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# Critical analysis of the impact of big data analytics on supply chain operations

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**ABSTRACT**

Undoubtedly, due to the increasingly competitive pressures and the stride of varying demands, volatility and disturbance have become the standard in today's global markets. The spread of Covid-19 is a prime example of that. Supply chain managers are urged to rethink their competitive strategies to make use of Big Data Analytics (BDA), due to the increasing uncertainty in both demand and supply side, the competition among the supply chain partners and the need to identify ways to offer personalised products and services. With many supply chain executives recognising the need of 'improving with data', supply chain businesses need to equip themselves with sophisticated BDA methods/techniques to create valuable insights from big data, thus, enhancing the decision-making process and optimising the efficiency of Supply Chain Operations (SCO). This paper proposes the building blocks of a theoretical framework for understanding the impact of BDA on SCO. The framework is based on a Systematic Literature Review (SLR) on BDA and SCO, underpinned by Task-Technology-Fit theory and Institutional Theory. The paper contributes to the literature by building a platform for future work on investigating factors driving and inhibiting BDA impact on SCO.

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Big Data Analytics; supply chain operations; optimisation; decision-making; task-technology-fit theory; institutional theory

## 1. Introduction

Over the past decade, the manufacturing sector has been in the midst of a fourth wave of technological advancement (Rüßmann et al. 2015). During this, a plethora of manufacturing and supply chain businesses have transformed their operations into intelligent/smart manufacturing. This is by adopting a variety of innovative technologies such as autonomous robots, simulations, horizontal and vertical systems integration, internet of things [IoT], cybersecurity, cloud services, additive manufacturing, and most importantly, big data analytics (Wamba et al. 2020). Several noticeable researchers and practitioners have recognised the significance and applicability of Industry 4.0 (I_4.0) for operations, logistics and production management at large (Sivarajah et al. 2017; Rahman et al. 2022). However, relatively little is known about the impact of BDA on SCO – particularly focussing on the five dimensions of SCO: demand planning, production and manufacturing, logistics, procurement, and inventory. Among the extant research studies published, a few shed light on the link between IoT and SCO (e.g. Ben-Daya, Hassini, and Bahroun 2019) and the impact of additive manufacturing on SCO, processes and performances (e.g. Li, Tang, et al. 2017).

The advent and pervasive use of such innovative digital technologies has resulted in producing substantial amounts of data, thereby creating challenges for the supply chain businesses that aim at realising the benefits from analysing this immense incursion of unstructured big data (Wang et al. 2016; Kamal 2020). New forms of data call for novel technologies that can handle the challenges posed by this data (Gupta and George 2016). These challenges include issues arising from managing large amount of data and dealing with the demand and supply uncertainty. Big Data (BD) refers to data with the following qualities: volume, velocity, variety, variability, veracity, visualisation and value (Sivarajah et al. 2017) and has emerged to describe the rapid generating of data from different sources represented in different forms, that is, structured, unstructured and semi structured (Wang et al. 2016). This data has useful hidden information, which makes it a valuable asset for any organisation (Sivarajah et al. 2017). BDA, on the other hand, involves the ability to gain insights from data by applying statistics, mathematics, econometrics, simulations, optimisations, or other techniques to help supply chain businesses to gain better understanding of the hidden value of BD and make better decisions (Sivarajah et al. 2017; Wang, Gunasekaran, et al. 2018; Dubey et al. 2020) as its business value is not yet achieved (Mikalef et al. 2020).

Yet, the role of BDA in SCO has not yet been thoroughly established. There has been a lack of research studies that comprehensively addresses the impact of BDA on SCO, or investigate opportunities for new theories or emerging

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practices in this area. Most of the existing research studies conducted on SCO focussed on one or two of the five dimensions of SCO e.g. demand planning, production and manufacturing, logistics, procurement, and inventory. For instance, Wang and Alexander (2015) and Wamba et al. (2015) – highlight and assess the BD benefits and its applications and opportunities in supply chain. Ranjan, Vijay, and Pralay (2016) examined the potential of ERP and SCO integrated with BDA contributing to improvement in the performance of manufacturing organisations. Few researchers discussed the impact of BDA on SCO theoretically in relevant to three key areas of operations i.e. logistic, manufacturing, and procurement (Wang et al. 2016; Wamba et al. 2018). Lamba and Singh (2017) considered three phases of a SCO i.e. procurement, manufacturing and logistics. Addo-Tenkorang and Helo (2016) stated that there is no clear picture that clarifies the valuable use or performance of BDA regarding SCO processes. A recent article by Nguyen et al. (2018) on BDA and SCO, discusses on how BDA compliments SCO including presenting BDA methods and techniques, although it misses depth in presenting how SCO challenges are handled by BDA. Furthermore, very few articles have also discussed theories that explain the role of BD and BDA in SCO. For instance, Wamba and Akter (2019) employed the dynamic capability theory, Wamba et al. (2015) highlighted the importance of developing theoretical grounds in utilising BDA in SC for better and in-depth understanding to clarify the impact of this change on the SCO performance related activities, and Gunasekaran et al. (2017) adopted the RBV theory to understand the role between BDA in SCO.

To address the aforementioned gaps, this paper investigates and assesses the impact of BDA on SCO. The aim of this research is to analyse, synthesise and present a state-of-the-art structured analysis of the normative literature on the impact of BDA on SCO to support the signposting of future research directions, resulting, in the development of a theoretical framework underpinned by Task-Technology Fit Theory (TTF) and Institutional Theory. In doing so, we propose the following two research questions: *Investigating the benefits of implementing BDA methods/techniques to achieve better decision-making for SCO?* and *Investigating the benefits of implementing BDA methods/techniques in achieving optimisation of SCOs?*

The remaining paper is structured as follows. Section 2 provides a brief review of the normative literature on BDA and SCO. Section 3 presents detailed Systematic Literature Review (SLR) methodology used for the literature search. Section 4 undertakes a review in line with the developed research design and presents the SLR findings. The key outcome from this SLR is a conceptual framework for analysing the impact of BDA on SCO underpinned by the TTF and Institutional Theory. Sections 5 and 6 conclude the research with discussions and implications, limitations and avenues for future research.

## 2. Literature review: conceptualising BDA and SCO

BDA is employed to support the intelligence and efficiency of the manufacturing processes (Tao et al. 2015). Among the extant research studies, several studies discuss on the significant role of BDA in enabling intelligent manufacturing systems, which in response accelerates the implementation of I_4.0 (e.g. Kamal 2020; Bag et al. 2020; Dubey, Gunasekaran, and Childe 2019). Sushil (2017) discussed that the use of big data can make the flexibility valuation more realistic and pragmatic, while Chehbi-Gamoura et al. (2020) stressed on an imperative need to work collaboratively and identify approaches for more intelligent use of BDA in SCO. On the other hand, Wan et al. (2017) proposed an architecture for generating BD in active preventive maintenance and analysed the methods used for collecting manufacturing BD. They concluded that active preventive maintenance has superior impact on implementation of I_4.0. Wang et al. (2016), on the other hand, argued that BDA are facilitating the implementation of the smart factory concept – as one of the key constructs of I_4.0. They proposed an intelligent negotiation mechanism for smart shop-floor objects such as machines, conveyers, and product to corporate with each other, and to reconfigure themselves for flexible production of multiple types of products while Ren et al. (2019) addressed the role of big data and AI to make more precise decisions for the optimal material delivery trajectory.

In the SCO context, analysing data generated from different supply chain entities and their respective communication channels (e.g. customers/consumers behaviour, IoT devices, social media) can result in developing cost-effective and strategic plans e.g. for optimised product design and innovation, precise demand planning, and capacity utilisation and capital effectiveness (Chien, Liu, and Chuang 2017; Kache and Seuring 2017). I_4.0 in supply chain context holds the promise of enabling automated business processes in manufacturing through implementing cyber-physical systems to facilitate real-time information sharing along the supply chain, in turn enhancing the ability to respond flexibly to disruptions and failures in timely manner (Gunasekaran et al. 2018). However, there are several challenges SC businesses face while performing SCO related to the aforementioned dimensions of SCO, which are detailed below:

### 2.1. The five dimensions of SCO

- **Demand Planning:** Predict precise demand is one of the most important challenges in the field of operations management, because of its role in supporting operational processes including inventory decision making and production planning (Jain, Rudi, and Wang 2015). On the other hand, Wang et al. (2016) report that demand planning is a critical function in SCO planning, as it helps to predict future demand and sale using data of real-time sale, marketing, and inventory information collected collaboratively by supply chain partners. **The main barrier in demand planning is the existence of time lags in the information flow (**Hosoda and Disney 2012**), which can be interpreted into lack of visibility of stock level, availability of sales' data, visibility of customer's need and market segmentation.** The transition from demand forecasting to demand planning is fulfilled by enriching the formal demand forecasts with any predicted exceptional influences coupled with their potential impacts on sales.

- **Production and Manufacturing:** In seeking to maximise profits, firms optimise their production through minimising the production waste, reducing the lead-time, and lowering the production cost at the level of satisfying customer demand. The most researched dimension in production field is integrated production including distribution, inventory, and demand modelling (Ekşioğlu, Edwin Romeijn, and Pardalos 2006). Integration of production with other operational function in supply chain is crucial to achieve optimal operational performance in most manufacturing industries (Chen 2010). The complexity generated in manufacturing activities due to the exploding product variety requires thorough designing, and sustainable and efficient manufacturing networks (Mourtzis 2016). In seeking to maximise profits, business managers tend to optimise their production through overcoming the following challenges: reduction of production waste, sustainability of products and processes, reducing the lead time, predicting and nullifying production disruptions, and lowering the production cost to satisfy customer demand (Pal, Sana, and Chaudhuri 2014). Prioritising green production and manufacturing are driving decision makers to consider energy consumption and to find ways to achieve energy-efficient production management (Irani et al. 2017; Chawla et al. 2020). That makes energy reduction as another challenge in manufacturing processes.
- **Procurement:** It refers to the procurement processes connecting manufacturers with suppliers representing the crucial link between the source of supply and the organisation itself (Zhou et al. 2014). Choosing reliable suppliers has been considered as a huge procurement process challenge for managers to address (Lamba and Singh 2017). The performance of suppliers in terms of the cost of component parts, raw materials, and service purchased is a vital constituent in an organisation's success or failure (Trivedi et al. 2017). In addition to choosing right supplier, order allocation decision process plays a significant role in improving firm's cost effectiveness, which determines different quantities of materials from different suppliers (Trivedi et al. 2017). Suppliers are evaluated on a range of criteria and performance attributes to set up trade-offs between qualitative and quantitative factors (Nazari-Shirkouhi et al. 2013).
- **Inventory:** Within supply chain, inventory embraces all required materials for downstream and upstream level in supply chain. Lack of information visibility for responsiveness and traceability is identified as a vital challenge for inventory. One of the sources of competitive advantage in supply chains is time-based competition, which is very challenging for inventory management to be efficient (Wu and Yang 2012). The cost of inventory considers a very costly operation that requires regular auditing of stock, whereas, the optimal level of inventory is one that maximises supply chain profitability (Chopra and Meindl 2010). The safety inventory emerged to face challenges resulting from demand and supply uncertainty, such as transportation delay, production delay, and increasing customisation, and capacity constraints. In addition, meeting the demand that exceeds the amount forecasted for given period and keeps organisation' position in marketplace.
- **Logistics:** Globalisation, online business, and a wide range of companies have played a pivotal role in raising the level of customer satisfaction, which has, in turn, raised the necessity to offer product with best quality, lower cost, shortest time, and best overall experience. Specifically focussing on logistics, some scholars tend to design knowledge-based logistics system to propose optimisation model for logistics problem in facing uncertainty about the future (Yu and Li 2000), and to discuss the role of the logistics capability, analytics and firm performance (Mikalef et al. 2019b).

