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On relating big data analytics to supply chain planning: towards a research agenda

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Abstract

Purpose – This paper aims to examine how the extant publication has related big data analytics (BDA) to supply chain planning (SCP). The paper presents a conceptual model based on the reviewed articles and the dominant research gaps and outlines the research directions for future advancement.

Design/methodology/approach – Based on a systematic literature review, this study analysed 72 journal articles and reported the descriptive and thematic analysis in assessing the established body of knowledge.

Findings – This study reveals the fact that literature on relating BDA to SCP has an ambiguous use of BDA-related terminologies and a siloed view on SCP processes that primarily focuses on the short-term. Looking at the big data sources, the objective of adopting BDA and changes to SCP, we identified three roles of big data and BDA for SCP: supportive facilitator, source of empowerment and game-changer. It bridges the conversation between BDA technology for SCP and its management issues in organisations and supply chains according to the technology-organisation-environmental framework.

Research limitations/implications – This paper presents a comprehensive examination of existing literature on relating BDA to SCP. The resulted themes and research opportunities will help to advance the understanding of how BDA will reshape the future of SCP and how to manage BDA adoption towards a big data-driven SCP.

Originality/value – This study is unique in its discussion on how BDA will reshape SCP integrating the technical and managerial perspectives, which have not been discussed to date.

Keywords Big data analytics, Supply chain planning, Supply chain management, Literature review

Paper type Literature review

1. Introduction

Data has never captured as much attention as it currently does. Having emerged rapidly in the last two decades, *big data* and *big data analytics* (BDA) have widely affected the way companies conduct their businesses. The knowledge and insights excavated from the mass amount of data generate competitive advantages for the organisations that master this technological innovation (Gunasekaran *et al.*, 2017; McAfee and Brynjolfsson, 2012; Waller and Fawcett, 2013). There is little doubt that the emergence of big data has an unmistakable impact on the amount and speed of data processed in supply chains.

Supply chain planning (SCP) is a data-driven process that focuses on the activities of developing plans to operate supply chains, translating requirements to feasible programmes and optimising outcomes under given constraints (Supply Chain Council, 2012). Big data and BDA demonstrate significant relevance and applicability to the SCP activities (Brinch, 2018), helping to balance requirements and resources and to determine planned capabilities for

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setting demand forecasts, inventory levels, material location and allocation and production schedules (Stadtler and Kilger, 2005). For instance, Walmart has stretched its demand forecasting to an hourly basis by analysing the customer-generated big data (ProjectPro, 2017). Amazon is piloting the "anticipatory shipping" that moves products close to their customer prior to the order placement (Mitchell, 2015). Recently studies also discussed the use of a BDA-based solution by start-ups to support decision making when facing grand sustainability challenges such as waste prevention in food supply chains (Ciccullo *et al.*, 2021).

Contributions on BDA application in supply chains have been steadily growing over the last decade. A handful of special issues, sections and literature reviews have hit the top-ranking supply chain-related journals elucidating the implications of BDA to the supply chain domain (Table A1). Yet, the extant literature still leaves behind several gaps. Firstly, despite the significance of BDA in SCP, current research often focuses broadly on supply chain management while falling short in providing an overview of how BDA changes the planning activities (Brinch, 2018; Jonsson and Holmström, 2016). Secondly, literature concerning the implementation of SCP-related innovation is scarce (Jonsson and Holmström, 2016). While, according to information system management literature, the adoption of technological innovation involves technological, organisational and environmental dimensions (Baker, 2012; Tornatzky and Fleischer, 1990), the technical advancement of BDA is often isolated from its managerial concerns in extant operations and supply chain literature (Hofmann and Rutschmann, 2018).

Therefore, this paper addresses how BDA will reshape the future supply chains with a specific focus on planning. By means of a systematic literature review, we provide a comprehensive overview of the influence of big data and BDA on SCP looking into the big data sources, objective of BDA adoption and changes to the SCP processes. We then bridge this discussion to the implementation of BDA, revealing how organisations and supply chains can reap the benefit from BDA through the technology-organisation-environment (TOE) framework (Baker, 2012; Tornatzky and Fleischer, 1990). In particular, the following research questions (RQ) will be answered:

RQ1. How do big data and BDA contribute to SCP?

RQ2. What are the factors determining BDA-adoption decisions in organisations and supply chains?

This study joins the conversation on the contribution of BDA to supply chains and the management of BDA adoption in the SCP context concerning endogenous and exogenous factors. In this paper, the BDA adoption is considered as the initial evaluation of the technological innovation (Fichman, 2000; Zhu *et al.*, 2006). While this paper serves managers and policymakers as a reference for understanding the potential and the management levers of BDA adoption in SCP, a research agenda is proposed for further scholarly development in the field.

The remainder of the paper is arranged as follows: section 2 explicates the conceptual background. Section 3 outlines the research design and review methodology; Sections 4 and 5 present respectively the descriptive result and the findings respectively, which are followed by the discussion and a future research agenda in sections 6 and 7.

2. Research background

2.1 Big data and BDA

Due to the high number of records and attributes in business nowadays, data being collected and processed are often large in size (i.e. *volume*), with high speed and frequency of generation and exchange (i.e. *velocity*), which give rise to the potential in elaborating real-time insights (Hofmann, 2017; Russom, 2011; Tiwari *et al.*, 2018). In contrast to traditional systems, big data are collected from a wide range of diversified sources with various perspectives and data formats (i.e. *variety*) (Richey *et al.*, 2016; Russom, 2011).

Applying advanced analytics to big data, *BDA* aims to extract meaningful patterns and insights to inform decision-making (Arunachalam *et al.*, 2018; Wang *et al.*, 2016). In the context of BDA, the data sources are no more limited to *structured* data (e.g. numbers and strings related to transactions) but also encompass *semi-structured* and *unstructured* ones (e.g. texts, audio and video in social media, geospatial information and Internet log) (Dubey *et al.*, 2018). BDA can be classified into descriptive, predictive and prescriptive analytics depending on its scope (Souza, 2014; Wang *et al.*, 2016). *Descriptive analytics* address "what is happening", identifying problems and opportunities; *predictive analytics* answer "what will be happening", forecasting future trends based on the analysis of historical data; while *prescriptive analytics* explain "what should be happening" to optimise business performance by assessing alternative scenarios (Souza, 2014; Wang *et al.*, 2016). The underpinning BDA models extend across classification, regression, clustering, association, visualisation, semantic analysis, graphical analysis, optimisation and simulation (Nguyen *et al.*, 2018).

2.2 Supply chain planning

The competitive advantage of supply chain management is achieved substantially though SCP (Jonsson and Holmström, 2016). SCP involves multiple functional areas where the processes and activities can be broadly distinguished by: (1) the focal supply chain process – that is sales, procurement, production and distribution, and (2) the planning horizon (Mauergauz, 2016; Stadtler and Kilger, 2005). Taking the *supply chain planning matrix* as a reference (Stadtler and Kilger, 2005), the processes in SCP span across *strategic network planning, demand planning, demand fulfilment & ATP, master planning, production planning and scheduling, purchasing and material requirement planning* and *distribution* and *transport planning*. Each of the abovementioned SCP processes comprise a series of sub-activities.

