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Published online: 23 Feb 2021.

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REVIEW

Big Data in operations and supply chain management: a systematic literature review and future research agenda

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ABSTRACT

In the era of digitalisation, the role of Big Data is proliferating, receiving considerable attention in all sectors and domains. The domain of operations and supply chain management (OSCM) is no different since it offers multiple opportunities to generate a large magnitude of data in real-time. Such extensive opportunities for data generation have attracted academics and practitioners alike who are eager to tap different elements of Big Data application in OSCM. Despite the richness of prior studies, there is limited research that extensively reviews the extant findings to present an overview of the different facets of this area. The current study addresses this gap by conducting a systematic literature review (SLR) to uncover the existing research trends, distil key themes, and identify areas for future research. For this purpose, 116 studies were identified through a stringent search protocol and critically analysed. The key outcome of this SLR is the development of a conceptual framework titled the Dimensions-Avenues-Benefits (DAB) model for BDA adoption as well as potential research questions to support novel investigations in the area, offering actionable implications for managers working in different verticals and sectors.

1. Introduction

Operations and supply chain management (OSCM) encompasses the internal and external activities of a firm, such as the supply of raw material and the assembly and delivery of finished goods (Mentzer, Stank, and Esper 2008). In the past decade, OSCM activities have become more networked, resulting in the generation of a huge volume of real-time data, referred to as 'Big Data' (Chen, Preston, and Swink 2015). Such data generation in supply chain networks is the result of advanced networking technologies, including embedded sensors, tags, tracks, barcodes, Internet of Things (IOTs), radio-frequency identification (RFID) tags, and several smart devices that capture such data (Gunasekaran et al. 2017). Big Data can be defined as the massive, real-time structured, semi-structured, and unstructured data that are beyond the capabilities of traditional data management tools (Sun, Chen, and Yu 2015) and that require advanced analytical techniques to provide valuable inputs (Wamba et al. 2015). Specifically, 5Vs broadly represent the core of Big

Data: volume, veracity, variety, value, and velocity (Hazen et al. 2018). Volume is the amount of generated data that challenges the storage capacity of the device (Chen and Zhang 2014), while veracity deals with the quality of generated data, and variety refers to different data sources, such as IoT, sensors, and so on (Tan et al. 2015). Value, meanwhile, represents the disclosure of underexploited insights from Big Data for forecasting and decision-making related to inventory, transportation, and sourcing (Viet, Behdani, and Bloemhof 2018), and, finally, velocity is the speed of data generation (Assunção et al. 2015).

A 2014 analysis of data sources for supply chains discovered that 46% of firms had achieved a 10% improvement in demand fulfilment using Big Data, followed by more than a 10% rise in supply chain efficiency for 36% of firms and better buyer-supplier relationships for 28% of firms (Accenture 2014). Furthermore, 70% of customers in a global logistics survey found an improvement in logistics optimisation in third-party logistics (3PL) due to Big Data management in the supply chain (Statista

Research Department 2016). With an increase in the amount of data generated, which is expected to reach an impressive 175 Zettabytes by 2025 worldwide (Holst 2020), Big Data application is expected to play an important role in firm performance, in general, and OSCM, in particular.

Supply chains have been transformed by Big Data applications during the past decade, resulting in an upsurge in academic interest in the area. This spike in interest is possibly driven by the fact that Big Data presents interesting research opportunities in several aspects of OSCM, including humanitarian supply chain networks (Papadopoulos et al. 2017; Dubey et al. 2018; Prasad, Zakaria, and Altay 2018), prediction of organisational performance (Gunasekaran et al. 2017), and supply chain agility (Giannakis and Louis 2016), among others. However, studies on such a wide range of topics have resulted in fragmented and scattered findings that make it challenging to further research in this area. Until quite recently, scholars have felt that the related research lacks depth and that there is still a limited understanding of Big Data's impact on various aspects of OSCM (Waller and Fawcett 2013; Richey et al. 2016). Thus, there is a clear need for motivating deeper research in this domain.

We argue that to create a platform to advance academic research, the current knowledge should be analysed and presented systematically for the reference of future researchers. Accordingly, we undertake a systematic literature review (SLR) of the extant literature on Big Data application in OSCM to synthesise the accumulated knowledge in the area, identify the gaps, and set the research agenda. We used the SLR methodology as it is an evidence-based scientific approach that helps in identifying, selecting, examining, evaluating, and encapsulating the published articles relevant to the research questions, as suggested by recent studies (Khanra et al. 2020; Seth et al. 2020; Tandon et al. 2020). Our review strengthens past efforts to evaluate the existing findings (e.g. Akter and Wamba 2019), wherein scholars have reviewed the progression of academic research in the related areas from time to time through systematic literature reviews and bibliometric analysis. These reviews have laid a foundation for catalysing further research in this area through their varied contributions. To begin with, Kamble and Gunasekaran (2020) reviewed 66 studies to delineate various performance measures and metrics to evaluate supply chains driven by Big Data. They identified 24 measures of performance to assess the capability of Big Data analytics and 130 measures for evaluating the supply processes. In another recent review, Chehbi-Gamoura et al. (2020) reviewed 83 studies examining methods of Big Data Analytics (BDA) in supply chain management

(SCM) using the supply chain operations reference model (SCOR). The review generated a SCOR-BDA matrix, underscoring the need for more intelligent use of Big Data in SCM. Similarly, Maheshwari, Gautam, and Jaggi (2020) reviewed 58 studies on the role of BDA in supply chain management, logistics management, and inventory management to uncover the issues that have not been addressed so far. Akter and Wamba (2019), meanwhile, examined 76 past studies on the application of Big Data in disaster management to provide a comprehensive understanding of its role in disaster relief. Ogbuke et al. (2020) analysed 120 studies related to Big Data application in supply chains and the benefit it accrues for organisations and society. Interestingly, the review also examined the ethical and reputational dimensions of using Big Data in businesses.

Furthermore, reviews by Gupta, Altay, and Luo (2019), Mishra et al. (2018), Nguyen et al. (2018), Lamba and Singh (2017), and Addo-Tenkorang and Helo (2016) are also quite remarkable in their contributions. Gupta, Altay, and Luo (2019) evaluated 28 studies on Big Data and the humanitarian supply chain to provide a bird's eye view of the existing findings, suggesting future research areas based on popular organisational theories. In comparison, Mishra et al. (2018) used bibliometric and network analyses to examine studies published from 2006 to 2016. They identified top contributing authors, geographies, and research clusters to aid future researchers. This study also revealed the need for further research in this area. Nguyen et al. (2018) presented a content analysis of 88 articles published from 2011 to 2017 on the Big Data application in SCM. Their study classified the articles based on various areas of SCM, the type of BDA, and the level of analytics used. Lamba and Singh (2017), meanwhile, reviewed studies published from 2010 to 2016 on Big Data implementation in three key areas of OSCM, namely logistics, procurement, and manufacturing. The study deployed the 3Vs (variety, velocity, volume) methodology of Big Data to reveal the lack of theory-building in this domain. Lastly, Addo-Tenkorang and Helo (2016) reviewed more than 100 studies on the application of Big Data in OSCM that were published between 2010 and 2015. They based their discussion on the 5Vs of Big Data, focusing on aspects, such as data-cluster storage systems, Big Data analytical processing tools like Apache Hadoop, and Big Data application in industrial SCM, to propose an IoT–value-adding framework.

Our SLR thus augments the findings of the previous reviews discussed above in two ways: (a) it presents the latest state-of-the-art literature available in this area by incorporating studies published up until October 2020, and (b) it adds an additional dimension to the

accumulated knowledge. Whereas prior reviews have evaluated the extant literature through different lenses, such as performance measures and metrics to evaluate supply chains driven by Big Data (Kamble and Gunasekaran 2020), Big Data analytical processing tools (Addo-Tenkorang and Helo 2016), bibliometric and network analysis (Mishra et al. 2018), level of analytics used (Nguyen et al. 2018), and humanitarian supply chain (Gupta, Altay, and Luo 2019), our SLR presents a broad view of Big Data application in OSCM with reference to a variety of sectors and verticals. Specifically, we address four questions (**RQs**): **RQ1**. What are the statistical dimensions of research evidence related to the existing studies on Big Data in OSCM? **RQ2**. What are the emerging themes and findings focused upon by the selected studies in the area? **RQ3**. What are the research gaps in the existing investigations? **RQ4**. How can the research and practice in this area be taken forward?

These research questions have been addressed using the rigorous review protocol proposed by Behera, Bala, and Dhir (2019). We address **RQ1** by generating detailed descriptive statistics of the selected studies through research profiling, which includes research contexts, research methods, variables, and theories related to the application of Big Data in OSCM. To address **RQ2**, we organised the accumulated learnings of these studies under eight themes. **RQ3,** pertaining to research gaps, is then answered by critically analysing the research profile and the identified themes. Finally, we responded to **RQ4** by (a) offering recommendations for future research by formulating potential research questions and developing a conceptual framework (i.e. the Dimension-Avenues-Benefits (DAB) model) for investigating various rudiments of Big Data application in OSCM, and (b) discussing managerial implications based on both the emergent themes and the identified research gaps.

2. Review methodology

In consonance with the recent SLRs by Sahu, Padhy, and Dhir (2020) and Khanra et al. (2020), the present study spans three distinct steps, namely, specification of research objectives and search protocol, collection of data using this pre-specified search protocol, and reporting the search findings through research profiling, as described below.

2.1. Specification of the research objectives and search protocol

Identifying the research objectives helps set the conceptual boundaries of the review (Behera, Bala, and Dhir 2019). Accordingly, the current SLR has identified

five distinct research objectives commensurate with the research questions discussed previously. These are: (a) investigate the descriptive dimensions of research evidence on Big Data application in OSCM, (b) distil key research themes, (c) identify research gaps, (d) set a future research agenda, and (e) develop a conceptual framework to measure varied aspects of Big Data application in OSCM.

