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Towards a conceptual framework**

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# **Understanding the value of big data in supply chain management and its business processes: Towards a conceptual framework**

**Purpose** – The value of big data in supply chain management (SCM) is typically motivated by the improvement of business processes and decision-making practices. However, the aspect of value associated with big data in SCM is not well understood. The purpose of this article is to mitigate the weakly understood nature of big data concerning big data's value in SCM from a business process perspective

**Design/methodology/approach** – A content-analysis-based literature review has been completed, in which an inductive and three-level coding procedure has been applied on 72 articles.

**Findings** – By identifying and defining constructs, a big-data SCM framework is offered using business process theory and value theory as lenses. Value discovery, value creation and value capture represent different value dimensions and bring a multifaceted view on how to understand and realize the value of big data.

**Research limitations/implications** – This study further elucidates big data and SCM literature by adding additional insights to how the value of big data in SCM can be conceptualized. As a limitation, the constructs and assimilated measures need further empirical evidence.

**Practical implications** – Practitioners could adopt the findings for conceptualization of strategies and educational purposes. Furthermore, the findings give guidance on how to discover, create and capture the value of big data.

**Originality/value** – Extant SCM theory has provided various views to big data. This study synthesizes big data and brings a multifaceted view on its value from a business process perspective. Construct definitions, measures and research propositions are introduced as an important step to guide future studies and research designs.

**Key words** – Big data, supply chain management, value, business processes, conceptual framework, literature review

**Paper type** – Literature review

# 1. Introduction

The practices of supply chain management (SCM) are faced with technological innovations that disrupt and change current supply chain configurations (MacCarthy et al., 2016). Noteworthy is that business processes become increasingly data dependent, and data-derived insights are seen as an instrument to improve supply chain performance, in which the concepts of big data and business analytics offer better decision-making practices to improve firm-level and process-level performance (McAfee and Brynjolfsson, 2012; Ramanathan et al., 2017). Big data is viewed as a new management paradigm and is based on the premise that intuition and discursive reasoning are being enhanced by logic, facts and evidence for more effective decision making (Mortenson et al., 2015). The emergence of big data is being introduced as a new frontier for IT-enabled SCM that has caught practitioner interest because it can increase the value delivered to customers, but, at this stage, not much is known about how to generate business value from big data (Fosso Wamba et al., 2015a). Scholars and practitioners recognize a valuable opportunity to utilize the vast, fast and diverse characteristics of data; however, the current body of literature has limitations concerning how to realize the expected value of big data (Kache and Seuring, 2017; Matthias et al., 2017; Schoenherr and Speier-Pero, 2015; Waller and Fawcett, 2013a). From a scholarly perspective, forward-looking research identifies big data, analytics and decision making as important themes for the future of SCM research (Wieland et al., 2016). Thus, value is expected from the utilization of big data, and, as this study will show, the value of big data in SCM includes several dimensions and cannot be understood as a singular concept.

Existing research on big data in SCM has steadily increased over the past few years with a primary focus on applications within procurement, manufacturing and logistics (Lamba and Singh, 2017). Researchers have sought to define big data in relation to “3Vs” (Volume, variety and velocity) or “5Vs” (Volume, variety, velocity, veracity and value), but it is questioned if all these conditions need to be met in order to qualify as big data (Roden et al., 2017). Therefore, the concept of big data in SCM is not well-established, fundamental theories are underdeveloped and researchers need a healthy skepticism towards our current knowledge until rigorous research has been done (Fosso Wamba et al., 2017b; Frizzo-Barker et al., 2016; George et al., 2014; Waller and Fawcett, 2013a). The result hereof is that the SCM construct of big data is somewhat confusing, weakly understood, perceived differently and showing that theory and practice are misaligned (Phillips-Wren et al., 2015; Richey et al., 2016). There is fundamentally a need to increase our understanding of big data, and

companies need guidance on how to leverage the enormous number of data available to achieve business value (George et al., 2014).