BDA has demonstrated high relevance and applicability to the SCP activities (Brinch, 2018). Advanced analytics, such as forecasting and optimisation techniques, provide fundamental support to demand planning, production planning, inventory plans and logistics planning by improving planning accuracy and flexibility (Russom, 2011; Seyedan and Mafakheri, 2020; Wang *et al.*, 2016).

2.3 Technological innovation adoption

While there is little doubt that BDA has noteworthy business value, not all organisations embracing BDA solutions have observed expected performance improvement (Maroufkhani *et al.*, 2020). The difference mainly lies in how such innovation is incorporated into the organisation, that is the technological innovation adoption process (Cooper and Zmud, 1990; Hazen *et al.*, 2012; Kapoor *et al.*, 2014). One classical framework differentiates the adoption process into three stages: (1) initiation – evaluating the potential benefit, (2) adoption – deciding to use the technological innovation and (3) routinisation – widely integrating the innovation into the organisation's value chain. An alternative view differentiates the stage of pre-adoption and post-adoption, where the latter includes acceptance – steady implementation, routinisation – adjustment in the organisational governance system, and assimilation – full diffusion into organisational functions and processes (Hazen *et al.*, 2012).

Rooted in the innovation diffusion literature, technological innovation adoption studies often rely on the diffusion of innovation (DOI) theory (Rogers, 1983), originally concerns the patterns and stages of innovation diffusion among a network of individuals, and the attributes of innovations. On the other hand, the TOE framework is broadly used in complementary to the DOI theory in explaining drivers, barriers and the context for a wide range of technological innovation adoption in inter-organisational networks (Maroufkhani *et al.*, 2020; Tornatzky and Fleischer, 1990; Zhu *et al.*, 2006).

3. Methodology

This paper adopts the standard process of systematic literature reviews (Seuring and Müller, 2008; Tranfield *et al.*, 2003) while considering the idiosyncrasies of the supply chain domain (Durach *et al.*, 2017). Three macro stages were conducted: (1) planning the review, where RQs are developed and research protocol is discussed and shared among the authors; (2) conducting the review, where *material collection* and *selection* are carried out and *literature analysis* was performed by full-article coding; (3) reporting, where findings are reported in *descriptive analysis* and *thematic analysis* (see Table 1).

3.1 Material collection

A list of search keywords was identified based on the research scope (Durach *et al.*, 2017; Tranfield *et al.*, 2003) consisting of three groups: (1) SCP-related, (2) "big data" and

	Number of articles**
*Material collection**	
Keyword group 1: "supply chain" OR "network design" OR "master planning" OR ("demand planning" OR "demand forecasting" OR "demand fulfilment" OR "demand fulfillment" OR {ATP}) OR (procurement OR sourcing OR purchasing OR "material requirements planning" OR {MRP}) OR (production OR manufacturing OR scheduling) OR (distribution OR logistics OR transport) OR inventory	*S*: 4,817 + *WoS*: 2,407
Keyword group 2: "big data"	
Keyword group 3: management OR planning	
Filter 1: Source type = journals AND Document type = article, review, editorial	*S*: 1,902 + *WoS*: 1,287
Filter 2: Subject area = engineering OR business, management and accounting OR decision sciences OR social sciences	*S*: 1,243 + *WoS*: 1,028
Filter 3: Language = English	1,719***
Material selection	
Step 1: Compliance with Research Topic	346
Step 2: Compliance with Research Objective	169
Step 3: Compliance with Research Questions, limit to contribution from Q1, Q2 journals****	*72*
Literature analysis	
Material selection based on inclusion and exclusion criteria	x
Discussion among authors for inclusion and exclusion of articles	x
Extraction and storage of descriptive information	x
Coding of literature based on the coding scheme	x
Development of framework and future research avenue	x
Incorporation of feedback collected from academic conference and journal review	x
Revision of conceptual framework and future research avenue	x

Note(s): *Keywords are combined by *AND* operator between groups and searched in *title-abstract-keywords*
***S* stands for Scopus, *WoS* stands for Web of Science.
***This number contains 415 papers duplicated in both databases, 698 papers only in Scopus and 606 papers only in Web of Science
****Journal ranking refers to the JCR Impact factor and Quartile published by Clarivate analytics available at: http://manuscriptlab.com/journals/

Table 1. Literature review method and milestones

(3) "management" and "planning". SCP-related keywords originated from the SCP matrix processes (Stadtler and Kilger, 2005) and were then validated with the search query employed in extant review papers on related topics (e.g. Nguyen *et al.*, 2018; Tiwari *et al.*, 2018; Wang *et al.*, 2016). "Management" and "planning" were attached in search of managerial implications in the primary studies. Similarly, the choice of not including other terminologies related to BDA (e.g. artificial intelligence, machine learning) was aimed at focusing on managerial implications rather than diving into the technical aspects in distinguishing the various technologies (Ardito *et al.*, 2019).

The literature collection was performed in two scientific publication databases – Scopus and Web of Science – which show a high literature coverage in science, management and technology disciplines (Lamba and Singh, 2017) from diverse publishers (e.g. Emerald, Science Direct, Wiley). The search was restricted to articles, reviews and editorials in peer-reviewed journals in English to ensure material quality consistency (Arunachalam *et al.*, 2018). Meanwhile, by checking a sample of conference proceedings, we observed that the insightful conference papers typically manage to become journal publications in a more extensive form with limited time lag. We regularly update the paper database during the review (Durach *et al.*, 2017), and the final consolidation in October 2020 resulted in 1,719 articles.

3.2 Material selection and analysis

The selection process adapts the three-step approach by Brinch (2018).

(1) *Step 1, compliance with the research topic.* Articles are screened by title, dissemination outlet and keywords for checking the research scope, removing papers from off-topic disciplines (e.g. urban planning, tourism management, energy transportation). Editorials were removed after careful assessment if they serve as an introduction to research papers with limited original contributions (Lamba and Singh, 2017).

(2) *Step 2, compliance with the research objective.* Based on the abstract and skimmed-through reading, articles were examined if both BDA and supply chain were discussed. Papers were removed if BDA was mentioned solely for future research, or if the focus on supply chain management was very limited.

(3) *Step 3, compliance with the research questions.* In this step, we also limited the scope to contributions from top-ranking journals, referred to as the Q1 and Q2 journals from the JCR ranking 2020. A reading cut was performed to check the contribution of the papers to the RQs, and articles were removed if they presented very limited managerial implications besides technical considerations (see details in Table 1). This process resulted in 72 articles for full-text analysis.

Multiple authors were involved in the selection process to cope with selection bias, and a shared database was used to track the entire selection history of the articles. Any mismatch in the decisions was thoroughly discussed and reviewed among the authors (Durach *et al.*, 2017).

4. Descriptive analysis

4.1 Publication trend

The selected articles show an evident growth over the years with a peak in 2018 (Figure A1), which coincides with the publication of several journal special issues as anticipated in the introduction (Table A1). A few journals dominate the contribution with six papers respectively (i.e. *Production and Operations Management*, *International Journal of Production Research* and *International Journal of Production Economics*), while a long tail is made up of twenty-two journals presenting only one or two publications (Table A2).