## 3. Research methodology

SLR offers a chronological viewpoint of the relevant research area and a comprehensive account of autonomous research endeavours (Mentzer and Kahn 1995). According to Gough, Oliver, and Thomas (2017), the philosophical stance behind using SLR is to undertake a in-depth review of the literature, using systematic and rigorous methods, as used in this SLR (i.e. in Figure 1). The latter viewpoint is supported by Boland, Cherry, and Dickson (2017), who state that SLRs are original empirical research studies (or considered as gold standard) that assess both primary and secondary data/studies on a specific subject area, which can be either quantitative, qualitative or those using mixed method. In using SLR, Denyer and Tranfield (2009) stress on some key points to focus e.g. the purpose and questions of the review must be clearly specified, the definition of literature review process must be organised and explicit, the search of printed and unpublished information is rigorous and broad, and the inclusion and exclusion criteria are pre-determined. To better understand and provide detailed insights to the phenomenon of BDA in SCOs, the authors follow the similar philosophical stance as stated above and adopt the SLR approach proposed by Tranfield, Denyer, and Smart (2003). A number of highly cited review papers, such as Sivarajah et al. (2017), Kamal and Irani (2014) and Delbufalo (2012) have adopted this approach. This SLR is conducted based on the three-phase approach and illustrated in Figure 2:

- Phase I – Planning the review process – defining the research aim and objectives (I.1); formulating the proposal (I.2) and developing the review protocol (I.3);
- Phase II – Conducting the review process – Identifying, selecting, evaluating and synthesising the pertinent research studies; and
- Phase III – Reporting and dissemination of the overall research results – descriptive reporting of results and thematic reporting of journal articles.

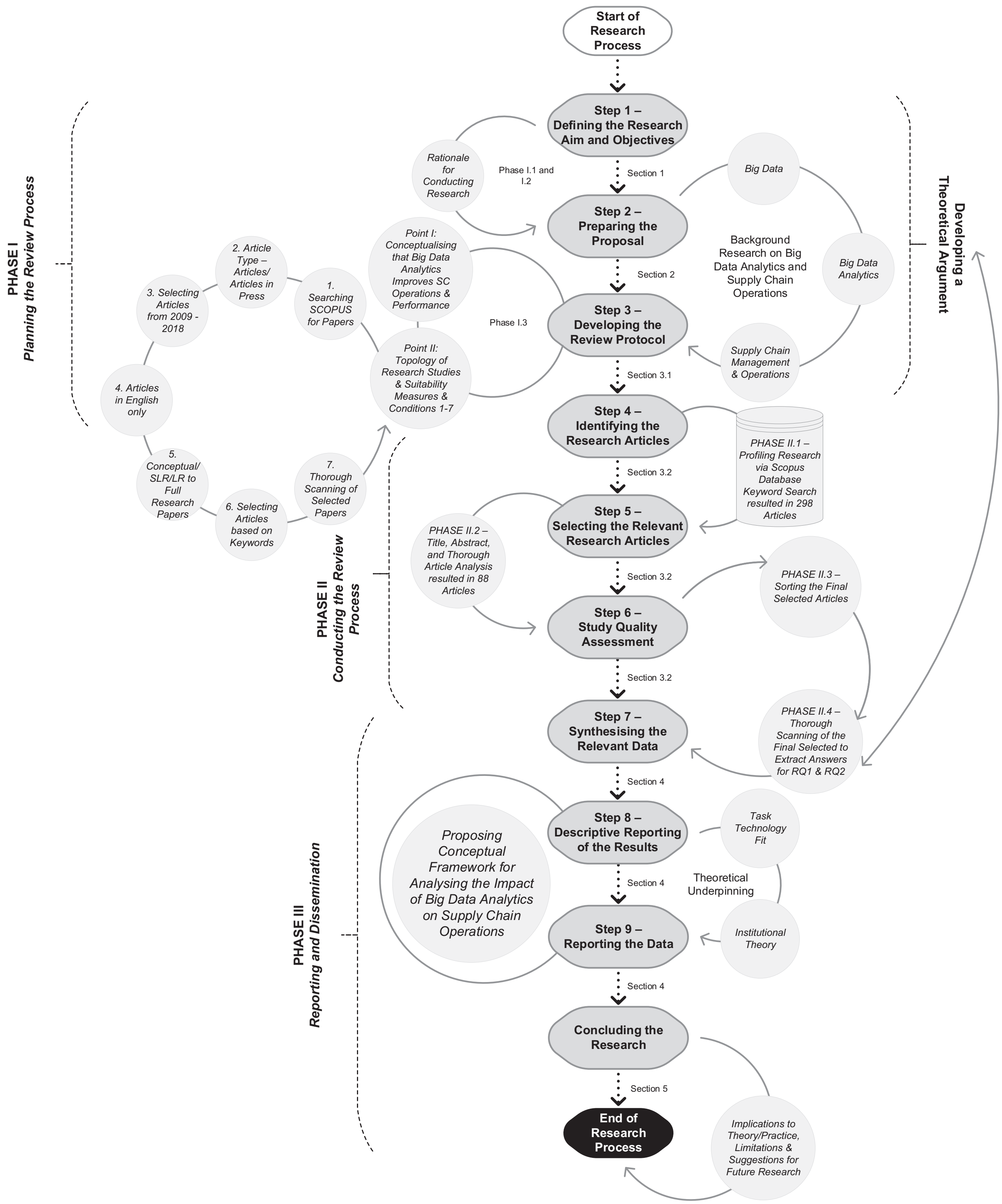


Figure 1. Systematic literature review methodology (Source: Authors).

### 3.1. The research protocol (phase I.3)

This SLR commenced by using an established review protocol based on the guiding principles and procedures of the SLR (Tranfield, Denyer, and Smart 2003). This protocol identifies the background review, search strategy, research questions as outlined in the abstract, data extraction, criteria for study selection and data synthesis – based on the prescriptive three-phased approach. As this SLR mainly focuses on analysing, synthesising and presenting a comprehensive structured analysis of the normative literature on BDA and its impact on SCOs, it was necessary to consider the domains for this research synthesis as both conceptual and empirical

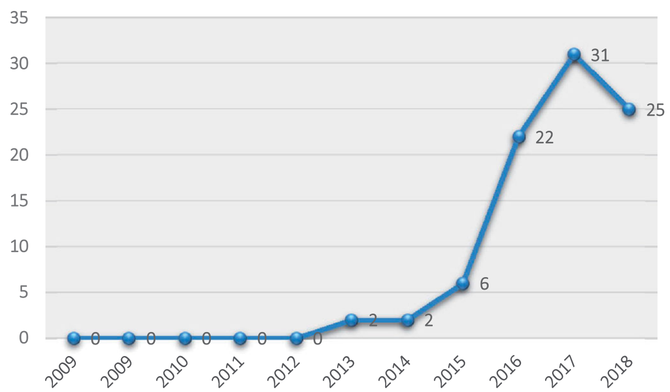


Figure 2. Total number of papers published (Source: Authors). (From 2009 to 2018 – based on Keywords Selected).

papers. The research protocol for this literature review paper provides details on the following two points:

- Point I – Conceptualising that BDA improves SCO (as discussed in subsection 2.1).
- Point II – Typology of research studies considered in this review and the appropriate measures.

Given the above, several selections in relation to the typology of research studies to be counted in and the suitability conditions have been made (Point II). The conditions itemised in seven points (as illustrated in Figure 1) were all rigidly followed to conduct an effective and reproducible database examining process.

### 3.2. Scopus database searching process and results – phase II

There are four steps of Scopus database searching process, e.g.:

- Phase II.1 – Following conditions 2, 3 and 4 (Figure 1), a number of keywords were entered into the Scopus database, resulting in 298 publications, of which 88 were left as relevant after filtering according to the barring conditions. The following keyword strings were used to extract the relevant articles for this paper:
  - ^ 'Big Data' OR 'Big Data Analytics' OR 'Big Data Management' AND 'Supply Chain Operations' OR 'Purchasing' OR 'Logistic' OR 'Distribution' OR 'Procurement' OR 'Buyer-Supplier' OR 'Demand Chain' OR 'Process Uncertainty' OR 'Inventory' OR 'Production' OR 'Manufacturing' OR 'Business and Strategy' OR 'Strategic Value' OR 'Decision Making' OR 'Decision-Making' OR 'Data Quality' OR 'Optimisation' OR 'Optimization'.
- Articles based on conditions 5 and 6 (Figure 1). Some further articles were discarded during this stage. At the end of this process, 88 articles were considered for further investigation.
- Phase II.3 – For this step, the authors followed the quality criteria matrix. In this step, the selected 88 articles were further scanned, searching for both conceptual as well as empirical studies through the criteria highlighted in conditions 6 and 7 (Figure 1).
- Phase II.4 – Following Phase II.3, the full-text version of 88 articles were thoroughly read by the authors to confirm the substantive relevance of both conceptual and empirical articles, as mentioned in conditions 6 and 7.

## 4. Empirical findings

The findings of this SLR study are presented in the following subsections followed by the development a theoretical framework for analysing the impact of BDA in SCO.

### 4.1. Yearly publications – descriptive analysis

Using the keywords as stated in Section 3.2, initial search resulted in 29,053 articles based on the number of subject areas including material sciences, energy, neuroscience, chemistry, etc. However, this research focussed on only three subject areas; i.e. business management and accounting, decision science and social science. Following the latter search, the second filtring process using the systematic literature review steps (explained and illustrated in Section 3 and Figure 1, respectively) resulted in 298 articles. Third detailed searched based on title, abstract and whole paper review resulted in 88 articles were finally selected. As presented in Figure 2, the largest number of publications were recorded for year 2017, followed by 2018 and 2016 respectivley. Howeve, the continuous increase leading to the peak of 2017 came to a slight drop in 2018, where 25 relevant artciles were found to be fulfilling the requirements set in Phase II.1. All these yearly publications are simply based on the keyword search, though the actual number of papers extacted for 2018 were 97.

Regardless, the rapid increase in the articles highlights the awareness and importance of this area among the academic community, practitioners, and even governments worldwide. The range of publications is in line with the frequency distribution found in Gandomi and Haider (2015). It suggests that the application of BDA on the SCO arena is a fast-growing and fruitful research field, being promoted by several special issue calls. Despite the increase in the number of articles on BDA in supply chain discipline, this research domain is still emerging. With the significance of BDA in SCO from a strategic perspective and the increasing number of articles, it appears that this research domain requires further in-depth conceptual and empirical research studies.

