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Systematic Review

An overview of big data analytics application in supply chain management published in 2010-2019

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Abstract

Paper aims: This study reviews the available literature regarding big data analytics applications in supply chain management and provides insight on topics that received a good deal of attention and topics that still require investigation. This review considers the expansion of big data analytics in supply chain management from 2010 to 2019.

Originality: Beyond displaying the increasing frequency of using big data analytics in supply chain management, the authors also aim to develop a useful categorization of applying business analytics in supply chain management and define opportunities for future research in the field.

Research method: This paper briefly discusses big data applications in supply chain management. Four common steps in review papers are performed: collecting articles (Thomson Reuters Web of Science), descriptive analysis, defining categories, and evaluating the material.

Main findings: According to both information technology development trends and the availability of data, more companies are using big data analytics in their supply chains. About 60% of the research on big data applications in supply chain management were published after 2017. These publications have increasingly focused on big data applications in predictive analysis, rather than in the other three types of data analysis: descriptive analysis, diagnostic analysis, and prescriptive analysis.

Implications for theory and practice: This review shows that the collected data by many companies can be analyzed using big data analytics methods to develop the business growth plan, market direction forecast, manufacturing process simulation, delivery optimization, inventory management, and marketing and sales processes, among many other activities in a supply chain. The number of articles using case studies in the literature is greater than the number of theoretical publications. This shows that big data analytics has now been properly developed for practical applications, rather than just being a theoretical concept.

Keywords

Big data analytics. Business processes. Manufacturing systems. Logistics systems. Supply chain management.

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1. Introduction

1.1. Big data

"I have just bought a house! I have bought a big house!" When people talk about big objects, generally there is a common sense of the word "BIG". When people use the word "big house", they are usually talking about the house area or the number of bedrooms. But, what does it mean when we use the word "big data", and what differentiates "big data" from the usual usage of the term "data"?

Big data is a developing phenomenon in the field of Information Technology (Vera-Baquero et al., 2015). Big data includes data sets that can't be analyzed by the common traditional data analysis tools (Costello & Prohaska, 2013). Big data refers to a high volume of data with a high velocity and a high variety; these properties require more efficient methods than the current ones used in conventional database systems for decision making (Laney, 2001a). Big data enables systems to manage their processes using a large volume of real-world data (Van der Aalst, 2012).

Big data entered the field of practical research in the 21st century; there was no noteworthy research applying big data analytics in other fields before 2000. The main characteristic of big data is simply its huge volume of data, but some other characteristics have been added to this definition over the years. The first time that Big Data was defined by the 3V model (Volume, Velocity, and Variety) was in a study by Laney (2001b). Volume refers to the amount of available data; Velocity refers to the timeliness of the data; and Variety refers to the diversity of the data types, including unstructured, semi-structured, and structured data sets.

Two other important Vs have been added to the definition of big data in the most recent decade. The economic Value refers to the profit gained by analyzing a huge volume of data (Idc-Vesset et al., 2012), and Veracity refers to the considerable amount of uncertainty and imprecision in the big data (Schroeck et al., 2012). (Wamba et al., 2015) integrated all of the Vs in one place and introduced the 5V big data framework for the first time. Figure 1 represents the evolutionary timeline of the big data concept, as well as the most-cited articles using big data in manufacturing, logistics, and supply chain management.

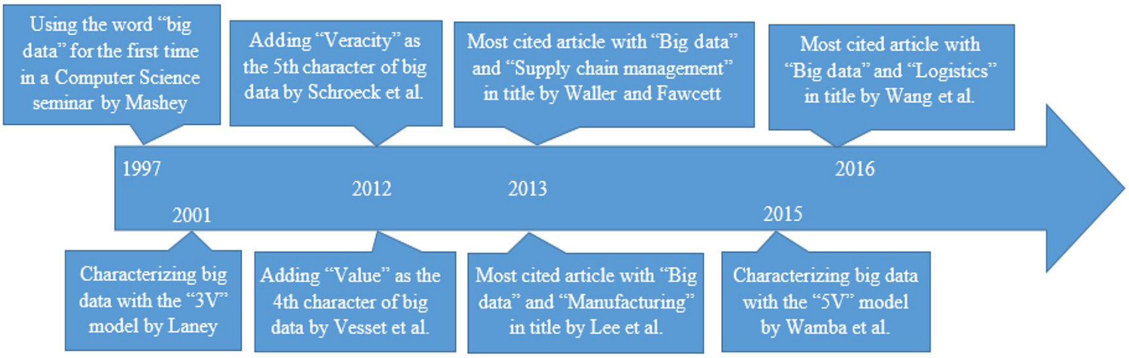

Figure 1. Big data framework evolution during the time (Idc-Vesset et al., 2012; Laney, 2001b; Lee et al., 2013; Mashey, 1997; Schroeck et al., 2012; Waller & Fawcett, 2013; Wamba et al., 2015; Wang et al., 2016).

Big data analysis is a process that transforms terabytes of low-value data into a small amount of high-value data, which shows an overview of the company using just a small slice of the overall picture (Fisher et al., 2012). A big data system can be separated into four consecutive phases: data generation, data acquisition, data storage, and data analytics (Hu et al., 2014).

1.2. Big data applications in a business environment

Because of recent technology developments, obtaining data is not a difficult task anymore, though the efficient use of data to achieve strategic and operational goals is still an area of concern (Gobble, 2013). Traditionally, businesses used their own data to make decisions, but the development of new technologies gives businesses access to various brand-new types of datasets (Jha et al., 2016). The usage of social networking is booming at a quick pace, and a huge volume of consumer data is being provided to businesses. Big data has become a major keyword in the technology world and has shown its useful applications in other areas as well. For example, big data has been successfully used for fraud prevention and detection in financial transactions (Jha et al., 2016).

Data plays a vital role in developing today's operational systems. Big data can be used to increase business competitiveness, according to the recent development of data. Today's business environment provides a huge opportunity, since a large volume of data is generated every minute. Most companies use big data for continual improvement. Four steps are commonly used in data analytics: The first step is to ensure that the available data is clean, structured and organized, which can then be used for further analysis. The second step is to ensure that the right data is accessible in the right form, the right time, and the right place. The third step is to do quantitative analyses, such as descriptive analytics. The fourth step is to apply advanced analytics such as predictive analytics, automated algorithms, and real-time data analysis. Using big data in the last step requires particular expertise in advanced data analytics (Sanders, 2016).

Various techniques such as statistics, data mining, machine learning, neural networks, pattern recognition, visualization, etc. are used to extract any valuable information out of big data (Mikavicaa et al., 2015). For example, cloud computing is one of the practices used to store, develop, and deploy big data in business processes.

Decreasing data management costs can increase the desirability of companies to use big data (Schwab et al., 2011). For example, in 2019, storing a terabyte of data using relational traditional databases could cost over $20000 for a company (Sonra, 2015), but storing the same amount of data could cost just $1000-$2000 using cheap big data technology such as a Hadoop cluster (StatSlice, 2013). Hadoop gained popularity in the area of technology development because of its price and capacity for data storage.

1.3. Methodology and research questions

There have been many developments in big data collection and analysis methods in recent years. The author of this paper used the Thomson Reuters Web of Science search tool (Clarivate, 2020) to track the number of "big data" publications over the last decade. Since several studies were performed on the topic of big data, we narrowed our search to the articles that have "big data" in their title. We also tried different combinations of title and topic searches in the Web of Science and came up with the solution that the best combination was to keep "big data" in the title search and the other keywords in the topic. For example, a search for articles with both "big data" and "supply chain" as a topic for the year 2019 gave us 173 articles; several of them were not related to the focus of our study at all. On the other hand, a search for articles with both "big data" and "supply chain" in the title for the year 2019 gave us only 15 articles, with many valuable articles not included. However, a search for articles with "big data" in the title and "supply chain" as a topic for the same year resulted in 54 articles that covered topics related to our study. Our methodology here was the same as that in many other review papers (Mishra et al., 2018; Nguyen et al., 2018) to collect the literature, provide the descriptive analysis (in this section), develop categories of interest, and evaluate the papers (sections 2, 3, and 4).

