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Big data analytics in supply chain management:

A state-of-the-art literature review

Abstract:

The rapid growing interest from both academics and practitioners towards the application of Big Data Analytics (BDA) in Supply Chain Management (SCM) has urged the need of review up-to-date research development in order to develop new agenda. This review respond to this call by proposing a novel classification framework that provides a full picture of current literature on where and how BDA has been applied within the SCM context. The classification framework is structured based on the content analysis method of Mayring (2008), addressing four research questions on (1) what areas in SCM that BDA is being applied, (2) what level of analytics is BDA used in these application areas, (3) what types of BDA models are used, and finally (4) what BDA techniques are employed to develop these models. The discussion tackling these four questions reveals a number of research gaps, which leads to future research directions.

Keywords: Literature review; Big data; Big data analytics; Supply chain management; Research directions.

1. Introduction

With the tremendous development of information and communication technologies (ICTs), Big Data (BD) has become an asset for organizations. BD has been characterized by 5Vs: volume, variety, velocity, veracity, and value (Wamba et al., 2015; Assunção et al., 2015; Emani et al., 2015). Volume refers to the magnitude of data, which has exponentially increased, posing a challenge to the capacity of existing storage devices (Chen and Zhang, 2014). Variety refers to the fact that data can be generated from heterogeneous sources, e.g. sensors, Internet of things (IoT), mobile devices, online social networks, etc., in structured, semi-structured, and unstructured formats (Tan et al., 2015). Velocity refers to the speed of data generation and delivery, which can be processed in batch, real-time, nearly real-time, or streamlines (Assunção et al., 2015). Veracity stresses the importance of data quality and level of trust due to the concern that many data sources, e.g. social network sites, inherently contain a certain degree of uncertainty and unreliability (Gandomi and Haider, 2015; IBM, 2012; White, 2012). Finally, Value refers to the process of revealing underexploited values from BD to support deciding making (IDC, 2012; Oracle, 2012).

Among those 5Vs, veracity and value, which represent the rigorousness of Big Data Analytics (BDA), are particularly important because without data analysis, other BD processing aspects such as collection, storage and management would not create much value (Huang et al., 2015; Chen and Zhang, 2014; Babiceanu and Seker, 2016).

BDA involves the use of advanced analytics techniques to extract valuable knowledge from vast amounts of data, facilitating data-driven decision making (Tsai et al., 2015). Supply chain management (SCM) has been extensively applying a large variety of technologies, such as sensors, barcodes, RFID, IoT, etc. to integrate and coordinate every linkage of the chain. Therefore, not surprisingly, supply chains have been revolutionized by BDA and its application in SCM has been reported in a number of special issues (Wamba et al., 2015; Gunasekaran et al., 2016; Wamba et al., 2017). Indeed, BDA is reported to be an emerging supply chain game changer (Fawcett and Waller, 2014; Dubey et al., 2016), enabling companies to excel in the current fast-paced and ever-changing market environment. Empirical evidence demonstrates multiple advantages of BDA in SCM including reduced operational costs, improved SC agility, and increased customer satisfaction (Sheffi, 2015; Ramanathan et al., 2017) and, consequently, there is an increasing interest in identifying specific skills set for SCM data scientists (Waller and Fawcett, 2013; Schoenherr and Speier-Pero, 2015). Although the expectation of BDA adoption to enhance SC performance is rather high, a recent report found that only 17% of enterprises have implemented BDA in one or more supply chain (SC) functions (Wang et al., 2016). The main reasons for low uptake are the lack of understanding of how it can be implemented, inability to identify suitable data (Schoenherr and Speier-Pero, 2015), low acceptance, routinization and assimilation of BDA by organizations and supply chain partners (Gunasekaran et al., 2017) and data security issues (Fawcett and Waller, 2014; Dubey et al., 2016). This *motivates* our exploration of the existing research and the applications of BDA in SCM.

There are a number of literature reviews of BDA applications in the SCM context, but most of them tend to focus on a specific operational function of the SC. For instance, O'Donovan et al. (2015), Dutta and Bose (2015) and Babiceanu and Seker (2016) conducted literature reviews on material flow in manufacturing operations while Wamba et al. (2015) focused on logistics applications. A literature review that takes a broad perspective of SC as a whole and cross-maps with BDA techniques in SCM is yet scarce (Olson, 2015; Addo-Tenkorang and Helo, 2016; Hazen et al., 2016; Wang et al., 2016; Mishra et al., 2016). Our literature review develops a classification framework, which identifies and connects SC functions with levels of analytics, BDA models and techniques. Our review scope aims to provide a full picture of where and how BDA has been applied in SCM, by mapping BDA models and techniques to SC functions.

To obtain the objective, the literature review attempts to address the following four research questions:

(1) What areas in SCM that BDA is being applied?

(2) Which level of analytics is BDA implemented in these SCM areas?

(3) What types of BDA models are used?

(4) What BDA techniques are employed to develop these models?

The paper is structured as follows Section 2 describes the review methodology used for the literature search and delimitation. It develops the classification framework for this review. Section 3 undertakes a review in line with the developed framework. Section 4 discusses the findings. Section 5 provides the avenues for future research. Section 6 concludes the review and research limitations.

2. Review methodology

To address the research questions, the review methodology is based on the content analysis approach proposed by Mayring (2008). This approach has been adopted by a number of highly cited review papers in SCM literature, such as Seuring and Muller (2008), Seuring (2013) and Govindan et al. (2015). In particular, the review is systemically conducted in accordance with the four-step iterative process:

- Step 1: Material collection, which entails a structured process of articles search and delimitation.
- Step 2: Descriptive analysis, which provides general characteristics of the studied literature.
- Step 3: Category selection, which aims to construct a classification framework based on a set of structural dimensions and analytic categories.
- Step 4: Material evaluation, which analyses articles based on the proposed classification framework and interpret the results.

