans are generated (Wang and Liang, 2005; Liu et al., 2011; Mirzapour et al., 2011; Li et al., 2013). Additionally, SCA provides useful insights to problems related to operations scheduling problems, which can be formulated as mixed integer linear programming problems (Wang and Lei, 2012, 2015; Wang et al., 2015). In routing problems, SCA can help in e.g. modeling the sequence of operations and the work centers that perform the work and dispatching (Chen and Vairaktarakis, 2005; Sawik, 2009; Chen, 2010; Leung and Chen, 2013).

3.2.2.4. Inventory. Business organizations are continuously amassing gigantic datasets within ERP systems because of Internet, electronic devices, and software applications. Data generated in ERP systems includes historic demand and forecasting data, replenishment lead times, the desired service level, holding cost, and fixed cost of placing a replenishment order. Challenges, such as diverse organizational needs and supply and demand fluctuations, impact on inventory levels (Sage, 2013). SCA can help organizations well design modern inventory optimization systems needed to handle the most complex retail, wholesale, and multi-channel challenges in inventory management (Hayya et al., 2006; Jonsson and Mattsson, 2008).

The use of SCA in Vendor Managed Inventory (VMI) systems enables collection, processing, and reporting on inventory data and can therefore inform decisions related to inventory performance improvement (Borade et al., 2013). SCA can also help in predicting accurately inventory needs and in responding to changing customer demands, utilizing statistical forecasting techniques (Downing et al., 2014; Wei et al., 2011), as well as to reducing dramatically inventory costs (Babai et al., 2009). Additionally, SCA is applied to address problems that occur within multi-echelon distribution networks (Wang and Lei, 2012, 2015; He and Zhao, 2012). It determines the appropriate inventory levels while taking under consideration factors such as demand variability at the network nodes as well as performance (e.g., lead time, delays, and service level) (Gumus et al., 2010; Guo and Li, 2014). SCA helps obtain a holistic view at inventory levels across the supply chain, while taking into account the impact of inventories at any given level or echelon on other echelons. SCA assists in decisions related to safety stock optimization (Fernandes et al., 2013; Guerrero et al., 2013).

3.2.2.5. Logistics. According to the Council of Supply Chain Management Professionals (Stroh, 2002), global logistics generates the massive amount of data as shippers, logistics service providers, and carriers manage logistics operations. Big data stemming from, for instance, RFID tags, mobile devices and EDI transactions (Swaminathan, 2012) can be harnessed for logistics planning purposes. This deals with the distribution of products from supply points (i.e., production facilities or warehouses) to demand points (i.e., retailers sites) through intermediate storage nodes (e.g., distribution centers). Logistics planning problems can be formulated as network flow problems where each arc represents a shipping mode with a given capacity and time period (Dong and Chen, 2005; Jharkharia and Shankar, 2007; Grewal et al., 2008). Logistics data is generated from different sources in distribution networks such as shipping costs, forecasts on supply capacity at suppliers' plants, demand forecasts in demand points, and network capacity (Najafi et al., 2013). Because of supply disruptions and demand uncertainty, predictive analytics tools are essential to design supply chain flexibility into logistics operations.

In logistics planning it is key to optimize both crew and equipment routing. The vehicle routing problem attempts to optimize the sequence of visited nodes in a route, such as for a parcel delivery truck, for a returns collection truck or for both (Drexl, 2012; Ozdamar and Demir, ,2012). The optimal sequence considers the distances between each pair of nodes, expected traffic volume, left turns, and other constraints placed on the routes, such as delivery and pickup time windows (Vidal et al., 2013). However, multiple vehicles, vehicle capacities, tour-length restrictions, and delivery and pickup time windows among others complicate the planning of transportation and distribution operations in global logistics network (Li et al., 2010). Analytics methodologies and techniques are used to optimize the routing of goods, vehicles, as well as crew (Novoa and Storer, 2009; Lei et al., 2011; Minis and Tatarakis, 2011) in order to balance between transportation costs and margins, and pay attention to maintenance and safety.

3.3. *Analytic techniques in SCA*

Based on our literature review and analysis as discussed before, in this section we outline popular techniques for SCA. As the central component of SCA, advanced analytics techniques are the basis for the success of supply chain strategies implementation, and daily operations for every business organizations. This taxonomy can be further developed in future research.