Figure 2 illustrates the number of published articles from 2010 to 2019 with the word "big data" in their title and "manufacturing", "supply chain", and "business" in the topic. As can be seen in Figure 2, there is an increase in the number of publications in the field in recent years. It is worth nothing that not much research was published on big data before 2010. About 15% of the big data publications have the word "business" in their topic, and many of publications were dedicated to other fields of study, such as engineering and science. Among the business-related studies, about 46% of publications focused on "supply chain" and "logistics" in their topic, and about 12% have manufacturing as their topic.

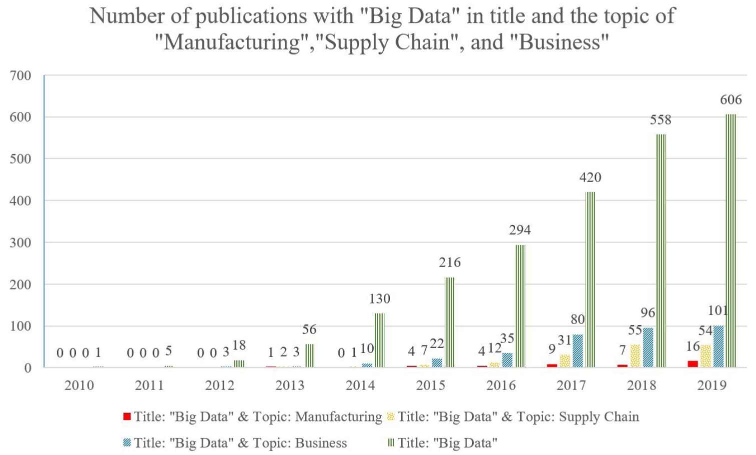

Figure 2. Number of publications with "Big Data" in title (Thomson Reuters Web of Science).

Different academic journals cover different subject areas; therefore, journals that publish most of the papers in an area of research can be a useful guide for those who are looking for the available literature or submitting their own contribution. The Thomson Reuters Web of Science was also used to develop a bibliometric of big data publications containing the terms "supply chain", "logistics", and "manufacturing" when looking at the journal title and impact factor, as can be seen in Figure 3.

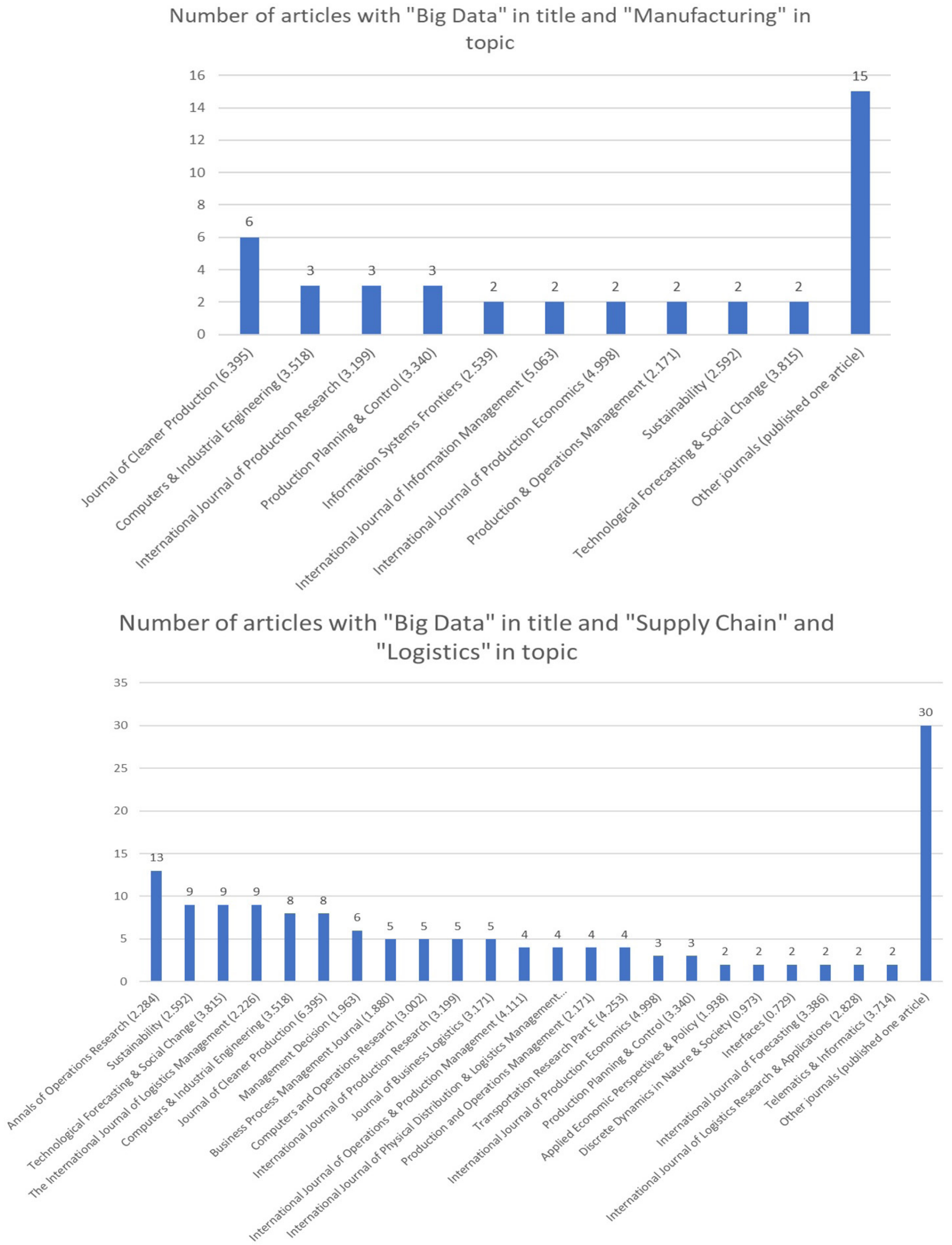

Figure 3. Publishing journal (impact factor in parentheses) with a topic of a) Manufacturing or b) Supply Chain and logistics.

Figure 3 shows that “Annals of Operations Research”, “Sustainability”, “Technological Forecasting and Social Change” and “The International Journal of Logistics Management” are the journals which published the most papers that applied big data analytics in supply chain management. The greatest impact factor among these journals is for the “Journal of Cleaner Production,” with an impact factor of 6.395.

Information technology developments encouraged many researchers and practitioners to use big data analytics in manufacturing systems, logistics processes, and other functions of a supply chain (Akter & Wamba, 2019; Dubey et al., 2018a; Feng & Shanthikumar, 2018). Moreover, since the benefits of big data analytics have attracted more researchers into the field, several more papers have been written that review the literature and define possible future directions (Barbosa et al., 2018; Dubey et al., 2019; Gupta et al., 2019a; Lamba & Singh, 2017; Rialti et al., 2019). According to Figure 2, most research in this area has been performed in recent years; therefore, a current literature review can give more insight for researchers who want to focus their work on big data applications in supply chain management. Moreover, our study categorizes the literature into three key areas: manufacturing systems, logistics processes, and supply chain functions. In each category, papers are grouped based on their main topic, and quality papers are summarized in tables to give more information about each paper. The current study is trying to answer the following questions:

- What are the different categories of big data analytics that are used in supply chain management?
- What are the factors that affect the attractiveness of using big data analytics in supply chain management studies?
- What supply chain management research topics are studied more often by big data analytics?
- What are the hurdles and advantages of using big data analytics in supply chain management research? What must be done in the future?