4.2 Patterns in research method

Conceptual and theoretical research outweigh the empirical ones among the primary studies (Table 2), which matches the common pattern of new and unexplored research fields (Seuring and Müller, 2008). Forward-looking research is predominant as the adoption of this technological innovation is still sparse. Among the conceptual pieces, *conceptual model or framework*, as the most popular research method, is often applied for presenting theoretical discussions, envisioning potential use-cases and developing conceptual models of BDA architecture (Babiceanu and Seker, 2016). *Analytical models* are mostly used to quantify the potential benefit of BDA in supply chains (Hou *et al.*, 2017). In empirical research, *survey* research takes the lead that is often applied for testifying to the impact of BDA technology and BDA capabilities (Mandal, 2018) on organisational performances (Wamba *et al.*, 2019), while *grounded methods* are commonly used to explore and elucidate the future of BDA in supply chains (Brinch *et al.*, 2018; Roßmann *et al.*, 2018).

4.3 Patterns in the theoretical lens

Table 2 presents the use of theories in the primary studies. The result shows that most articles do not take explicit theoretical perspectives, supporting the discussion in previous studies (Durach *et al.*, 2017). Among the theoretical pieces, the resource-based view (RBV) and dynamic capabilities share the lead. These theories are commonly applied to understand the relationship between BDA capabilities and supply chain performance. For instance, Fosso Wamba and Akter (2019) investigated the impact of supply chain analytics capability on company performance with RBV, under the moderating effect of supply chain agility. Mandal (2018) explored the link between BDA personnel capability (i.e. technical knowledge, technology management knowledge, business knowledge, relational knowledge) and supply chain agility performance with dynamic capabilities. Richey *et al.* (2016) argued that big data constitute a company's dynamic capability by improving organisational responsiveness through reconfiguration and adaption of company resources. The other theory-based studies include Sodero *et al.* (2019) that use the sociotechnical system to investigate BDA, while viewing BDA itself that accommodate technological capabilities; and Roßmann *et al.* (2018) that uses the information processing theory, and states that BDA reduce uncertainty and increase decision-making speed while requiring organisational changes for their successful application.

4.4 Perspective of SCP in literature

We adapted the *unit of analysis* in supply chain literature review (Durach *et al.*, 2017) as the focal process of SCP analysed in the primary studies. Five clusters emerged in the content coding.

Process level refers to the cases when the investigation of BDA is restricted to a single SCP process, or when the discussion on BDA is drawn respectively on single isolated SCP processes even if multiple processes are commented. For instance, Zhong *et al.* (2015) expounded a big data approach to estimate shopfloor manufacturing delivery time, while Boone *et al.* (2018) proposed an analytical model for reducing forecast errors in demand forecasting.

Process level + contains papers that explicitly elucidate implications and interrelationships between diverse processes, while the primary focus is still on a single SCP process. For instance, while exploring offline order prediction with clickstream data and social media comments, Huang and Van Mieghem (2014) and Choi (2018) related the consequence of improved demand planning to superior inventory performance in supply chains.

Organisational level highlights the essence of a cross-functional perspective of SCP. The link between various processes is better clarified, and SCP is considered as a holistic issue

Table 2.
Research methodology and theories adopted in the papers

Method/ Methodology		Conceptual and theoretical contribution					Empirical contribution					Total
		Conceptual model or framework	Analytical model	Literature review	General review	SubTotal	Survey	Grounded method	Simulation	Case study	SubTotal	
Theory	Absent	25	16	8	3	*52*	3	5	3	2	*13*	*28*
	Resource-based view	–	–	–	–	*0*	3	–	–	–	*3*	*3*
	Dynamic capabilities	–	–	–	–	*0*	3	1	–	–	*4*	*3*
	Agent-based system	2	–	–	–	*2*	–	–	–	–	*0*	*2*
	Diffusion of innovation theory	–	–	–	–	*0*	2	–	–	–	*2*	*2*
	Information processing theory	–	–	–	–	*0*	–	1	–	–	*1*	*0*
	Institutional theory	–	–	–	–	*0*	1	–	–	–	*1*	*1*
	Others	1	–	–	–	*1*	1	1	–	–	*2*	*2*
SCP unit of analysis*	Process level	19	6	2	–	*27*	–	–	–	1	*1*	*28*
	Process level +	2	4	4	3	*13*	–	–	–	1	*1*	*14*
	Organisational level	3	–	1	–	*4*	6	3	–	–	*8*	*12*
	Supply chain dyad	–	5	–	–	*5*	2	–	1	–	*3*	*8*
	Full supply chain level	2	–	–	–	*2*	3	4	1	–	*8*	*10*
Sub total		*28*	*16*	*9*	*3*	*56*	*11*	*8*	*3*	*2*	*23*	*79*

Note(s): *If an article exhibits multiple units of analysis, the broader one is considered in this table within the company. For instance, Liu *et al.* (2019) raised a cyber-physical system-based big data model to simultaneously support decisions in smart manufacturing, intelligent logistics and in-shop service. Dubey *et al.* (2019) investigated big data capabilities required taking an organisational standpoint.

Supply chain dyadic level considers a specific dyad in the supply chain when investigating the SCP problem. Hofmann (2017) assessed the impact of three big data dimensions on the bullwhip effect, considering a supply chain of one retailer and one manufacturer.

Holistic supply chain level emphasises the complexity of multiple supply chain relationships. For instance, Kache and Seuring (2017) investigated the challenges and opportunities of BDA in supply chain management treating the supply chain as an integrated system consisting of multiple partners. Giannakis and Louis (2016), viewing SCP as a cross-organisational activity, denoted the implications of BDA in collaborative planning.

Intersecting with the research methodology, conceptual and analytical modelling has the tendency to take a process-specific or relationship-focused view, while empirical studies, such as survey and grounded methods, are more developed under a holistic perception of supply chains (Table 2). Although literature on relating BDA to supply chains often views SCP processes in functional silos, there is an emerging trend to emphasise the interrelations between multiple SCP processes.

5. Findings

5.1 Perspective of big data and BDA in supply chain research

When it comes to big data terminologies, supply chain literature has the tendency to take them for granted without providing explicit definitions. We found the primary studies refer to *big data* in the following sense:

(1) the *dimensions* a dataset must exhibit that differentiate it from the traditional ones (in 20 papers). These dimensions are typically referred to as the "*V*"s of big data, ranging from volume, variety and velocity (e.g. Boone *et al.*, 2019; Hou *et al.*, 2017; Nguyen *et al.*, 2018) to veracity (Richey *et al.*, 2016; Sodero *et al.*, 2019) and value (Fosso Wamba and Akter, 2019; Lai *et al.*, 2018; Nguyen *et al.*, 2018; Yu *et al.*, 2018). These features of big data exceed the management and processing capability of traditional data systems, thus presenting substantial *challenges*.

(2) the *abilities* and *attempt* to manage and process large and complex datasets (Mandal, 2018; Wang *et al.*, 2016) leading to value creation and development of competitive advantage. The technological capabilities and the ability to manage data pools and validation tools are some of the examples (Sodero *et al.*, 2019).

(3) a new *paradigm* of computing that involves the entire span of activities to extract knowledge from the fast, diverse and massive amount of data, comprising data collection, processing and analysis (Lee *et al.*, 2018).