With regard to the search protocol, we first identified the databases for the literature search. To ensure that this study covered multiple research areas of OSCM, two widely used digital databases, Scopus and Web of Science (WoS), were used to search for relevant literature and to select the appropriate studies, as suggested by scholars (Dhir et al. 2020; Ruparel et al. 2020). Next, we specified the inclusion and exclusion criteria, given in Figure 1, to shortlist the congruent studies. Forward and backward citation searches also ensure that all relevant studies were identified and evaluated. Furthermore, quality scores were calculated to make sure that the study selection process was robust. Accordingly, different quality evaluation (QE) questions were formulated to generate quality scores, as proposed by Behera, Bala, and Dhir (2019). The scores generated by applying the criteria were evaluated, with the studies scoring at least four and a half out of a total of nine being selected for the review. Specifically, the five quality evaluation criteria used in the current study are: (QE1): The study contains evidence that is quantitatively or qualitatively analysed [quantitative research (+2), qualitative research (+1.5), and no evidence (+0)];

(QE2): The study unequivocally examines the benefits and limitations. We considered this score to be partial if only one of the study's advantages or challenges was reported [yes (+2), no (0), and partially (+1)]; (QE3): The output of the study is justifiable. This score was partial if only limited techniques were explained, or one of the techniques used was not detailed [yes (+2), no (0), and partial (+1)]; (QE4): The study was published in a reliable and recognised source [(+2) if the sum of citations and H-Index > 100, (+1.5) if the sum of citations and H-Index = 50–99, (+1) if the sum of citations and H-Index = 1–49, and (+0) if the sum of citations and H-Index = 0]; and (QE5): The study compares the proposed method with other methods [yes (+1) and no (0)].

2.2. Data collection

Using Scopus and WoS as our databases, we conducted our search using the selected keyword combinations of 'Big Data' AND 'supply chain' OR 'operations management' OR 'operations' on October 23, 2020. The search
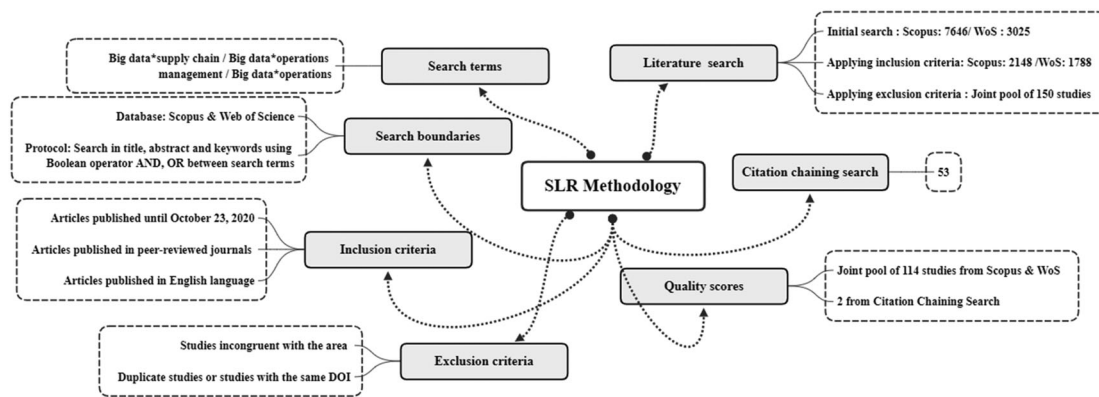
Figure 1. Study selection process.

yielded an initial tally of 7,646 and 3,025 probable studies from Scopus and WoS, respectively. After applying the specified inclusion criteria, we shortlisted 2,148 (Scopus) and 1,788 (WoS) studies for further consideration. Next, we applied the exclusion criteria to eliminate duplicate studies as well as those lacking immediate congruence with the topic at hand, resulting in a joint pool of 150 studies to take forward. The specified quality evaluation criteria were then applied to generate a quality score, which helped us identify 114 congruent studies that satisfied these criteria. Finally, we used a citation chaining search to examine if there were any other relevant studies that should be considered for inclusion in the review. This process helped us identify two more congruent studies that met the inclusion, exclusion, and quality evaluation criteria, leaving us with a final tally of 116 studies for review. The entire process is illustrated in Figure 1.

2.3. Research profiling

The summary statistics presented below include the number of publications by year, average citations per year, the geographic scope of the studies, the respondent profile, research design, methods of data analysis, theories invoked, and variables examined, including dependent, explanatory, control, mediating, and moderating variables.

Figure 2 suggests that the annual scientific production of research articles on Big Data and the OSCM area is rapidly increasing, indicating the rising importance of this research area. While the annual production of articles was slow between 2015 and 2017, the number of publications has increased from 2018 onward. Figure 3 exhibits the average citation per year for various articles published in this domain. The highest average citation per year is noted in 2015 with 158. In addition, Figure 4 displays the geographical scope measured by the number

of contributions, with China and India contributing the most studies from our sample.

Regarding the respondent profile of the studies, the scholars selected participants based on their designation, age, work experience, type of industry, firm size, and educational qualification. The industries investigated by these studies included (a) service industries, such as healthcare, distribution and logistics, finance, hotel, restaurants, third party logistics, software, telecommunication, travel and tour operators, and (b) manufacturing industries, such as auto components, cement manufacturers, wood products, automobiles, transportation, machinery, mining, metal products, electrical and equipment, pulp and paper, rubber and plastic, and chemical products. Furthermore, the respondents included heads of non-governmental organisations (NGOs), analytics managers, logistics managers, procurement managers, supply chain experts, functional heads of the supply chain of manufacturing, retail, consulting, and e-commerce firms, employees at different levels in market research firms, logistics analysts, foreign trade analysts, transport analysts, SCM and IT professionals at different levels in the trading, construction, retail, textile, and service industries, employees working in firms that have already implemented Big Data, and experts from academia and politics/associations.

The sample further included top, middle, and junior-level employees: C-suite officers, presidents, vice presidents, IT directors, senior supply chain managers, IT managers, functional heads, and junior executives. Concerning participants' demographic profile, the selected samples included respondents with undergraduate to doctoral qualifications, experience ranging from fewer than five years to more than 15 years, and ages ranging from younger than 30 years to older than 50. However, most of these studies did not report their gender ratio, while those that did had a largely male-skewed sample.
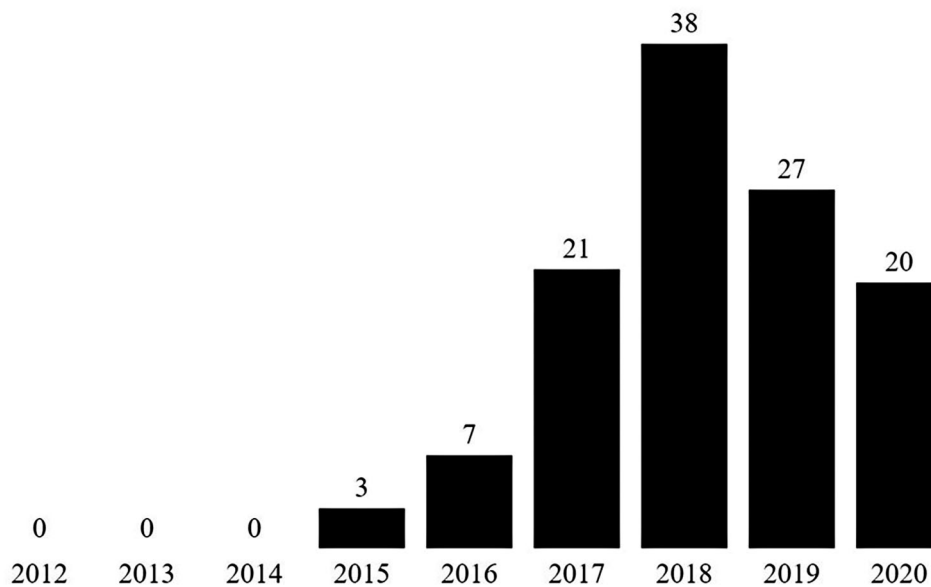
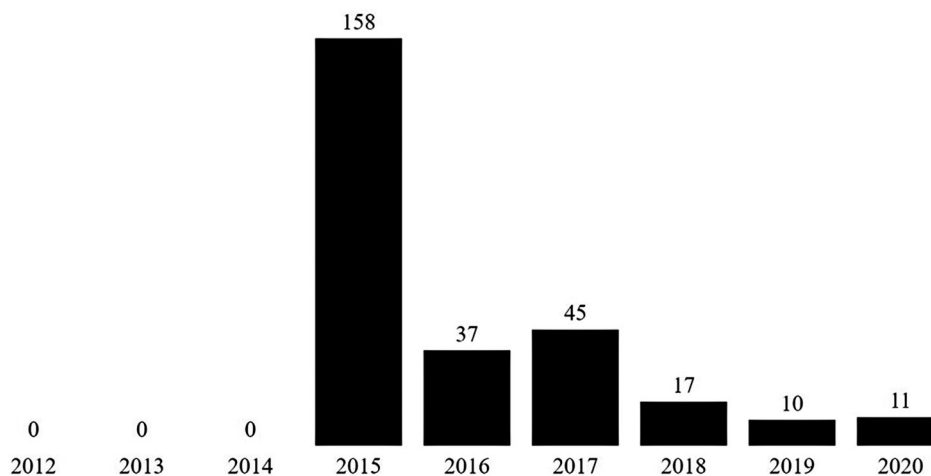**Figure 2.** Annual scientific production of research articles.

Figure 3. Average annual citations of the studies.

Concerning the research methods employed, the selected studies utilised a wide variety of methods, as presented in Figure 5, with quantitative (n = 66) and qualitative (n = 27) being the most popular ones. In regard to data analysis methods, however, Figure 6 reveals that thematic analysis (n = 31) and SEM (structural equation modelling) (n = 24) were the most commonly used. Furthermore, the selected studies utilised twelve theories, as presented in Table 1, clearly indicating a dearth of theory-based research, with only 39 studies invoking theories to propose their conceptual model. An interesting array of variables were also examined by the chosen studies, which are presented in Figure 7. Notably, very few studies have examined the effect of controlling (n = 13), mediating (n = 11), and moderating (n = 20) variables (Figure 7).

Table 1. Theories employed by the studies.