2.1 Material collection

Before searching for articles, it is essential to identify an effective set of keywords that can capture the synthesis of existing literature related to our research topic. We classified keywords into two groups:

- Group 1: words related to BDA: "Big Data"; "Data analytics"; "Data mining"; "Machine learning"; "Descriptive analytics", "Predictive analytics", "Prescriptive analytics".
- Group 2: words related to SCM: "Supply Chain"; "Purchasing"; "Procurement"; "Manufacturing"; "Inventory"; "Storage assignment"; "Order picking"; "Logistics"; "Transport".

Note that "inventory", "storage assignment" and "order picking" indicate three major functions of warehousing operations in SCM. The reason we used these specific terms rather than "warehouse" is to avoid the confusion with "data warehousing", a well-established, technical research topic of BDA.

The search was conducted based on all possible pairs between those two types of keywords within the timeline from 2011 to the first half of 2017 on well-known academic databases, i.e. Science Direct, Emeralds, Scopus, EBSCO, and IEEE Xplore. This particular timeline is chosen based on the facts: (1) BDA has become a global phenomenon from 2011 even though the term of 'Big Data' emerged back to 2007. The research before 2011 was rather insignificant in terms of volume and lacked of considerable contributions to theory and practices (Manyika et al., 2011) (2) this review intends to provide the latest development in BDA-SCM research.

The initial search generated a total of 1,565 papers. After eliminating duplicated results, the total number of papers dropped to 875 papers. Then, we checked overall relevance of the remaining papers by removing the papers that do not contain both keywords related to BDA and SCM functions in title or abstract. This screening process reduced the number of papers to 598. The remaining papers were then filtered based on inclusion and exclusion criteria. These criteria were developed and justified by the authors in order to minimize the impact of the subjective bias, as suggested by (Tranfield et al., 2003). 413 papers met the inclusion criteria and went into the final filtering with exclusion criteria.

After critically reading the introduction and discussion section of the remaining 413 papers, the following exclusion rule was applied: removing the papers that only mention the application of BDA on SCM as a fleeting point of reference or as collateral research topics. In fact, many BDA-related papers only point out the potential benefits and applications of BDA to SCM without investigating *how* they are actually implemented, i.e extracting, loading and transferring massive datasets, and use advanced analytic techniques to support SCM decision-making. In the end, 88 papers were kept for full review. Figure 1 summarizes our systematic articles search and selection process.

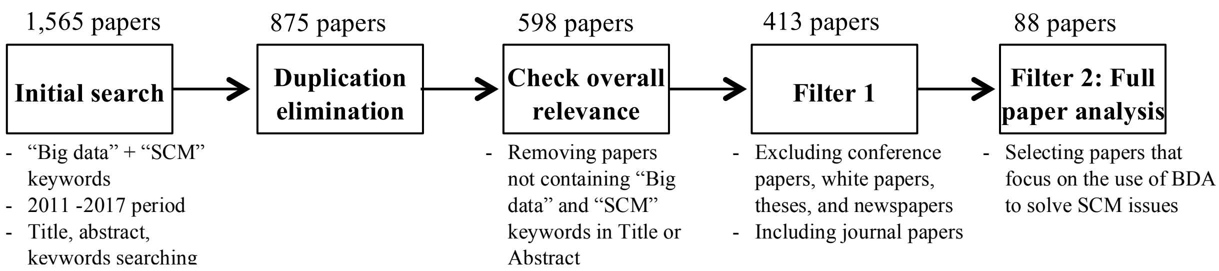

Figure 1: Systematic literature search process

2.2 Descriptive analysis

Figure 2 indicates that a number of papers published in this field have grown up over the last five years, and especially rocketed since 2014. This spreading of publications is consistent with the frequency distribution found in Gandomi and Haider (2015). It suggests that the application of BDA on SCM arena is a fast-growing and fruitful research field, being promoted by several special issue calls.

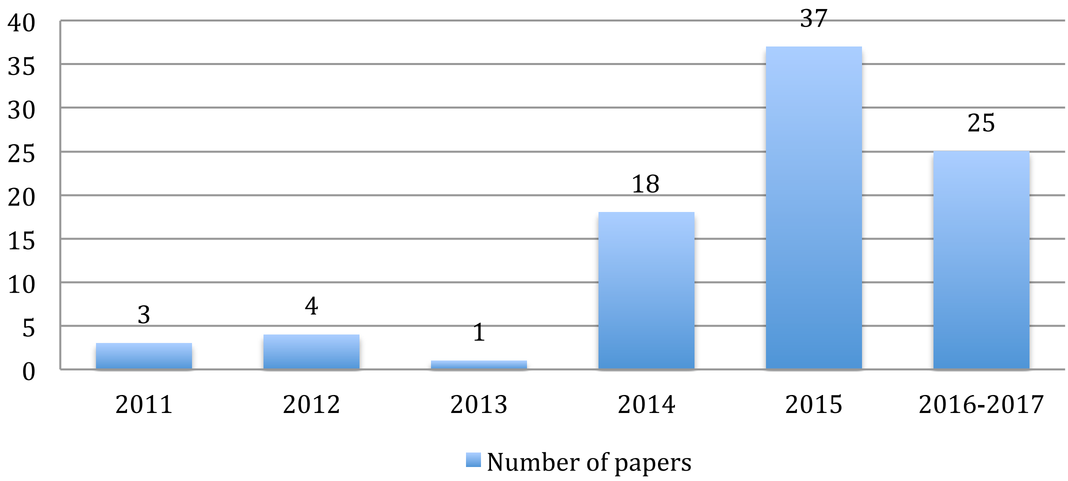

Figure 2: Distribution of reference papers by year

The selected 88 papers are from 46 different journals in which only 14 published more than one paper. Figure 3 illustrates the distribution of the reference papers in these 14 journals. It suggests that the publication spreads out in a great variety of journals. Furthermore, the research topic has attracted real interests from highly regarded academics as most of these papers are published by journals with high impact factors.