The remainder of this article is dedicated to reviewing published research in the specialized fields. Section 2 surveys published research that looks at applying big data analytics to manufacturing systems. Sections 3 and 4 review the published research with a focus on using big data analytics in supply chain management and logistics processes. In each subsection the subjects most often studied are introduced, and some of the quality papers are summarized in relevant tables. Section 5 concludes this study by discussing the hurdles and advantages of using big data analytics. Moreover, some directions for the future studies are hypothesized in Section 5.

2. Big data in manufacturing systems

Manufacturing can be defined as the hard segment of an economy which applies resources such as labor, machines, tools, and raw materials in order to produce physical products (Terziovski, 2010). The manufacturing industry contains a huge volume of data created by sensors, electronic devices, and digital machines in factories (Zhong et al., 2015). Manufacturing is a traditional industry which can be highly affected by big data, since the approach for many companies has been changed to operate based on forecasts. Moreover, big data could simplify data visualizations and improve automation applications regarding production design and engineering (Cochran et al., 2016).

Manufacturing plants collect data using different channels such as manufacturing processes, supply chain management systems, and tracking the products sold. Using big data can help to develop new products based on customer needs. Moreover, manufacturers have the opportunity to better plan out their supply chain with a more accurate demand forecast (Nedelcu, 2013). Managers believe that using big data can help diagnose defective products, improve process quality, and better plan supply chains (Nedelcu, 2013).

Manufacturing processes can't be firmly separated from either logistics processes or supply chain management activities. For example, many of the logistics processes in manufacturing plants are performed by tools with radio-frequency identification (RFID) tags, which allows real-time tracking of the products (Dai et al., 2012). Using data analysis on the shop floor enables the system to efficiently implement real-time manufacturing, planning, and scheduling, which is directly affected by both the material delivery time and the real-time information coming from the manufacturing processes. Moreover, analyzing the big data can level the material flow and help the plant manager to better plan space limitations regarding material flow and warehousing operations (Zhong et al., 2015).

There are a lot of process, personnel, and departments data generated during a product's lifecycle. The nine stages of a product's lifecycle were introduced by Tao et al. (2018): product concept, design, raw material purchase, manufacturing, transportation, sale, utilization, after-sale service, and recycle/disposal. In each stage, a lot of data is generated, and by collecting this data for all products, we can have a dataset with big data characteristics. Five areas of big data application in manufacturing are (Benhenni, 2017): 1- using data to forecast a complex process's output; 2- using data to capture that which is difficult to measure under regular conditions, 3- developing algorithms which can more accurately control the quality and safety of the final product; 4- using image metrology to reduce the amount of human supervision required; and finally, 5- obtaining the optimal time for doing predictive maintenance.

The continued growth of the Internet of Things has also influenced the amount of data available to manufacturing companies. It has been forecasted that by 2025, about 175 trillion gigabytes of data will be available, and the manufacturing industry will be the second-fastest-growing sector for data generation, after the healthcare industry (Reinsel et al., 2018). In spite of this huge volume of data - which is generated and kept by manufacturing plants - the number of studies on big data applications in the manufacturing industry is still considerably less than that in the service industries such as finance, information technology, and E-commerce (Weng & Weng, 2013). However, despite the lack of big data studies in the manufacturing industry, data mining has been used frequently in manufacturing decision making problems (Hanumanthappa & Sarakutty, 2011).

There are several different areas of manufacturing—including new product development (Niebel et al., 2019; Zhan et al., 2018), smart manufacturing (O'Donovan et al., 2015), cloud-based manufacturing (Kumar et al., 2016), process improvement (Gupta et al., 2020), predictive manufacturing (Lee et al., 2013), and redistributed manufacturing (Zaki et al., 2019)—in which the application of big data analytics can improve system outputs. (Belhadi et al., 2019) studied the major contributions of big data analytics in manufacturing systems by examining several case studies. In order to have a better overview of the recent applications of big data in manufacturing systems, the Thomson Reuters Web of Science was used to categorize the most frequent big data studies in manufacturing. Figure 4 shows the relative frequency of published studies on big data analytics as applied to manufacturing. Studies are categorized based on their research focus in Figure 4, with most categories explained afterwards. It is worth noting that review papers are not being discussed further, since we are studying research contributions in the literature and "review" categories as mentioned in Figure 4 are just there to give further insight. Moreover, the "Marketing" and "Flexibility" categories are not discussed further, since each makes up less than 5% of the total publications.

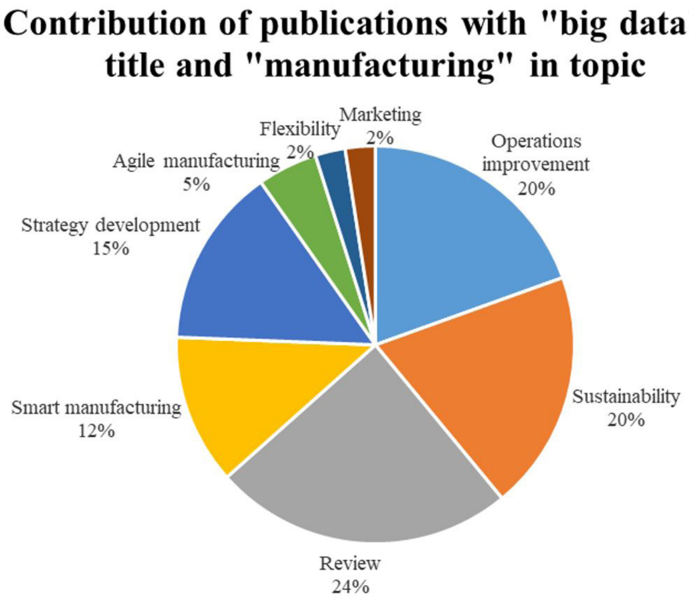

Figure 4. Publication frequencies with "big data" in title and "manufacturing" in topic (Thomson Reuters Web of Science).

2.1. Operations improvement

A number of studies show that big data analytics can improve the entire operational performance in manufacturing systems. (Yadegaridehkordi et al., 2018) developed a hybrid approach to study the effect of the adoption of big data analytics on manufacturing companies' performance. (Popovič et al., 2018) showed that big data analytics' capability, along with organizational readiness and certain design factors, could enhance a business's performance. In another study, Guo et al. (2017) applied data visualization and machine learning algorithms to better inform the operations manager of the product's market situation. Some other applications of big data analytics in manufacturing systems are shown by implementing big data analytics in a manufacturing company (Dutta & Bose, 2015) and using big data to improve the trading performance of emitting companies (Liu et al., 2017).

2.2. Sustainability

Big data can provide useful tools for manufacturers to perform their operations in a sustainable manner, keeping the environment better for future generations. Xu et al. (2019) showed how using the available big data on used products can increase the efficiency of remanufacturing systems and save more resources. Dubey et al. (2016) performed a field study and used the responses by 405 senior managers to develop a framework that could use big data to determine the most important factors for maintaining a sustainable manufacturing system. Lowering service costs, increasing the level of trust between stakeholders, respecting customers' privacy, and increasing data-sharing security are among the benefits that big data analytics may bring to sustainable manufacturing systems (Rehman et al., 2016). In another study, (Huang et al., 2019) developed a theoretical approach to demonstrate the application of big data analytics in the area of production safety management.