Theory	Number of studies
Resource-Based View (RBV) theory	13
Dynamic Capability theory	10
Contingency theory	3
Organisational Information Processing theory	3
Stakeholder theory	2
Institutional theory	2
Innovation Diffusion theory	1
Transaction Cost Economics theory	1
Theory of Information Economics	1
Systems theory	1
Social Capital theory	1
Standard Model Effective Field theory	1

3. Identification of key themes

The selected studies (n = 116) reviewed herein have examined diverse aspects of Big Data application in
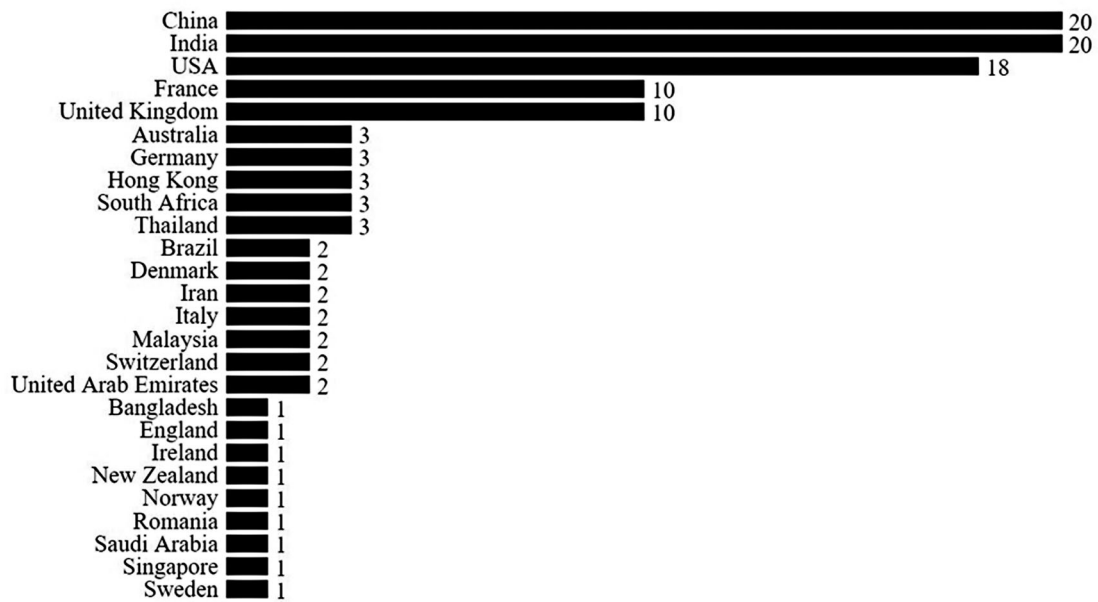
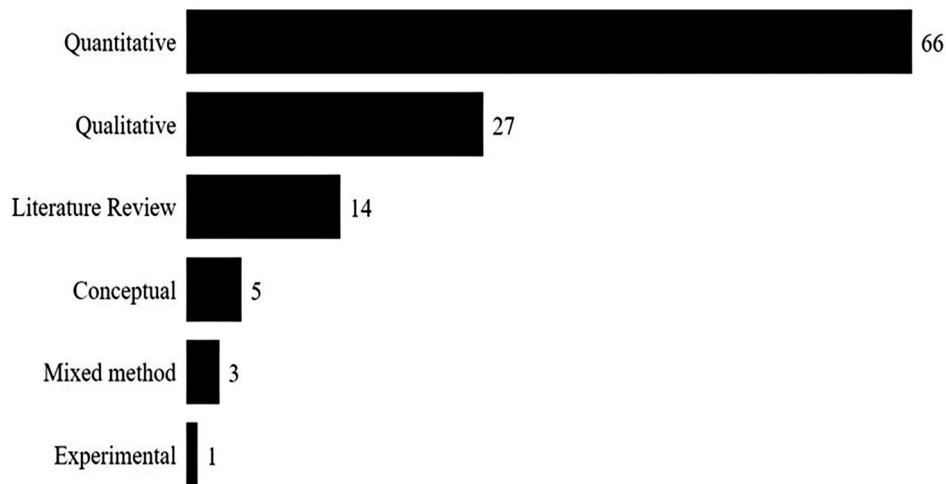**Figure 4.** The geographical scope of the studies.

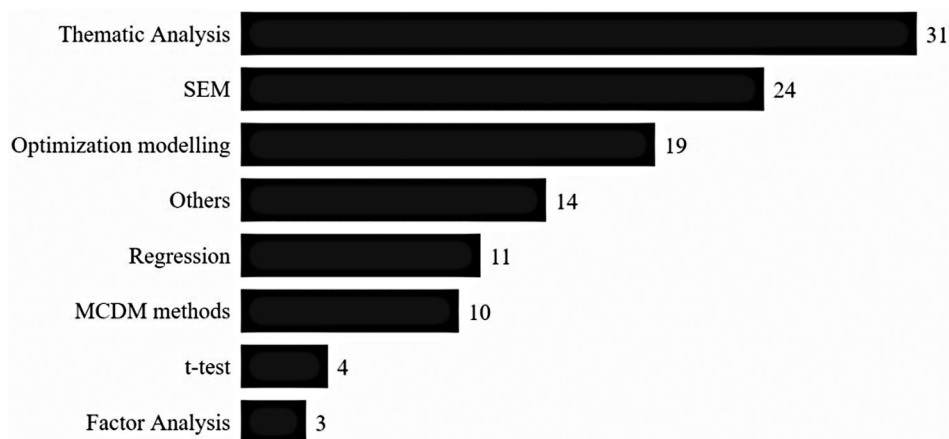**Figure 5.** Research methods used by the studies.

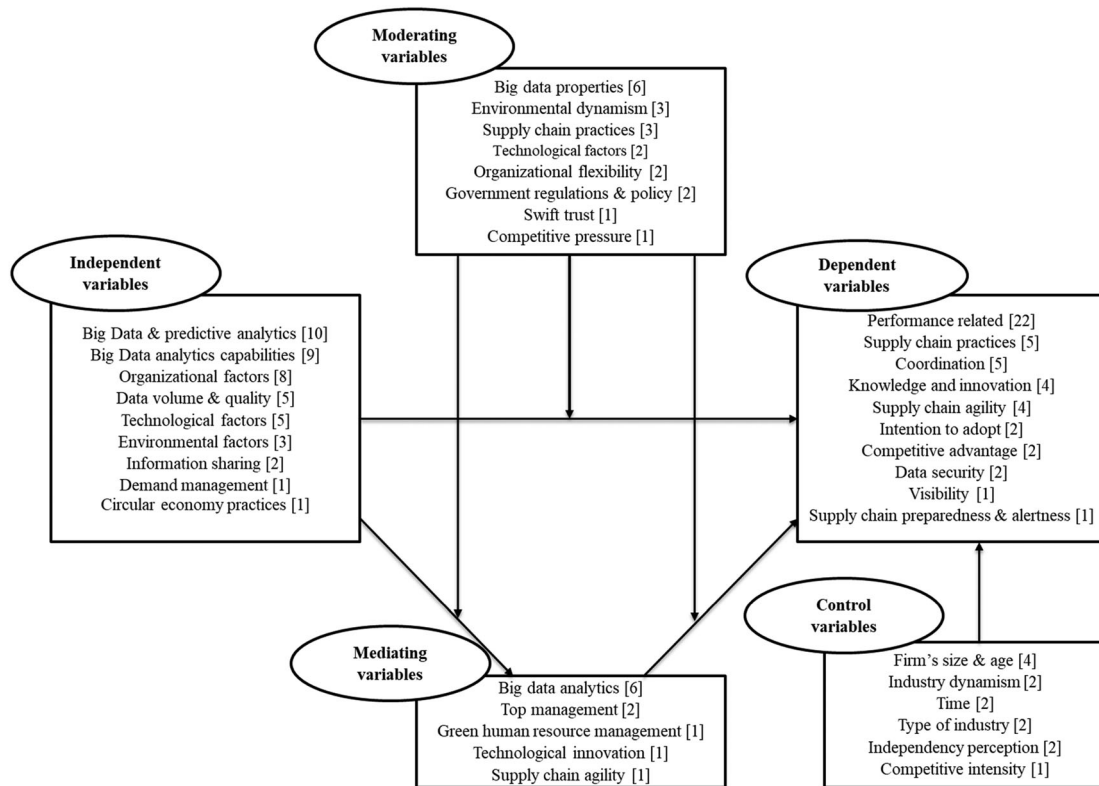**Figure 6.** Methods of analysis used by the studies.

Figure 7. Variables investigated by the studies.

Note 1: '[ ]' represents the number of studies.
Note 2: Some studies have considered multiple independent, dependent, control, mediating, and moderating variables.

OSCM. To synthesise such an extensive collection of findings systematically, we evaluated each study in-depth to uncover common themes. This is in consonance with recently published SLRs (e.g. Talwar et al. 2020). Accordingly, we used content analysis to delineate the key themes in the selected studies, following the recommendation of Seth et al. (2020). To ensure that the thematic foci we presented would provide a lucid and unbiased narrative of the reviewed literature, we observed a robust three-step approach. First, three researchers undertook open coding of the selected studies in Microsoft Excel, 2010. They then applied the deductive and inductive approach of axial coding to identify relationships among these open codes. Finally, to ensure inter-rater reliability and present a consensus view, the three researchers discussed the individually delineated codes and worked on settling the differences. As the selected studies had clearly discussed their findings related to Big Data application in OSCM, there were no divergent views about the eight emergent themes identified. The debate largely centred, instead, on determining the most coherent presentation order. Finally, we invited two professors from the operations management area with expertise in Big Data application to review the identified themes. Upon receiving their feedback, the eight themes were finalised, as presented in the mind map in Figure 8.