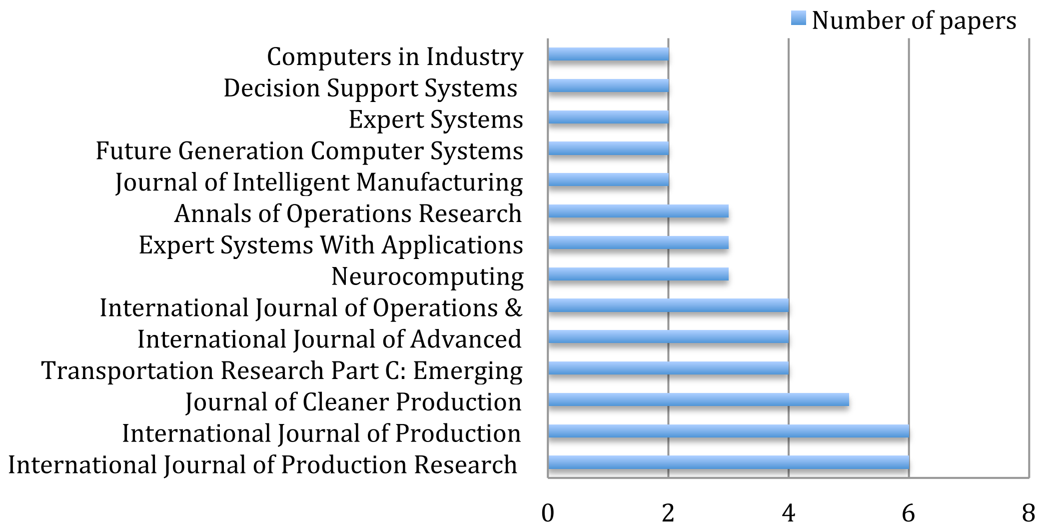

Figure 3: Distribution of reference papers by publication

2.3 Category selection

The category selection step is to conceptualize our classification framework, which is constituted by structural dimensions and analytic categories.

In order to address the proposed research questions, we select four structure dimensions to layer the classification framework – SCM functions, levels of analytics, BDA models, and BDA techniques. Analytic categories, i.e. key topics in each dimension, were derived deductively based on various classification frameworks from prior literature. Table 1 presents those analytic categories.

Table 1. Literature review classification

Structure Dimension		**Analytic categories**
SC functions	Procurement	Supplier selection, sourcing cost improvement, sourcing risk management (Olson, 2015; Rozados and Tjahjono, 2014; Sanders, 2014, p.132)
	Manufacturing	Product Research and Development (R&D), production planning and control, quality management, maintenance and diagnosis (Meziane and Proudlove, 2000)
	Logistics/ Transportation	Intelligent transportation system, logistics planning and in-transit inventory management (Wegner and Küchelhaus, 2013)
	Warehousing	Storage assignment, order picking, inventory control (Rozados and Tjahjono, 2014)
	Demand management	Demand forecasting, demand sensing, demand shaping (Chase, 2016)
Level of analytics		Descriptive, Predictive, Prescriptive (Saumyadipta et al., 2016, p.15)
BDA models		Visualisation, association, clustering, classification, regression, forecasting, semantic analysis, optimisation, simulation (Erl et al., 2016, p181)
BDA techniques		Association rule mining, clustering algorithms, support vector machine, linear/logistics regression, neural network, fuzzy logic, Naïve Bayes, text mining, sentiment analysis, feature selection, OLAP, statistics, to name a few.

In order to ensure the exhaustive categorization of each articles being reviewed, there are some supplement categories, for example, 'General SCM', 'Mixed' and 'N/A. To avoid confusion, those categories are not presented in the graphical classification framework in Figure 4.

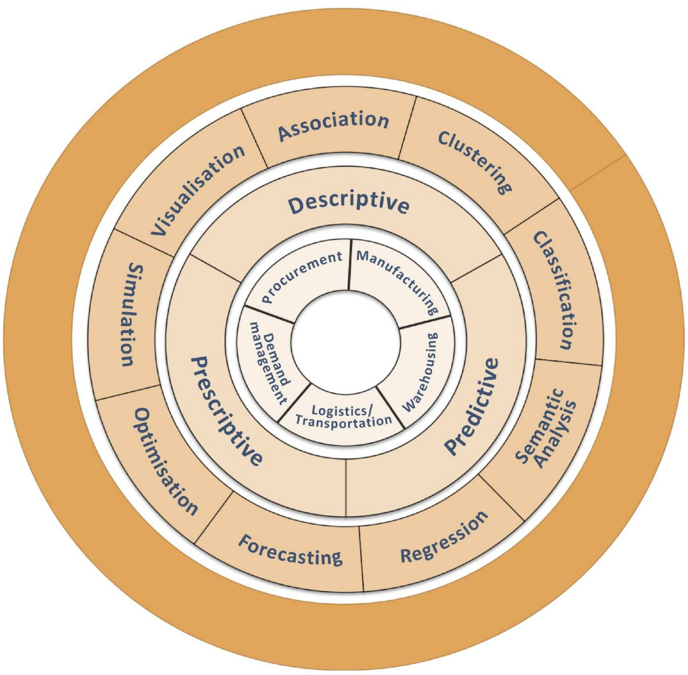

Figure 4: Classification framework

The first layer lies on the key functions of SCM. In the second layer, we classify the BDA-SCM literature based on three levels of data analytics, namely descriptive, predictive and prescriptive. This taxonomy has been widely adopted in BDA studies as it reflects complexity of both BDA-applied problems and data analytics techniques (Delen and Demirkan, 2013; Duan and Xiong, 2015). Descriptive analytics are the simplest form of BDA, which describe what happened in the past; while predictive analytics are to predict future events, and prescriptive analytics refer to decision making mechanism and tools (Rehman et al., 2016). The third layer is nine most common types of BDA model in general (Erl et al., 2016, p181). The final is the layer of BDA techniques, which can be adopted from multiple data analytics disciplines such as data miming, machine learning, etc.