The purpose of this study is to mitigate the weakly understood nature of big data and to move towards a higher level of understanding concerning the value of big data in SCM from a business process perspective. Thus, business processes are adopted as the unit of analysis with the aim of identifying the pertinent constructs and assimilated measures. By drawing upon business process theory and value theory as theoretical lenses, the aim is furthermore to offer a big-data SCM framework and to make propositions that can direct future research. A content-analysis-based literature review has been conducted using existing big data and SCM peer-reviewed literature. An inductive coding procedure has been used to synthesize the content of 72 articles that have been systematically analyzed in three iterations.

Following this introduction, the article continues with a literature section to outline big data, business process theory and value theory. Section 3 describes the methodology and the activities conducted. Section 4 presents the big-data SCM framework, its value dimensions and the constructs. Section 5 discusses and introduces research propositions. Finally, section 6 concludes the findings and highlights implications.

## **2. Literature**

SCM is mostly described in terms of processes, more specifically, as chains of activities (Burgess et al., 2006). The nature of business processes is to deliver value on a consistent basis to customers and consumers (Al-Mudimigh et al., 2004). Several frameworks have been introduced in the history of SCM, e.g., the supply chain integration model that emphasizes the need to control materials and information flows through value-adding processes (Stevens, 1989), the global supply chain forum model that conceptualizes eight generic cross-functional processes (Lambert et al., 1998) and the supply chain operations reference model that introduces plan, source, make, deliver and return as the central processes (Stewart, 1997). Stevens and Johnson (2016) argue that supply chain integration is the foundation for SCM through the alignment, linkage and coordination of people, processes, information, knowledge and strategies across the supply chain to facilitate the efficient and effective flows of material, money, information and knowledge in response to customer needs. These central contributions to SCM have business processes as a grounded element of SCM. Therefore, this study adopts business processes as an appropriate unit of analysis.

## *2.1. Big data in SCM*

Big data, associated with prior and adjacent terminologies like business analytics and business intelligence, has emerged as a stand-alone concept, in which traditional analytic techniques are advancing and require new ways of handling (Chen et al. 2012). The general assumption is that big data can help companies understand their business environments at a more granular level and thereby meet market requirements in relation to products and services (Davenport et al., 2012). From a business process perspective, big data and business analytics may create a new class of economic asset and help companies redefine their business and outperform their competitors (Fosso Wamba and Mishra, 2017). Existing literature tends to agree that big data can be defined with 3V's: volume, variety and velocity (Fosso Wamba et al., 2015b; Frizzo-Barker et al., 2016). Scholars have introduced several aspects to the concept of big data in SCM. Waller and Fawcett (2013a) use the term "SCM data science" and describe it as the application of quantitative and qualitative methods from a variety of disciplines in combination with supply chain theory to solve supply chain problems and predict outcomes. Richey et al. (2016) argue that big data is structured and unstructured relationship-based information unique to its holder. Wang et al. (2016) address big data and business analytics as synonyms for supply chain analytics, and Kache and Seuring (2017) relate big data to the application of advanced analytics.

## *2.2. Business process theory*

Business processes are widely described as series of interrelated activities crossing functional boundaries with inputs and outputs (Armistead and Machin, 1997). The early literature on business processes distinguishes between business process reengineering (BPR) and total quality management (TQM), with a focus on either effectiveness or efficiency (Nadarajah and Kadir, 2014). The essence of BPR is to break away from old rules and traditional assumptions by taking advantage of information technology and redesigning business processes to achieve dramatic improvements in performance (Hammer, 1990). Consequently, reengineering decisions come with certain risks and cases of failure, which have abridged the radical approach to a less radical nature assimilated to, e.g., business transformation, process innovation and business process redesign (Grover and Malhotra, 1997). TQM represents an approach for incremental improvements as an opponent to the one-off radical changes associated with BPR (Armistead and Machin, 1997). TQM, along with

other philosophies like lean and six sigma, seeks to improve productivity on an ongoing basis by following certain practices and methods (Stevens and Johnson, 2016).