The application of big data analytics in Bosch Car Multimedia's (Braga-Portugal) organization (Santos et al., 2017) reviews the challenges of collecting, integrating, storing and processing the data in a manufacturing environment. The Bosch organization study shows the potential opportunity that is created when the volume, variety, and velocity of data is used for sustainable innovations in a future manufacturing environment. In another article, the importance of risk management in developing sustainable manufacturing supply chains was studied (Mani et al., 2017). The paper showed that applying big data analytics in order to mitigate the supply chain's social risk can help improve social and economic sustainability.

2.3. Smart manufacturing, strategy development, and agile manufacturing

Big data analytics can be used in smart manufacturing to solve company problems at the speed the business requires. However, there are some organizational and technological barriers that may prevent manufacturing companies from using big data solutions to initiate a smart factory (Li et al., 2019). Big data analytics has been proven to be a valuable tool for manufacturers to help them develop strategies, share data, design predictive models, and connect factories in order to control processes (Kusiak, 2017). A study by Bumblauskas et al. (2017a) studies big data applied to designing a smart maintenance decision support system, which is shown to improve an asset's lifecycle. Liu et al. (2019) used big data analytics for routing order pickup and delivery as well as assigning orders to laundry terminals in smart laundry service enterprises. Big data applications in strategy development and agile manufacturing have also been studied by Opresnik & Taisch (2015), Waller & Fawcett (2013), Guha & Kumar (2018), and Gunasekaran et al. (2018). Ren et al. (2019) reviewed the available research in big data applications that support sustainable smart manufacturing. Agility in a manufacturing system is the capability to better deal with unpredictable events, and deal with them in a business environment that can even turn these events into benefits (Swafford et al., 2008).

Several other studies developed quality research on using big data analytics in the manufacturing field. Some of the selected journal articles and conference proceedings are summarized in Table 1. The criterion for us consider a paper in the current review is that it must have been cited, on average, more than 10 times each year.

Table 1. High-quality articles using big data in manufacturing processes (Citation count is as of March 2020).

Author / Journal	Contribution	Study approach	Case study (NA stands for Not Applicable)	Citation#	Future research topic(s) in the article
Lee et al. (2013)/ Manufacturing letters	Studying the applications of big data in predictive manufacturing systems	Analytical study	NA	697	-Developing systems to integrate, manage, and analyze machinery data during different stages of machine life cycle
O'Donovan et al. (2015)/Journal of Big Data	Studying the requirements for implementing equipment maintenance	Analytic field study / Simulation	DePuy manufacturing facility in Ireland	84	-Deployment of big data pipeline in DePuy -Using data pipeline to feed predictive maintenance applications
Dubey et al. (2016)/ The International Journal of Advanced Manufacturing Technology	Studying the role of big data in sustainable manufacturing	Statistical analysis / Field study	NA	174	-Using big data to redefine the focus of advanced manufacturing technology -Using big data innovations like new materials development
Kumar et al. (2016)/ International Journal of Production Research	Solving a data imbalance problem in cloud-based manufacturing systems	RHadoop programming / MapReduce framework	Steel plate manufacturing company	56	-Executing the dissimilar types of feature selection approaches -Improving performance of classifiers

Table 1. Continued...

Author / Journal	Contribution	Study approach	Case study (NA stands for Not Applicable)	Citation#	Future research topic(s) in the article
Mourtzis et al. (2016)/ Procedia CIRP	Studying the applications of the Internet of Things in developing industrial big data	Analytic field study	Mould-making industry	131	NA
Zhang et al. (2017)/ Journal of Cleaner Production	Integrating big data analytics and service-driven patterns to create cleaner manufacturing and maintenance processes	Analytical study / Product life cycle analysis	Unnamed axial compressor manufacturer	170	-Using big data analytics to work out a mathematical model to discover rules for making cleaner production decisions -Representing and visualizing knowledge gained from big data
Zhong et al. (2017)/ International Journal of Production Research	Creating a RFID-enabled intelligent shop floor using the Internet of Things	Smart manufacturing objects / Wireless network	Unnamed collaborative company	177	-Developing a mathematical model to formulate physical internet-based logistics systems -Developing a systematic procedure to examine big data analytical approaches
Gunasekaran et al. (2018)/International Journal of Production Research	Studying the role of big data in agile manufacturing	Analytic field study	Four organizations in United Kingdom	46	-Studying the applications of the Internet of Things, Industry 4, and Blockchain technologies in developing agile manufacturing systems
Moktadir et al. (2019)/ Computers & Industrial Engineering	Studying the barriers to applying big data analytics in manufacturing supply chains	Delphi-based analytic hierarchy process (AHP) / Sensitivity analysis	Five manufacturing companies in Bangladesh	20	-Using international data to examine big data analytics barriers -Utilizing the extensions of AHP method to further explore the direction of the studied research
Popovič et al. (2018)/ Information Systems Frontiers	Using a qualitative approach to study the impact of big data analytics in manufacturing sector	Comparative analytic field study	Three manufacturing companies in Europe	70	-Studying the impact of big data analytics on low-performing firms -Studying failed cases instead of successful cases
Tao et al. (2018)/ The International Journal of Advanced Manufacturing Technology	Developing a method using a digital twin to design a product, manufacture, and service it	Product life cycle analysis	Author created applications as case	434	-Digital twin data construction and management -Developing smart service analysis based on digital twin data
Dubey et al. (2019a)/ Technological Forecasting and Social Change	Studying the impact of big data analytics on the social performance and environmental performance of manufacturing companies	Partial Least Squares / Hypothesis testing	Sample of 205 manufacturing companies in India	84	-Studying the exact role of the flexibility or control orientation on big data and predictive analytics on manufacturers' social and environmental performance
Moktadir et al. (2019)/ Computers & Industrial Engineering	Studying the critical barriers to the adoption of big data analytics in manufacturing systems	Delphi-based analytic hierarchy process	Five manufacturing companies in Bangladesh	20	-Using international data in the same study -Using other decision-making techniques to study the interaction among barriers
(Raut et al., 2019) / Journal of cleaner production	Using big data analytics to improve manufacturing sustainability in terms of operations management	Structural equation modelling-artificial neural network	Survey data from 316 Indian experts	16	-Studying this same issue in other geographical locations besides India -Studying other technologies that firms may adopt for sustainable purposes

3. Big data in supply chain management (other than manufacturing and logistics)

A supply chain is a sequence or network of suppliers, manufacturers, transporters, warehouses, retailers, and customers. Supply chain management is trying to manage the flows of funds, information, and products in a supply chain to ensure a high level of product availability and service to the customer with the lowest possible cost (Chopra & Meindl, 2007). These days, there are so many records generated by transactions between the suppliers and the purchasers. Choi et al. (2018) discussed the application of big data techniques and strategies in various supply chain management topics such as forecasting, revenue management, risk analysis, etc. and provided examples from top branded firms. Even with all the increased usage of big data in supply chain management, there are still several managers that don't apply big data analytics in their decision-making processes.

It is an important issue to consider the availability of data when developing decision models in a system (Kaur & Singh, 2018). There are three major flows in each supply chain: information, material, and money. Using data analysis, supply chain managers are able to monitor these flows and apply the results in order to better accomplish their jobs (Arunachalam et al., 2018). Researchers believe that information assumes the role of an invisible string between the supply chain members in order to achieve the most efficient cooperation and make the right decisions at the right time, apply the resources at an optimized level, and direct all of the supply chain activities in the right direction (Biswas & Sen, 2016).