The lack of consensus in the use of terminologies, together with the constant evolution of the concepts, has made it difficult for supply chain researchers to agree on a common boundary (Barbosa *et al.*, 2017). Hence, drawing on the extant literature, we attempt to propose the following definitions in seeking to develop a coherent use of terminologies in future studies:

(1) *Big data for supply chains* are extremely large (i.e. volume) information assets that are continuously generated from diversified sources (i.e. velocity) and not restricted by the format (i.e. variety). While exceeding the capturing, storage, handling and analytical capability of traditional systems, they hold fact-based actionable knowledge and insight (i.e. value, veracity) for supply chain decision-making.

(2) *BDA for supply chains* are the application of advanced analytic models and techniques on big data with the aim of extracting valuable knowledge and insight, by identifying trends, detecting patterns, assessing scenarios and gleaning invaluable information to facilitate data-driven supply chain decision-making.

5.2 Research on big data and BDA application in SCP process

Big data and BDA can be applied to various SCP processes and activities with different scope (Table 3).

5.2.1 Demand planning and fulfilment. BDA employs user-generated big data (e.g. product review, user data, search data) to understand the pattern in purchasing decision from final consumers (Boone *et al.*, 2019; Hou *et al.*, 2017; Lau *et al.*, 2018; See-To and Ngai, 2018). Analysis of data from social media (Choi, 2018), point of sales (Boone *et al.*, 2019), query (Bertsimas *et al.*, 2016; Papanagnou and Matthews-Amune, 2018) and clickstream (Huang and Van Mieghem, 2014) helps to improve mid-term sales and demand forecasting accuracy and flexibility, and thus, informs inventory decisions and enhances agility in highly uncertain contexts (Ren *et al.*, 2019). For online product sales, the use of sentiment and neural network analysis on customers' reviews (Hou *et al.*, 2017; Lau *et al.*, 2018), user characteristics (Hou *et al.*, 2017), product-level customer reviews (See-To and Ngai, 2018) and search keywords (Boone *et al.*, 2019) help to improve forecasting accuracy (Hou *et al.*, 2017; Lau *et al.*, 2018), reduce out-of-sample forecast error and support *available to promise* (See-To and Ngai, 2018).

5.2.2 Purchasing and material requirement planning. Supplier selection in long-term purchasing planning benefits from the wide range of non-traditional sources that BDA can handle (e.g. news data, supplier option and alternatives) (Maghsoodi *et al.*, 2018). Moreover, sustainability attributes can be fully integrated into the decision-making process of materials programme planning and supplier selection (Gholizadeh *et al.*, 2020) when BDA is introduced.

5.2.3 Production planning and scheduling. BDA in production planning is rather mature compared to the other processes, justified by a higher rate of models and algorithms proposed and tested. Owing to the high velocity of big data, research has mainly focused on improving short-term production planning sensors and RFID-equipped smart objects collect mass real-time data from the shop floor and manufacturing processes that can be used to identify potential bottlenecks, predict cycle time, perform dynamic production scheduling and manage shop floor material flows (Zhong *et al.*, 2015).

5.2.4 Distribution and transport planning. BDA supports distribution planning primarily in short-term planning. Through the use of local and network data (Ilie-Zudor *et al.*, 2015), information on weather and traffic condition (van der Spoel *et al.*, 2017), transport planning gains higher efficiency and transparency where predictive analytics can even forecast arrival time for individual trucks.

5.3 Response to RQ1: three distinctive roles of big data and BDA

Big data and BDA influence SCP based on three distinctive roles – *supportive facilitator, source of empowerment* and *game-changer* – which differ from each other by the following dimensions: (1) *what type* of big data can be introduced to support SCP (i.e. source of big data), (2) *why* integrate BDA for SCP (i.e. objective of adoption) and (3) *how* BDA can be integrated in existing SCP processes (i.e. changes to SCP).

BDA as *supportive facilitator* in SCP primarily aims to assist and facilitate improvement in extant SCP processes which consequently improves SCP performance (Gunasekaran and Ngai, 2004), such as demand forecasting accuracy (Andersson and Jonsson, 2018; Hou *et al.*, 2017), production and transportation planning efficiency (Wu *et al.*, 2018; Zhong *et al.*, 2017) and effectiveness of ordering decisions in spare parts inventory management system (Zheng and Wu, 2017). These BDA initiatives overcome the limitations of traditional systems, often

Table 3. Paper distribution by SCP process

Supply chain process	SCP process	SCP activity	Horizon	# Articles	Big data source**			BDA scope***		
					Structured	Semi-structured	Unstructured	Descriptive	Predictive	Prescriptive
Cross-functional	Strategic network planning	Physical distribution structure	Long-term	*0*	–	–	–	–	–	–
		Plant location and production system	Long-term	*0*	–	–	–	–	–	–
Sales	Demand planning	Product program and strategic sales planning	Long-term	*0*	–	–	–	–	–	–
		Mid-term sales planning	Mid-term	*9*	2	2	9	–	8	2
		Spare parts demand planning*	Mid-term	*3*	2	2	1	1	3	–
		Inventory planning*	Varies	*7*	1	2	7	–	5	2
	Demand fulfilment and ATP	Short-term sales planning	Short-term	*3*	1	1	2	–	3	1
	Not specified		–	*2*	2	2	2	–	1	–
Procurement	Purchasing and material requirement planning	Materials program and supplier selection	Long-term	*2*	–	1	1	–	1	1
		Material requirement planning	Mid-term	*1*	1	1	–	–	–	1

(*continued*)

Table 3.

Supply chain process	SCP process	SCP activity	Horizon	# Articles	Big data source** Structured	Semi-structured	Unstructured	BDA scope*** Descriptive	Predictive	Prescriptive
Production	Master planning	Master production scheduling and capacity planning	Mid-term	*1*	–	1	–	–	–	1
		Personnel planning	Mid-term	*0*	–	–	–	–	–	–
	Production planning and Scheduling	Lot-sizing, machine scheduling and shop floor control	Short-term	*15*	5	14	6	1	9	5
		Short-term personnel planning	Short-term	*1*	–	1	1	1	1	–
	Not specified		–	*1*	–	–	–	–	1	–
Distribution	Distribution and transport planning	Distribution planning	Mid-term	*0*	–	–	–	–	–	–
		Warehouse replenishment	Short-term	*0*	–	–	–	–	–	–
		Transport planning	Short-term	*4*	1	2	3	–	2	2
Generic or not specified			–	*29*	2	2	3	4	11	6
	*Total**			*78*	*17*	*31*	*35*	*8*	*44*	*21*

Note(s): *One article may cover more than one SCP process or having no specific focus on any SCP process (i.e. Generic or not specified)
**One article may refer to more than one big data source or not specifying the big data source
***One article may refer to more than one BDA scope or not specifying the BDA scope

targeting the short- or mid-term, and are capable of collecting, storing and processing richer and more granular data stemming from diversified sources. They could be attained in parallel with extant planning processes to affirm planning decisions or as add-on modules to extend existing planning capacities.

BDA as *source of empowerment* in SCP enable new processes and capabilities in SCP processes compared to traditional planning systems, empowering decisions such as short-term ATP for fast delivery programmes, internal process improvements, sourcing strategy analysis and supplier evaluation and negotiation (Gholizadeh *et al.*, 2020). Most sources of these big data that are new to the SCP (e.g. weather forecast, supplier performance and customer purchasing behaviour) are used to enable process-oriented improvements, such as reducing dependency on forecasting performance (Boone *et al.*, 2019), acquiring higher flexibility and improving the speed and frequency of the decision-making process (Hofmann, 2017).