3. Material evaluation

3.1. Reviewing by SC functions

Figure 5 depicts the distribution of each function in the examined literature.

Overall, logistics/transportation and manufacturing have extremely dominated over the current literature on this topic, together taking up more than half of the publications. Research on the other three fundamental SC functions, namely warehousing, demand management and procurement are limited, but relatively well distributed.

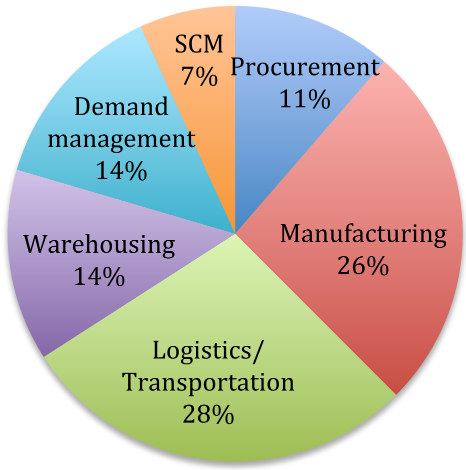

Figure 5. Distribution of each SC function in BDA

Among five areas of SCM, logistics/transportation (25 out of 88 papers, 28%) is the most prevalent area where BDA is used to support decision-making. The majority of research papers in this area (15 papers, 60%) focus on using BDA to develop Intelligent Transportation System (ITS), while BDA supporting logistics planning has increasingly gained attentions from recent research (8 papers or 32%). Only two papers (8%) are concerned about the use of BDA for inventory management during in-transit logistics process.

Another area in which BDA applications have been studied extensively is manufacturing. It takes up 26% of total publications. Out of the 23 manufacturing-related articles, more than half (13 papers, 57%) are related to production planning and control, while production R&D and maintenance & diagnosis equally represent 26% of publications (6 papers each). Noteworthy, the use of BDA for quality control during manufacturing process is little discussed, appearing only in 4 papers.

In demand management literature, sensing current demand (7 papers) and shaping future demand (6 papers) are among the most prominent initiatives of BDA, while surprisingly, demand forecasting is seldom the focus of the study (only 3 papers).

In warehousing, BDA has been widely recognised to improve storage assignment (5 papers) and inventory management (5 papers), whilst the use of BDA to support order picking process is under-examined (3 papers).

BDA research focusing in procurement is well-balanced over three major issues: supplier selection (5 papers), sourcing improvement (4 papers) and sourcing risk management (4 papers).

While most studies in the literature examine the application of BDA to specific SC functions, we found 6 papers (7% of total publications) that analyse BDA applications while considering SCs as multi-level interconnected networks. These papers address different SC issues concerning resilience, sustainability, risk management and agility.

Table 2: Summary of literature by SC functions

SC Function	Key activity	Paper
Procurement	Supplier Selection	Choi et al., 2016; Huang and Handfield, 2015; Jain et al., 2014; Kuo et al., 2015; Mori et al., 2012
	Sourcing cost improvement	Ahiaga-Dagbui and Smith, 2014; Huang and Handfield, 2015; Kuo et al., 2015; Tan and Lee, 2015
	Sourcing risk management	Ghedini Ralha and Sarmento Silva, 2012; Huang and Handfield, 2015; Ling Ho and Wen Shih, 2014; Miroslav et al., 2014
Manufacturing	Product R&D	Bae and Kim, 2011; Do, 2014; Lei and Moon, 2015; Opresnik and Taisch, 2015; Tan et al., 2015; Zhang et al., 2017
	Production planning & control	Chien et al., 2014; Krumeich et al., 2016; Li et al., 2016; Wang and Zhang, 2016; Zhang et al., 2017; Zhong et al., 2015; Shu et al., 2016; Dai et al., 2012; Zhang et al., 2015; Zhong et al., 2015; Zhong et al., 2016; Zhong; Xu, et al., 2015; Helo and Hao, 2017
	Quality management	Krumeich et al., 2016; Wang et al., 2016; Zhang et al., 2017; Zhang et al., 2015
	Maintenance & diagnosis	Shu et al., 2016; Guo et al., 2016; Kumar et al., 2016; Zhang et al., 2017; Wang et al., 2016; Wang et al., 2015

Warehousing	Storage assignment	Chuang et al., 2014; Li, Moghaddam, et al., 2016; Tsai and Huang, 2015; Chiang et al., 2011; Chiang et al., 2014
	Order picking	Ballestín et al., 2013; Chuang et al., 2014; Li et al., 2016
	Inventory control	Alyahya et al., 2016; Hofmann, 2015; Hsu et al., 2015; Huang and Van Mieghem, 2014; Lee et al., 2016; Stefanovic, 2015
Logistics and Transportation	Intelligent Transportation system (ITS)	Cui et al., 2016; Li et al., 2015; Shi and Abdel-Aty, 2015; St-Aubin et al., 2015; Toole et al., 2015; Wang et al., 2016; Xia et al., 2016; Yu and Abdel-Aty, 2014; Zangenehpour et al., 2015; Dobre and Xhafa, 2014; Ehmke et al., 2016; Sivamani et al., 2014; Toole et al., 2015; Zhang et al., 2016; Hsu et al., 2015
	Logistics planning	Lee, 2016; Prasad et al., 2016; Yan-Qiu and Hao, 2016; Zhao et al., 2016; Shan and Zhu, 2015; Tu et al., 2015; Li et al., 2014; Mehmood et al., 2017
	In-transit inventory management	Ting et al., 2014; Delen et al., 2011
Demand management	Demand forecasting	Berengueres and Efimov, 2014; Chong et al., 2016; Jun et al., 2014; Li, Ch'ng, et al., 2016; Ma et al., 2014
	Demand sensing	Berengueres and Efimov, 2014; Chong et al., 2016; Fang and Zhan, 2015; He et al., 2015; Li, Ch'ng, et al., 2016; Salehan and Kim, 2016; Wang et al., 2014
	Demand shaping	Chong et al., 2016; He et al., 2015; Marine-Roig and Anton Clavé, 2015; Salehan and Kim, 2016; Schmidt et al., 2014
General SCM	Ong et al., 2015; Papadopoulos et al., 2017; Sheffi, 2015; Ting et al., 2014; Wu et al., 2017; Zhao et al., 2016, 2015	

3.2. Reviewing by level of analytics

The rationale of using this taxonomy is to examine the extent to which BDA is being used to support decision making processes, as well as understanding what types of SC problems being solved.