3.1. Dimensions

The multiple dimensions of Big Data, including sources, ecosystem, analytics techniques, and capabilities, were examined by the selected scholars in considerable detail. The key Big Data sources discussed by the studies were: product-in-use data in spare parts supply chains (Andersson and Jonsson 2018), point of sales data, in-store data (e.g. traffic counter data, path data), Google trends, and social media (Wu et al. 2017; Boone et al. 2019). The prior literature also highlighted Big Data's contribution to the supply chain ecosystem in terms of serving as an evaluation tool for economic progress and emphasising the need for more intelligent use of Big Data in SCM (Gravili et al. 2018; Chehbi-Gamoura et al. 2020). The studies suggest that Big Data assists in generating new product ideas, integrating operations capabilities, and facilitating new product development (Boone et al. 2019; Xu, Li, and Feng 2019; Zhan and Tan 2020). Furthermore, Big Data helps in selecting suppliers using forecasting methods and cloud computing technology (Singh et al. 2018a; Yu et al. 2019). Concerning Big Data analytics techniques, data mining, optimisation, machine learning, and statistics were some of the key techniques applied in OSCM (Choi, Wallace, and Wang 2018; Raman et al. 2018; Lakshmanaprabu et al. 2019; Ren et al. 2019; Xu,
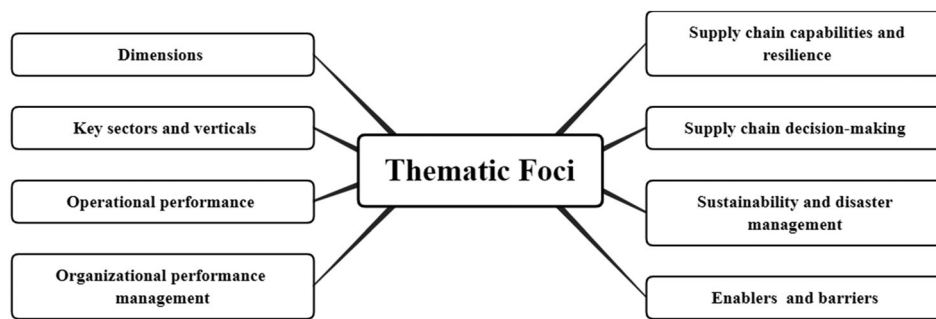
Figure 8. Thematic foci of research on Big Data application in OSCM.

Li, and Feng 2019). Finally, the studies discussed Big Data management capabilities, such as planning, investing, coordination, and control (Arunachalam, Kumar, and Kawalek 2018; Dubey et al. 2018; Jeble et al. 2018; Mandal 2018b).

3.2. Key sectors and verticals

Scholars have emphasised the transformative effect of Big Data through investigating varied aspects of OSCM, such as service operations, manufacturing, supply chains, and logistics. Their findings show that Big Data can detect trends and patterns to better explain customer behaviours and preferences in the case of service operations, such as financial services, banking, transportation, hospitality, information systems, healthcare, and online platforms (Li et al. 2016; Boone et al. 2018; Cohen 2018; Guha and Kumar 2018; Hung, He, and Shen 2020). In the context of retail supply chains, Big Data can be used to analyse the changes in past purchases and pricing to forecast costs, make personalized recommendations for consumers, provide superior products and services and vastly improve the shopping experience; however, various temporal and spatial discontinuities in Big Data use still need to be kept in mind (Sodero, Jin, and Barratt 2019; Gawankar, Gunasekaran, and Kamble 2020; Maheshwari, Gautam, and Jaggi 2020). For manufacturing operations, applying Big Data offered critical information like the link between product lifecycle decisions and process parameters, which can help managers in complex situations (Zhong et al. 2016; Ren et al. 2019). Meanwhile, for redistributed manufacturing, the key contribution of Big Data comes from its capability to digitalise the process using upgraded technologies (e.g. digital fabrication) to address changes in customer demand and the business environment (Zaki et al. 2019). In the case of banking, Big Data was found to improve banks' marketing and risk management performance (Hung, He, and Shen 2020), while the key areas addressed regarding the application of Big Data to the supply chain

included the attributes affecting consumers' beef purchase decision, selection of suppliers with low carbon emission in the beef supply chain, right supplier selection for right lot-sizes to reduce supply chain carbon footprint, enhancement of firms' financial performance in the manufacturing sector, and a data-driven scheduling optimisation model to ascertain the trustworthiness of the agricultural product supply chain (Mishra et al. 2017; Tao et al. 2018; Singh et al. 2018a; Singh et al. 2018b; Lamba, Singh, and Mishra 2019; Sommanawat, Vipaporn, and Joemsittiprasert 2019). Some specific benefits that can be reaped from the use of Big Data are: (a) the development of a resilient transport city system (Mehmood et al. 2017), (b) prediction of a maintenance schedule for railway transportation (Ghofrani et al. 2018), and (c) optimisation of fuel purchasing, and improvement in the routing of trucks (Hopkins and Hawking 2018).

3.3. Operational performance

Big Data offers several benefits in today's competitive business environment (Brinch 2018). The benefits of Big Data highlighted by the extant studies cover diverse aspects, including value creation and improvement in the supply chain's overall performance (Richey et al. 2016; Brinch 2018).

Specifically, the capabilities of Big Data application and analytics enable the use of available information to gain an operational advantage, optimise supply chain costs, reduce logistics services costs by improving customer service, support information sharing, promote transparent communication, aid in tracking across networks, and enhance swift trust and collaborative performance among multiple stakeholders (Liu and Wang 2016; Kache and Seuring 2017; Matthias et al. 2017; Mehmood et al. 2017; Shen and Chan 2017; Singh et al. 2018a; Kerdpitak et al. 2019; Kamble and Gunasekaran 2020; Mangla et al. 2020). In addition, BDA provides real-time information about fluctuations in demand with changes in downstream inventories, promotions, and sales (Dubey

et al. 2018; Hofmann and Rutschmann 2018), and helps in improving supply forecasting, leading to lower safety stock requirements and better supplier performance (Bag 2017; Roßmann et al. 2018). Furthermore, it enables data tracking and monitoring tools to assist in location and allocation optimisation, as well as improvements in the on-shelf availability across the supply chain (Li and Wang 2017; Singh et al. 2018b; Viet et al. 2020). Other key areas where the positive impact of Big Data application to SCM has been observed are: enhanced data security, improved service supply chain performance, decreased uncertainty of demand planning through data of product-in-use, and a lower bullwhip effect, leading to less process time and better supply chain network performance (Hofmann 2017; Andersson and Jonsson 2018; Engelseth and Wang 2018; Fernando, Chidambaram, and Wahyuni-TD 2018).

3.4. Organisational performance management

Big Data capabilities with effective resources for information sharing significantly enhance both the supply chain and the organisational performance (Gunasekaran et al. 2017; Arunachalam, Kumar, and Kawalek 2018; Badiezadeh, Saen, and Samavati 2018; Jeble et al. 2019; Singh and El-Kassar 2019). From an overall organisational perspective, the application of Big Data enables the assessment of key supply chain performance indicators (KPIs), aids management decision-making through visualisation of customers' behaviour, reduces the ripple effect, and helps in revamping information processing capacity (Gunasekaran et al. 2017; Matthias et al. 2017; Mishra et al. 2017; Dev et al. 2019; Dubey et al. 2019d). Additionally, the application of Big Data helps in minimising externalities, promoting a culture of data-driven predictive performance management, enhancing operational efficiency, improving the buyer-supplier relationship, and supporting technological innovation at both product and process levels (Hazen et al. 2016; Bag 2017; Mehmood et al. 2017; Dubey, Gunasekaran, and Childe 2019b; Saleem et al. 2020). Furthermore, Big Data management capabilities, such as planning, coordination, investment, control, and talent, prominently improve the supply chain performance and support employee development (Mandal 2019, 2018b; Bag et al. 2020b). Finally, del Giudice et al. (2020) provide unique insight, reporting that a supply chain driven by Big Data increases the effect of circular economy human resource management on the performance of firms.

3.5. Supply chain capabilities and resilience

Visibility and coordination are two important capabilities of the supply chain, which depend on the flow of information among the supply chain partners (Liu and Yi 2017; Dubey et al. 2018; Mandal 2019), while preparedness, alertness, and agility represent its resilience (Papadopoulos et al. 2017; Mandal 2019). Prior studies have also revealed the efficacy of Big Data application in enhancing the capabilities and resilience of the supply chain processes. With regard to the impact of Big Data on supply chain capabilities, scholars contend that it reduces order-to-delivery lead time, enhances innovation capabilities of the supply chain by making it more flexible, responsive, and reliable, and improves the quality of the supply chain to respond to external changes with speed (Fernando, Chidambaram, and Wahyuni-TD 2018; Srimarut and Mekhum 2020). Scholars have also revealed that Big Data management capabilities, such as planning, are important enablers of supply chain resilience (Mandal 2019, 2018a, 2018b). Adopting Big Data further enables the supply chains to be restored when disrupted and increases their risk resilience capacity (Giannakis and Louis 2016; Papadopoulos et al. 2017; Dubey et al. 2018; Mandal 2019, 2018a; Singh and Singh 2019). Most importantly, BDA resolves the connectivity issue of long-linked supply chains by making them linear, enabling smooth information flow, and ensuring tracking, tracing, and pushing forward of imported goods, thereby reducing the risk of supply failure (Engelseth and Wang 2018). In sum, prior findings suggest that logistics, transparency, and supply chain visibility offer the highest Big Data usage opportunities in OSCM (Chen, Preston, and Swink 2015; Kache and Seuring 2017).

3.6. Supply chain decision-making

Two key aspects of supply chain decision-making are forecasting and optimisation. Forecasting is important for planning and enacting the supply chain processes, such as sourcing, preparing, and distributing goods to the end-users (Pan and Yang 2017; Boone et al. 2018). Since data is the key input required for forecasting, and the use of BDA for synthesising structured or unstructured data is well-recognised (Andersson and Jonsson 2018; Barbosa et al. 2018; Hofmann and Rutschmann 2018), the application of Big Data can thus be expected to positively impact forecasting decisions. Scholars have further noted that the use of Big Data expedites the decision-making process by reducing uncertainty in the supply chain and improving the accuracy of predictions by combining different forecast situations with suitable analytics techniques (Andersson and Jonsson 2018; Hofmann and Rutschmann 2018; Lau et al. 2018; Roßmann et al. 2018). This efficacy has been observed in varying contexts, such as oil consumption, hotel occupancy, pricing decisions, daily milk production estimation, and supplier selection

(Pan and Yang 2017; See-To and Ngai 2018; Ren et al. 2019; Yu et al. 2019).