### 4.2. Focus of research in selected articles

To capture the main themes discussed in the articles reviewed, we used NVIVO™ 11 software. All selected 88 articles were defined in a specific format to easily identify coded data (Caldera, Desha, and Dawes 2017), then they were imported as xml files to NVIVO™ 11 software to analyse the content. NVivo software was selected due to its ability in managing, visualising and analysing qualitative data (Jackson and Bazeley 2019). The data was synthesised by

Table 1. Theme of research articles reviewed.

| Focus of research/Theme | Description | References |
|---|---|---|
| Optimum Assets Work | Detection, recognition, and diagnosis of fault and irregularities in timely manner to ensure that all production processes are under control. In addition to optimising machine task list, prioritising maintenance and autonomous (automated decision, control, and diagnostic). | Kumar et al. (2016); Ahmadov and Helo (2018); Preethi, Sankar, and Mathew (2016); Wang et al. (2016); Bumblauskas et al. (2017); Chien, Liu, and Chuang (2017); Yang, Wen, et al. (2017); Wan et al. (2017); Khakifirooz, Chien, and Chen (2018). |
| Energy Saving | Pertaining to using BD of manufacturing processes to reduce energy consumption and managing waste electronic and electronic equipment. | Li et al. (2018); Rao, Muller, and Gunn (2017); Chawla et al. (2020) |
| Mass Customisation | Mass customisation for product and service according to requirement of certain group of customers. To provide accurate high quality, personalised product and service. | Xu, Chen, and Zheng (2016); Li et al. (2018). |
| Visualise IoT Data | Use of RFID data, for instance, to gain insight from huge amount of data and support advanced decision-making. By identifying different behaviours of smart manufacturing objects. | Zhong et al. (2016); Zhong et al. (2015); Zheng et al. (2018); Zhong et al. (2017). |
| Predict Risk Analysis | Predict risk analysis to avoid cost in operating and maintaining the systems. | Chen and Kezunovic (2016); Pang, Zhao, Yan, et al. (2021). |
| Resolve Delivery Queries on Social Media Platform | Resolving delivery queries on social media platform to clarify the effective use of social media strategies. | Bhattacharjya et al. (2016). |
| Demand Forecasting | Optimal inventory solution and optimising logistics services. The real time sales nowcasting offers an optimised solution to manage inventory, therefore reducing the cost of stocking and avoiding the under stocking. | See-To and Ngai (2018); Huang and Van Mieghem (2014); Kato and Kamoshida (2020); Ren, Chan, and Siqin (2020); Lee and Nair (2021); Li et al. (2018); Y. Zhao et al. (2018); Liu and Yi (2018). |
| Understanding and Controlling Manufacturing Industry Process Performance | Using event-based process prediction to predict decisive event from collected sensor data in a timely manner, forecasting their most optimal further sequence and proactively controlling them based on this knowledge. | Krumeich, Werth, and Loos (2016); Liu et al. (2016); Ranjan, Vijay, and Pralay (2016); Bock and Isik (2015); Brandau and Tolujevs (2013); Gunasekaran et al. (2017); Li et al. (2017); Dubey, Gunasekaran, and Childe (2019); Wang et al. (2018); Min et al. (2019); Pang, Zhang, Xiao, et al. (2021); Wang et al. (2018). |
| Emergency Rescue | Design emergency rescue for the daily supervision of dangerous objects in chemical industry. | Lele and Lihua (2016). |
| Product Design | Product design like generalised product and quality assurance. Providing customisation and personalisation product at low cost. | Li et al. (2018); Li et al. (2017); Yang, Lan, et al. (2017); Tao et al. (2018). |
| Implementing Smart Manufacturing | Enabling technologies play a key role in data mining, data analysis and data transformation, which provides support for optimising production efficiency, optimising production, and optimising service quality. | Yue et al. (2015); Lee et al. (2017); Ren et al. (2019); Chawla et al. (2020); Shan et al. (2020); Sang, Xu, and de Vrieze (2021). |
| Identifying Customers' Preferences | Identifying customers' preferences to enhance engagement including extracting consumers' sentiments over topics of product reviews (i.e. product aspects) to enhance sales predicting performance. | Li et al. (2018); Yuan et al. (2018); Lau, Zhang, and Xu (2017); Mishra et al. (2017); Chen (2022); Wong and Wei (2018). |
| Determining the Allocation of Products and DCS | Determining the allocation of products to distributors' centres including allocation of the distributors' centres. | Wang et al. (2016); Liu et al. (2016); Nnamdi (2018). |
| Improving Procurement Processes | Improving suppliers' performance in terms of cost but also potentially in terms of time, quality, innovation, flexibility, and sustainability, in addition to accuracy and reliability of supplier choice. | Jin and Ji (2013); Moretto, Ronchi, and Patrucco (2017); Pramanik et al. (2020) |
| Predict Truck Arrival Time | Identifying factors predicting arrival time to optimise logistic service. | van der Spoel et al. (2015). |
| Logistics Firm Strategy | Supporting logistic firm strategy to lower operation cost, improve driver safety, and reduce the environmental impact of their vehicle | Hopkins and Hawking (2018); Lai, Sun, and Ren (2018); Bhattacharjya et al. (2018); Sharma et al. (2018); P. Zhao et al. (2020); Mishra and Singh (2020); Bag et al. (2021); Sugrue and Adriaens (2021); Bhattacharjya et al. (2018); Singh et al. (2018); Wang et al. (2018); Hazen et al. (2018). |
| SC Resilience | SC agility, coordination, and resilience | Davenport (2014); Waller and Fawcett (2013); Bag (2017); Queiroz and Telles (2018); Brinch et al. (2018); Brouer, Karsten, and Pisinger (2018). |

Source: Authors.

identifying themes originating from the findings reported in each of the articles selected this study as this software has the ability to systematically manage data aided the process of thematic analysis to identify frequent themes and synthesise the results (Barnett-Page and Thomas 2009). The final investigation focussed on several themes as presented in Table 1.

### 4.3. Source of data – inbound and outbound

Based on the in-depth SLR exercise, we developed a taxonomy of BDA sources that can be considered for decision-making in SCO. Based on the research works of Rehman et al. (2016), in this SLR we divided source of data into two types – inbound data (Business generated into the five dimensions of SCO) and outbound (Customer generated from the five dimensions of SCO) data sources. Results are detailed below:

- **Inbound Data:** The inbound data sources handle data generated from the results of business operations, such as manufacturing, management of supply chain and human capital, and marketing, etc. In SCO context, the convergence of development technologies has resulted in increasing data at an exponential rate. Inbound sources of BDA in manufacturing are grounded on the implementation of IoT technologies in products and processes, which generate massive amounts of data on daily basis – data that provides insights to the entire process of design, production, and service of a product. The emerging transitioning trend towards I_4.0 has become a requisite due to recent developments in BDA, cloud computing, and IoT devices, which play a significant role in streamlining operations and integration activities. Similarly, generating vast amounts of data in inventory, logistics, and processes, is a result of using advanced IoT devices like barcodes, RFID, sensor data, etc. Figure 3 illustrates the inbound sources of big data extracted from the 88 articles reviewed using NVIVO 12.
- **Outbound Data:** The outbound data sources handle customer-generated data, which are acquired directly or indirectly from customers, market analysis, surveys, product reviews, and transactional histories. Continuous technological advancements have stirred the pace of knowledge production which make customers' information is dominantly the main data source in SCO, and this paves the way for managers to sense customer feeling on their products design and service through analysing data generated from different commercial website. The scope and scale of outbound data have the potential to revolutionise SCO performance by collecting real-time data of e.g. customer's hits, browsing time, shopping cart, reviews, and all customers-related data. It is evident from Figure 4 that the outbound manufacturing data rely on customers' preferences, needs and requirements, we can generalise that to demand planning, logistic, and inventory, the outbound data generates mostly from customers interaction on commercial websites including transaction data, customer review data, and customer order data.

### 4.4. Big data analytics methods

To facilitate evidence-based decision-making, supply chain businesses need efficient approaches to process large volumes of assorted data into meaningful knowledge (Gandomi and Haider 2015). The potential of using BD is limitless, however, it is restricted by the availability of technologies, tools and skills available for BDA. Given BDA can enhance decision-making and increase supply chain operational output, this is possible when a selection of analytical methods is used to extract sense from the data. The following description provides an overview of results for BDA methods classified into predictive, descriptive, and prescriptive analytics with a summary illustrated in Table 2:

- **Predictive Analytics:** The main contribution of BDA research in the SCO discipline is represented in the application of predictive analytics models. This analytics approach is related to predicting future events such as best delivery time, individual customer behaviour, out-of-stock and shortages predictions, demand forecasting, point of failure for equipment predictions, and sales performance prediction (e.g. Kumar et al. 2016). The findings of our investigation indicate that the common methods used in predictive analytical approach are data mining algorithms (i.e. decision tree, clustering and classification algorithms), statistical techniques (e.g. PLS-SEM used by Akter, Fosso Wamba, and Dewan (2017), hidden markov models and cost minimisation algorithms), machine learning, fuzzy logic approach, visualisation methods (RFID-cuboid model), logistic regression modelling, optimisation methods, and sentiment analysis.
- **Descriptive Analytics:** From the total 88 papers extracted, seven research articles used descriptive approaches for collecting and analysing data describing current and past events, and individual product functions and features to identify the cause of problem and identify the main reasons behind past success or failures; in other words, explanatory definition of fault and success condition. For example, collecting and analysing tweets data related to beef products to express customers' likes and dislikes, which helps in backtracking supply chain processes and mitigate the waste generated through these processes (Mishra and Singh 2018). Another potential of using descriptive BDA is discussed by Bhattacharjya, Ellison, and Tripathi (2016) to explain the complexity of logistics – related interaction between e-retailer and their customer on social media platforms and reach out consumer's base more frequently. Research papers related to descriptive analytical approach have implemented mathematical model techniques, data mining techniques, and descriptive statistic techniques.
- **Prescriptive Analytics:** From our SLR analysis of 88 articles, it is evident that growing attention has been paid to prescriptive analytical approaches recently (e.g. Tayal and Singh 2018; Nnamdi 2018). Manfacturing was the core interest for prescriptive analysis for detecting, recogniting, and diagnosing of fault and irregularities in timely manner (Chien, Liu, and Chuang 2017). However, this approache is still under researched and investigated as it requires highly skilled personnel and more comlpes tools.