Finally, BDA as *game-changer* target radical changes to SCP by integrating new objectives with significant strategic implications in parallel to the traditional planning goals, such as risk detection (Nguyen *et al.*, 2018), disruptions management in global supply chains (Boone *et al.*, 2018), uncertainty-oriented capability development (Wang *et al.*, 2016) and flexibility and agility reinforcement (Fosso Wamba and Akter, 2019; Giannakis and Louis, 2016). A handful of literature has unfolded the link of BDA to sustainable supply chain management (Ren *et al.*, 2019; Singh and El-Kassar, 2019), not limited to the enhancement of energy efficiency (Feng and Shanthikumar, 2018). The integration of the additional goals to extant SCP leads to more complex, multi-objective planning problems, and a range of new data sources must be introduced (e.g. social network data, customer reviews, product lifecycle information). The initiative of game-changer in SCP should be a long-term endeavour that requires full integration of BDA into the existing planning process and practices, extending active coordination and collaboration to the entire supply chain.

5.4 Response to RQ2: the determining factors

The determining factors are identified and classified into the TOE framework (Baker, 2012; Tornatzky and Fleischer, 1990) together with the examples from the primary studies (Table 4). For survey-based papers, we also highlighted if the factor was supported in the original paper. The application of the TOE framework shows that, besides technological ones, also the organisational and environmental factors are also relevant drivers of BDA adoption in SCP.

Technological factors include *relative advantage*, *compatibility* with the current system, *complexity*, *trialability*, *observability*, *stability* and *availability of the technology*, as well as *data quality*. When the implication from extant business cases is unclear or no particular benefit is interpreted, and the *complexity* of the BDA technology is high, organisations will experience reluctance in adopting BDA for SCP (Kache and Seuring, 2017; Richey *et al.*, 2016). However, existing literature shows conflict results in assessing the impact of relative advantage and technology complexity.

Organisational factors cover organisational structure, readiness, strategy and competence at both organisation and personnel level. *Organisational structure* and *supply chain structures* affect BDA adoption decision in terms of organisational complexity (Lamba and Singh, 2018; Sodero *et al.*, 2019). *Organisational readiness* refers to the preparedness of an organisation to accept the technological innovation from the cultural, managerial, financial and human resource perspectives (e.g. top management commitment, presence of slack human resources) (Dubey *et al.*, 2019; Lamba and Singh, 2018). BDA adoption should also seek appropriate *organisational competence,* which stands for BDA knowledge, big data management capabilities and current IT system in place on a company level (Kache and Seuring, 2017; Lai *et al.*, 2018; Queiroz and Telles, 2018), and BDA technical knowledge, BDA technology

Table 4.
Factors affecting BDA adoption in SCP

Factors	Definition and reference	Example and measures	Reference
Technological			
Relative advantage of BDA	The degree to which BDA is perceived as being better than the idea it supersedes to provide benefits such as cost reduction, operation improvement and marketing performance (Lai *et al.*, 2018; Gunasekaran *et al.*, 2017)	Relative advantage***	Maroufkhani *et al.* (2020)
		Improved decision making; Operational efficiency	Richey *et al.* (2016)
		Awareness of BDA benefit	Queiroz and Telles (2018)
		Perceived benefit*	Lai *et al.* (2018)
		Unclear business case or value; No need/not necessary/no benefit	Schoenherr and Speier-Pero (2015)
BDA technology complexity	The degree to which BDA can be regarded difficult to be understood and used for the organisation. (Lai *et al.*, 2018; Roger, 1983)	BDA complexity*	Maroufkhani *et al.* (2020)
		Technology complexity***	Lai *et al.* (2018)
		(challenge of) Data storage; (need of) Climbing the learning curve One version of truth (single integrated system, usability);	Richey *et al.* (2016)
		Difficult to manage; Inability to make sense of available data	Schoenherr and Speier-Pero (2015)
		Information (complexity) management	Kache and Seuring (2017)
BDA technology compatibility	The degree to which BDA is perceived as being compatible to current information system and consistent with the existing values (Lai *et al.*, 2018)	BDA compatibility***	Maroufkhani *et al.* (2020)
		Data scalability	Arunachalam *et al.* (2018)
		Lack of integration with current systems	Schoenherr and Speier-Pero (2015)
BDA trialability	The degree to which BDA may be experimented with (Lai *et al.*, 2018; Fosso Wamba *et al.*, 2016)	BDA trialability	Maroufkhani *et al.* (2020)
BDA observability	The degree to which the results of BDA are visible to the organisation (Lai *et al.*, 2018; Fosso Wamba *et al.*, 2016)	BDA observability	Maroufkhani *et al.* (2020)
Big data quality	The degree to which the data needed for BDA are accessible, consistent, and complete, and is integrated between the data collected (Lai *et al.*, 2018; Rai *et al.*, 2006)	Data quality	Arunachalam *et al.* (2018)
		Data quality**	Lai *et al.* (2018)
		Lack of data	Schoenherr and Speier-Pero (2015)
		Data pools (data acquisition); Validation tools	Sodero *et al.* (2019)
		Dealing with data growth and amount of accessible data	Yudhistyra *et al.* (2020)
BDA availability and stability	The degree to which BDA is stable and available (or already in use) both internally and externally (Baker, 2012; Oliveira and Martins, 2011)	BDA uncertainty*	Maroufkhani *et al.* (2020)
		Lack of techniques and procedures	Arunachalam *et al.* (2018)
		Lack of appropriate solutions for SCM; Current applications unable to meet business needs	Schoenherr and Speier-Pero (2015)
		Availability for real-time analysis	Yudhistyra *et al.* (2020)

(*continued*)

Table 4.