Past findings also indicate that forecasting data can come from various sources, with the type of data required dependent on the level and scope of the forecast to be made. For example, customer data generated at the point of sales, as well as traffic and customers' purchasing behaviour data, can help in demand estimation and generation of a multi-product perspective, resulting in lower demand fluctuations and aggregated sales forecasts (See-To and Ngai 2018; Boone et al. 2019). Similarly, data related to customer reviews and ratings are useful in predicting future purchasing decisions (See-To and Ngai 2018; Ren et al. 2019). Furthermore, operational, sensor, product-in-use, and item-use data, along with fault codes, which fulfil the common criteria of Big Data (Tan et al. 2015; Richey et al. 2016; Andersson and Jonsson 2018; Boone et al. 2019), have been found to support management and demand planning effectively (Andersson and Jonsson 2018; Raman et al. 2018).

Optimisation in OSCM implies optimal decision-making for cost minimisation, profit maximisation, capacity sharing, distance optimisation, and efficient warehousing (Liu and Yi 2018; Singh et al. 2018b; Lakshmanaprabu et al. 2019). In this regard, scholars suggest that applying Big Data facilitates the strategic transformation of supply chain operations to create and maintain the value of remanufactured products (Chan et al. 2017; Roden et al. 2017; Xu, Li, and Feng 2019). Furthermore, it helps optimise location and allocation decisions and vehicle routing, thereby leading to cost reduction (Li et al. 2018; Singh et al. 2018b; Lakshmanaprabu et al. 2019).

3.7. Sustainability and disaster management

Scholars contend that Big Data application can improve the social responsiveness of supply chain processes, both in terms of sustainability and disaster management effectiveness. Underscoring the role of Big Data in enhancing the ecological sustainability of supply chain processes, the selected studies addressed this capacity in terms of logistics and procurement. In this regard, a remarkable contribution comes from the use of real-time data for developing a logistics and procurement model that is environmentally sustainable and an optimisation model for green SCM (Shukla and Tiwari 2017; Zhao et al. 2017; Kaur and Singh 2018). Other noteworthy findings in this context are: (a) identification of supply chain risks and uncertainties that could serve as a guideline for supply chain network sustainability (Mani et al. 2017; Wu et al. 2017), (b) formulation of the operational model using Big Data-targeted advertising that could be used to determine pricing policies, products' green degree, and

their correlation with a green supply chain (Liu and Yi 2017; Badiezadeh, Saen, and Samavati 2018), (c) proposal of a Big Data framework for sustainable production of palm oil (Shukla and Tiwari 2017), (d) revelation of valuable insights on smart manufacturing to aid decision-making for sustainable production (Ren et al. 2019), (e) use of Big Data to support sustainable transportation and reduce information fraud while sharing information with various elements of the supply chain (Gholizadeh, Fazlollahtabar, and Khalilzadeh 2020), (f) application of Big Data to enhance sustainability management in supply chain design for valorising agricultural waste (Belaud et al. 2019), and (g) use of BDA to help in efficient achievement of sustainable development goals by making various aspects of supply chain more responsive (Zhang, Yu, and Zhang 2020).

Disaster management, meanwhile, depends on the complex operation of the humanitarian supply chain, which includes multiple stakeholders. Big Data applications in such supply chains can make this entire complex network more visible and coordinated (Dubey et al. 2018; Prasad, Zakaria, and Altay 2018). In fact, BDA can not only significantly improve the coordination and performance of the humanitarian supply chain but also enhance swift trust and collaborative performance of the civil and military organisations undertaking disaster relief operations (Dubey et al. 2018; Jeble et al. 2019; Dubey et al. 2019c). The reviewed studies have also provided empirical evidence that quality information sharing and swift trust increase the resilience of the disaster supply chain, thereby making it more sustainable (Papadopoulos et al. 2017; Dubey et al. 2019c; Dubey et al. 2019d).

Since humanitarian data consists of situational awareness, operational data, and past information, Big Data application can help improve the quality of deliverables, decrease operating costs, shorten the processing time, increase the resilience of the disaster management process, and support logistical planning and timely execution of rescue missions (Prasad, Zakaria, and Altay 2018; Swaminathan 2018; Nagendra, Narayanamurthy, and Moser 2020). Furthermore, since Big Data can not only visualise and analyse disasters but also predict them, it has the power to positively transform humanitarian operations and crisis management approaches to a large extent (Akter and Wamba 2019).

3.8. Enablers and barriers

While successful adoption of Big Data is driven by a set of enablers, barriers can limit its use in OSCM. Prior scholars have investigated these enablers and barriers to integrating Big Data into OSCM processes. The enablers of Big Data implementation include risk and security
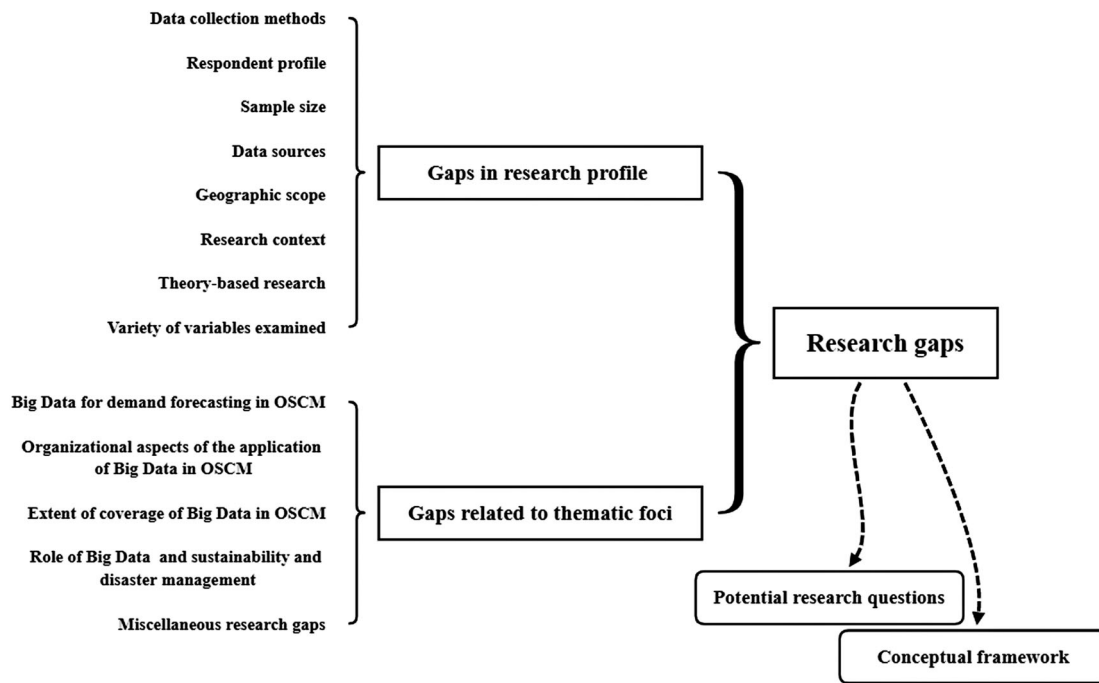
Figure 9. Research gaps and the way ahead

governance, storage, operational efficiency, and human capital (Richey et al. 2016; Papadopoulos et al. 2017; Lamba and Singh 2018), as well as perceived benefits, ease of use, technological resources, Big Data quality, top management commitment and support, financial resources, Big Data skills, Big Data-driven supply chain analytics capability, Big Data availability and prioritisation, and supportive government regulations (Lai, Sun, and Ren 2018; Lamba and Singh 2018; Yadegaridehkordi et al. 2018; Wamba and Akter 2019; Wilkin et al. 2020).

Offering an interesting but novel perspective on Big Data adoption, Dubey et al. (2020) underscored the enabling role of entrepreneurial orientation in promoting the use of BDA powered by artificial intelligence. Another unique viewpoint was offered by Wamba et al. (2020), who emphasised the role of environmental dynamism as a moderator, which can influence the gains accruing from BDA in SCM in the form of agility, adaptability, and improved organisational performance. Similarly, providing a practical insight into Big Data application in the agri-food supply chain in developing countries, Protopop and Shanoyan (2016) argued that the advancement of ICTs, fall in data storage cost, and increased mobile phone usage in rural areas are key enablers of Big Data adoption in this sector.

In comparison, the barriers to the adoption of Big Data in OSCM include deficiency in human knowledge and supply chain partnerships (Queiroz and Telles 2018; Behera 2019), as well as challenges related to technical, cultural, ethical, and procedural issues, particularly in the case of the service supply chain (Zhong et al. 2016; Khan 2019). Other barriers include data and technology-related issues, such as inadequate infrastructure, data variety, quality and visualisation challenges, the complexity of data integration, availability of BDA tools, data privacy, ethics, security considerations, and cost, particularly for manufacturing firms (Schoenherr and Speier-Pero 2015; Moktadir et al. 2019; Oncioiu et al. 2019; Ogbuke et al. 2020). With specific reference to the humanitarian supply chain, culture and learning at the organisational level also play a critical role in enabling or obstructing the application of Big Data (Dubey et al. 2018; Dubey et al. 2019c; Bag, Gupta, and Wood 2020a).

4. Gaps and potential research questions

We undertook a systematic review of the extant literature to present a research profile and the thematic foci of Big Data research in OSCM (Figure 9). A critical analysis of this research profile and the eight themes therein helped us identify gaps in the literature on Big Data application in this domain. In turn, these gaps indicate the path for future academic research that can aid effective managerial decision-making and propose a conceptual framework, as presented in Figure 9.

4.1. Gaps in the research profile

The selected studies have certain limitations related to their research designs, such as the type of study, respondent profile, methods of data analysis, geographical scope, and research context. Accordingly, these issues indicate gaps in the existing findings.

4.1.1. Data collection methods

To begin with, several of the reviewed studies utilised cross-sectional survey data to test the proposed hypotheses (Chen, Preston, and Swink 2015; Bag 2017; Papadopoulos et al. 2017; Dubey et al. 2018; Jeble et al. 2018; Mandal 2018b). As cross-sectional data collected from self-report instruments on one occasion from homogenous participants may suffer from issues of respondent bias and generalizability, there is a need for greater empirical studies employing other research designs, such as longitudinal surveys, which will help address these issues.