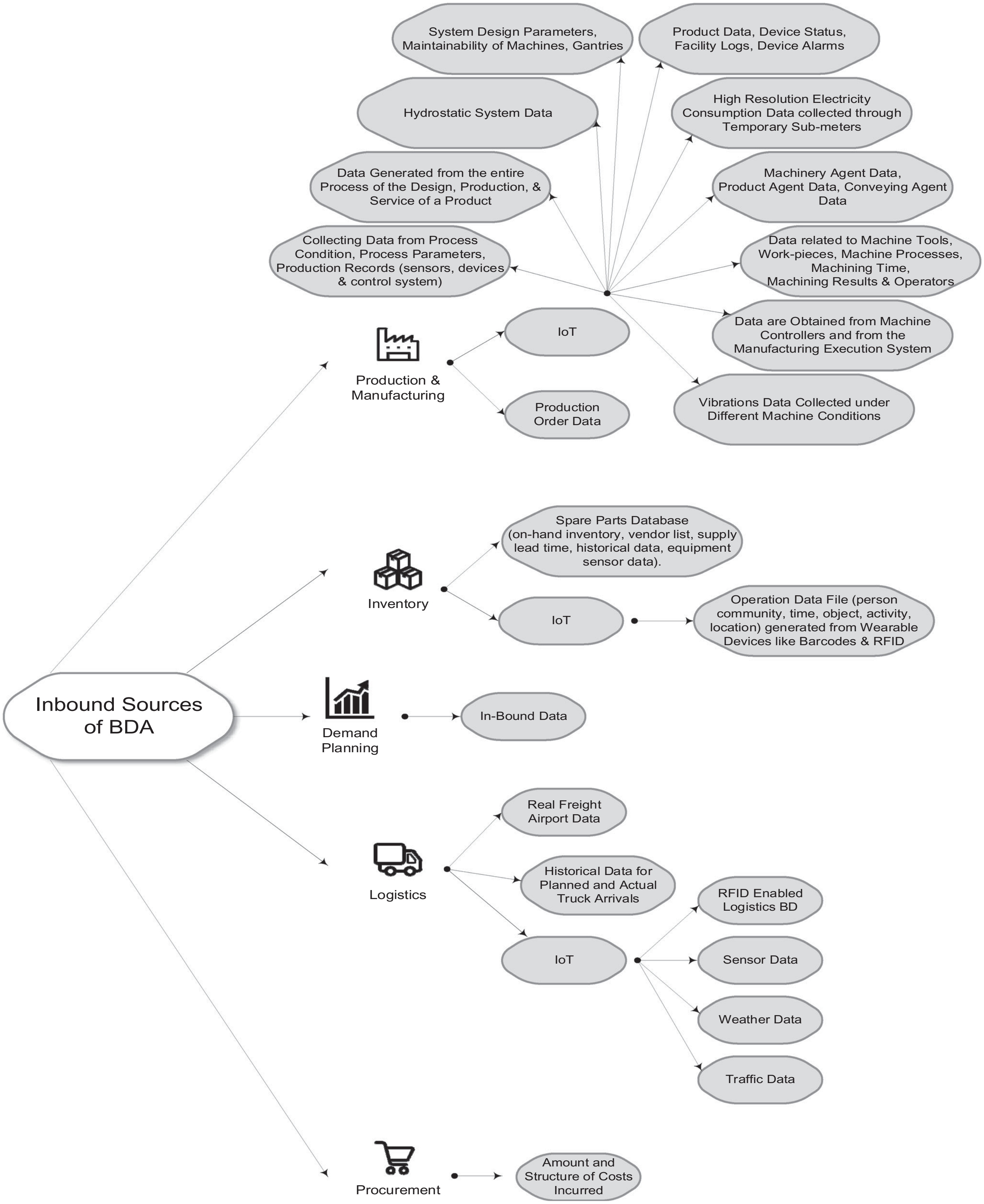


Figure 3. Inbound data (Source: Authors).

### 4.5. Type of big data analytics techniques

A broad range of techniques have been developed to explore the patterns from large volumes of data by number of disciplines such as computer science, economics, mathematics, and statistics. For instance, Manyika et al. (2011) identified a number of widely used BDA techniques that includes: cluster analysis, genetic algorithms, natural language processing, machine learning, neural networks, predictive modelling, regression models, social network analysis, sentiment analysis, signal processing and data visualisation. Each of these techniques have been applied to each of the

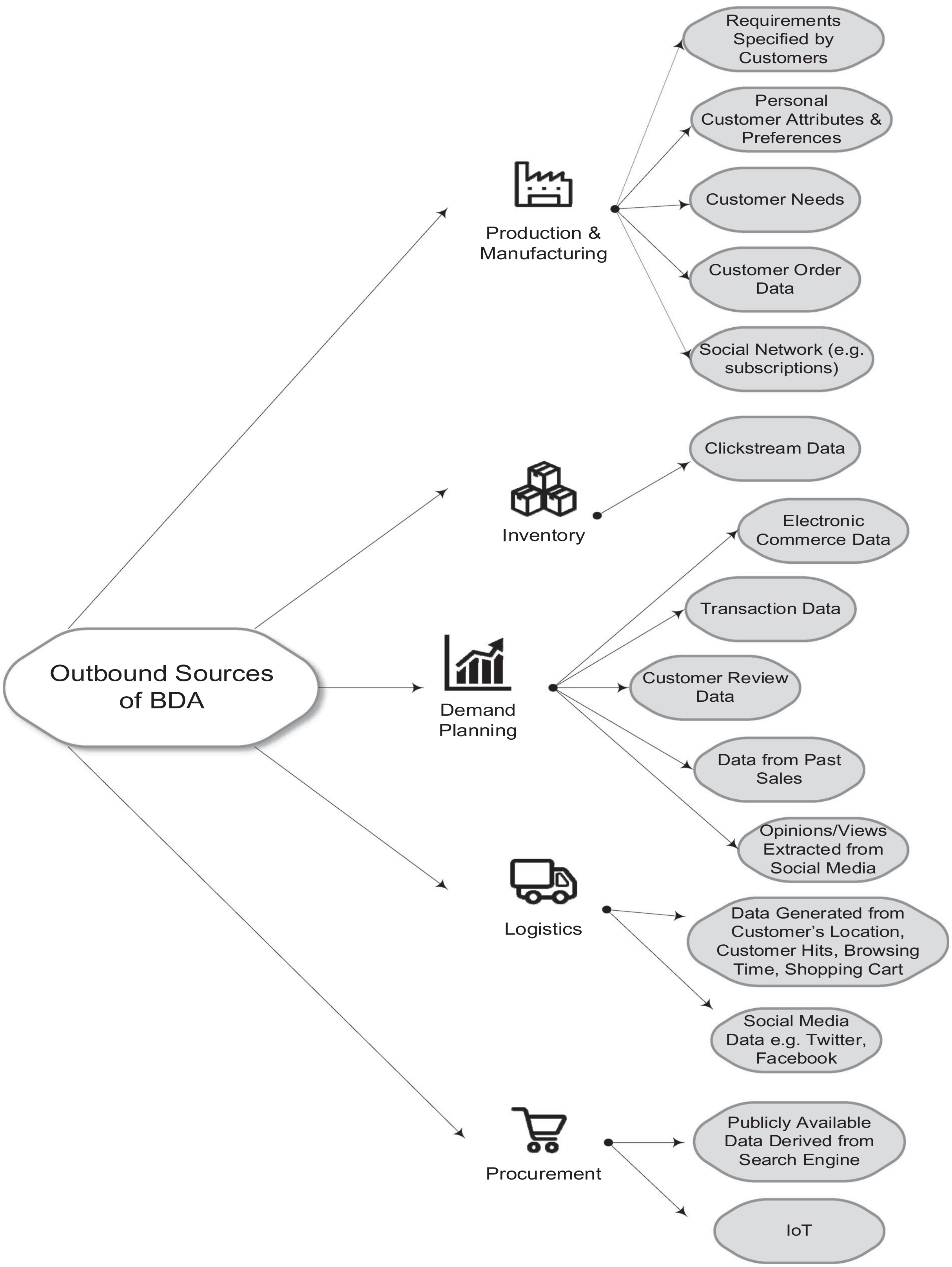


**Figure 4.** Outbound data (Source: Authors).

five dimensions of SCO to achieve specific goals relevant to each of the dimensions with specific computational strategy. Table 3 illustrates the type of BDA techniques used and or discussed in the articles reviewed in correspondence with the five dimensions of SCO.

### 4.6. BDA enhancing the decision-making process in SCO

Businesses need to make informed supply chain and operational decisions to improve effectiveness and efficiency. Organisations, thus, need to focus on reshaping proactive strategy formulation and decision-making based on BDA in

Table 2. Big Data analytics methods employed in articles reviewed.

| Predictive analytics | Descriptive analytics | Prescriptive analytics |
|---|---|---|
| Waller and Fawcett (2013) | Bhattacharjya et al., (2016) | Ahmadov and Helo (2018) |
| Hu et al. (2014) | Wang et al. (2016) | Giannakis and Louis (2016) |
| Huang and Van Mieghem (2014) | Moretto, Ronchi, and Patrucco (2017) | Krumeich, Werth, and Loos (2016) |
| Bock and Isik (2015) | Mishra et al. (2017) | Li et al. (2016) |
| Li et al. (2015) | Kozjek et al. (2018) | Xu, Chen, and Zheng (2016) |
| Zhong et al. (2015) | Mishra and Singh (2018) | Chien, Liu, and Chuang (2017) |
| Chen and Kezunovic (2016) | Yu et al. (2018) | Ji, Hu, and Tan (2017) |
| Kumar et al. (2016) | Bhattacharjya et al. (2018) | Lee et al. (2017) |
| Li et al. (2016) | Brouer, Karsten, and Pisinger (2018) | Lee (2017) |
| Preethi, Sankar, and Mathew (2016) | | Hopkins and Hawking (2018) |
| Yan-Qiu and Hao (2016) | | Nnamdi (2018) |
| Akter, Fosso Wamba, and Dewan (2017) | | Sharma et al. (2018) |
| Bumblauskas et al. (2017) | | Tayal and Singh (2018) |
| van der Spoel, Amrit, and van Hillegersberg (2017) | | |
| Jang and Kim (2017) | | |
| DiBiano and Mukhopadhyay (2017) | | |
| Ji and Wang (2017) | | |
| Lee et al. (2017) | | |
| Lau, Zhang, and Xu (2017) | | |
| Yunusa-Kaltungo and Sinha (2017) | | |
| Ku (2018) | | |
| See-To and Ngai (2018) | | |
| Yuan et al. (2018) | | |
| Khakifirooz, Chien, and Chen (2018) | | |
| Li et al. (2018) | | |
| Liu and Yi (2018) | | |
| Singh et al. (2018) | | |
| Wang et al. (2018) | | |
| Wong and Wei (2018) | | |

Source: Authors.

SCO. The following provides summary results of BDA decision processes within the context of each of the five dimensions of SCO:

- **Demand Planning:** With the dilemma of continuously changing customers' demands, BDA is an effective tool that enables companies to predict precise demand from an increasing volume of data. A study conducted by Kato and Kamoshida (2020) used gross domestic product and population as future data, models are built to predict the demand by body type in Japan on a monthly basis, up to 36 months ahead. The utilisation of all generated big data sources not only enables customers to explore their needs on fashion products but also could recommend products that customers they would possibly pay for eventually (Ren, Chan, and Siqin 2020). An accurate prediction of sales performance is highly beneficial for long-term development, as it has significant impact on marketing strategies and inventory management through enabling managers to make a competent market strategy (Lau, Zhang, and Xu 2017). Another advantage of analysing BDA aiming to real demand planning is developing consumer centric sustainable supply chain, by means of means of carrying out cluster analysis on consumers' information from Twitter in the form of BD (topic sentiment mining) to investigate the purchasing behaviour of consumers (Mishra et al. 2017). This mined information helps to sharpen the competitiveness and to timely (Yuan et al. 2018)
- **Production and Manufacturing:** Researchers shed light on the diverse potential use of BDA through classifying the different sources of data concerning manufacturing, and its analytics impact on reducing customer's order time in addition to achieve sustainability. For instance, Kumar et al. (2016) developed a Map-Reduce framework for automatic pattern recognition based on fault diagnosis by solving data imbalance problem in cloud-based manufacturing on steel plate manufacturing data-set to help in reducing the occurrence of fault conditions. The framework proposed by Xu, Chen, and Zheng (2016) utilised a hybrid approach to deal with BDA set for making smarter decisions. Conversely, extracting useful information of personal customer' attributes and preferences datasets in the atmosphere of mass customisation for product design has been credited with providing a rule base for designers to make design decisions according to real requirements of customers (Xu, Chen, and Zheng 2016; Kache and Seuring 2017). Considering the maintenance prioritisation, Bumblauskas et al. (2017) clarified the function of BDA of establishing parameters to predict the point of failure in a specific part, in order to replace it in a timely manner, along with receiving a comprehensive proposal for service to fulfil the recommendations created by analytical model.
- **Procurement:** Undeniably, cost reductions and improving the customer satisfaction are some of the leading objectives of decision-makers. In order to mitigate or eliminate the ever increasing driving costs and facilitate evidence-based decision-making, organisations need efficient methods to process large volumes of assorted data into meaningful knowledge (Gandomi and Haider 2015). The potentials of using BDA are endless but restricted by the availability of different technologies, tools and skills available for BDA. Nevertheless, these technologies, tools and