Factors	Definition and reference	Example and measures	Reference
Organisational			
Organisational readiness	The organisational preparedness for adopting the BDA change (Lai *et al.*, 2018; Hameed and Arachchilage, 2016)	Organisational culture and change management (e.g. data-driven culture, mindset of employee towards new system, transformational change management, culture change management, organisational resistance, entrepreneurial orientation)	Arunachalam *et al.* (2018), Dubey *et al.* (2019), Dutta and Bose (2015), Kache and Seuring (2017), Lamba and Singh (2018), Schoenherr and Speier-Pero (2015), Yudhistyra *et al.* (2020), Dubey *et al.* (2020)
		Top management support*	Lai *et al.* (2018), Maroufkhani *et al.* (2020)
		Top management support (or, top management commitment, top management involvement)	Lamba and Singh (2018), Richey *et al.* (2016), Schoenherr and Speier-Pero (2015), Sodero *et al.* (2019)
		Financial readiness***	Lai *et al.* (2018)
		Financial support and investment	Kache and Seuring (2017), Lamba and Singh (2018), Queiroz and Telles (2018)
		Slack (human) resource (e.g. talent management and HR, Organisations' talented professionals, human capital)	Kache and Seuring (2017), Queiroz and Telles (2018), Richey *et al.* (2016)
Organisational competence	The internal competence of the organisation in adopting the BDA change (Oliveira and Martins, 2011)	Personnel level competence (e.g. human skill, lack of skill, technical knowledge business knowledge, relational knowledge, employees are inexperienced, technological capabilities)	Arunachalam *et al.* (2018), Dubey *et al.* (2019), Mandal (2018), Schoenherr and Speier-Pero (2015), Sodero *et al.* (2019)
		Organisational-level competence (e.g. tangible resources, BDA skill and knowledge, company's IT tool unitization, data generation capability, data integration capability, advanced analytics capability, inability to identify most suitable data, IT capabilities and infrastructure)	Dubey *et al.* (2019), Lamba and Singh (2018), Queiroz and Telles (2018), Arunachalam *et al.* (2018), Schoenherr and Speier-Pero (2015), Kache and Seuring (2017)
		IT infrastructure and capabilities***	Lai *et al.* (2018)
Organisation strategy	The business strategy at the organisational level that deal with the adoption of BDA technology	Business strategy and objective	Kache and Seuring (2017)
		Company's projects to use BDA in short term; Company's BDA utilization in LSCM; Company's formal strategies to SCM innovation	Queiroz and Telles (2018)
Organisational structure	Organisational structure intends for organisational size, stability, business scope, interconnectedness, presence of slack resources (Russel and Hoag, 2004; Baker, 2012)	Organisational structure	Lamba and Singh (2018), Schoenherr and Speier-Pero (2015)
		Organisational complexity	Sodero *et al.* (2019)

(*continued*)

Table 4.

Factors	Definition and reference	Example and measures	Reference
Supply chain structure	The possibility to gather and deliver information within organisations through some information technologies that facilitates the cooperation and coordination between supply chain members (Lai *et al.*, 2018)	SC integration (governance and compliance, integration and collaboration, SC connectivity, SC system integration, partner transparency, coordination)	Kache and Seuring (2017), Lai *et al.* (2018), Richey *et al.* (2016), Sodero *et al.* (2019), Yu *et al.* (2018), Wamba *et al.* (2019), Fosso Wamba and Akter (2019)
		SC agility (e.g. SC agility, SC adaptability, responsiveness)	Wamba *et al.* (2019), Yu *et al.* (2018)
		SC capability (e.g. SC management capability, SC technology capability, SC talent capability, SC analytics capability)	Fosso Wamba and Akter (2019)
Environmental			
Security and privacy concerns on BDA	The degree to which organisations concern about privacy invasions and security risks in the use of BDA technology. (Accenture; Salleh *et al.*, 2015)	Privacy and security concern; privacy of the data; IT concern; Risk and security governance; Information and cyber security;	Arunachalam *et al.* (2018), Yudhistyra *et al.* (2020); Kache and Seuring (2017), Queiroz and Telles (2018), Richey *et al.* (2016), Schoenherr and Speier-Pero (2015)
BDA adoption of competitors	The degree to which organisations perceive pressure from business competitors on using BDA technology to maintain competitive (Lai *et al.*, 2018)	BDA adoption of competitors* Competitive pressure***	Lai *et al.* (2018) Maroufkhani *et al.* (2020)
Regulatory environment	The administrative and regulatory environment where the organisation operates, which can be both pressure or support in government policies (Lai *et al.*, 2018; Baker, 2012; Oliveira and Martins, 2011)	Government policy and regulation* High degree of regularity*** Lack of policies and governance structure	Lai *et al.* (2018) Maroufkhani *et al.* (2020) Schoenherr and Speier-Pero (2015)
Presence of BDA service providers	The degree to which it presents BDA service providers and other third-party vendors in the market when most organisations are still unable to build and maintain the technology in-house (Baker, 2012)	Market's talented professionals Cost of currently available solutions	Queiroz and Telles (2018) Schoenherr and Speier-Pero (2015)

Note(s): *indicate measures result as *supported*, **indicate measures result as *supported by not significant*, ***indicate measures result as *not supported* management knowledge, business knowledge and relational knowledge (Arunachalam *et al.*, 2018; Dubey *et al.*, 2019; Mandal, 2018) at a personnel level.

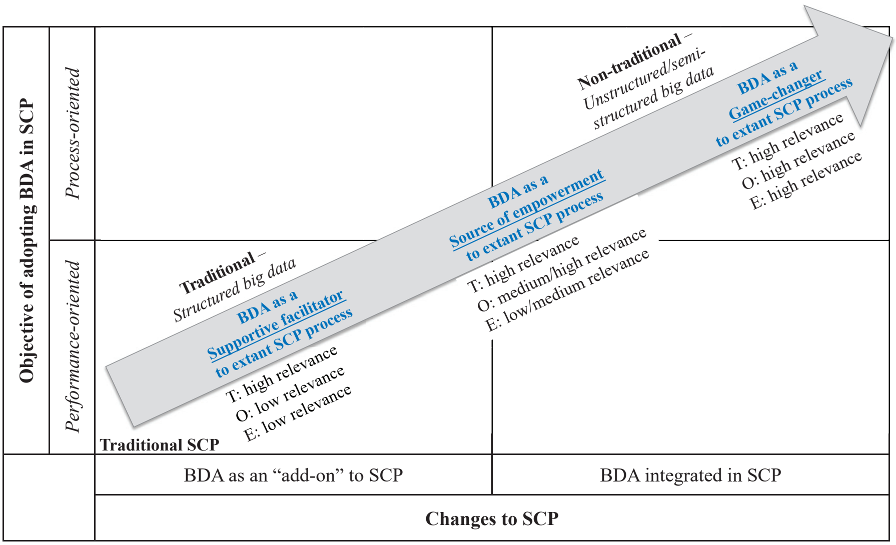
Environmental factors consider the general operational context external to the organisation, where *security and privacy concerns* (Kache and Seuring, 2017; Queiroz and Telles, 2018) and the *presence of BDA service providers* (Schoenherr and Speier-Pero, 2015) are outlined. Meanwhile, *BDA adoption of competitors* and the *regulatory environment* potentially trigger or prohibit the diffusion of BDA in industry depending on the incentive (Lai *et al.*, 2018; Schoenherr and Speier-Pero, 2015).

6. Discussion and research agenda

6.1 Implications from the roles of big data and BDA in SCP

There is little doubt that the technological advancement of BDA substantially drives its application. Data quality, data availability and technological peculiarities have a significant influence on the relative advantage that BDA can bring in comparison with the existing SCP processes. However, in addition to the organisational and environmental aspects, the determining factors for BDA adoption decision differ depending on the role that big data and BDA play in SCP (Figure 1).

As a *supportive facilitator*, BDA solutions are either internally developed or acquired to stimulate evolvement of existing SCP processes for better performance (Schlegel *et al.*, 2020). Technological capabilities are vital for the effective use of the emerging technology (Sodero *et al.*, 2019), including the extraction and cleansing of the desired data from the organisation's system (Sodero *et al.*, 2019), and for coping with the high volume of data (Lai *et al.*, 2018). Data preparation, automated dashboard and data visualisation are typically standard descriptive BDA solutions (Schlegel *et al.*, 2020) that can be acquired directly from the market. With a relatively low maturation level in the journey towards BDA-driven SCP, they require the least integration across supply chain functional areas (Jonsson and Holmström, 2016) where organisational and environmental factors are not the central concern of the adoption decision.