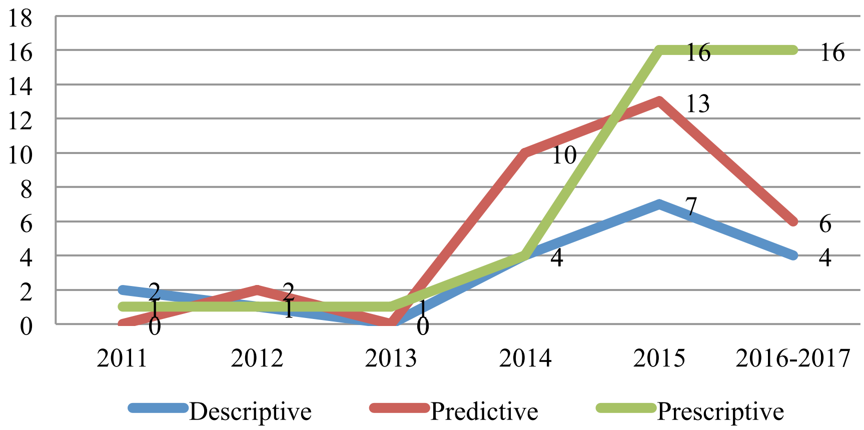

Figure 6: Distribution of analytics level by year

Figure 6 depicts the popularity of each analytics type by year. Although the trend from 2011 to 2013 is underrepresented due to the insufficient number of BDA-SCM studies, we still can see that the majority of studies in this early stage used BDA for descriptive analytics, while predictive and prescriptive analytics had been little discussed. However, these minorities have changed drastically along with the upsurge in the publication level since 2013. Particularly, predictive analytics dominated in 2014, accounted for 55% of publications (10 out of 18 papers). Meanwhile, prescriptive analytics has been the fastest growing since 2014 and has become the most common type in 2015 with 16 out of 36 papers (44.4%). Descriptive analytics have also been align with these upward trends, but not remarkably soared like prescriptive analytics.

Table 3: Level of analytics in each SC function

	Descriptive	Predictive	Prescriptive
Procurement	3	5	2
Manufacturing	4	7	12

Warehousing	3	3	6
Logistics/Transportation	4	6	15
Demand management	2	10	0
Other SC topics	2	0	4
Total papers	18	31	39

To reveal more insights from this taxonomy of BDA, we further investigate how each level of analytics has been studied in each specific SC domain. Table 3 presents the result. Overall, prescriptive analytics is the most discussed type in the examined literature, taking up 44.3% of publications (39 out of 88 papers), while predictive analytics is just behind with 31 papers (35.2%), and finally, descriptive analytics (18 papers, 20.5%). In particular, the result found that manufacturing (12 papers) and logistics/transportation (15 papers) are those areas which have mainly contributed to the prominence of prescriptive analytics, thanks to the increasing adoption of various state-of-the-art systems such as Cyber Physical System (CPS), and Intelligent Transportation System (ITS). Meanwhile, predictive analytics is the most often used type in demand management (6 out of 12 papers) and procurement area (4 out of 10 papers). Accurate demand forecasting and early detection of various sourcing risks are among foremost applications of BDA-enabled predictive models in these two areas. It should be noted that prescriptive applications of BDA in demand management and procurement are seldom studied.

3.3. Literature review by types BDA models

The result is summarised in Table 4.

Table 4: Distribution of articles by BDA models

	Procurement	Manufacturing	Warehousing	Logistics/ Transportation	Demand management	General SCM	Total papers
Optimisation	1	5	4	11	0	0	**21**
Classification	2	5	0	3	0	0	**11**
Mixed/ Others	0	4	0	3	0	3	**10**
Association	2	1	3	2	2	0	**10**
Semantic analysis	1	1	0	0	6	1	**9**
Forecasting	1	0	2	2	3	0	**8**
Simulation	1	3	2	1	0	0	**7**
Clustering	1	0	0	2	1	1	**5**
Regression	0	1	1	1	0	0	**3**
Visualisation	0	2	0	0	0	0	**2**

As discussed in Section 3.2, since the majority of reviewed papers focus on the prescriptive applications of BDA, the adoption of optimisation and simulation modelling to support decision-making seems to be natural. Optimisation is adopted in 21 papers in Table 4, but surprisingly enough, simulation is only applied in 6 papers. Route optimisation and logistics planning in logistics/transportation areas (9 papers) have mainly attributed to the dominance of optimisation, whereas in contrast, there is no paper found in examined literature that uses simulation in this area.

For the predictive level of analytics, classification is the most used BDA model in SCM context (11 papers). The model aims to classify a huge set of data objects into predefined categories, thereby generating prediction with high accuracy (Mastrogiannis et al., 2009). Classification has been largely employed in manufacturing (5 out of 11 papers, or 45%), logistics/transportation (3 papers, 27%), and procurement (2 papers, 11%). Other popular models for predictive analytics are semantic analysis (9 papers) and forecasting (8 papers). While the application scope of forecasting models is quite diversified, ranging from demand management, warehousing, and logistics/transportation to procurement, more than half of studies using semantic analysis (6 out of 9 papers or 66,7%) are still limited to demand management area.