**Table 3.** Types of BDA techniques employed in empirical based articles.

| Supply chain operations | Analytics techniques | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | Statistics | Data mining | Machine learning | Optimisation | Social network | Visualisation | Mathematical model | Sentiment analysis |
| Manufacturing | Ahmadov and Helo (2018)<br>Krumeich, Werth, and Loos (2016)<br>Li et al. (2016)<br>Xu, Chen, and Zheng (2016)<br>Bumblauskas et al. (2017)<br>Chien, Liu, and Chuang (2017)<br>Wan et al. (2017)<br>Jang and Kim (2017)<br>Li et al. (2017)<br>Khakifirooz, Chien, and Chen (2018)<br>Sang, Xu, and de Vrieze (2021) | Ji and Wang (2017) | Kumar et al. (2016)<br>Kozjek et al. (2018)<br>Min et al. (2019)<br>Wang et al. (2018) | Giannakis and Louis (2016)<br>Liz et al. (2016)<br>Lee et al. (2017) | Yang, Lan, et al. (2017) | Zhong et al. (2017) | Wang et al (2016)<br>Rao, Muller, and Gunn (2017)<br>Liu et al. (2016)<br>Yang, Wen, et al. (2017)<br>Ku (2018) | – |
| Demand Planning | Liu and Yi (2018) | Yuan et al. 2018)<br>Li et al. (2018) | Li et al. (2018) | Ji, Hu, and Tan (2017)<br>Lee and Nair (2021) | – | See-To and Ngai (2018) | Mishra et al. (2017)<br>Wong and Wei (2018) | Lau, Zhang, and Xu (2017) |
| Inventory | Huang and Van Mieghem (2014) | – | Demey and Wolff (2016)<br>Nnamdi (2018) | – | – | – | Zheng and Wu (2017) | – |
| Logistics | van der Spoel et al. (2015)<br>Preethi, Sankar, and Mathew (2016)<br>Mishra and Singh (2020)<br>Sugrue and Adriaens (2021) | Lee et al. (2017)<br>Bhattacharjya et al. (2016)<br>Yan-Qiu and Hao (2016)<br>Brandau and Tolujevs (2013)<br>Bhattacharjya et al. (2018) | Pang, Zhang, Xiao, et al. (2021) | – | – | Zhong et al. (2015)<br>Zong et al. (2016) | Chen and Kezunovic (2016)<br>Wang et al. (2016)<br>Brouer, Karsten, and Pisinger (2018)<br>Singh et al. (2018)<br>Wang et al. (2018) | – |
| Procurement | Choi, Lee, and Irani (2018) | – | – | – | – | – | Bock and Isik (2015) | – |

Source: Authors.

skills have proved a success in many aspects such as quantifying the intricacy in purchase order sizing, in context of identifying the amount and structure of occurring costs, processes with a significant and simple structured error pattern, may improve self-awareness skills of decision-makers through analyse of known entropy-based complexity measures entropy (Bock and Isik 2015). With adequate information from supply chain partners enterprises can make better-informed decisions.

- **Inventory:** The core usefulness of BDA in inventory is leveraging visibility for responsiveness and traceability of item. Several empirical research findings reveal the operational value of BDA when making inventory completely visible to members. For instance, Demey and Wolff (2016) illustrated a model called Semantic Inventory Management for International Space Station (SIMISS). Where possible locations of lost items are calculated based on contextual features in three dimensions i.e. spatial, temporal and human. Demey and Wolff (2016) revealed that by using SIMISS, it was possible to reduce re-supply cost for long duration missions on international space station, reduce waste of crew time, and assure mission success. Data accuracy is pivotal for decision makers for supply chain, especially in spare part inventory management, requiring informed decision-making to face demand, supply uncertainty, and achieve just in time inventory (Zheng and Wu 2017).
- **Logistics:** Supply chain businesses seek to capitalise on logistics for gaining customer satisfaction through selecting the appropriate delivery methods in accordance with customer reference on the shopping platform, delivering the right item to right person at the right place (Ma, Nie, and Lu 2015). The primary areas the use of BDA can drastically enhance logistic decision-making process include: (a) precise outage prediction, (b) visualisation of the logistic trajectory, (c) fleet monitoring, and (d) predict customers' behaviour. Chen and Kezunovic (2016) analysed weather data using fuzzy logic approach to devise strategies aiming to mitigate weather impacts; this allows utility operators to achieve more precise outage predictions and optimise real time operation including maintenance scheduling. BDA can deal with the challenges of data analysis, capture, curation, information privacy, visualisation of RFID-Data, and mining invaluable trajectory knowledge to support advanced decision-making (Zhong et al. 2016). In using predictive approach to analyse data generated from sensor used to support fleet truck monitoring system, Mishra and Singh (2020) found that BD predictive analysis can generate information such as ultimatum for repair or replace items even before they break; suggestions on driving patterns on various road conditions to both the driver and fleet owner.

Relying on the importance of information sharing in decision-making processes, BDA has a powerful data processing capability to improve transparency of information, reduce information asymmetry, reduce cost, save time and improve business efficiency (Ma, Nie, and Lu 2015). Figure 5 illustrates a summary of the BDA benefits related to improved decision-making, within each of the five dimensions of SCO, as extracted from the articles reviewed.

### 4.7. Big Data Analytics optimising SCO

Herein we present how BDA optimises SCO in terms of enabling autonomous corrective control action, agility, and enhancing real forecasting (Pang, Zhang, Xiao, et al. 2021) – i.e. achieving the benefits of adopting BDA for each of the five dimensions of SCO.

- **Demand Planning:** Customer demand forecasting is the most crucial concept of prediction leading to reducing uncertainty and increasing profitability in the entire supply chain. One of the leading examples is predicting customer demand using electronic commerce data. Accurate demand prediction result in less inventory pressure and cut down its direct factor for bullwhip effect (Li et al. 2018). See-To and Ngai (2018), who provided analysis of the BD collected from transactions data and customer review data to improve sales forecasting, and to reveal the influence of customer sentiment on product sales, have addressed the effectiveness of demand planning. They found that utilising BDA for demand planning has a profound consequence for inventory. Real time sales forecasting offers an optimised solution for the online inventory management, reducing the cost of stocking and avoiding under stocking.
- **Production and Manufacturing:** Analysing production and manufacturing data embedded in IoT drives to improve manufacturing processes that significantly enhance productivity and improve production scheduling (Kumar et al. 2016; Wang et al. 2019). Ever growing manufacturing requirements have carried on the necessity of timely fault detection, early warning, and avoid recall minimising the downtime and improve efficiency. Thus, relying on the potential of analysing manufacturing data and new requirements of production operations. It is evident that BDA has ability to revolutionise the manufacturing process to reach optimal production level. Shukla and Tiwari (2017) discussed the constraints faced in incorporating smallholders in sustainable palm oil production and they proposed a BDA framework enabled by innovative technologies to incorporate smallholders in the Roundtable on Sustainable Palm Oil (RSPO) certification process investigated the impact of real data from machinery and data from production to solve sequencing problem in short time, besides optimising the machine task list. They found that conducting BDA by applying; clustering, nearest neighbour, and travelling methods, saved more than 10% of the setup time and solved the sequencing problems in less than 30s in average.
- **Procurement:** Several areas of procurement performance (e.g. measuring and managing third party spending, enhancing the accuracy reliability of partner choices, and improving suppliers' performance) have drawn the academic attention to achieve optimised procurement

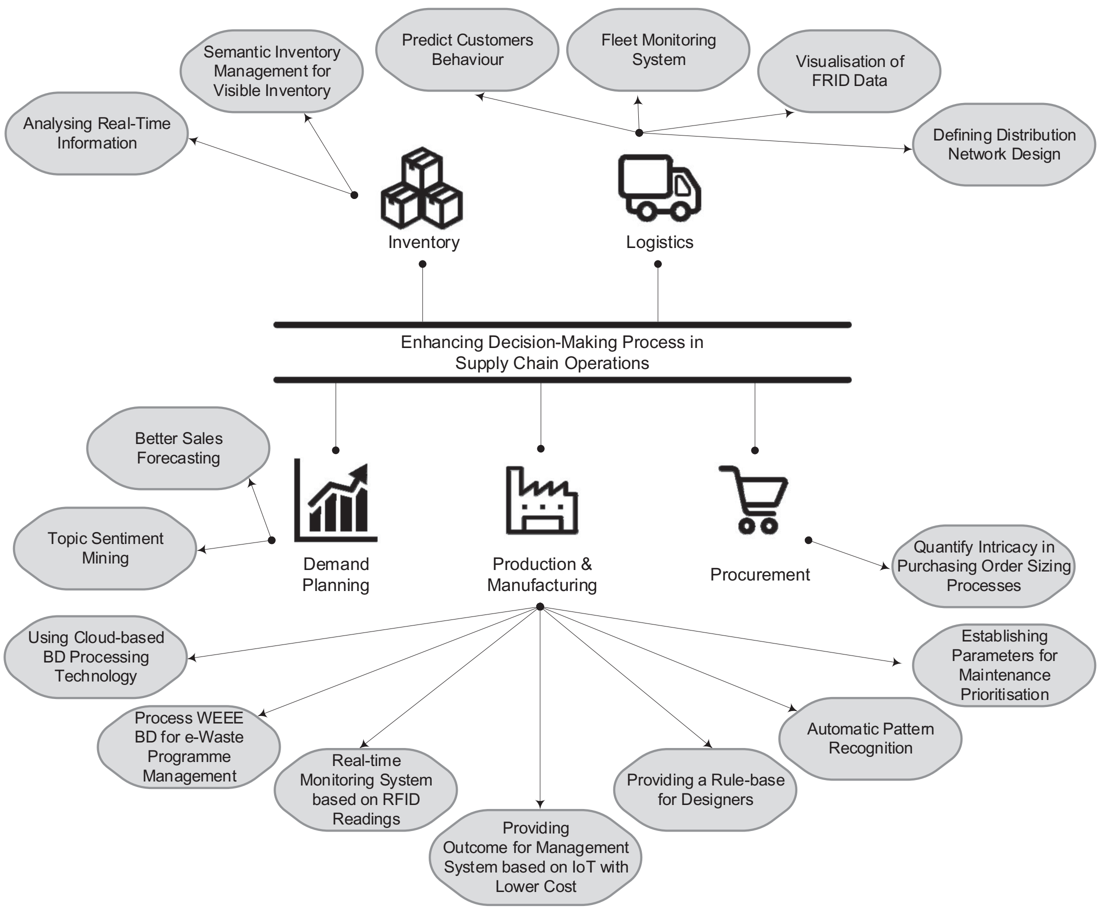


Figure 5. Benefits – enhancing decision-making process in supply chain operations (Source: Authors).

operations. Using publicly available data as sources for implementing ERP systems provides a foundation for measuring and managing third party spending. This is expected to form the basis for effective supply management strategies, including strategic sourcing, category management, and supplier relationship management (Huang and Handfield 2015; Pramanik, Mondal, and Haldar 2020). Moretto, Ronchi, and Patrucco (2017) discussed to what extent adopting BDA may affect diverse practicing in the procurement process by running a focus group including procurements managers in attempt to get their perceptions on BD support. They point out that embracing BD on the phases of procurement processes improves suppliers' performance and internal procurement performance.