The convergence of certain factors has recently increased the desire to use data analysis in supply chains (Ittmann, 2015): 1- the increased volume of available data in supply chains; 2- the lower cost of data storage compared to past years'; 3- powerful hardware which can speed up data analysis; 4- continuous access from mobile data; 5- powerful tools which simplify working with data; and 6- methods which can graphically show a large amount of data (advanced visualization). Available information in a supply chain is mostly regarding customers, sales, markets, service level requirements, demand forecasts, inventory, capacity deployment, quality control, human resources, skills levels, logistics, resources, warehouse planning, and pricing (Biswas & Sen, 2016).

Big data enables companies to better evaluate their suppliers and control the procurement process (Sanders, 2014). Using big data, companies are also capable of simulating their supply chains. Simulation allows for the possibility of finding bottlenecks, virtually running the production process in different locations, and examining prototypes (Kynast & Marjanovic, 2016).

Big data can improve the supply chain throughput by increasing the visibility (Barratt & Oke, 2007), resilience, robustness (Brandon-Jones et al., 2014), and organizational performance (Schoenherr & Speier-Pero, 2015) of the supply chain. Big data also improves the knowledge management in supply chains, which can increase the supply chain throughput by improving product development. Moreover, big data can positively affect demand predictions, inventory management, production and service scheduling, and product development in a supply chain (Lin, 2016).

Supply chains benefit from big data because of the cycle time reduction, cross-functional views, decision-making process improvement, and supply chain performance optimization. For example, big data can reduce the bullwhip effect in a supply chain by reducing the uncertainties of the future demand (Militaru et al., 2015). Using big data analytics has been shown to be useful in improving the logistics and supply chain management processes (Arunachalam et al., 2018; Brinch et al., 2018; Dubey et al., 2019b; El-Kassar & Singh, 2019). The Thomson Reuters Web of Science is used to study various contributions in the supply chain management and logistics fields by using big data analytics. Figure 5 shows the relative frequency of the published works in big data analytics applications with regards to logistics and supply chain management. Studies are categorized

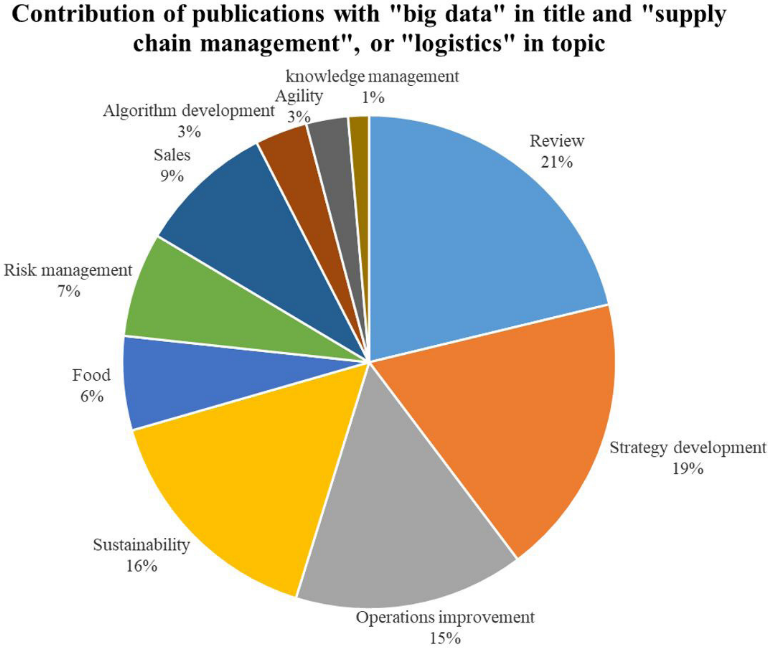

Figure 5. Publication frequencies with "big data" in title and "supply chain management" or "logistics" in topic (Thomson Reuters Web of Science).

based on their research focus in Figure 5; most categories are explained in more detail afterwards. It is worth nothing, however, that review papers are not discussed further, since we are studying research contributions in the literature; the “review” category is mentioned in Figure 5 just to help give more insight. Moreover, the “Knowledge Management”, “Agility”, and “Algorithm Development” categories are not further discussed, since each includes less than 5% of the publications.

3.1. Strategy development

Management’s decision to use big data analytics in a company would be a strategic one. Management commitment positively affects the level of accepting big data analytics in a company (Gunasekaran et al., 2017). Using big data analytics lets the manager have access to analysis which based on dynamic data, and can make the supply chain more competitive (Chen et al., 2015). Applying big data analytics to planning, decision making, and supply chain coordination and control can improve the preparedness, alertness, and agility of the supply chains in question (Mandal, 2019). The aspect of value creation by big data has not been studied often in supply chain management literature. Therefore, Brinch (2018) studied the value discovery, creation, and capture that can be achieved using big data analytics in a business supply chain.

All benefits considered, there still is not enough empirical research that applies big data analytics to supply chain management, so there is a lack of ability to adopt an informed strategy just by comparing different methods (Kache & Seuring, 2017). Investing money in the required hardware and software to apply big data analytics may affect the strategies of a supply chain. As for training, our educational system can train a good number of data scientists, but may have ignored the managerial abilities of these data scientists in many cases (Carillo, 2017). As a consequence, converting the available data into applicable knowledge which can mitigate supply chain risks is still an obstacle for many supply chains (Bumblauskas et al., 2017b).

3.2. Operations improvement

Dealing with varying numbers of suppliers, manufacturers, logistic providers, etc. creates big data sets that can be used for optimization projects in a supply chain. Big data analytics improves demand forecasts, reduces the safety stock, and improves a supplier’s management practices (Roßmann et al., 2018). It has been shown that big data predictive analytics can be combined with other methods such as enterprise resource planning to improve the performance of supply chains (Gupta et al., 2019c). Oncioiu et al. (2019) studied the role of big data analytics applications in improving Romanian supply chain companies’ performance and implementing assessment processes. Big data analytics has also been used by Boone et al. (2017) to improve the practices of service parts management.

In another study, Hofmann (2017) shows that the velocity of big data can be used to reduce the bullwhip effect (increasing the safety stock levels in upward echelons) in supply chains. Working with omni-channel supply chains generates a huge amount of data from different sources. Big data analytics can make more accurate sales predictions in different channels and develop optimal delivery plans to minimize transportation costs (Lee, 2017). In another application, sharing the data through a big data framework can reduce the uncertainty cost in a supply chain (Liu & Yi, 2016).

3.3. Sustainability

Another application of big data analytics in supply chains can be the optimization and adjustment of the operations based on sustainable objectives. Big data can improve the environmental, financial, and operational management of the supply chain in order to help combat climate change (Seles et al., 2018). Badiezadeh et al. (2018) developed a network data envelopment analysis with big data in order to help assess the performance of sustainable supply chain management. Open access to big data can facilitate innovation, create resilient supply chains, and improve the performance of the distribution network (Weerakkody et al., 2017). Liu (2019) demonstrates how applying big data analytics to the targeted advertising of products can reduce the carbon emissions in a supply chain.

It is worth noting that using big data analytics is not beneficial in all supply chains. There are several barriers that may interact together and prevent big data analytics from establishing a sustainable system (Shukla & Mattar, 2019). Cheng et al. (2018) considers a sustainable supply chain with a manufacturer and a retailer and shows that the proficiency in big data analytics depends on the service level adopted by the retailer. Available big data from transportation and logistic provider companies can be used to satisfy delivery requirements while also keeping in mind carbon emission constraints (Ji & Sun, 2017; Zhao et al., 2017). In another study, the application of Big data analytics in enabling the resilience of supply chains after disasters was studied by (Papadopoulos et al., 2017), where they used the example of Nepal to prove their analysis.