BPR and TQM as two distinct approaches have evolved into an overarching concept of business process management (BPM; Paim et al., 2008). BPM analyzes, designs, develops and executes business processes while also ensuring the interaction, control and optimization of these processes (Morais et al., 2014). In this regard, generic capability and maturity models have been offered to orient and pave the way for process improvements by describing the development from immature to highly developed BPM practices (Röglinger et al., 2012). BPM operates with process principles and BPM tools to increase the business process orientation of the company, which emphasizes that processes should grant special attention to outcomes and customer satisfaction (Hammer, 2010; Škrinjar and Trkman, 2013). By this, BPM seeks to make a transition from functional-based management to process-oriented management with three archetypes of organizational structures: functional, functional with transversal processes and horizontal processes (Aparecida da Silva et al., 2012). Opponents of BPM argue that BPM mostly is focused on continuous improvement of processes rather than thorough reengineering (Škrinjar and Trkman, 2013); however, BPM supports companies' improvement in both organizational efficiency and effectiveness and has been moving away from its operational roots (Işik et al., 2013).

With this background on business process theory, this study adopts effectiveness and efficiency as central elements to SCM. Benner and Tushman (2003) highlight the tension between effectiveness and efficiency as ambidexterity and state that the difference exists in either exploring or exploiting resources to improve performance. For business process effectiveness, the aim is to introduce innovations and process redesigns by exploring company resources as a means to address business process goals. For business process efficiency, the aim is to continuously exploit existing company resources to better manage and improve the output of the current process configurations.

### *2.3. Value theory*

The term value has been widely associated with big data, and there have been contributions studying the relationship between big data and firm performance (e.g., Côte-Real et al., 2017; Gunasekaran et al., 2017). However, firm performance does not solely cover the concept of value. George et al. (2014) argue that we need to understand big data through value creation and value capture, and Sheng et al. (2017) find that big-data value

originates in the process of value discovery, value creation and value realization. Neither publication, however, thoroughly explains and studies the concept of value.

Bowman and Ambrosini (2000) argue that a resource is valuable if it exploits and/or neutralizes threats in a firm's environment and enables the firm to implement strategies to improve effectiveness and efficiency. They distinguish between "use value" as a subjective measure perceived by the customer and "exchange value" which is realized when the product is sold and represent the price of the product. Lepak et al. (2007) further elaborate that use value refers to the specific quality of a new job, task, product or service as perceived by users in relation to their needs; they also state that exchange value is either the monetary amount realized at a certain point in time, when the exchange of the new task, good, service or product takes place, or the amount paid by the user to the seller for the use value of the focal task, job, product or service. Later, Bowman and Ambrosini (2010) propose that value has different meanings to different stakeholders of the company, i.e., suppliers, investors, employees and customers. To the company, use value is either embedded as human resources or is made of bought and built separate assets that, when combined, create new use value for customers. In this regard, the firm applies tangible resources (e.g., people and components) and intangible resources (e.g., data and information) to provide high use value for the optimal exchange value.

Value creation strategies require different organizational structures and processes, e.g., by the reconfiguration of assets and resources or by leveraging a replication of process or system to another domain area (Ambrosini et al., 2011). In SCM, the term "value chain" refers to a series of integrated, dependent processes through which specifications are transformed to finished deliverables, with the main focus of delivering value to customers (Al-Mudimigh et al., 2004). Treacy and Wiersema's (1993) work on value disciplines (i.e., customer intimacy, operational excellence and product leadership) represents strategic trade-offs and outlines different requirements to the configuration of processes.

### **3. Methodology**

For this study, a content-analysis-based literature review has been conducted. Big data is a rather new phenomenon and the literature is moving fast, with a significant growth in academic contributions (Frizzo-Barker et al., 2016; Lamba and Singh, 2017; Sheng et al., 2017). Therefore, there is a substantial amount of literature upon which to ground a content-analysis-based literature review. Previous literature reviews on big data in SCM have focused

on strategic and operational applications (Wang et al., 2016); trends within procurement, manufacturing and logistics (Lamba and Singh, 2017); and the identification of research clusters to suggest future research directions (Mishra et al., 2016). This literature review differs in its unit of analysis and its inductive synthesis of literature.