- **Inventory:** Coordination between supply chain activities can be a source of superior optimised operations. For instance, timely information about demand distribution offers an optimised solution for the online stores to manage their inventory. Thus, it is important to identify the demand distribution as an input to the newsvendor model (See-To and Ngai 2018). Estimating ordering probability, amount, and timing by analysing clickstream data, can achieve advanced demand patterns, which have a significant role of reducing the inventory holding and its cost and accordingly reducing operational cost and reaching optimal inventory (Huang and Van Mieghem 2014).
- **Logistics:** Bhattacharjya, Ellison, and Tripathi (2016) investigated the impact of the logistics-related customer service interactions of e-retailers via Twitter to reach out to their consumer and resolve delivery related queries rapidly and effectively. Li et al. (2018) reviewed the role of BDA in optimising demand chain management performance through using BDA tools; they found that BDA enables companies to understand their customer's habits, needs, behaviours, and thoughts, which in turn play a crucial role in improving customer satisfaction. Thus, the importance of BDA comes from its ability to support sharing information more easily and efficiently among supply chain partners. Brandau and Tolujevs (2013) applied data mining algorithm to extract information from location and sensor devices in order to identify causes and dependencies of the irregularities in the logistics process to achieve a transparent flow of goods while Pang, Zhao, Yan, et al. (2021) addressed the use of big data to achieve a significant reduction in environment prediction variance. Hopkins and Hawking (2018) presented a real case which utilised a truck telematics, geo-information, and camera-based technologies to improve driver safety, promote eco-driving, and reduce fuel consumption and $CO_2$ emissions. Similarly, Sugrue and Adriaens (2021) discussed the direct applications to short sea shipping and inland waterways systems in supporting logistics strategy by improving efficiency or maximising value for operational expenses.

Real-time and accurate prediction is one of the most significant BDA benefits supply chain businesses can utilise to

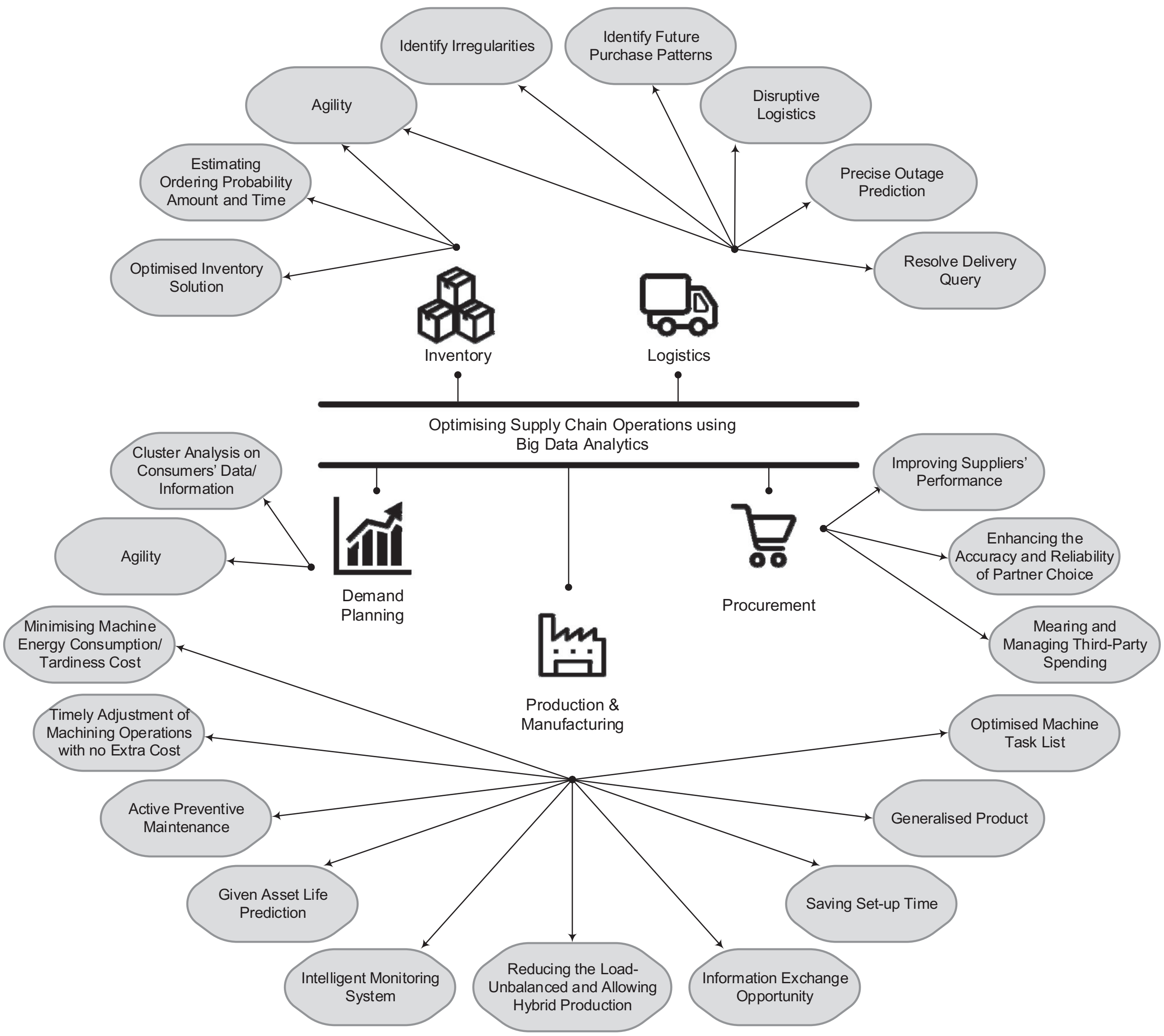


Figure 6. Benefits – optimising supply chain operations using big data analytics (Source: Authors).

optimise their operations. Literature indicates that optimisation is the most popular approach when it comes to prescriptive analytics (Sivarajah et al. 2017), especially when it is about optimising SCO related to logistics and transportation area. According to Nguyen et al. (2018), literature on logistics and transportation provides limited understanding on real-time routeing optimisation based on streamline data. Conversely, there is plethora of research on real-time optimisation in the manufacturing domain using modelling and simulation (Kumar et al. 2016). Using the appropriate optimisation methods, it is highly likely for logistics and transportation practitioners to adapt a similar BDA approaches to optimise routeing problem in real-time and enhance their SCO. Empowering BDA in supply chain is not about evaluation but necessarily changing for optimising operational performance, and enhancing informed decision-making (Srinivasan and Swink 2018). Figure 6 illustrates a summary of the BDA benefits related to optimisation extracted from the articles reviewed.

### 4.8. Gaps analysis

We observed a strong focus of the literature on production, operations and manufacturing, predominantly using statistics and mathematical modelling BDA techniques (Kumar et al. 2016). Both in terms of the inputs and outputs of using BDA, the literature analyses how information sharing can enable powerful data processing capabilities to improve efficiency and effectiveness (Bumblauskas et al. 2017). Similarly, real-time and more accurate prediction of events is a strength of BDA that benefits supply chain operations and many researchers have developed and used optimisation techniques to solve operational inefficiencies. Nevertheless, based on the literature we analysed; we observed some areas in BDA that provide excellent opportunities for further research.

In terms of BDA techniques, our review has shown a significant scope for further analyses on how using these techniques can support decision making as well as show how this decision making can be shared across the enterprise. For example, visualisation techniques and sentiment analysis in terms of collecting and streamlining multi-sourced data can significantly bridge the gap between demand planning and production and at the same time prepare logistics (delivery) processes and support decision making and rapid (re)deployment. Relevant to that, collecting data from social networks is also an area that needs further development, as it is a promising area to operations without being limited to linking awareness to production (Chavez et al. 2017). Understanding real time decision-making in logistics and transportation processes is an important area that is currently under-researched both from the theoretical and the practical perspective. Therefore, in conclusion of the gap found as a result of this study, the following are the most important ones:

- Literature on logistics and transportation provides limited understanding on real-time routeing optimisation based on streamline data.
- The researchers overwhelmingly focus on manufacturing and there is very limited focus on other sectors. Based on the findings, manufacturing was the most researched followed by in descending order, logistics, demand planning, inventory, and procurement sector.
- In the context demand planning, there is no inbound data used to enhance decision and optimise operations (handle data generated from the results of business operations).
- Theoretical underpinning is scarce on BDA in SCO. Literature indicates that there is shortage of articles in the area of BD, BDA and SCO, testing theories as an interpretation for the response to their research questions (Kamal and Irani 2014). Findings report that most of articles do not discuss any theory underpinning research. However, only three papers (from 88 analysed) were based on Gratification Theory (Bhattacharjya, Ellison, and Tripathi 2016), the Resource Based View (Yu et al. 2016), and the Entropy Information Theory (Bock and Isik 2015).
- Procurement operations that rely only on inbound source of data like the one publicly available data derived from search engine terms, and amount and structure of occurring costs.

The most important observation is the lack of a theoretical framework that supports impact assessment of BDA initiatives to enterprises. As discussed above, the papers analysed have a very applied and practical orientation and as such, the theoretical background used, from the management perspective, is limited and contextual to specific cases. Thus, we propose a theoretical framework that may help address the impact assessment of BD and BDA in SCO.

## 5. Proposed framework

We propose the development of theoretical and practical frameworks to underpin BDA impact in conjunction with SCO, which is of outmost importance for this area to grow further. Whilst there is currently a strong focus on the production and manufacturing dimension, more work is needed for the other dimensions of SCO (i.e. logistics, procurement, inventory and demand planning) where they could benefit from such analytical and theoretical frameworks. Therefore, the section presents a proposed theoretical framework that aims at bridgeing the above gaps which are generated from the literature review. The first part provides the theoretical underpinings of the frameworks followed by a section on the building blocks of the framework.

### *5.1. Theoretical underpinning of the framework*

Despite the remarkable benefits of BDA that have been clarified in theoretical research and little of empirical research, yet the full picture of BDA potential and implementations in SCO context still in its infancy stage. Lavalle et al. (2011) reported that one of the main constrains to adopt BDA is poor understanding of the potential of BDA on business environment. Thus, a broad view of BDA utilisation may be needed to explain the role of BDA in SCO. Furthermore, many researchers reported the limitation of theory-driven research in this domain (Wamba et al. 2018), and they suggested further research to determine theories which can be mobilised for studying BDA in SCO. Most of the theories (e.g. Resource Based View, Dynamic Capabilities Theory and Gratification Theory) used to study BDA in SCO fail to encompass the notion of big data's 7(V) – forces that potentially shape organisations' initiation to BDA use and as a result improve performance. Based on the above, this paper uses an integration of TTF and institutional theory. TTF theory argues that the actual use of a new technology and performance benefits are attained when technology characteristic fits the task requirements (Lai, Sun, and Ren 2018). On the other hand, institutional theory provides a comprehensive understanding of the intention behind adoption of practices and the implementation through examining the causes of isomorphism represented in three dimensions of institutional pressures: coercive pressures, normative pressures, and mimetic pressures (Dubey et al. 2017).