3.4. Food supply chains

The lack of information in food supply chains can bring about huge costs in the forms of deterioration and waste. Accordingly, using the information excluded from big data analytics is gaining more attention from the decision makers in food supply chains. Big data analytics has applications in agricultural supply chain management, farm management, food sustainability assurance, consumer demand management, new product development, and food safety (Coble et al., 2018; Giagnocavo et al., 2017; Jagtap & Duong, 2019; Shukla & Tiwari, 2017; Wolfert et al., 2017). Ji & Tan (2017) considers five major benefits of using big data in food supply chain management: 1- data sharing over supply chain echelons; 2- doing experiments to find frauds and anomalies in the supply chain; 3- accurate clustering of customers in order to target the marketing of each cluster; 4- developing automated algorithms to support the decision-making processes; and 5- developing new products, services, and business models.

Big data analytics was used by (Liu, 2017) to develop new e-commerce methods for marketing fresh products with a short shelf life by keeping in mind the critical aspects of humidity and temperature. In another research paper, Mishra et al. (2017) used social media big data to determine factors that influence customers' beef purchasing decisions. They believe that the available unstructured big data in social media can help businesses to design their supply chain to be more consumer centric. Big data applications have also been developed for cold chains (temperature-controlled supply chains). However, there is an important lack of understanding regarding what data in a cold chain should be collected, and what is the appropriate method to collect and analyze that data (Chaudhuri et al., 2016).

3.5. Risk management

Any supply chain that is dealing with uncertainties in its decision-making processes is using risk management methods at some level. Risk is one of the consequences of a lack of information, and big data can be applied to reduce this lack of information. In the context of logistics processes, transportation risk can be defined as the deviation from the estimated delivery time. Big data analytics can be applied to predict these delivery time deviations, as well as prevent transportation risks such as missing cargo flights (Shang et al., 2017). Engelseth & Wang (2018) used big data analytics to manage the risks in long-linked supply chains. They used an analytical framework to mitigate the risks of a case study that looked at machine parts imported from China to Norway.

The establishment of big data analytics could resolve bargain issues between a supplier and a retailer. Tsao (2017) used big data analytics and game theory to show the way that a supplier and a retailer could determine the period in which to use their credit in order to minimize their risk of defaulting. A type of common risk is that of hazardous materials and waste in closed supply chains (supply chains with remanufacturers and recyclers) (Deleris et al., 2004; Van Asselt et al., 2017). Big data analytics has also proven to be useful in recognizing powerful demand signals and minimizing the negative environmental impacts of remanufacturing (Niu & Zou, 2017; Wu et al., 2017).

3.6. Marketing and sales

Big data analytics can help inform marketing managers of current trends in product sales beyond simply the demand forecasts. For example, product reviews can be approved more easily to help influence sales performance in many studies (Li et al., 2016). The impact of big data analytics on improving sales forecasting was studied in an analytical review by Boone et al. (2019). Sagaert et al. (2018) shows that using big data analytics can improve the transparency of market dynamics to sales managers. Using big data analytics in the case study of a tire company could improve forecasting accuracy by 16.1% over the traditional method (Sagaert et al., 2018). Moreover, Li et al. (2018) showed that managing a demand chain with big data and electronic commerce works much better than traditional methods of supply chain management.

Using product-in-use data has been proven to reduce the uncertainty for aftermarket (spare parts) demand planning (Andersson & Jonsson, 2018). Gawankar et al. (2020) studied the impact of new technologies—such as the Internet of Things and big data analytics—on the retail environment in India. They found that the retailing industry in India is eager to use new technologies in the retailing environment that they call "Retail 4.0" in their study. Big data analytics was also used by (Liu & Yi, 2017) to show the correlation between the price and the products' environment friendliness degree. It shows that the available data can used for targeted advertisements in a supply chain's green environment. Another study in big data pricing application was done by (Liu, 2017), in which he considered the data company to be an echelon in the supply chain, and determined its benefits using the Stackelberg game.

Analyzing social media data can help supply chains increase their number of customers in the system through personalized services. Companies can analyze social networks, mobile, and web data to track the way that a customer wants to use the product (Agrahri et al., 2017). On the other hand, Aloysius et al. (2018) survey of a group of retail store customers showed that many people have concerns about how much of their personal information is collected, which can negatively affect the store's image.

Some of the selected journal articles regarding big data applications in supply chain management are summarized in Table 2.

Table 2. High-quality articles using big data in supply chain management practices (Citation count is as of March 2020).

Author / Journal	Contribution	Study approach	Case study (NA stands for Not Applicable)	Citation#	Future research topic(s) in the article
Hazen et al. (2014)/ International Journal of Production Economics	Studying the importance of data quality in supply chain management decisions	Statistical process control / Field study	Remanufacturing company for jet engines and related components for military aircraft	527	-Developing new methods for controlling data
Chen et al. (2015)/ Journal of Management Information Systems	Studying the role of big data analytics in value creation and competitive advantage	Technological, organizational, and environmental (TOE) framework	Collected data from supply chain executives through a questionnaire	192	-Examining the influence of firm-level employment of big data analytics on organizational performance -Examining the intervening variables between organizational IT practices and performance outcomes
Tan et al. (2015)/ International Journal of Production Economics	Providing firms an analytic infrastructure to combine their competence sets	Deduction graph technique	SPEC company, a leading eyeglasses manufacturer in China	252	-Testing the contributed approach on other supply chains to determine its general applicability -Simplifying the contributed mathematical approach
Giannakis & Louis (2016)/Journal of Enterprise Information Management	Developing a big data analytics system that exerts autonomous corrective control actions in a supply chain	Analytical study / Supply chain agility theories	NA	77	-Studying the application of an agent-based technology in supply chain sustainability -Studying the influence of the attributes of supply chain managers on the implementation of agent-based technology in decision making
Prasad et al. (2018)/ Annals of Operations Research	Developing a model to connect big data analytics to superior humanitarian outcomes	Resource dependence theory	Three focal non-governmental organizations' supply network in India	42	-Doing research to clearly identify stages regarding big data attributes -Examining the scenarios of non-linear patterns emanating from distributed supply chain networks
Richey Junior et al. (2016)/International Journal of Physical Distribution & Logistics Management	Developing a framework in which supply chain managers can use big data	Native category approach	Interviewing 27 supply chain experts in 6 countries	68	-Developing unbiased managerial guidance for using big data analytics in supply chain management
Gunasekaran et al. (2017)/Journal of Business Research	Studying the impact of big data and predictive analytics on supply chain performance	Statistical analysis / Field study	E-mail survey of a sample of companies in India	279	-Investigating top managers' commitment towards developing big data predictive analytics capabilities
Kache & Seuring (2017)/International Journal of Operations & Production Management	Investigating the impacts of big data analytics on information usage in a supply chain	Delphi survey / Statistical analysis	Collect data from 15 experts by questionnaire	195	-Studying the constituents of a big data ecosystem as keys for optimal supply chain productivity
Roßmann et al. (2018)/Technological Forecasting and Social Change	Studying expert assessments of big data analytics applications in supply chain management	Delphi survey / Fuzzy c-means clustering	Interview with 73 experts	38	-Interviewing other fields' experts -Studying the impact of potential technological applications on social dynamics in supply chain management
Choi (2018)/ Transportation Research Part E	Studying the impact of social media comments on quick response supply chains in fashion	Analytical mathematical modeling / Newsvendor model	NA	30	-Incorporate the correlation of consumer voices and a product's demand -Studying the impact of a government's role in local sourcing and emissions taxes on a supplier-market relationship

Table 2. Continued...