At the descriptive level of BDA, association is the most used approach (11.36%, 10 out of 88 papers), which refers to the discovery of recurring and strong relationships among items in large-scale datasets. It should be noted that association is also the most diversified model in the BDA-SCM field as it can support decision making in every stage of SC process, from procurement, manufacturing, warehousing, logistics/transportation to demand management. Visualisation, surprisingly, is the least used model in descriptive analytics as well as in the BDA-SC literature as a whole. There are only two papers in the examined literature studying this type of model as the main research focus.

Finally, a number of papers are classified into mixed/others models (10 papers, 11.36% of publications). Those papers fall into three SC functions, namely manufacturing (3 papers), logistics/transportation (3 papers), and general SCM (4 papers), as seen in the table.

3.4. Review of articles by BDA techniques

This section focuses on what types of BDA techniques and algorithm have been used to develop BDA models discussed in Section 3.3. The result is summarised in Table 5.

Table 5: Distribution of articles by BDA techniques

	Association	Clustering	Classification	Regression	Forecasting	Semantic analysis	Optimisation	Simulation	Visualisation	Mixed	Total papers
Association rule mining	8		1				4				**12**
Mixed*		1	2				3			7	**12**
Heuristic approach							7	1			**8**
Spatial-temporal visualisation							5	1	1		**7**
Decision tree	1		3		3						**7**
Support vector machine			6								**6**
Sentiment analysis						3			2		**5**
Logistic regression			1	3	1						**5**
Generic Algorithm							4				**4**
Neural network					3	1					**4**
Text mining		1	1			2					**4**
K-mean clustering		1	1		1			1			**4**
Time-series forecasting					3		1				**4**

Tables 5 highlights the prevalent use of some techniques to particular types of BDA models. For instance, support vector machine (SVM) (6 papers) prevails in classification models, while heuristic approaches (7 papers) along with spatial/temporal-based visual analysis (5 papers) are key methods to develop BDA-driven optimisation models. In addition, there are some techniques that can be used flexibly to different types of BDA modelling. For example, K-means clustering algorithm is among the most adaptable techniques as it can be applied in clustering, classification, forecasting, and simulation model. Another versatile technique, and also the most frequently used technique in the BDA-applied SCM literature is Association rule mining (ARM). This method has been extensively studied in descriptive association model (7 papers) but recently, is increasingly used to facilitate more complicated analytics models in predictive and prescriptive level such as classification (1 paper) and optimisation (4 papers).

4. Results and discussion

(1) What areas in SCM that BDA is being applied?

In logistics, transportation management prevails with particular focus on three fundamental functions of ITS, i.e. routing optimization, real-time traffic operation monitoring and proactive safety management. It is noteworthy that the BDA-driven routing problem is mainly studied in static environment based on historical databases (Ehmke et al., 2016; Zhang et al., 2016), while the use of BDA for dynamic routing optimisation in real-time context is only conceptualised in some theoretical platform-based paper such as (Sivamani et al., 2014; Hsu et al., 2015). Moreover, the application of BDA on logistics network planning has gained rising attentions recently, but is still under-examined in both strategic and operational levels (Zhao et al., 2016; Mehmood et al., 2017). Finally, the monitoring and control of product condition through sensors during in-transit process is seldom addressed (Delen et al., 2011; Ting et al., 2014).

Production planning and control is currently receiving the most research interest, and the application of BDA theories and tools on this topic is in a relatively mature stage (Wang and Zhang, 2016; Zhong et al., 2015). Although BDA adoption in product R&D and equipment diagnosis and maintenance is less often studied, papers in this area make a significant contribution to predictive and prescriptive analytics in manufacturing research (Lei and Moon, 2015; Wang et al., 2015; Wang and Zhang, 2016; Zhang et al., 2017). Noteworthy, research on BDA-enabled quality control during manufacturing processes is rather limited (Krumeich et al., 2016; Zhang et al., 2015).

With regards to warehousing operation, storage assignment and inventory control taking advantage of BDA are well-studied. However, inventory control-related dynamics, such as the Bullwhip effect, have just recently been theoretically discussed (Hofmann, 2015). Furthermore, few studies addressed order-picking problems in BDA-enabled warehousing (Ballestín et al., 2013; Chuang et al., 2014). The study of how BDA can optimise order picking processes, such as order batching, routing, and sorting, is still scare.

Studies of BDA in procurement area is evenly spread over the three major applications, i.e. supplier selection, sourcing cost improvement and sourcing risk analysis. BDA has been well-adopted to facilitate supplier selection process and recent research efforts have been made to integrate this activity with order allocation problems and to reduce sourcing cost (Kuo et al., 2015). In terms of sourcing risk management, most studies have only exploited the benefit of BDA to accurately detect procurement risk based on the massive supplier database, while models and DSS that provides proactive preventing actions are still lacking (Ghedini Ralha and Sarmento Silva, 2012; Miroslav et al., 2014).

The examined literature provides numerous contributions in terms of capturing demand changes in real-time. BDA can help in sensing demand behaviours to increase the agility and accuracy of demand forecasting (Fang and Zhan, 2015; Salehan and Kim, 2016; Wang et al., 2014). Another common application of BDA in demand management is shaping demand to be aligned with production and logistics capacity. However, current studies on this issue have taken a marketing intelligence perspective rather than an operational supply chain management perspective (Marine-Roig and Anton Clavé, 2015; Schmidt et al., 2015).

Finally, the review shows that recent research has increasingly recognised the importance of studying BDA with a holistic perspective cognisant of SC as a multi-level inextricably interlinked system. Most of those studies examined the SC integration in the context of SC resilience (Papadopoulos et al., 2017; Sheffi, 2015), sustainability (Papadopoulos et al., 2017; Wu et al., 2017), risk management (Ong et al., 2015) and agility (Giannakis and Louis, 2016). However, the research on this issue still strongly emphasises on theoretical development with the limited studies of advanced data mining modelling.