- Task-Technology Fit Theory (TTF) is based on the idea that IT has positive effects on individual and organisational performance, subject to fit between the task's characteristics and technology's characteristics (Goodhue and Thompson 1995). In their research, they found supportive evidence that IT has a positive impact on performance when there is harmony between the functionalities of technology and the task requirement. Furneaux (2012) linked TTF theory to contingency theory that argues that fit between practices and the environment should be in organisation, which determines performance improvement. TTF theory has been founded on the premise that the motivation to use a particular technology will be driven by the fit between tasks' characteristics and the technology' attributes. The effect of fit on performance occurs either directly or indirectly through TTF impact on utilisation of technology (Furneaux 2012). In order to operationalise the TTF theory, we identify some dimensions of IT capabilities related to BDA approach

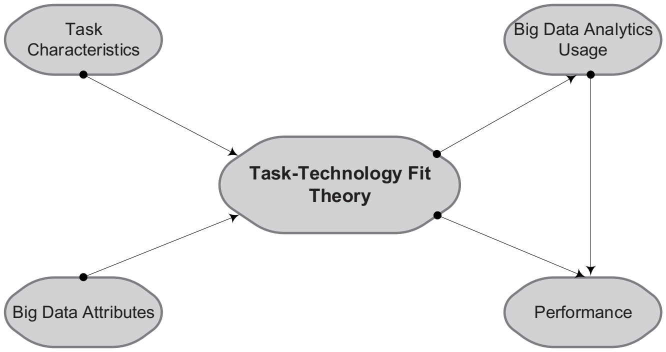


Figure 7. TTF-BDA attributes framework (Source: Adapted from Goodhue and Thompson [1995]).

representing in prediction, description, and prescription (Mikalef et al. 2019a). To determine SCO portfolio of tasks we constructed tasks derived from analysing literature within the context of SCO and then classified the required tasks as follow:

- information quality for effective information system.
- achieving the optimal level of inventory and minimising inventory cost, while maintaining the required customer service level.
- outsourcing logistic activities is a quick way to introduce products and service innovations into market.
- optimum assets work to ensure that all production processes are under control.
- product design e.g. generalised product, and quality assurance.
- sales nowcasting for optimal inventory solution and minimising demand uncertainty.
- improving procurement processes.
- enhancing visibility of customer's needs and market segmentations.
- determining the allocation of products and distributors centres.

It seems rather reasonable to assume that the match between SCOs task portfolio and BD characteristics may directly affect the utilisation of BDA and organisational performance. In Figure 7, we link TTF theory with BDA attributes, BDA usage, to identify the overall performance.

- Institutional Theory considers the processes by which structures (including routines, norms, rules, and schemas) are established as authoritative guidelines for social behaviour (Scott 2005). This theory was previously used by Dubey, Gunasekaran, Childe, et al. (2019) to explain the direct performance implications of big data predictive analytics on organisational performance. The core assumption of institutional theory is that organisations and organisational actors attempt to gain legitimacy, status, and reputation in their environments in order to be accepted and ensure long-term survival (Mignerat and Rivard 2009) and organisations are obliged to select safer technologies, which can adhere to social pressures rather than economic benefits (Dubey, Gunasekaran, Childe, et al. 2019). Two elements have been examined in institutional theory: (a) institutionalisation process and (b) institutional effects (Pishdad, Koronios, and Geursen 2014). In this study, we focus on institutional effects – refering to coercive, mimetic, and normative isomorphism.

^ **Coercive Isomorphism:** it is the outcome of formal and informal external pressures by other organisations, and by culture expectations in the society within which organisations are embedded (Dimaggio and Powell 2000). Organisations globally have a significant role to raise the level of customer satisfaction and change customer expectations, which has raised the necessity to offer product with best quality, lower cost, shorter time, and best delivery service. All these factors increase the pressure on organisations to implement precise customer assessment to personalise service and customise product, through implementing sophisticated analytics tool to analyse data generated from customer's location, customer's hit, browsing time, and shopping cart (See-To and Ngai 2018).

^ **Mimetic Isomorphism:** it occurs by organisational desire to mimetic other organisation action, especially when the environment creates symbolic uncertainty (Dimaggio and Powell 2000). Mimesis is more existent in anxiety than in rational action as a measure that reduces uncertainty and increases predictability (Pishdad and Haider 2013). One of the main challenges in SCO that influences the operational efficiency and causes problems is the bullwhip effect, which is demand and supply uncertainty, and uncertainty related to timely delivery of items as a row materials or finished products (Bag 2017). The causes of uncertainty in supply chain are not limited to reasons mentioned above; there is a high uncertainty at every stage of the supply chain. The increased level uncertainty raises the need to adopt mimetic predictable analytics tool and use predictive analytics to uncover future event pattern and make predictions.

^ **Normative Isomorphism:** it is stemmed from professionalisation (Dimaggio and Powell 2000). Normative pressures consider the moral aspect of legitimacy by assessing whether the organisation performs in desirable way (Pishdad and Haider 2013). Normative pressures imply that strategic processes taken by organisations are subject to the values and norms shared among members of their social networks such as organisation-supplier and organisation-customer inter-organisational channels (Son and Benbasat 2007). In SCO context, there are several normative pressures related to environmental concerns, individual safety, and supply chain sustainability. Therefore, making informed operational decisions is an important step needs to be adopted by organisations to execute their operations productively in this new changing environment. This can be achieved through reshaping proactive strategy formulation and decision-making based on BDA in SCO. In this research, the role of institutional isomorphic pressures is the intention behind BDA implementation. In Figure 8, we link institutional theory with BDA usage.

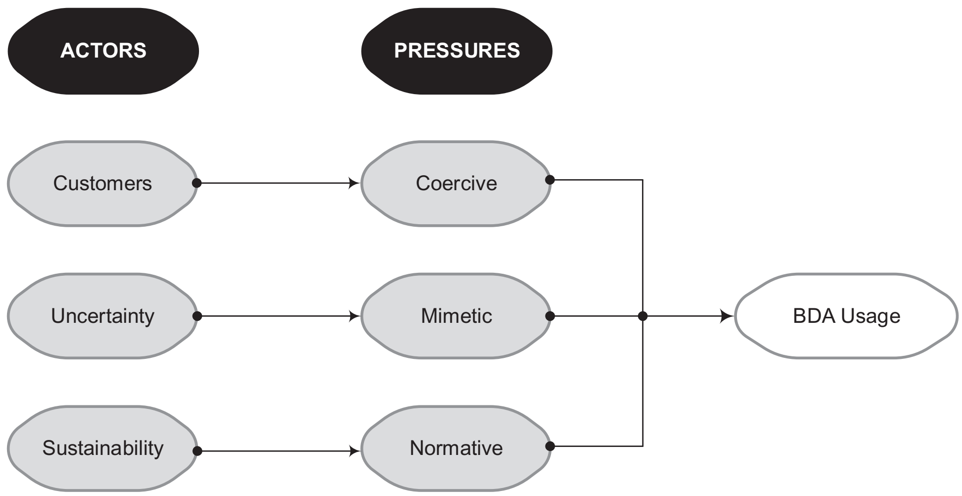


Figure 8. Institutional theory and BDA usage framework (Source: Adapted from Scott [2005]).

### 5.2. Building blocks of the proposed conceptual framework

BDA enabled SCO is not simply about adopting or integrating innovative technologies, it is poised to profoundly transform the way a wide range of manufacturing organisations and supply chain businesses approach the procurement, processing, and distribution of raw materials and finished products. How and why organisations adopt innovative technologies has motivated several academic researchers and practitioners to investigate the drivers and opportunities of technology utilisation. For instance, Straub (2009) stressed the importance of doing research on technology adoption models to create a holistic understanding of how technology changes influences the organisation. A common bearing in studies that dealt with BDA is to try to figure out the potential impact of BDA implementation through presenting BDA utilisation drivers, BDA capabilities, and its roles in solving different issues. We developed a theoretical framework to conceptualise the benefits of implementing BDA in SCO and to explain the motives behind adopting BDA in SCO. We utilised two theories to better understand how and why firms adopt BDA as a novel technology, along with the drivers and opportunities of this technology utilisation.

TTF theory was developed based on the attributes of required tasks and their relationship to relevant characteristics of technology, it assumes that the fit between task technology and users promotes the user's work performance (Zigurs and Buckland 1998). From the above, we deduce that the fit between tasks characteristics in SCO and BD attributes is a rational action towards adopting BDA. In this case, we need new lens for taking into account the limitations arising within the institutional context that surrounds organisational actors (Mignerat and Rivard 2009). The institutional theory compensates for the limitation of TTF theory in understanding the social forces behind utilising BDA. In this research, the institutional theory adds to the constructs (IT capabilities and tasks characteristics) of the TTF theory the external pressures, which speeds up the processes towards utilising BDA. These pressures include from the competitors and pressures exerted by trading partners (Oliveira and Martins 2011). The objective of this framework is to explore the inner factors (fit between technology and task characteristics) and outer factors (social factors) affecting the overall effective utilisation of BDA in the SCO context, resulting in realising the benefits of BDA implementation. Figure 9 presents the building blocks of proposed framework that may support other researchers in better understanding BDA initiatives in SCO with the objective of making robust investment decisions in BDA.

## 6. Discussion and implications

This study offers useful insights on BDA subject area within a SCO context in primarily addressing the strategic fit of the organisation to implement BDA. The analysis of the theory showed that there are two main drivers that guide an organisation's decision to adopt BDA, and institutional factors and external factors. We will call the proposed conceptual framework, the 'BDA Strategic Assessment Framework', which aims to support the practitioners in their strategic decision-making. Studying the implementation of BDA in SCO including assessing the taxonomy of academic sources supports in better understanding the underlying reasoning. Clearly, the need to implement BDA, may come either as a result of the external environment (Institutional Change) or as an impetus from the company itself (Technological Change). As per the literature review, the external pressures that force the implementation of BDA include competitors' pressures as well as those exerted by partners (Oliveira and Martins 2011). Once the origin of the pressure is understood, selecting the right tools becomes easier in adapting the BDA techniques to the specific SCO context. The findings of Li et al. (2018) support this statement when discussing how BDA enables companies to improve customer satisfaction by understanding their habits, needs, and behaviours.