Author / Journal	Contribution	Study approach	Case study (NA stands for Not Applicable)	Citation#	Future research topic(s) in the article
Coble et al. (2018)/ Applied Economic Perspectives and Policy	Studying the challenges and opportunities of using big data analytics in an agricultural value chain	Analytical study	NA	65	-Studying data ownership rules in an agriculture supply chain -Developing access to technology infrastructure for rural areas
Dubey et al., 2019)/ Management Decision	Studying how to use big data analytics to improve the agility of a supply chain	Statistical analysis / Hypotheses tests	Collected data from 173 experts by questionnaire	46	-Using other theoretical perspectives to study the effect of big data analytics on the agility of a supply chain -Using case-based methods instead of survey-based research
Dubey et al. (2018b)/ The International Journal of Logistics Management	Studying big data predictive analytics' impact on coordination and visibility in humanitarian supply chains	Least squares regression / Hypothesis tests	Survey responses from 205 International Non-Government Organizations	26	-Considering country culture and/or supply base complexity in a predictive model -Applying agent-based simulation methods
Irani et al. (2018)/ Computers & Operations Research	Studying organizational factors that impact the amount of waste in a food supply chain	Fuzzy cognitive map / Simulation	Data from surveying 34 stakeholders in food industry in Qatar	21	-Use Delphi method to involve a wider set of participants -Develop the same approach in countries besides Qatar
Jeble et al. (2018)/The International Journal of Logistics Management	Studying the impact of big data and predictive analytics on sustainable business development	Resource-based view logic / Contingency theory	Survey data from 205 individuals in auto components industry	40	-Studying the actual impact of big data and predictive analytics on a business firm rather than just the perception of the impact -Explore data that can be more generalized
Lai et al. (2018)/The International Journal of Logistics Management	Studying the factors that determine the adoption of big data analytics in supply chains	Technology-organization-environment (TOE) framework	Survey data from 210 Chinese IT managers and business analysts	28	-Increase the environmental safety of big data -Studying the other factors that may affect the adoption of big data analytics, such as supply chain scale and delivery complexity
Lau et al. (2018)/ Production and Operations Management	Using consumer social media comments for sales forecasting	Parallel sentiment analysis / Machine learning	Consumer comments datasets in English and Chinese	31	-Combining parallel topic models with lifelong learning strategies -Examining parallel ensemble models for better sales forecasting
Gupta et al. (2019b)/ Technological Forecasting and Social Change	Using big data analytics to support data-driven decision making in circular economical supply chains	Stakeholder perspective on circular economy	Interview data from 10 expert employees	19	-Using larger empirical data for this study -Studying inter-organizational relationships, intra-organizational dynamics, and informational privacy issues in supply chains
Lamba & Singh (2019)/Technological Forecasting and Social Change	Using big data analytics to study a supplier's selection and lot-sizing problem under carbon cap-and-trade regulations	Mixed integer non-linear program	Experimental problem sets	15	-Developing heuristics that can obtain the solution via a faster method -Studying the same model's behavior under various carbon emission regulations
Lamba et al. (2019)/ Computers & Industrial Engineering	Studying a supplier selection and lot-sizing problem in dynamic supply chains	Mixed integer non-linear program	A randomly generated dataset	23	-Studying the stochastic demand with the same problem settings -Focusing on the veracity and value characteristics of big data
Shen et al. (2019)/ Technological Forecasting and Social Change	Using big data analytics to find if a retailer must sell green or non-green products first, according to shelf space limitations	Bayesian analysis	NA	19	-Studying incentive contracts in order to achieve a coordinated supply chain -Studying the role of government interventions on selling green products -Studying this case with enough shelf space for both green and non-green products
Singh & El-Kassar (2019)/Journal of Cleaner Production	Studying the impact of the integration of big data with green supply chain management and human resource management on a firms' sustainability	Statistical analysis / Hypotheses testing	Survey data from 215 employees in Saudi Arabia, the United Arab Emirates, Egypt, and Lebanon	40	-Using the same research framework of this study with multisource and/or multi-time datasets -Using mixed methods instead of quantitative data within the same research framework
Yu et al. (2019)/ International Journal of Forecasting	Using Google trends to forecast the oil consumption in an oil supply chain	Cointegration tests / Granger causality analysis	Data from Google trends	38	-Considering the dynamic between Google trends and oil consumption over time -Introducing other types of big data, such as social networks, to the proposed model

4. Big data in logistics

Since the 1980s, optimizing resource consumption and outsourcing non-specialized activities such as logistics processes had been a major practice in most businesses. Today, logistics is a critical part of both the manufacturing and service industries (Briggs et al., 2010). Many multinational companies have outsourced their logistics processes to third-party logistics providers and consider them their strategic partners.

Many research projects have been developed in the transportation and logistics industries that use available data that generated by road sensors, GPS devices and customers' websites (Ayed et al., 2015). Logistics providers manage a high volume of product flow and have access to a considerable volume of data. Any measurable criterion of product flow—such as origin, destination, size, weight, price, load content, etc.—can be a valuable method by which to use information for value creation (Mikavicaa et al., 2015). Improvements in GPS efficiency, applications of sensor networks, and developments in the Internet of Things have opened up new areas in logistics and supply chain automation (Ashton, 2009).

Optimizing service experiences such as delivery time, resource application, and geographical coverage are continuous challenges for logistics systems (Mikavicaa et al., 2015). Both delayed and early deliveries would be costly for logistics providers. This time difference between the planned delivery and the actual delivery is one of the key risk factors for logistics companies. Weather forecasts and vehicles' performance reliability data can be used to minimize the risk of inaccurate delivery times (Shang et al., 2017).

Big data logistics can be defined as modeling and analyzing logistics systems using big data sets which have been generated by GPS devices, cell phones, and the logistics companies' operations. Considering the current trend of big data applications in the logistics industry, it can be safely said that the logistics industry is in a transition phase from product-based services to information-based services (Mehmood & Graham, 2015).

There are important business processes in the logistics industry such as forecasting, transportation, inventory management, and human resource planning and management that can be improved by using big data (Chen et al., 2014; Robak et al., 2014). Jin & Kim (2018) combined big data analytics and business intelligence to minimize the analysis cost for the sorting and logistics processes of a courier firm. The other possible applications are forecasting delivery times, managing customer relationships, developing real-time scheduling, and managing supplier relationships.

Data mining applications for logistics management are threefold: 1- Data analysis to match the needs of both logistics process management and the customer; 2- Data analysis to manage the logistics process based on methodical decisions; and 3- A supporting role for logistics managers (Iannone, 2012). Network technology developments can improve logistics processes by using information regarding real-time transactions. As a result of the increased adaptability of logistics information, logistics has been transformed into a dynamic data process (Xu, 2016). Niu et al. (2019) studied two competing air cargo carriers and showed how using big data analytics benefits a carrier by allowing them to receive updated demand signals. There are many quality papers in this field; some of these journal articles are summarized in Table 3.

Table 3. High-quality articles using big data in logistics processes (Citation count is as of March 2020).