4.1.2. Respondent profile

For these survey-based studies, respondents were chosen based on their designation in the organisation, working experience, and departmental responsibilities (Brinch et al. 2018; Dubey et al. 2018; Jeble et al. 2018; Queiroz and Telles 2018; Khan 2019). However, this approach limits the sample selection to a specific category of respondents. For instance, Lai, Sun, and Ren (2018) collected data from IT managers only, thereby failing to capture the viewpoint of the entire firm. Similarly, Roßmann et al. (2018) and Li et al. (2016) used industry professionals and expert opinions only in their investigation, while Bag (2017) targeted only top senior management. Such a skewed sample belonging to a specific category is thus likely to restrict the outcomes. It is also worth noting that Mandal (2019) and Roßmann et al. (2018) were the only authors to investigate age and gender factors. The lack of demographic details, particularly gender-related, severely constrains managerial decision-making. There is thus a need for future studies to include more diverse respondents in their sample to offer more gender-specific and representative findings.

4.1.3. Sample size

The prior literature similarly suffers from smaller sample sizes. Most of the selected studies had a limited sample size of fewer than 300 respondents. For example, Roßmann et al. (2018) focused on only 73 experts from the industry, academia, and politics/association in their study. Similarly, Brinch et al. (2018) also used the opinion of a small group of experts for their research, while Moktadir et al. (2019) interviewed only 15 industrial managers to investigate the role of Big Data in SCM. Such

a small number of respondents may cause issues related to the generalizability of findings and their representativeness. Future studies with a more robust sample size are, therefore, required to enrich the extant knowledge in this area.

4.1.4. Data sources

The limited sources of data used for the analysis also present a gap in terms of the quality of the accumulated learnings. Several of the studies examined data collected from a single source only. For example, Yu et al. (2019) tested the oil consumption forecast model solely using Google trends, while Singh et al. (2018b) targeted only online data sources. Similarly, Chan et al. (2017) used social media alone as a data source, and Li et al. (2016) focused only on online reviews that were listed under the most helpful reviews category. Future research employing multiple data sources is thus required to provide more valuable insights.

4.1.5. Geographic scope

Most of the studies examined Big Data in OSCM concerning specific regions or countries. For instance, Behera (2019) studied the impact of Big Data on reverse supply chain performance in the context of the Indian manufacturing sector only, whereas Queiroz and Telles (2018) investigated the challenges to Big Data adoption in the supply chain organisation in Brazil. Similarly, Khan (2019) studied the Big Data adoption challenges in the United Arab Emirates' service supply chain, while Brinch et al. (2018) studied Big Data application in the Danish supply chain. Such country-specific studies have led to a shortage of cross-country research in the area, presenting a gap to be bridged.

4.1.6. Research context

In the case of research context or area, manufacturing was the sector most investigated by the selected studies. In comparison, research on supply chains and Big Data for service firms have been mainly related to hotels, banks, hospitals, and healthcare, and educational and non-governmental organisations (Dubey et al. 2018; Fernando, Chidambaram, and Wahyuni-TD 2018; Mandal 2018b; Khan 2019). Not only has the focus remained confined, but the extent of the investigations has been narrow. For instance, Hofmann and Rutschmann (2018) examined only the primary demand forecast, excluding secondary and tertiary demand. Similarly, Andersson and Jonsson (2018) excluded the investigation of real-time data of product-in-use data and casual-based forecast intervention, while Jeble et al. (2018) captured the firm's perception of the impact of Big Data predictive analytics rather than the actual impact. These limitations,

both in terms of the sectors examined and the depth of analysis, indicate further gaps to be addressed.

4.1.7. Theory-based research

From a theoretical perspective, RBV was the most widely-adopted theory to assess the effect of Big Data in OSCM (Mandal 2019; Dubey et al. 2019b). Very few studies utilised other theories, as listed in Table 1, which included institutional theory and innovation diffusion theory, among others (Lai, Sun, and Ren 2018; Khan 2019; Dubey et al. 2019b). Consequently, this indicates limited theoretical advancement in the research in this area.

4.1.8. Variety of variables examined

As presented in Figure 7, most studies have examined only the direct associations between the independent and dependent variables. The key variables examined as antecedents were Big Data, predictive analytics, and BDA capabilities (Fernando, Chidambaram, and Wahyuni-TD 2018; Kerdpitak et al. 2019; Wamba et al. 2020; del Giudice et al. 2020). At the same time, the key dependent variables examined were performance-related instead (Dubey et al. 2018; Dubey et al. 2019b). In comparison, very few variables have been examined as mediating and moderating variables, indicating the need for more complex and dynamic models to generate deeper insights for researchers and practitioners.

4.2. Gaps related to thematic foci

The critical analysis of the above themes has allowed us to identify various gaps in the prior literature. We have thus classified these gaps into five categories:

4.2.1. Big Data for demand forecasting in OSCM

The first gap concerns the extent that product-in-use data can be employed to reduce uncertainty in demand and supply chain cost during the demand planning process. While scholars have accepted that the modern-day systems track the data of products sold together as well as how the availability of one product influences the demand of others, research on the use of such data for demand forecasting is relatively scarce. Similarly, while sales and inventory data are analysed to forecast demand for multiple products and willingness to substitute them, there is still limited research on the utilisation of such data for product-level demand forecasting. Furthermore, while past research and practice have used sales and traffic data to forecast demand in the context of brick-and-mortar stores, the effectiveness of incorporating traffic data in improving demand forecasting has remained unclear in the academic scholarship.

4.2.2. Organisational aspects of the application of Big Data in OSCM

Although scholars have argued that organisational competence is important in Big Data application, the research on personnel expertise and the infrastructural facilities required to incorporate Big Data in OSCM can still benefit from deeper analysis. Though some studies have investigated Big Data application-based capabilities, such as technical knowledge and infrastructure-based capabilities, their focus has been confined to supply chain agility. These capabilities need to be further investigated in other contexts (e.g. supply chain resilience). With regard to the skills and competence of staff, research on the personnel management expertise required for implementing Big Data in OSCM should be expanded beyond management capabilities related to the supply chain performance. There is also a need for further research on the impact of Big Data predictive analytics and top management commitment on organisational performance under the influence of institutional or external pressure. Lastly, there is limited research on the inter-relationship between the available Big Data personnel and infrastructure capabilities.

4.2.3. The extent of coverage of Big Data in OSCM

The selected studies have focused on OSCM Big Data application largely in service industries, such as financial services, healthcare, transportation, hospitality, and online platforms. Multi-disciplinary spaces, including retail, media streaming, cloud computing, and e-commerce firms, such as Amazon, however, continue to remain underexplored. There is also a need to examine the application of Big Data in advanced science and technology services, such as aviation, for primed decision-making. Additionally, redistributed manufacturing has been only investigated in the consumer goods industry; thus, it needs to be extended to other sectors, such as automotive, metal and steel, machinery, and additive manufacturing.

4.2.4. Role of Big Data and sustainability and disaster management

So far, the prior research has only investigated the application of Big Data to the selection of suppliers with low carbon emission in the beef supply chain, thus presenting a gap in terms of similar studies in non-food sectors, such as automobiles, steel, and cement. Similarly, stochastic parameters related to long deliveries and shortages have been relatively under-explored. They need to be further examined in the context of using Big Data for developing sustainable procurement and transportation. In addition, more research is required to examine the

relief supply chain in various disasters, such as floods, landslides, earthquakes, and pandemics.

4.2.5. Miscellaneous research gaps

The investigation of enablers and barriers related to Big Data adoption in OSCM has been rather general, with limited clarity on industry-specific factors that can obstruct or facilitate its implementation. For instance, there are limited insights related to the drivers and barriers for Big Data application in developing countries, particularly in verticals related to the agri-food supply chain. Similarly, though prior scholars have discussed the benefits of Big Data, such as improved decision-making, partner transparency, operational efficiency, and performance, the challenges or issues resulting from the integration of Big Data in OSCM have not been explored. There are also hardly any studies offering learnings related to the adverse effects of Big Data applications in OSCM. Furthermore, while some studies have examined the effect of Big Data on data security and the service supply chain performance to some extent, there is still a shortage of studies exploring how service supply chain networks share information in real-time. Another aspect of Big Data application in OSCM that has remained under-researched is how BDA can enhance interpersonal relationships and boost trust and collaboration, both in the context of OSCM in firms, as well as in disaster management activities. This is a vital gap, particularly in the context of the humanitarian supply chain, where people from diverse cultural backgrounds may come together to conduct rescue operations, which creates complex situations. In such an environment, the collection, compilation, and transparent dissemination of information can improve trust and the effectiveness of the operation. In addition, limited insights are available on how Big Data can improve firm performance in the context of the circular economy. Finally, the present SLR has also observed that more research examining the effectiveness of the volume, variety, and velocity of Big Data in the transformation of supply chain resilience is required.

4.2.6. Potential research questions

The gaps discussed above help in the formulation of potential research questions that need to be addressed for advancing research and practice in the area of Big Data application in OSCM (Table 2).

5. Framework development

We have developed a conceptual framework based on the content analysis of the selected studies and the gaps identified therein to underscore various aspects of Big Data adoption in OSCM that are worth further exploration (Figure 10). The framework, titled the *Dimensions-Avenues-Benefits model for BDA adoption (DAB model),* presents various aspects of the pre-adoption and post-adoption phase associated with a firm's decision to use BDA. The model thus provides the key variables that firms need to consider when making decisions related to applying Big Data in OSCM.

The *pre-adoption phase* comprises Big Data dimensions (Big Data predictive analytics and BDA capabilities) that act as antecedents for the use of Big Data in OSCM (agility, sustainability, coordination, alertness, customer insights, and visibility). These dimensions influence the firms' intentions to adopt Big Data through their effect on the above avenues. The framework further hypothesises that the actual adoption of Big Data is a net outcome of the moderating influence of enablers (management commitment, organisational infrastructure, and government policy) and barriers (technical, procedural, and cultural, as well as data privacy and ethical issues).