3.3.1. *Statistical analysis*

Statistical techniques include two types of techniques: qualitative and quantitative. Qualitative methods, based on subjective judgment of consumers or experts, are appropriate when past data are not available. Quantitative approaches are used to make predictions as a function of past data. Both methods are applied to short- or intermediate-range decisions. Two widely used quantitative techniques in SCA are 'time series analysis and forecasting' and 'regression analysis'. Time series analysis analyses data to extract meaningful patterns and statistics. Time series forecasting 'predicts' the future based on historically observed data. Regression analysis helps in understanding relationships and causality effects between variables.

Big data is characterized by velocity, volume, and variety, which leads to the following challenges to BA (Fan et al., 2014): (a) volume accumulates data noise, and incidental homogeneity; (b) high volume creates high computational costs and algorithmic instability; (c) high variety requires different techniques and methodologies. These challenges result in heterogeneity, experimental variations and statistical biases. Hence, more adaptive and robust procedures are required because traditional statistical methods were designed for moderate sample sizes and low-dimensional data, but not for massive data. Due to BD features, effective statistical procedures have received increasing attention for exploring BD.

3.3.2. *Simulation*

Big data brings more challenges to modeling and simulation (Sanyal and New, 2013; Parashar, 2014). Firstly, depending on reductionism and causality, the basic simulation theory cannot meet the demand of processing BD on LSCM, although it predefines concepts such as target, boundary, entity, constraints, among others. Secondly, BD makes modeling methods difficult to perform well and requires new types of models because of more complex problems and large amount of computation.

However, modeling and simulation can benefit from BD (Belaud et al., 2014; Pijanowski et al., 2014). SCA offers more in-depth analysis and processing, and new methods for the simulation problems with massive amounts of data. Moreover, SCA makes it possible for modeling and simulating complex systems as it focuses on the interrelationship between supply chain operations, and emphasizes the analysis on integral data associated with supply chain integration. SCA can aggregate the disintegrated data from different supply chain operations and achieve global optimization (Ranjan, 2014).

3.3.3. *Optimization*

The use of optimization techniques as part of SCA helps improve the accuracy of demand forecasting and supply chain planning, while creating challenges that relate, for instance, on applying penalized quasi-likelihood estimators on high-dimensional data creates large-scale optimization problems (Slavakis et al., 2014). BD optimization is not only expensive and instable, but presents slow convergence rates, thus making traditional techniques difficult to succeed in SCA. To deal with the massive size of BD, hence, it is necessary to implement large-scale non-smooth optimization procedures, develop randomized and approximation algorithms and parallel computing based methods, and simplify implementations (Fan et al., 2014).

Conversely, optimization techniques are suitable for data analysis in LSCM. Optimization helps analyze highly complex dynamic systems with huge data volumes, multiple constraints and factors, and can gain insights that allow decision makers to make appropriate decisions. In addition, optimization helps analyze the measures of supply chain performance such as cost reduction and demand fulfillment, among others. Another benefit associated with optimization is its flexibility because it can uncover new data connections, turn them into insights, and unlock more business value from huge amounts of data (Balaraj, 2013).

4. SCA maturity, sustainability, and holistic business analytics

Based on the results of our literature review, this section presents a maturity framework, relates SCA to supply chain sustainability, and proposes the inclusion of SCA into a wider idea of holistic business analytics for LSCM strategies and operations.

4.1. *SCA maturity framework*

SCA is strategically important to an organization's business operations. Hence, it must be aligned with both strategy and operations for LSCM. In this section, a SCA maturity framework is developed on the basis of different supply chain goals, including five different levels, namely, functional SCA, process-based SCA, collaborative SCA, agile SCA, and sustainable SCA. This framework is presented in Fig. 1, and extrapolates the relationship between the different levels of SCA maturity to LSCM strategy and operations, as reviewed in the previous sections. The majority of maturity frameworks and models in the field of supply chain management aim at examining and explaining the processes through which supply chains improve their effectiveness (e.g. Lockamy and McCormack, 2004; McCormack et al., 2008; Mortensen et al., 2008; Gupta and Handfield, 2011; Varoutsa and Scapens, 2015). Recently, the impact of ERP systems on supply chain maturity using big data has also been studied, but only by using big data