Author/Journal	Contribution	Study approach	Case study (NA stands for Not Applicable)	Citation#	Future research topic(s) in the article
Mehmood & Graham (2015)/Procedia Computer Science	Improving transportation system efficiency by sharing load and capacity	Mathematical modelling	Healthcare transport operations in the United Kingdom, US, France, and the Middle East	67	-Exploring load optimization in fields such as "bike sharing", "waste management", and "manufacturing plant location / freight delivery"
Zhong et al. (2015)/ International Journal of Production Economics	Using RFID logistics big data to develop a smart manufacturing environment	Spatio-temporal sequential RFID patterns / RFID-Cuboid algorithm	Unnamed collaborative company with 4 manufacturing shop floors	277	-Developing a mathematical model to integrate production planning, scheduling, and material delivery strategy -Extending the evaluations of the aforementioned approach to big data
Kaur & Singh (2018)/Computers & Operations Research	Developing a big data analytics model to make optimal sustainable logistics decisions	Mixed integer linear & nonlinear programming / Heuristic method	Unnamed manufacturing industries	45	-Considering stochastic parameters along with big data -Considering late deliveries and shortages in a mathematical model

Table 3. Continued...

Author/Journal	Contribution	Study approach	Case study (NA stands for Not Applicable)	Citation#	Future research topic(s) in the article
Witkowski (2017)/ Procedia Engineering	Creating smart solutions for logistics in the global market	Analytical study	NA	192	NA
Hopkins & Hawking (2018)/The International Journal of Logistics Management	Using big data analytics and the Internet of Things to increase driver safety, reduce operating costs, and improve vehicles' environmental impact	Analytical framework	Data from 2012 to 2016 from a company in the logistics field	32	NA
Wu & Lin (2018)/ Telematics and Informatics	Generating logistical strategies by using unstructured big data	Analytical field study	Open-access logistic e-commerce professional websites	20	-Investigating various types of unstructured data to develop logistical strategies -Implementing studies on structured e-commerce logistics data

5. Conclusions

5.1. Hurdles

Despite of all the big data benefits for businesses, applying big data has not been accepted at the management level of many companies yet; this may be because the cost of using big data requires a high initial investment. Management support has a crucial role in the successful implementation of a big data analysis system. An initial cost-and-benefit assessment of big data in terms of how it will be utilized long-term is a very difficult task. It is not easy to determine applying big data analysis is beneficial for businesses that make fewer than a certain number of transactions every day. In some companies, such as Amazon, Walmart, Google, etc., traditional systems cannot be used to analyze the data because of how enormous the volume is. However, in some other companies, the V characteristics of big data are more questionable, and there is no rule of thumb to help tell the manager that the available data is suitable for establishing a big data analytics framework.

One of the problems with big data applications is knowing how, where, and by which means to collect useful data. Another issue has to do with inadvertently separating valuable information out of the available data. The analyst should know the information that he/she wants to exclude from the data; additionally, the available data should be able to answer the analyst's questions. Yet another problem regards finding the methods by which one can provide the most accurate answer while still using a reasonable amount of time and financial cost. There is an increasing demand for employees who are qualified to analyze big data as companies respond to the rapid pace of technology developments. It is also a challenge to create trust between data analysts and the managers. Most systems originally resist change, so it is vital to have the higher-level managers' support in order to use the results of data analysis to change a system.

A computers' Central Processing Unit (CPU) could be an obstacle for big data analysis because of the underdeveloped capability of traditional computers to store and effectively process a big data set. On the other hand, not all of the available raw data is complete and consistent; therefore, effective cleaning and integration methods are required to make the dataset ready for analysis.

The 5^{th} "V" added to the definition of big data refers to the value that can be obtained from a big data analysis. Unfortunately, whenever value comes in, hacking can start to crop up as well. Information security can be a hurdle to applying big data analysis in companies. A huge data volume increases the probability of having confidential and valuable information in the system, and this may increase data vulnerability and the chance of cybercriminals (Kshetri, 2014).

Another issue can be selecting the appropriate type of decision-making data for most of a system. More explicitly, not all of the available data in a system is used for making each and every decision. These decisions are based on the knowledge and experience of the data analyst that determine the part of a dataset that should be used. Moreover, it is an unfortunate fact that the available big data may not necessarily be created by the target population. For example, there is a huge volume of information on Twitter, but not everyone in a community will have Twitter accounts. Thus, there is a part of community which creates a lot of data, while the other part is not involved in creating any of the available information in a dataset. This fact continuously emphasizes statistical uncertainties such as biased statistics.

Applying the results of a non-real-time data analysis can lead to a significant difference between the analysis for both the historical data and the real-time data; for example, the initial assumption of the forecasting analysis that "the future follows the past" would not be true. As an additional example, when the data shows the proficiency of a transportation path in terms of cost and time (many companies have access to this data), other companies may start to use this same path. By increasing the demand for the mentioned path, it may lose its attractiveness both in terms of cost and time.

Another old and common challenge is sharing data between the echelons of a supply chain, or even various departments of a plant. It is challenging to ensure that all the stakeholders who share data receive some benefits from this cooperation. Moreover, it is vital to have a supportive information technology department which provides both the hardware and software requirements for working with big data. Data analysts who can work with big data should be hired, or knowledgeable instructors should be easy to contact so that they can educate the big data analysts for the plant.

5.2. Advantages

Big data analytics can help companies better understand their business needs. Many companies plan their business growth model according to a demand boom, which may be the result of business growth in general. However, they should consider that a change in market growth may leave them with several empty warehouses and idle manufacturing plants. Big data enables these firms to predict the market direction and plan development strategies based on this analytical information.

Using big data enables companies to simulate a digital model of an entire manufacturing process. Collected data from the customers can be used to improve the marketing and sales processes. Clustering the customers into various groups, providing service according to the needs of each group, and using customers' data to target where/when to advertise these new products are the other applications of big data in marketing.

The importance of big data analytics in improving customer loyalty is not negligible. Most customers would be loyal to the company which provides them a high-quality service the first time. Companies can use big data analysis to predict customers' needs and satisfy those needs in order to make them loyal customers.

Optimizing activities which are out of the normal boundaries of the company—such as supplier selection or technological adjustments—require a high level of information-sharing between the stakeholders in a supply chain. Sharing information has always been an obstacle in supply chains, but big data technological developments can help simplify and speed up this process (Swaminathan, 2012).

From a logistical point of view, big data can be applied in order to forecast delivery times or optimize delivery routing by using traffic, weather, and drivers' information. Another possible application is to use the products' information in making inventory management and sales decisions (Waller & Fawcett, 2013).

5.3. Directions for future studies

Both the literature and a review of companies' experience in the area of using big data analytics in manufacturing shows that the number of applied case studies are more than the number of theoretical publications. It is likely that researchers will develop more novel applications for big data in manufacturing systems, such as developing methods that can obtain high-quality solutions using less time and money.

Big data has been widely used for predictive studies in the literature, but there are not many prediction error measurement studies in big data. More precisely, beyond simply the quality of the input data, the accuracy of big data analysis is significantly affected by the quality of the model used to analyze the data. We still have a way to go regarding developing measures which can determine the accuracy of a big data analysis method.

The current studies regarding big data applications in supply chain management are mostly theoretical and conceptual, and there is a noticeable shortage of studies of analytical models. Moreover, the existing analytical models mostly study big data applications in modeling sustainability. Therefore, there is still a gap in the application of big data regarding optimizing operations (such as logistics and procurement) in a supply chain.

There are some study directions in big data that can significantly improve the performance of logistics systems: 1- Developing an efficient collaboration among all the decision makers, transporters, retailers, and door-to-door delivery service providers; and 2- Applying cloud-based services in smart transportation systems and integrating them in an online planning framework in order to provide a connection between vehicles, traffic managers, and the final customers.

Finally, a good research topic to follow would be to find out if analyzing a sample of a big data set could give us the same quality results as the basic big data analytics. Design of experiment methods can be used for categorizing big data into different groups in order to save time regarding analysis.

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