In the *post-adoption phase*, the framework proposes satisfaction as an outcome of Big Data adoption, which, in turn, leads to benefits for the firm (bullwhip effect, competitive edge, assets productivity, and business growth). Additionally, we present firm features (size and type of firms) as *control variables*. All components of the framework have established relationships in the Big Data context, as discussed by the selected studies (Table 3).

The framework is grounded in the theoretical contributions of the dynamic capability view (DCV) theory and organisational information processing theory (OIPT). DCV contends that dynamic capabilities represent the ability of a firm to adapt its internal and external competencies and available resources to the demands imposed by changing milieu in response to uncertainties (Teece, Pisano, and Shuen 1997; Teece 2016). DCV is thus relevant to the present context since prior scholars have viewed BDA as a dynamic capability, which represents an outcome of the firm's ability to adapt to a mutating environment (Wamba et al. 2017; Singh and El-Kassar 2019; Wamba and Akter 2019).

Big Data predictive analysis and Big Data analytics are hypothesised in our framework as similarly dynamic capabilities that can enable organisations to maintain the resilience of the supply chain in terms of its agility, sustainability, coordination, alertness, customer insights, and visibility. On the other hand, OIPT deals with organisational design, capabilities, and structures to handle information processing needs to gain a competitive advantage (Smith et al. 1991; Fairbank et al. 2006; Dubey et al. 2019b). This theory relates to the present context as prior research has contended that proper integration of Big Data is crucial for improving the supply chain as

well as organisational performance (Gunasekaran et al. 2017; Arunachalam, Kumar, and Kawalek 2018). Barriers and enablers are further identified as moderators per the OIPT, as they are likely to influence the proper integration of Big Data in OSCM, thereby yielding competitive growth advantages to the firm.

Table 2. Theme-based research questions.

Thematic Foci	Description	Potential Research Questions (RQs)
Dimensions	Big Data sources, ecosystem, analytics techniques, and capabilities	1. What is the role of the product-in-use data in reducing the uncertainty in demand and supply chain costs during the demand planning process? 2. How does one product's availability influence the demand for other products, and how does the data for such products help in forecasting the demand for that product? 3. What is the effectiveness of integrating traffic data with sales data for improving the demand forecast? 4. What are the differences in the need for each of the Big Data V's (e.g. volume, veracity) based on the characteristics of the decision to be made?
Key sectors and verticals	Uses of Big Data in OSCM in varied sectors	1. What are the applications of Big Data in multi-disciplinary spaces such as the e-commerce industry? 2. How is Big Data applicable in advanced science and technology services such as geographical information systems? 3. What are the applications of Big Data in non-consumer goods industries, for example, automotive, metal and steel, machinery, and additive manufacturing? 4. What are the potential issues in applying Big Data to domains such as smart healthcare, cloud computing, predictive manufacturing, and 3-D printing? 5. How can the views of third-party service providers, suppliers, practitioners, and customers associated with different domains of retail supply chains be integrated to fully benefit from Big Data application in this sector? 6. Which vertical as a whole, i.e. large firms or small and medium enterprises, has witnessed more improvement in the efficiency of the decision-making processes after the implementation of BDA?
Operational performance	Competitive advantages offered by Big Data in SCM	1. What are the challenges or issues in applying BDA to locational and optimisation problems? 2. How does BDA transform the traditional city logistics system to smart transportation? 3. How can BDA be better leveraged for improved decision-making and reduction in costs associated with the logistics service supply chain?
Organisational performance management	Contribution of Big Data to enhancing organisational performance	1. How can BDA enhance the performance of the service supply chain with real-time data information? 2. What is the impact of personnel capabilities related to BDA on organisational performance? 3. How does BDA affect supply chain performance with top management commitment under external pressure? 4. Which measures can be used to evaluate the contribution of various dimensions of Big Data-driven supply chain analytics capabilities on firm performance? 5. How effective are Big Data-driven supply chains in improving firm performance in the context of a circular economy?
Supply chain capabilities and resilience	Impact of Big Data on visibility, coordination, and transparency of the supply chain	1. How do BDA personnel and infrastructure-based capabilities affect the capabilities and resilience of the supply chain? 2. What are the potential inter-relationships between BDA personnel management and infrastructure-based capabilities? How do such linkages influence supply chain capabilities? 3. What is the effectiveness of Big Data volume, velocity, and variety in building supply chain capabilities and resilience? 4. What are the different diagnostic tools that can be used to assess the gaps in the BDA capabilities of firms? 5. How can BDA customer relationship analysis be extended to develop better supply chain risk detection capabilities?

(*continued*).

Table 2. Continued.

| Thematic Foci	Description	Potential Research Questions (RQs)
Supply chain decision-making	Demand forecasting and optimising allocation decisions	1. What are the factors that affect forecasting based on BDA in the manufacturing supply chain? 2. How is BDA applicable in facility location and inventory management optimisation? 3. What are the key optimisation problems that can be most effectively addressed through BDA to improve the operational performance of supply chains?
Sustainability and disaster management	Big Data in ecological and disaster supply chains	1. How has the role of Big Data in the management of supply chains in different disasters such as floods, landslides, and earthquakes transformed over time? 2. How can Big Data with stochastic parameters be used to develop a sustainable model for the supply chain? 3. How can Big Data be used to identify risks and uncertainties in service and manufacturing supply chains to improve their sustainability? 4. How can Big Data be leveraged to improve interpersonal relationships during rescue operations to increase their effectiveness?
Enablers and barriers	Big Data adoption in OSCM	1. What are the possible adverse outcomes of the adoption of Big Data in OSCM? 2. What are the industry-specific enablers and barriers of Big Data adoption in OSCM? 3. How are the enablers and barriers for Big Data application different for emerging economies compared with developed ones? 4. What are the enablers and barriers to integrating real-time BDA with OSCM-related tracking systems?
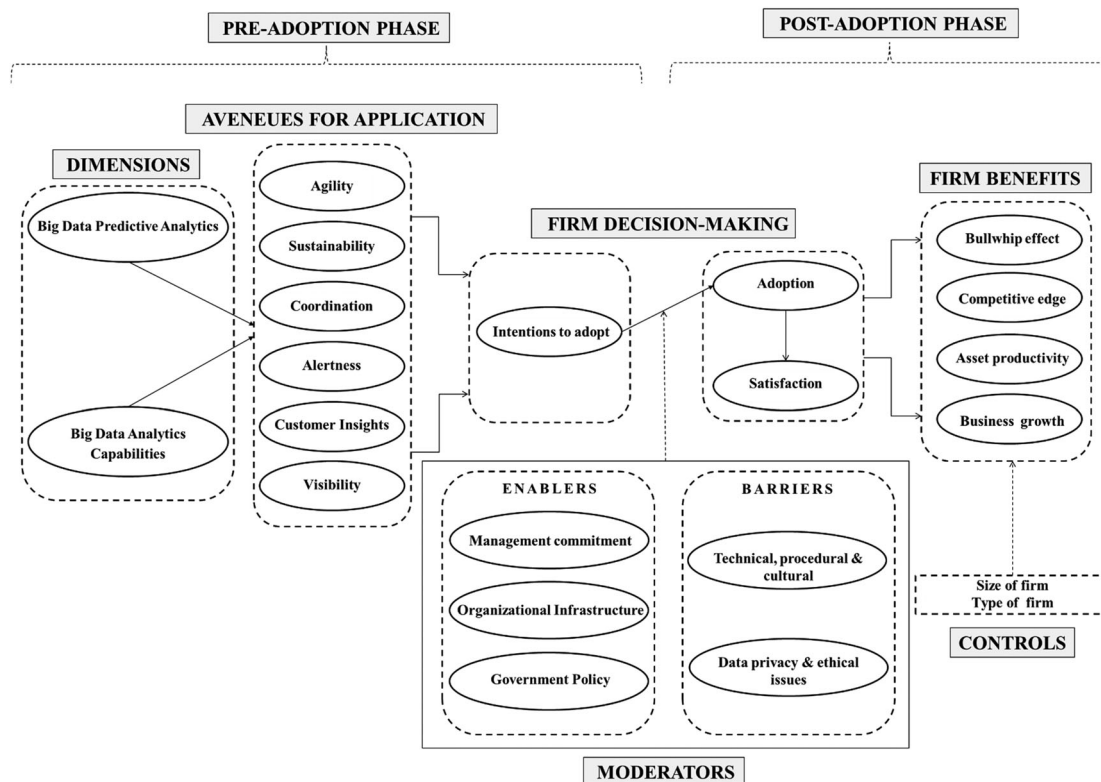
Figure 10. Dimensions-Avenues-Benefits model for BDA adoption (DAB model).

Table 3. Variables investigated in the selected studies.