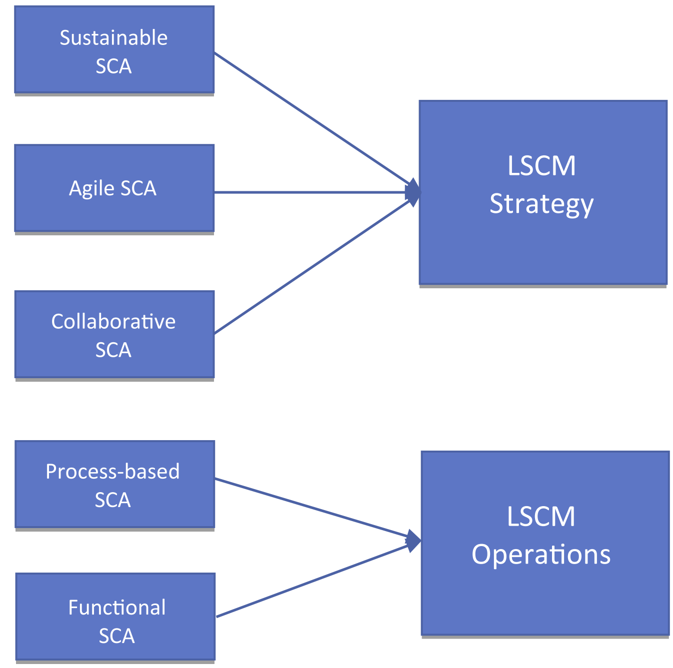

Fig. 1. SCA maturity framework.

(Huang and Handfield, 2015). However, there are calls for future research especially with regards to those mechanisms that enable a supply chain to move towards various phases of maturity (Huang and Handfield, 2015; Varoutsa and Scapens, 2015). Our proposed maturity framework does not focus on supply chain effectiveness per se, but extends existing LSCM maturity models and frameworks in that it focuses on SCA maturity that is important for both LSCM strategy and operations and relates the level of use of SCA to the achievement of different supply chain goals.

4.1.1. *Functional SCA*

Supply chains that are organized functionally and are not fully integrated present challenges related to the duplication of activities and processes, and absence of coordination between supply chain partners. To solve such problems while keeping the costs at low levels, functional SCA is used. It analyzes and solves problems relevant to supply chain functions and thus improves supply chain operations efficiency.

4.1.2. *Process-based SCA*

Process-based SCA refers to the techniques or tools of SCA used to solve such related problems with the integration of internal supply chain processes within an organization. This type of SCA focuses primarily on helping companies achieve operational effectiveness in supply chain processes. Supply chains, where SCA is applied to help in integrating processes, are cross-functionally organized, offer seamless flow across functions, and are fully aligned with the objectives of the business.

4.1.3. *Collaborative SCA*

Supply chain collaboration enables and secures the sharing of information and knowledge and its exploration and exploitation for key activities, inter alia, product design or inventory management, while reducing operational complexity through standardization of processes and interfaces and the rationalization of products. Collaborative SCA deals with situations at the strategic level, in which an organization collaborates with external business partners to perform supply chain operations. External data from suppliers or partners are combined with the process of decision making to help companies make better decisions and achieve supply chain integration using formal quantitative methodologies and sensitivity analysis.

4.1.4. Agile SCA

Supply chain flexibility is the ability to respond to changes, and it is extremely important in today's uncertain environment. Changes may occur in the modification of product or service features in relation to the design and development of product or service, the customer requirements, or the marketing mix that an organization offers. Real time monitoring of supply chains, as facilitated by the use of SCA, can contribute towards real-time monitoring and uncertainty reduction, flexibility and speed in addressing changing customer demands, and short lead times related to the transformation of supply chains, if needed. Companies, hence, need to develop agile SCA capabilities to cope with high uncertainties in supply chain operations and gain competitive advantage.

4.1.5. Sustainable SCA

Sustainable SCA is defined as the use of business analytics in the collection, analysis, and dissemination of sustainability-related data. The goal is to provide the appropriate information that can be used for effective and efficient decision-making on sustainability issues (Deloitte, 2013). The literature has highlighted the need by organizations to manage and collaborate closely with suppliers and customers on sustainability issues (Leppelt et al., 2013) to achieve better control of risks and organizational sustainability (Foerstl et al., 2010; Paulraj, 2011). To this end, SCA can gather and analyze sustainability-related data efficiently and effectively, thus supporting a variety of informational needs that include forecasting, analysis, and evaluation of economic, environmental, and social issues. Organizations need to develop and acquire capabilities to enable sustainable SCA. Therefore, we do recognize that sustainable SCA requires broader thinking and alignment between strategic goals and big data analytics as well as supportive organizational culture (SAP, 2013). Scholars have highlighted the role of organizational culture (Mello and Stank, 2005; Gunasekaran and Spalanzani, 2012) for sustainability. Carter and Rogers (2008) have highlighted the relationship between strategic goals, culture, transparency, and risk management as the building blocks of sustainable SCM. To enable this relationship, BD and SCA come to the foreground in order to secure the collection, cleansing, analysis and distribution of information seamlessly across functions and processes (SAP, 2013). It is important that leaders understand the role of SCA as the 'glue' that enables information to be transformed in the format needed for taking strategic decisions related to sustainability. This will enable leaders to acquire the appropriate analytical capabilities as well as the appropriate resources needed on adopting SCA to create organizational value through the attainment of the organizational goals (Bertels et al., 2010; Deloitte, 2011). Top and senior management commitment is a priority for those organizations and supply chains that are embracing sustainable practices (Gattiker and Carter, 2010; Foerstl et al., 2015).