Note(s): *T = technological factors, O = organizational factors, E = environmental factors*

Figure 1.
The role of BDA in SCP

BDA solutions as *source of empowerment* require the integration of new data sources and new processes – for example supply chain partners integration (Richey *et al.*, 2016) and cross-functional planning (Schlegel *et al.*, 2020), individualization and tracking of the material flow (Jonsson and Holmström, 2016) – as combinatorial interventions to the extant processes and systems. In order to allow the enabling mechanisms to extend the capability and scope of SCP (Jonsson and Holmström, 2016), and unfold its value in more dynamic and complex situations (Schlegel *et al.*, 2020), it is necessary to develop a favourable data-driven culture with a precise understanding of the business problem and appropriate top management support (Dutta and Bose, 2015). The presence of clear norms and values towards supply chain information sharing (Roßmann *et al.*, 2018), availability of technology partners and the regulatory environment are of significant importance to ground domain knowledge in the ad hoc BDA solutions in order to integrate the new processes and data sources to the specific operational context (Feng and Shanthikumar, 2018; Schoenherr and Speier-Pero, 2015; Sodero *et al.*, 2019).

BDA as a *game-changer* assist strategic turnaround based on the reconsideration of organisations and supply chain strategy and processes, resulting in the adaptation of the SCP objectives. Instant coordination of changes along supply chain activities (Jonsson and Holmström, 2016) and efficient decision-making on sustainability issues (Wang *et al.*, 2016) are examples of technological innovations that bring the scope of SCP beyond its current level. These initiatives require the rethinking of the strategic alignment of BDA solution and SCP scope where all TOE dimensions act as strategic levers. While companies may decide to outsource the unfamiliar technological activities to professionals, for example development of BDA solutions concerning the tools for data collection and analysis, the management issues as well as the integration process cannot be outsourced (Lai *et al.*, 2018). Decision recommendations and cross-functional impact assessment by BDA should be based on SCP processes and activate redesign, to appropriately reflect the new objectives (Schlegel *et al.*, 2020). The lack of organisational support and human inaction will leave the decision making for value creation "continued reflecting [on] existing, pre-established goals" even if the underpinning technology changes (Sodero *et al.*, 2019). Issues on data security and data ownership will also become obvious when it comes to necessary data sharing in supply chains (Richey *et al.*, 2016).

6.2 Towards a research agenda

6.2.1 Developing comprehensive knowledge on the impact of big data and BDA on SCP. While our study highlights that BDA can contribute to SCP in various forms, three major research gaps are revealed. Firstly, extant literature has mainly covered BDA application in a few SCP processes, while how BDA can support other SCP processes is underexplored. Secondly, current research primarily leverages on big data to achieve short-term oriented improvements, owing to its breakthrough in granularity and timeliness. Despite its contribution to the tactical SCP activities, current knowledge falls short in understanding how BDA influences strategic planning decisions focusing on the mid- to long-term, and whether the long-term benefit is simply the accumulation of short-term improvements. Lastly, on relating to BDA, extant literature commonly assumes SCP in functional silos involving single organisations and planning processes. Research needs to clarify how BDA will transform SCP as a holistic process that extends across the boundary of multiple organisations.

Future research should firstly consider the development of conceptual and empirical pieces in investigating how BDA can be applied to support mid- to long-term planning processes (e.g. capacity planning, plant location, supply network planning), potentially integrated with related technologies (e.g. artificial intelligence, IoT and cyber-physical systems).

(1) *How can BDA assist planning decisions of plant location?*

(2) *How can BDA outperform existing methods in capacity planning?*

With regards to the supply chain level, future research may delve into the implication of BDA in collaborative SCP and the coordinating planning actives at the boundary of organisations. The focus can range from the clarification of applications to the assessment and quantification of expected benefit.

(1) *How do BDA create shared value for supply chain partners?*

(2) *How to manage the coordination of BDA-enabled anticipatory shipping?*

Lastly, studies are needed to further elucidate the three roles of big data and BDA developed in this research, thus presenting examples and discussions on BDA in assisting, empowering and radically changing the traditional SCP processes. Future studies should specify the objective of BDA adoption, the consideration of big data sources and how integration to the existing processes can be orchestrated.

(1) *How can BDA support the integration of sustainability considerations in SCP?*

6.2.2 Defining the roadmap towards successful BDA adoption for SCP and supply chains. The research field to date is dominated by contributions discussing the technical aspects of BDA in supply chains (Tiwari *et al.*, 2018). Most studies focus on the pre-adoption stage, neglecting how organisations and supply chains manage the phases from adoption onwards (Hazen *et al.*, 2012; Zhu *et al.*, 2006). Practitioners struggle with the implementation of BDA in a SCP context to generate desired outcomes (Jonsson and Holmström, 2016; Schlegel *et al.*, 2020). Despite the fact that a wide range of determining factors for BDA adoption decisions have been researched, it is not clear how they affect the adoption mechanism and how they may interrelate with the distinctive roles of BDA in SCP. Thus, future research is left with ample space to crystalise the adoption and implementation process (Schlegel *et al.*, 2020). The following research directions could address these issues:

Firstly, with a particular focus on a single organisation, empirical research may explore the mechanism of how the factors influence BDA adoption decisions for each role of BDA. We have highlighted the relevance of the TOE factors on a categorical level, while, in connection with the three roles, future work may also explore the hierarchical or casual relationships among the individual factors.

(1) *How do the determining factors affect BDA adoption in the context of supportive facilitator, source of empowerment and game-changer?*

(2) *How do BDA adoption determining factors contribute to the development of tangible, human-related and intangible BDA capabilities?*

Moreover, it is necessary to establish a BDA technology adoption roadmap for SCP, elucidating the behavioural aspects on how organisations react and interact during the post-adoption of the technological innovation. As empirical research is scarce on BDA implementation, especially in specific contexts (Jonsson and Holmström, 2016; Schlegel *et al.*, 2020), future studies may highlight the paths of transformation for organisations and supply chains into a BDA-driven SCP paradigm, scrutinising how such transformation may relate to the development of tangible, human-related and intangible BDA capabilities (Schlegel *et al.*, 2020).

(1) *How do strategies, processes, systems and people in supply chains adapt with a view to BDA adoption for SCP?*

(2) *How does the behavioural aspect work in the BDA adoption process for different roles of BDA in SCP?*

(3) *How do BDA capabilities interact with the BDA adoption process?*

Finally, taking a holistic view of supply chains, it is possible to develop research in addressing the multi-stakeholder perspective on BDA adoption in SCP, addressing, for example: *What are the potential synergies and conflicts among the supply chain actors in the management of BDA adoption?*

7. Conclusion

This study presents a systematic literature review to establish a holistic overview on relating BDA to SCP from prior publications. It reveals the contributions of BDA on SCP and the factors determining the adoption decision of this technology innovation. We synthesised definitions for big data and BDA in the supply chain domain in search of a consensus on big data-related terminologies in future supply chain literature. As extant research on relating BDA to SCP mostly focuses on short-term oriented planning problems in isolation, our study questioned the relevance of BDA for long-term SCP activities. Moreover, we argued that, to make effective use of BDA in SCP, it not only requires strong technical infrastructures but also appropriate BDA adoption management actions concerning the organisational and environmental changes. Successful BDA adoption management for SCP should follow a long-term, inter-organisational perspective, orchestrating the determining factors of BDA adoption once the scope of BDA has been clarified.