(2) What level of analytics is BDA used in SCM?

The rationale of this research question is to investigate the level of data analytics required in the SC application, as well as indicating the types of problem being solved.

In the trend analysis, the results show that prescriptive analytics is the most common and fastest growing in the BDA-driven SCM, which is closely followed by predictive analytics, while descriptive analytics are receiving less consideration. To be more specific, logistics/transportation, manufacturing, and warehousing domains are the major contributors of prescriptive analytics, thanks to the increasing adoption of various state-of-the-art systems such as Cyber Physical System (CPS) in Industry 4.0 (Wang et al., 2016; Helo and Hao, 2017), and ITS (Wang et al., 2015). On the other hand, predictive analytics are still the primary actors in demand management and procurement, especially for demand forecasting and sourcing risks detection while prescriptive analytics are still rarely discussed (Ghedini Ralha and Sarmento Silva, 2012).

(3) What types of BDA models are being employed in SCM?

Optimisation is the most popular approach when it comes to prescriptive analytics, especially in logistics and transportation area. As aforementioned, literature in logistics/transportation has little insights so far on real-time routing optimisation based on streamline data. On the other hand, the study of real-time optimisation appears to be quite mature in the manufacturing domain with the use of modelling & simulation to develop real-time production control system based on streamline context-aware data generated from tracking devices such as RFID (Babiceanu and Seker, 2016; Kumar et al., 2016). It is highly possible for transportation controllers and warehouse operators to adapt the similar approach of modelling & simulation to optimise routing problem in real-time, as suggested in (Wang et al., 2016).

Classification is the most common approach in predictive analytics level and has been widely applied in manufacturing to support production planning & control (Chien et al., 2014; Wang and Zhang, 2016) and equipment maintenance & diagnosis (Kumar et al., 2016; Shu et al., 2016; Wang et al., 2016). This type of BDA model also plays a key role in logistics/transportation (Li et al., 2014; Yu and Abdel-Aty, 2014; Zangenehpour et al., 2015) and procurement research (Ling Ho and Wen Shih, 2014; Mori et al., 2012) but apparently, current studies in those areas have not been fully exploited the advantages of classification.

Another popular model for predictive analytics is semantic analysis, but its scope of application is still considerably limited to demand sensing. It could be beneficial for future research to extend the application of this approach to more SC and operational management such as fraud detection (Miroslav et al., 2014) and behaviour-based safety analysis (Guo et al., 2016).

For descriptive analytics, association is the most widespread as it has been applied for every stage of SC process, from procurement (Ghedini Ralha and Sarmento Silva, 2012; Jain et al., 2014), manufacturing (Bae and Kim, 2011), warehousing (Chiang et al., 2011, 2014; Chuang et al., 2014), logistics/transportation (Cui et al., 2016), to demand management (Jin et al., 2016). Noteworthy, visualisation model is rarely considered as the main focus of a study (Zhong et al., 2016; Zhong et al., 2015), but is commonly used as a complement to other advanced data mining models (Shan and Zhu, 2015; Zhang et al., 2016).

Finally, the review classified 10 papers (11.6% of total papers) under "mixed/others" models. Most of those papers focus on the intelligent DSS that enables real-time control of the entire operational process in manufacturing (Dai et al., 2012; Krumeich et al., 2016; Zhang et al., 2017; Zhong et al., 2016), logistics/transportation (Delen et al., 2011; Dobre and Xhafa, 2014; Hsu, Lin, et al., 2015) and SC agility (Ong et al., 2015; Papadopoulos et al., 2017). Not surprisingly, mathematical models are missing in many of those papers since such state-of-the-art systems normally require a complex mixture of various models and techniques from a number of data mining disciplines.

(4) What types of BDA techniques are being used in SCM context?

There is a wide range of BDA techniques and algorithms that have been used in SCM context. Some of them are prevalent to particular modelling approaches, for example, SVM in classification models, heuristics approach in optimisation models and neural network in forecasting models. The review also identifies some versatile techniques that can be adapted to different types of models. For instance, k-means clustering algorithm is among the most adaptable techniques as can be adopted in clustering (St-Aubin et al., 2015; Tan and Lee, 2015), classification (Chien et al., 2014), forecasting (Stefanovic, 2015), and modelling & simulation (Lei and Moon, 2015). In those studies, K-means is often performed in the initial phase of data analytics process to partition the raw heterogonous datasets into more homogenous segments. Studies find out that advanced data mining techniques such as decision trees and neural network would develop more accurate predictive models by leveraging the result of cluster analysis (Krumeich et al., 2016; Lei and Moon, 2015; Stefanovic, 2015).

However, other than for descriptive analytics, scholars have increasingly used this method to facilitate more complicated analytics in predictive and prescriptive level. As yet, we only found one paper, (Ling Ho and Wen Shih, 2014), conceptualise the notion of using ARM along with decision tree to develop the highly accurate prediction models for procurement risk. However, the mathematical model and algorithm to put this idea into practise is still missing. Interestingly, although the predictive application of ARM is little discussed in literature, its contribution to prescriptive analytics seems to be more recognised. Indeed, we found 4 papers incorporating ARM with optimisation models to effectively solve allocation problems in various SC areas. For example, Li et al. (2016) use ARM and Generic algorithm (GA) to optimise storage assignments, thus enhancing order-picking processes. Tsai and Huang (2015) optimise shelf space allocation by using ARM, sequential pattern mining and combinatorial optimisation approach. For logistic and transportation planning, Lee (2016) use ARM to extract purchase patterns and perform if-then-else rules to predict customer purchase behaviour, thus proposing GA approach to optimise anticipatory shipping assignment. Finally, ARM can also be used in the hybrid optimisation problems of supplier selection and order allocation (Kuo et al., 2015).