4.2. Holistic business analytics

Although SCA has an extremely important role in LSCM operations, it should be integrated into other business activities, such as financial/accounting performance analysis, marketing, human resource management, and administration, to facilitate integrated business analytics capabilities. To this purpose, managers would need to have an understanding of the impact of SCA practices across the organization and supply chain and aim to adapt these practices, considering at the same time, their impact on organization and other partners. Paying attention to the social, organizational, and technological implications of SCA adoption is, hence, a challenge; but leveraging the organizational capacity for extending SCA across the organization and supply chains to create holistic business analytics will result in benefits across organizational levels and, ultimately, competitive advantage.

5. Managerial implications

From the literature review we conducted, we demonstrated the diversity of methodologies and techniques related to LSCM strategy and operations that relate to prescriptive, predictive, and descriptive analytics (Trkman et al., 2010; Demirkan and Delen, 2013; Souza, 2014).

We highlight the importance of managers to pay attention to the diverse methodologies and techniques in order to harvest the benefits from BD in their organizations and supply chains. We, however, acknowledge that there are diverse objectives, risks, agendas and requirements as expressed by various stakeholder groups, as well as costs related to the use of the methodologies and techniques that need to be considered in combination with the nature of the BD problems or opportunities that have been identified by managers. Hence, in this paper we call for managers to consider these factors and adapt the methodologies and techniques. Attention should be paid not only to the scope of analytics and the criticality of the task to the clients' activities, but also, to whether the type of industry (manufacturing or service industry), organizational goals and objectives, the market, and the technological capabilities and competencies of the organization/supply chain (Gunasekaran and Kobu, 2007; Gunasekaran et al., 2015). To be able to use the suggested methodologies and techniques, organizations and supply chains are heavily depended on (i) robust data collection and data cleansing, and this is a major task in SCA; and (ii) major investments in technological infrastructure (e.g. computerized systems) and human resources (e.g. data analysts). Auditing of these systems would have to be conducted regularly to ensure that appropriate data is collected and analyzed, and identify any needs to upgrades (e.g. computing power).

Apart from updating the technological infrastructure, new challenges for managers stem out from the need to constantly improve and update the methodologies and techniques for SCA, as well as different key performance indicators so as to measure the maturity of their SCA. This need does not always come from the different type of data to be analyzed, but also from the different strategies that organizations may pursue, which will have a direct impact on the type of BD collected, and the subsequent methodologies and techniques for SCA. Finally, challenges are related to the underlying organizational culture and politics, which play an important role in selecting business strategies, and subsequently determining and deploying SCA methodologies and techniques. To address this issue, we call for the relevant stakeholders to participate in the process of business strategy making and subsequently to the selection of the appropriate methodologies and techniques for SCA, aligning thereby different stakeholder and business targets/goals. Our taxonomy and review, we believe, can enable managers to think about the different methodologies and techniques they can adapt, explore and exploit when deciding on LSCM strategy and operations.

6. Limitations and further research directions

This paper has a number of limitations:

(1) The findings of the literature review are based mainly on data

collected from academic journals (Eksoz et al., 2014). We believe that the inclusion of practitioners' articles in future research will inform our literature review from the practitioners' point of view.

(2) Our review spanned 10 years (2004–2014) and we believe it is representative of the literature on methodologies and techniques for SCA. Although the list is not exhaustive, we believe it is comprehensive as it covers many academic –including highly ranked– journals.
(3) We followed Eksoz et al. (2014), Ngai et al. (2008) and Chen et al. (2014) who used particular keywords in conducting their literature reviews. Any disagreements on including particular keywords or articles were solved through discussion. Inspired by Esposito and Evangelista (2014), we focused on considering the latest research in the area of SCA.
(4) Although in this paper we used the taxonomy of prescriptive, predictive, and descriptive analytics (Trkman et al., 2010; Demirkan and Delen, 2013; Souza, 2014), we could use other frameworks from the literature. However, our choice was based on the fact that it reflects the recent views of scholars who work in the field of BDBA.
(5) Our SCA maturity framework aims at depicting the relationship between the different levels of SCA maturity and LSCM strategy and operations. We have not included different measures and metrics (and hence, KPIs) for SCA maturity and have not proposed a SCA maturity model since this was not the purpose of our research.