Furthermore, the proposed conceptual framework (Figure 9) will guide practitioners and executives in making more robust investment decisions. More precisely, we are proposing a decision-making matrix (Table 4), where depending on the intensity of the pressure (institutional vs technological),

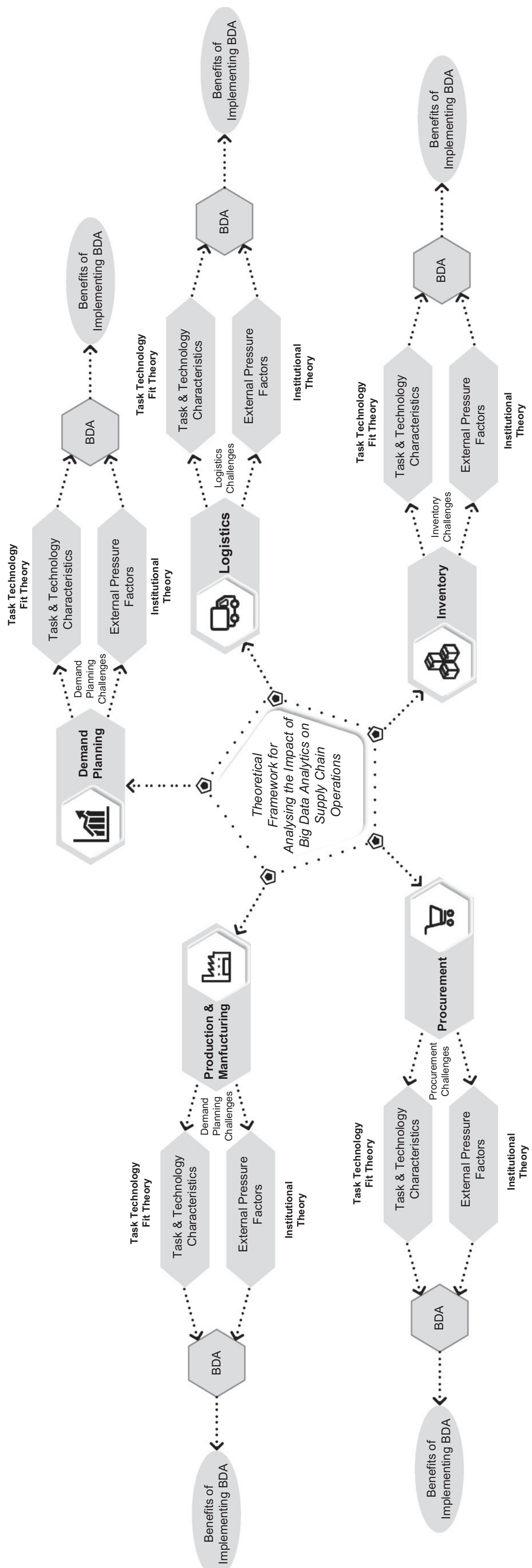


Figure 9. Proposed theoretical framework (Source: Authors).

we qualify different tools, different frameworks and diverse approaches in implementing the BDA techniques.

According to Ivanov and Dolgui (2021), organisations are still at the stage of figuring out different methods to utilise large volumes of data to both predict risks and assess vulnerability. The above proposed decision matrix is based on the analysis of the different tools and BDA methodologies that were collected from the SLR sourcing. We categorised the different tools along the two dimensions, Institutional and Technological, following Section 4.9 above. The value of this proposed decision matrix is to help practitioners in their decision making process for selecting the most appropriate BDA initiative based on the different market / industrial challenges.

### 6.1. Implications to theory and practice

The main theoretical contribution of this study is a framework conceptualising the benefits of implementing BDA in SCO. The framework combines two theories, TTF and Institutional Theory, and improves the understanding as to how and why firms adopt BDA as an innovative technology, along with the drivers and opportunities of this technology utilisation. TTF theory was developed based on the attributes of required tasks and their relationship to relevant characteristics of technology. It is assumed that the fit between functionalities of technology and the task requirement promotes the user's work performance. Institutional theory compensates for the limitations of TTF theory in understanding the social forces behind utilising BDA. The objective of this framework is to further explore the inner factors (fit between technology and task characteristics) and outer factors (social factors) affecting the overall effective utilisation of BDA in the SCO context, thus resulting in realising the benefits of BDA implementation.

In addition, this study contributes to practitioners, because it provides a rationalisation ground for managers to explore the critical role of BDA across the SCO as it will impact multiple SC capabilities, specifically BDA enhanced agility, sustainability, and collaboration. It is believed to enhance the decision-making process and sustain firms' competitive advantage (Yuan et al. 2018; Mikalef et al. 2020). The findings of our study indicate that interpreting and analysing data from across the SC channels enables more-timely solutions and actions through improving the following capabilities: optimum asset work, energy saving, mass customisation, dealing with variation in demand, identifying different behaviour from smart manufacturing objects, improving supplier's performance in term of cost and quality, and resolving delivery quires on social media platform.

The proposed framework facilitates the quicker and more relevant application of BDA techniques that enable a sustainable competitive advantage in terms of enabling a vast range of BDA techniques, for example autonomous corrective control, real-time forecasting, and fact-based decision making. Integrating advanced analytics technologies like BDA is a very important initiative for supply chain and operations management and although the approaches are still

Table 4. Proposed decision matrix.

<table>
<tr><td rowspan="2">Institutional Changes</td><td>Radical<br>Incremental</td><td>• Energy Saving<br>• Resolve Delivery Queries on Social Media Platform<br>• Real time sentiment analysis / mining<br>• Real time monitoring and reporting<br>• Analysing real time information and risk management<br>• Reliable partner search / selection<br>• Predict Truck Arrival Time<br>• Optimum Assets' Work<br>• Visualise IoT Data<br>• Using Cloud based Big Data Technologies<br>• Information exchange<br>• Sensor data exchange</td><td>• Implementing Smart Manufacturing<br>• Understanding and Controlling Manufacturing Industry Process<br>• Predict Risk Analysis<br>• Identifying Customers' Preferences<br>• Emergency Rescue<br>• Active preventive maintenance<br>• Improving Procurement Processes<br>• Determining the Allocation of Products and DCS<br>• Product Design<br>• Mass Customisation<br>• Sales Nowcasting<br>• Performance management</td></tr>
<tr><td></td><td>Incremental</td><td>Radical</td></tr>
<tr><td></td><td></td><td colspan="2">Technological changes</td></tr>
</table>

Source: Authors.

exploratory, the SLR based descriptive insight offers practitioners and applied researchers the opportunity to support their analysis with a novel theoretical framework.

The proposed decision-making matrix (Table 4) is a tool that managers may use in making robust investment decisions. For those organisations that have been applying BDA, the study's findings provide them with a deeper understanding of state-of-the-art techniques and help them assess the BDA gap as discussed in the SCM literature context. The findings also help practitioners to understand why they have not been able to capture the full potential of their BDA investments. In addition, the findings will guide them to the right aspects of this technology. Such aspects are expanding the use of BD sources, applying more sophisticated analytics techniques, and mainstreaming a culture of BDA in organisation. For these to be achieved, managers at different levels should be aware of BDA concept and its potential benefits. Organisational diffusion of such technology and embedding BA decision making into the fabric of the organisation, are the biggest inhibitors in realising the business value from BDA investment (Mikalef et al. 2020).

## 7. Conclusions

Arguably, SCO and BDA can enable the dynamic capabilities of firms, allowing decision makers to enhance the corporate or company abilities or to better sense emerging opportunities and threats. This paper presents the past trends and current state of BDA research published specifically in the context of SCOs and its respective dimensions. We proposed a conceptual framework based on two research questions: *Investigating the benefits of implementing BDA methods/techniques to achieve better decision-making for SCO?* and *Investigating the benefits of implementing BDA methods/techniques in achieving optimisation of SCOs?* The continuing interest and the use of BDA specifies that in future research studies academics, researchers and practitioners may focus on the factors driving and inhibiting BDA to further propose robust solutions to the service related problems. The intention in conducting this detailed investigation was to provide a useful and yet usable source of information for future researchers. The discussion also highlighted several research limitations and future directions for BDA applications within the SCO research area to catalyse the research development of the topic.

### 7.1. Research limitations

The study has the following limitations. While the authors conducted a thorough literature search through the Scopus database to identify all possible relevant articles, it is possible that some research articles could have been missed in this review from some other leading databases (i.e. Web of Science and EBSCO). So to avoid duplication, every effort was exhausted to acquire and analyse all relevant information essential, regarding the two questions from the articles reviewed from the Scopus database. Additionally, the analysis and synthesis are based on the research team's interpretation of the selected articles. The authors attempted to improve objectivity by cross-checking papers individually and by collaboratively synthesising the results. This approach has mitigated embedded bias and increased robustness of the recommendations. One of the other limitations of this paper is that the categorisation in the overall work presented herein including the conceptual framework remains interpretative and theoretical, as this could lead to concern on subjective bias.

### 7.2. Suggestions for future research

Building upon the rich underpinning of the research findings described and overall understanding acquired in this paper, the authors presents the concerns that merit further research and anticipate that these issues may hold the potential in contributing towards the future research studies. Despite a considerable body of literature examining many aspects of BDA in the context of SCOs, there are still several areas that remain under-explored. For instance:

Innovative technological developments, e.g. I_4.0, artificial intelligence and IoT, are challenging the traditional supply chain business models, and adapting these is key to a sustainable competitive advantage. BDA is also a cross-cutting theme, and many connections exist with established topics across computing, engineering, mathematics, business and management, social sciences, etc. It would be valuable to expand the scope of the subject area and to repeat this exercise to identify and draw links with established theoretical contributions in other different associated area. A publication based on such analysis would provide an extremely valuable platform for the BDA research and practitioners' community.

The studied literature is fairly limited and relies on conceptual studies, and few empirical studies aiming at theory building. In terms of future research directions, we acknowledge the importance of (a) the business value of big data analytics, (b) of their mechanisms and (c) of the supporting systems. The main arguments around SCO and BDA implementation are that these systems may lead to more informed decisions, resulting in improved performance. Despite this assertion, there is a lack of paradigmatic case studies, predominantly studies that will monitor not only short-term but equally importantly medium- and long-term impact of the systems. The studies assumed a linear relationship between BDA and performance, based on the availability of technology and/or the application of the systems without considering sufficiently the organisational capabilities nor the human element in decision making. The limitations and the strengths of each BDA initiative are sufficiently discussed; however they assume that decision makers follow these outcomes accurately and promptly, even outside a testing environment. We expect this will not be always the case and this assumption has to be further analysed, e.g. from the inventory forecasting point of view or from the purchasing.

The technological side is also another area that needs further assessment. We anticipate an increase in developing new tools and techniques that will improve data quality, will accelerate the cleaning of big data and will reduce the cost of collecting high-quality data. SCO and BDA will require new data management strategies both intra- and inter-firm which necessitates studying new cloud-based architectures. Furthermore, most of the data used are structured, however the commercial expectations involve complex data that are a mix of both structured and unstructured, either internal or external data. To this extend, issues like time lags, volume of data and better visibility will also pose interesting research and practitioner questions. Lastly, based on our study, we propose more research on the three elements of analytics, namely, predictive, descriptive and importantly prescriptive analytics in all elements of the SCO. Especially for the prescriptive analytics, there is a significant lack of both understanding how this works and formulating how this could be applied in the commercial context.

Finally, another important element is policy related research, especially considering the proper use of data as well as the ways the data can be efficiently disseminated under the data protection rules and additionally any intellectual property rights. Part of this element is also training requirements, as this field is fairly new, and the need for interdisciplinary training is vaguely acknowledged. More importantly, a robust return on the training investments has to be studied. Lastly, we advocate in favour of BDA is being introduced in a circular economy context, and more precisely using the opportunities to embrace the digital uprising to accomplish zero waste. There is a growing need for more focus and research on how BDA go hand-in-hand with circular economy business models and avoid any disjointed research. Supply chain businesses can offer shift from a traditional and dated strategies to a more sustainable digitally enabled service-oriented supply chain business models that provides resource efficiency-related services for customers, which may result in being most resilient and cost-effective.

## Disclosure statement

No potential conflict of interest was reported by the author(s).

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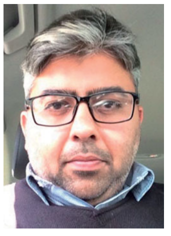

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