Aspects	Variables	Operational description	Studies
Dimensions	Big Data predictive analytics	A technological tool for analysing the available data to forecast demand	Fernando, Chidambaram, and Wahyuni-TD (2018); Behera (2019); Queiroz and Telles (2018); Singh and El-Kassar (2019); Wamba et al. (2020)
	Big Data analytics capabilities	Comprises three capabilities required for the application of Big Data: management, infrastructural, and personnel capabilities	Mandal (2019); Dubey et al. (2018); Dubey, Gunasekaran, and Childe (2019a); Kerdpitak et al. (2019); Bag et al. (2020b); del Giudice et al. (2020)
Avenues for application	Agility	Represents the ability to respond speedily to customer requirements, handle market changes and uncertainties effectively, develop and customise products in a timely manner, and quickly access arising opportunities	Giannakis and Louis (2016); Dubey et al. (2018); Mandal (2018a); Srimarut and Mekhum (2020); Wamba et al. (2020); Wamba and Akter (2019)
	Sustainability	The ability of the supply chain to minimise environmental impact, risk, waste, and social cost	Mandal (2018b); Singh and El-Kassar (2019); Kaur and Singh (2018); Wu et al. (2017); Zhao et al. (2017)
	Coordination	The horizontal or vertical relationships and interconnections among multiple supply chain stakeholders	Dubey et al. (2019d); Dubey et al. (2018)
	Alertness	The ability of organisations to become aware of any potential opportunities/ disasters quickly	Mandal (2019)
	Customer insights	The volume of the total number of online reviews for a product/service	Li et al. (2016)
	Visibility	The in-transit transparency that enables tracking of a product from end to end, i.e. its movement from supplier to manufacturer and, finally, the buyer	Dubey et al. (2018); Dubey et al. (2019c)
Firm decision-making	Intentions to adopt	The positive intent of firms to use BDA	
	Adoption	The actual implementation and use of BDA by firms	
	Satisfaction	The firms' perception of the extent of their organisation	
Firm benefits	Bullwhip effect	The variability in demand that gets distorted and amplified as it moves from one end (consumer) of a supply chain to the other (supplier)	Hofmann (2017)
	Competitive edge	The bundling of certain resources and capabilities that create value and sustain the firm in a competitive environment	Dubey et al. (2018); Dubey et al. (2019d)
	Asset productivity	Assesses supply chain performance based on current and fixed assets	Chen, Preston, and Swink (2015)
	Business growth	The ability of a firm to create temporal advantages for itself	Chen, Preston, and Swink (2015)
Moderators: Enablers	Management commitment	The role of top management in building and supporting BDA capabilities	Chen, Preston, and Swink (2015); Gunasekaran et al. (2017)
	Organisational flexibility	The ability of a firm to speedily and effectively deploy resources in response to changes in market conditions	Dubey et al. (2018); Dubey, Gunasekaran, and Childe (2019a); Dubey et al. (2019d)
	Government policy	The governmental policy that firms seeking governmental support are required to refer to when adopting new technology. These guidelines are effective means to encourage the use of new technology	Lai, Sun, and Ren (2018); Gawankar, Gunasekaran, and Kamble (2020)
Moderators: Barriers	Technical, procedural, and cultural barriers	Technical barriers refer to the issues in collecting and integrating real-time data; procedural barriers refer to the issues related to transmission speed and data storage; cultural barriers refer to the issues that arise while interpreting the data originating from different cultures	Khan (2019)

(*continued*).

Table 3. Continued.

Aspects	Variables	Operational description	Studies
	Data privacy and ethical barriers	The concerns associated with the privacy and misuse of data collected from and linked with multiple sources	Khan (2019); Moktadir et al. (2019)
Controls	Size of firm	Some measures, such as sales/revenue that can be used to distinguish between the big and small organisations	Dubey et al. (2018); Dubey, Gunasekaran, and Childe (2019a); Dubey et al. (2019b); Dubey et al. (2019d); Dubey et al. (2020); Wamba et al. (2020)
	Type of firm	The industry/sector that the firm is operating in	Fernando, Chidambaram, and Wahyuni-TD (2018); Queiroz and Telles (2018); Jeble et al. (2018); Khan (2019); Kache and Seuring (2017); Wamba et al. (2020); Dubey et al. (2020)

6. Conclusion

The present study conducted an SLR aiming to synthesise the existing literature on Big Data application in OSCM. Toward this end, we searched two digital databases, Scopus and WoS, to identify studies for inclusion in the review. To ensure a robust selection of studies, we specified and applied stringent inclusion, exclusion, and quality evaluation criteria to select 116 congruent studies. We then proposed and addressed four research questions (RQs). In our response to **RQ1**, we presented the research profile of the selected studies to offer a bird's eye view of the research design and publication details. We addressed **RQ2** by undertaking a content analysis of the studies to extract eight themes that make the extant findings discernable and meaningful. To address **RQ3**, we critically analysed the research profile and themes to reveal gaps in these findings. Finally, in our response to **RQ4**, we identified theme-based potential research questions and developed a conceptual framework (DAB model) for future research based on two theories, namely, dynamic capability theory and organisational information processing theory. In addition, we offered actionable inferences for practice. The contribution of this study is summarised through the theoretical and managerial implications discussed below.

6.1. Theoretical implications

Research on the application of Big Data in OSCM is critical since there are several challenges associated with the successful integration of BDA in any organisation's daily operations. Our SLR creates a comprehensive platform to motivate further research in the area by offering three key theoretical implications: first, it presents the research profile of the congruent studies published in terms of the number of publications each year, average citations per year, the geographic scope of studies, respondent profile, research design, methods of data analysis, theories invoked, and variables examined, including dependent, explanatory, control, mediating, and moderating variables. It further analyses the research profile to uncover patterns and gaps that can be addressed by scholars to ensure theoretical advancement in this domain. Second, the present study has classified the state-of-the-art literature into various logical themes that make it simple for researchers to visualise the varied aspects of Big Data application in OSCM and determine the facets that need to be focused on to offer richer takeaway to the practitioners. The eight themes delineated by the content analysis are dimensions, key sectors and verticals, operational performance, organisational performance management, supply chain capabilities and resilience, supply chain decision-making, sustainability and disaster management, and enablers and barriers. Third, the study proposed a conceptual framework (DAB model) that captures the pre-adoption phase, which comprises the dimensions and avenues for Big Data application that are associated with the firm's BDA adoption intentions. The framework also proposes a post-adoption phase that maps the organisational benefits that accrue after implementing BDA. This framework thus highlights a theoretical view of adopting Big Data in OSCM. We contend that the DAB model can help future researchers understand and investigate various elements of BDA and the capabilities that can affect both pre-adoption intentions and post-adoption satisfaction in terms of supply chain process capabilities and competitive advantages in an uncertain operating environment.

6.2. Managerial implications

The key managerial implications of our findings are: first, the study underscores the fact that the analysis of point of sales, in-store, Google trends, smartphone, and social media data can be used to forecast buying behaviour and sales demand, as discussed by prior studies (e.g. Boone

et al. 2019). In addition, since the availability of one product may affect the demand for others, managers should expand demand forecasting models to integrate multi-product level data while estimating demand for products whose sales are influenced by the availability of other products. Similarly, demand forecasting for brick-and-mortar retail stores can be improved by including more data-related variables, such as the availability of other products, traffic in-store, and store layout, in the forecast model. The current study further suggests that managers should implement the data infrastructure in such a way that it can capture information about multiple products from multiple sources at the same time and also handle a wide variety of semi-structured and unstructured data. Such capabilities can enable firms to harvest and combine data from varied sources to improve forecast accuracy(e.g. Hofmann and Rutschmann 2018). This is particularly relevant for organisations that are increasingly using IoT devices that produce a huge amount of data.

Second, since BDA can help in gaining better insights into consumers' behaviours and needs (e.g. Fernando, Chidambaram, and Wahyuni-TD 2018; Li et al. 2018), Big Data should be expressly exploited by managers to better anticipate customer requirements and to aid in the development of appropriate operational strategies that also provide scope for service innovation. Furthermore, firms can leverage the insights generated from BDA to attract potential customers, strengthen relationships with existing clients, and have better B2B collaborations.

Third, given the ability of BDA to increase supply chain agility, resilience, and stability, managers should focus on developing both the employees' capability (e.g. Giannakis and Louis 2016; Dubey et al. 2018; Mandal 2019) and the IT infrastructure to ensure better coordination. This is crucial as improved coordination can improve synchronisation of operations with BDA and enable firms to respond to changes quickly. Employee capabilities can further be enhanced through training and development, matching tasks to skills, and tracking employee performance.

Fourth, since BDA allows organisations to keep track of suppliers' past performance and spending patterns (e.g. Talluri and Narasimhan 2004), managers should use the generated inputs for better supplier management. Furthermore, they should develop and utilise Big Data capabilities to share real-time data with the firms' suppliers as this would increase transparency and improve relationships between them (e.g. Bag 2017; Roßmann et al. 2018; Mandal 2019).

Fifth, by (a) reaffirming the benefits and competitive advantage that firms can gain from effectively applying Big Data, and (b) revealing how the barriers in terms of data quality, prioritisation, and visualisation can impede the effectiveness of Big Data application, our study underscores the need for organisations to focus extensively on developing the right infrastructure capabilities, which are geared toward processing data to provide insightful business intelligence to decision-makers. Since organisations face challenges related to the integration of BDA in OSCM, we further suggest that managers work toward building a repository of integration issues arising from the use of Big Data and possible solutions for them at the firm level or, better still, at the sector level for future reference. Knowledge about what can go wrong in Big Data integration can benefit managerial decision-making immensely by offering insight into what to avoid and the way forward. Other useful implications are: (a) Managers need to focus not only on implementing Big Data in OSCM but also on the volume, variety, and velocity of Big Data in augmenting supply chain resilience, and (b) Top management should ensure that the HR department has personnel with adequate experience related to hiring and training of functional managers to smoothen the transition of their firms to Big Data-driven OSCM. Furthermore, data officers should be empowered to design the required data governance processes to reduce any security issues.

6.3. Limitations of the study

This SLR synthesised the existing evidence on Big Data from the OSCM perspective to identify research gaps and future research avenues. However, its contribution should be considered in light of three limitations: first, this SLR did not include studies that dealt only partially with the research context, which implies that the extended literature was not considered. Second, book chapters, theses, unpublished articles, short notes, and editorials were excluded from consideration. Such exclusions might have resulted in the loss of some information useful for this review. However, we eliminated them due to the scope-related constraints. Finally, non-English publications were discarded from this study, which could have offered interesting insights.

6.4. Future research direction

The conceptual scope of our SLR is limited to exploring the dimensions, benefits, sectors, enablers, and barriers of application of Big Data in OSCM. Our study synthesises the related literature in a systematic manner to motivate further research. Since BDA uncovers hidden patterns and interesting associations in the data (Birek et al. 2018), the drivers of successful implementation of Big Data in OSCM are important and need to be thoroughly

understood from different perspectives, as argued by recent studies (Siddique et al. 2020). Accordingly, we suggest that researchers expand our work to further enrich the literature by (a) conducting SLRs focused on specific service verticals, such as hospitals and healthcare, as this would yield more granular insights, (b) conducting empirical studies by surveying different companies to strengthen and support the future research agenda, (c) reviewing studies focused on BDA techniques by using keywords, such as Big Data and 'machine learning'; 'predictive analytics', and 'prescriptive analytics', and (d) examining challenges in BDA adoption in developing and emerging economies.

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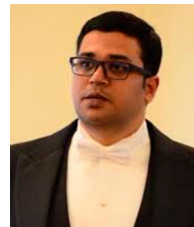
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Disclosure statement

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

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