Not surprisingly, there are a large number of papers under the “mixed” category (i.e the combination of more than three different methods) since there is no single technique that is fully capable of managing the complex and diverse nature of BD (Chen and Zhang, 2014).

5. Future direction

Those findings discussed above suggest some future directions to capitalise the research development of BDA applications in the SCM context.

1. Further investigation of BDA application to SC function level

The review suggests a number of research gaps in each SC function. For example, quality control in manufacturing, dynamic vehicle routing and in-transit inventory management in logistics/transportation, order picking and inventory control system in warehousing, demand shaping in SC and operational research, procurement are some of those areas that are currently much less discussed.

2. Functional alignment strategy for the horizontal integration of BDA-driven SC

SCM is the multi-level process of which functions are all interlinked. Hence, fragmental efforts of BDA adoption to only one or two functions will not yield any significant, long-lasting competitive advantage. To avoid such fragmented efforts, the entire SC should be horizontally integrated by aligning BDA applications in different functions effectively. For example, production and logistics planning could incorporate with real-time demand sensing for cost reduction and higher service level. Indeed, alignment dissolves the boundary across functions.

To facilitate the horizontal integration throughout the SC, future BDA research should focus more on cross-functional problems such as vehicle routing and facility location, supplier selection and order allocation, demand-driven storage assignment and order picking.

3. Three levels of analytics should be equally examined

As aforementioned, current research focuses more on prescriptive analytics than descriptive and predictive analytics. Nonetheless, the application of BDA in any subjects, not just SCM, is always a linear process. In this process, the performance of prescriptive analytics would heavily rely on those of descriptive and predictive analytics as they dictate the value of critical parameters in prescriptive models (Duan and Xiong, 2015). To catalyse the rapid progression of BDA application in SCM, future research should balance the focus to all three levels of analytics.

4. Combining different data analytic techniques to develop more advanced and adaptive BDA models for DSS

Literature review has identified a number of BDA models commonly used in SCM applications as well as popular and versatile BDA techniques to build those models. Dynamic optimisation and simulation modelling should be further investigated in the context of BDA as they are baseline approaches for prescriptive analytics and DSS.

Moreover, although literature has extensively adopted visualisation techniques as supplement techniques to predictive and prescriptive models, little attention has been paid on improving data visualisation techniques. Future research should call for this gap because visualising of complex BD would expedite decision making.

5. Application of BDA on closed-loop supply chain management

It is rather surprising that research on applying BDA on reverse logistics and closed-loop supply chain (CLSC) is scarce. This might be due to the fact that collecting data for used products is extremely hard, which hinders introducing BDA into CLSC management. Nevertheless, the development of new technologies such as Internet of Things, machine-to-machine, would be able to overcome this barrier. The BDA that has already been applied in product life cycle design and assessment (Ma et al., 2014; Song et al., 2016) would be useful for predicting product returns and estimating the return quality. This is important for capacity planning and remanufacturing scheduling in a reverse logistics system.

Managing a CLSC has always been challenging due to the uncertainties and possible conflicting goals, i.e. profit vs. environment vs. social wellbeing. In this sense, big data would be useful in understanding people perception, devising multi-KPIs, monitoring operational process, and then taking corresponding actions. To achieve this, developing knowledge database, tools and techniques of BDA must be on the research agenda.

6. BD-driven business models in SC

Big data revolutionises SC business models. On the one hand, it shorten the supply chain layers; On the other hand, it expands revenue streams from exiting products to servitization, and creates new revenue streams from entirely new (data) products (Opresnik and Taisch, 2015). Nevertheless, the ecosystem that supports new business model is underdeveloped, the enablers and obstacles of the new business models remain unclear.

This leads to the research questions that we propose here: (1) what are the big data strategies in SCM; (2) how to increase the VALUE of big data, the most important five Vs; (3) how various stakeholders contribute to adding value of big data and what is the revenue sharing mechanism among the stakeholders in SC; (4) what is the dynamic impact of new business model on SC performance as whole; (5) what are the tipping points that transfer a conventional business model to a big data-driven business model.

7. New tools and BDA techniques for distributed SC and distributed computation

Cloud computing, countless sensors around us, distributed service resources, and distributed operational processes generate voluminous amounts of data. Coordinating a *distributed* SC and managing the complex procedures of different BDA are challenging (Li et al., 2016).

The review suggests that majority of current research have been focusing on one-location one-computer scenario. This doesn't reflect the reality of *distributed* systems. We call for research on developing SC system-wide feedback and coordination based on BDA to optimise system performance (Wang et al., 2016). It is anticipated that the framework and operational mechanism of nowadays smart factory would be scalable to entire SC. This SC system should be self-organised reconfiguration and big-data-based feedback and coordination without or with very limited human intervention. To achieve this, apart from hardware and infrastructure, future research should develop more efficient data-intensive techniques and technologies (Chen and Zhang, 2014).

6. Conclusion

Based on the content analysis methodology of Mayring (2008), this literature review examined 88 journal papers to provide a full picture of where and how BDA has been applied within the SCM context. In particularly, we developed a classification framework based on four research questions: (1) what areas in SCM that BDA is being applied, (2) what level of analytics is BDA used in these application areas, (3) what types of BDA models are used, and finally (4) what BDA techniques are employed to develop these models. Addressing these questions, the discussion has highlighted a number of research gaps and future directions for BDA applications to catalyse the research development of the topic.

One of the limitations of this paper is the categorisation in classification framework remaining interpretative, which could lead to the concern on subjective bias. This is also one of the well-established issues of the content analysis method despite a number of validations being done (Seuring, 2013). Another concern could be on the period time selected in this review, from 2011 to 2016. Although Figure 1 and Figure 2 indicate the fact that BDA literature has made major contributions since 2013, the topic of data-driven SCM and data analytics have been long studied over a decade.

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