Notwithstanding the aforementioned limitations, we suggest future research directions on methodologies and techniques for SCA based on the literature review as well as our 20-year experience working in the area. Further testing of our suggestions may build new knowledge and robust theories (Corley and Gioia, 2011). Therefore, we propose the following:

(1) Based on the taxonomy of methodologies and techniques for SCA at LSCM strategy and operations, researchers could develop a model that enables the management of BD focusing on both strategy and operations. The model could consider the role of link SCA and BDBA to the organizational and supply chain performance, and could be validated empirically by collecting data from SC partners.
(2) Our review and analysis suggests that equal importance should be paid to both strategy and operations of LSCM. Although the papers extrapolated in Table 1 outline mainly prescriptive and predictive analytics methodologies and techniques, we call for more research in descriptive analytics, as well as on the relationship between the three categories, namely, prescriptive, predictive, and descriptive. Studying the degree of fit between LSCM strategy and operations by considering the different types of BDBA will enable researchers to shed light upon the formulation and implementation of BDBA strategies.
(3) The SCA maturity framework presented in this study can be extended into a SCA maturity model that measures how mature the use of SCA for LSCM is. Appropriate measures could be identified and used through interviewing and/or surveying logistics and supply chain practitioners. However, these measures, if identified by future studies, need to be adapted to the goals and needs of organizations.
(4) We have introduced the concept of sustainable SCA that refers to the use of methodologies and techniques to collect, analyze, disseminate, and use sustainability-related information for both strategy and operations. We call for more research on SCA sustainability. Possible research questions could include, for instance, what are the tools and techniques that enable sustainability performance through SCA? What are the enablers of sustainable SCA?
(5) We stress the need for scholars and practitioners to understand SCA and BDBA as strategic assets that should be integrated across business activities to enable integrated enterprise business analytics capabilities. Frameworks and/or models could be developed that enrich our understanding of how SCA could be integrated within business analytics and, to this purpose, the capabilities that need to be exploited and explored and the measures for assessing business analytics' performance.
(6) Our review demonstrates the significance of BDBA for LSCM and our classification may be useful in developing evaluation frameworks, models, and benchmarks to monitor and evaluate supply chain performance at strategy and operations. The process for developing such frameworks could involve the steps suggested by Gunasekaran et al. (2015), that is, (i) identify the area (strategy or operations or both); (ii) choose, adapt, and put into practice methodologies and tools for BDBA; and (iii) include a feedback mechanism to inform their future application. The validation process (Wisner and Fawcett, 1991), would include (i) understanding of the two areas (LSCM strategy and operations) and their role in realizing the organizational objectives and business strategy; (ii) communication of relevant methodologies and techniques across the organization/SC and in particular to top managers, and ensuring that they align with the business strategy and objectives; (iii) application of the methodologies and techniques and their periodic evaluation to ensure they are appropriate in light of the competitive environment.
(7) Our proposed classification could be developed through conducting interviews with practitioners to understand the importance, adaptation, and application of these methodologies and techniques, as well as their similarity with the ones revealed in this literature review. The classification we present could, therefore, be further enhanced and inform both academia and practice.

7. Concluding remarks

This study reviewed the literature on BDBA in logistics and supply chain management and explored the application of BDBA in supply chain strategies and operations, that is, SCA. SCA helps organizations measure the performance of various areas in logistics and supply chain management and provide them with the ability to establish a benchmark to determine value-added operations. Furthermore, SCA help companies monitor these metrics on an ongoing basis, troubleshoot poor performance, and identify a root cause, as well as enable the delivery of better business decisions and provide tremendous benefits through the improvement of business processes.

Our review of extant literature on SCA reveals a gap between theory and supply chain practices. Based on the investigation of the literature on SCA a framework of the maturity of SCA was developed to the extent at which companies apply SCA through four capability levels: functional, process-based, collaborative, and agile SCA. Given that supply chain sustainability has been receiving much attention from companies across the world, SCA sustainability brings additional benefits, financially or otherwise, to companies. In the context of integrated supply chain management, companies need to see SCA as a strategic asset that should be applied holistically to give rise to holistic business analytics.

The findings in this study may serve as the foundation for further discussion and research by both researchers and practitioners. Academics may consider the significant factors derived from our investigation of the literature in applying BDBA (and hence, SCA) in logistics and supply chain management.

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