The theoretical contribution of this paper is mainly threefold. Firstly, it shows that big data and BDA can be used to improve the SCP performance, i.e. with the role of *supportive facilitator* or *source of empowerment*, but can also be leveraged to determine a radical innovation in the supply chain, i.e. when it plays the role of *game-changer,* by enabling SCP to be guided by new objective functions, for example environmental sustainability, or be the compass of the supply chain in case of disruptions. Secondly, it endeavoured to show that the BDA adoption decision is mainly driven by technological factors only when the aim is to improve SCP performance. Organisational and environmental dimensions instead play a determinant role in ensuring that BDA is adopted to reach radical innovation, thus showing the relevance of managerial concerns over technological ones when it comes to extracting value from the adoption of technology innovations. Lastly, this paper has identified several research directions to be addressed by future research.

This work has some limitations. While the material collection and selection process aimed to be inclusive and representative, it may still fail to capture some relevant contributions. Firstly, the explicit search of "big data" in the primary studies could result in omitting relevant papers that coined the technology differently. For instance, artificial intelligence, machine learning, IoT, digital twin and cyber-physical systems all overlap somewhat with what we referred to as big data. The inclusion of these additional keywords could result in an expansion of the journal base. Moreover, we deliberately concentrated on journal papers targeting quality research, while this choice could have led to discarding some recent discussions from conferences. However, despite the potential shortcomings, we still believe that our study offers an accurate and distinctive angle to the existing work while stimulating future conversations on relating BDA to SCP.

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Appendix

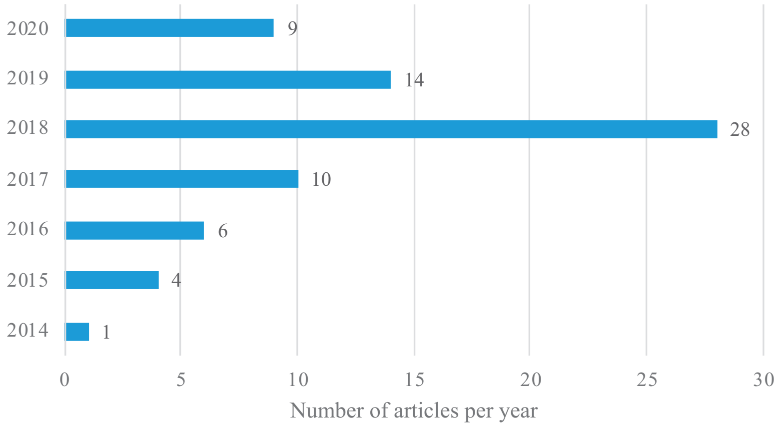

Figure A1.
Paper distribution by year of publication

Table A1.
List of relevant special issues and sections, and relevant literature reviews

Journal	Year	Issue – Volume	Topic
Special issues and sections			
International Journal of Production Economics	2015	*vol. 165*	Big data for Service and Manufacturing Supply Chain Management
Computers and Industrial Engineering	2016	*vol. 101*	Big data and Predictive Analytics Application in Supply Chain Management
Production Planning and Control	*2017*	*vol. 28, issue 11–12*	Big data and analytics in operations and supply chain management: managerial aspects and practical challenges
International Journal of Logistics Management	2018	*vol. 29, issue 2*	Big data analytics in logistics and supply chain management
Production and Operations Management	2018	*vol. 27, issue 10*	Big data in supply chain management
Annals of Operations Research	2018	*vol. 270, issue 1–2*	Big data analytics in operations and supply chain management
Transportation Research Part E: Logistics and Transportation Review	2018	*vol. 114*	*(special section)* Big data analytics and application for logistics and supply chain management

Reference	Summary and main focus
Literature reviews of BDA in supply chain management domain	
Wang *et al.* (2016)	Review of supply chain analytics (SCA, defined as application of BDBA on logistics and supply chain management) applications on the nature of analytics and focus of SCA. A maturity framework of SCA is proposed
Addo-Tenkorang and Helo (2016)	Review of big data and its application in operations and supply chain management, shedding lights on the trends and perspectives in the research area

(*continued*)

Reference	Summary and main focus
Lamba and Singh (2017)	Review of big data integration in operations and supply chain management focusing on the key areas of application . Managerial implications and challenges are revealed
Nguyen *et al.* (2018)	Review of BDA application in supply chain management focusing on the application field (area of supply chain management) and technical perspective (i.e. level of analytics, types of BDA models and BDA techniques applied)
Tiwari *et al.* (2018)	Review of extant supply chain analytics (SCA, defined as big data analytics in supply chain management) applications according to the supply chain management areas, as well as the application of BDA in different types of supply chains
Arunachalam *et al.* (2018)	Review of BDA capability in the supply chain management domain, highlighting the dimensions of BDA capabilities maturity and the key elements
Brinch (2018)	Review of the value of big data in supply chain management from business process perspective. The author developed a big data SCM framework concerning the value dimensions on value discovery, value creation and value capture
Chehbi-Gamoura *et al.* (2019)	Review of the application of BDA in supply chain management focusing on the BDA method and BDA techniques

Table A1.

Paper distribution by journal	Impact factor	JCR quartile	Count
Production and Operations Management	2.590	Q2	6
International Journal of Production Research	4.577	Q1	6
International Journal of Production Economics	5.134	Q1	6
International Journal of Logistics Management	3.325	Q2	5
Transportation Research Part E: Logistics and Transportation Review	4.690	Q1	4
Computers and Industrial Engineering	4.135	Q1	4
Production Planning and Control	3.605	Q1	3
Annals of Operations Research	2.583	Q2	3
International Journal of Physical Distribution and Logistics Management	4.744	Q1	3
Sustainability	2.579	Q2	3
Computers and Operations Research	3.424	Q2	2
Computers in Industry	3.954	Q1	2
International Journal of Advanced Manufacturing Technology	2.633	Q2	2
IEEE Access	3.745	Q1	2
Journal of Cleaner Production	7.246	Q1	2
Technological Forecasting and Social Change	5.846	Q1	2
International Journal of Operations and Production Management	4.619	Q1	2
Industrial Management and Data Systems	3.329	Q2	1
Benchmarking	2.600	Q2	1
International Journal of Forecasting	2.825	Q2	1
Journal of Big Data	3.644	Q1	1
Sensors	3.275	Q2	1
Cogent Engineering	1.350	Q2	1
Expert Systems with Applications	5.452	Q1	1

(*continued*)

Table A2.
Paper distribution by journal

Table A2.

Paper distribution by journal	Impact factor	JCR quartile	Count
International Journal of Computer Integrated Manufacturing	2.861	Q2	1
IEEE Transactions on Systems, Man, and Cybernetics: Systems	9.309	Q1	1
Supply Chain Management – An international journal	4.725	Q1	1
Journal of Enterprise Information Management	2.659	Q2	1
Management Research Review	1.680	Q2	1
British Journal of Management	3.023	Q2	1
Journal of Business Logistics	4.697	Q1	1
International Journal of Information Management	8.210	Q1	1
Sum			*72*

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