A literature review is defined as “a desk-based method involving the secondary analysis of explicit knowledge, so abstract concepts of explicit and tacit knowledge are explored ... creating a new dimension of fresh perspective that makes a distinct contribution” (Jesson et al., 2011, pp. 9–10). Literature reviews are considered an effective approach to creating a firm foundation for advancing knowledge and facilitating further theory development, e.g., by establishing conceptual models and propositions (Webster and Watson, 2002). A content analysis is a method for text analysis through the subjective interpretation of the content of text data and involves a systematic process of coding to identify themes or patterns (Hsieh and Shannon, 2005). A content-analysis-based literature review synthesizes the content of a research phenomenon by systematic coding and qualitative analysis of existing research articles. Seuring and Gold’s (2012) approach has been adopted through the milestones of material collection, descriptive analysis, pattern of analytic categories and material evaluation. An inductive approach is embedded throughout this study by constantly comparing categories and data (Seuring and Gold, 2012). The milestones have been completed in three iterations; an overview of these activities is provided in Table 1.

### **INSERT TABLE 1 ABOUT HERE**

#### *3.1. Material collection*

The databases selected as search engines were EBSCO, Web of Science, Science Direct, Engineering Village and IEEE Explore, thereby covering the majority of business, operations management, SCM, decision science and information science research. Advanced searches used the following criteria: “big data” in title “AND” “supply chain\*” in text as dual criteria. The inclusion criteria were that all articles should be peer-reviewed, in English and available for full-text download. Conference publications were included because of the immature research phase of big data. The material collection added up to 391 hits. After duplicates were removed, 241 articles met the search criteria. Articles were excluded if they did not have a significant focus on SCM or a SCM discipline either throughout the entire article or within a specific section. The SCM definition by Mentzer et al. (2001) was used as a



guideline to exclude articles: “the systemic, strategic coordination of the traditional business functions and the tactics across these business functions within a particular company and across businesses within the supply chain, for the purposes of improving the long term performance of the individual companies and the supply chain as a whole” (p. 18). The exclusion process had three phases:

1. A rough cut based on title and dissemination outlet to remove articles that were out of SCM scope;
2. An abstract, keyword and skim-through cut to remove articles that did not include any section on SCM or a SCM discipline;
3. And a reading cut to remove articles whose SCM sections or related sections had too little focus on SCM.

Finally, 72 articles met the criteria and were selected as a basis for the content analysis. The full reference list of the included articles is provided in Appendix 1.

### *3.2. Descriptive analysis*

Descriptive information for each article was documented for author(s), title, year, outlet type, outlet name, method and empirical basis. As presented in Figure 1, there are 49 journal publications and 23 conference publications and all work has been published within a five-year period. Table 2 presents the methods applied. Conceptual research designs are most used, followed by case studies and experiments. The least-used methods are grounded methods, mixed methods, literature reviews and surveys. In total, there are 38 non-empirical contributions, including conceptual methods and literature reviews, and 34 empirical contributions, including case studies, surveys, mixed methods and grounded methods. Experiment contributions include 4 empirical experiments and 6 non-empirical simulations.

**INSERT FIGURE 1 ABOUT HERE**

**INSERT TABLE 2 ABOUT HERE**

### *3.3. Analytic categories*

To analyze the large amount of text, core sections and figures/tables related to big data and SCM were identified. These sections were typically found in the chapters of introduction,

literature, analysis and conclusion. Each identified section and figure/table went through a coding procedure, with the aim of highlighting concepts and sentences related to the input, activity and output in business processes within the scope of big data. In order to process the concepts identified, the methodology of Gioia et al. (2012) was adopted as a systematic approach for developing new concepts, and is used to ensure qualitative rigor in the research results by providing a three-level data structure. By identifying first-order concepts and second-order themes, a conceptual framework related to the third-order aggregate dimensions of value discovery, value creation and value capture was developed. Then, based on construct definitions, each concept was linked to a specific construct to ensure that no construct had been overlooked. For the first and second iteration, all articles went through a coding process. In the third iteration, an overview of the articles was developed to understand their contributions, and sample articles were selected for coding to scan for any new concepts or categories; however, no new constructs were discovered.

### *3.4. Material evaluation*

The interpretation of the material required several drafts of the framework to be discussed among academia and practitioners, who have continuously refined the framework and improved the final result. The first draft was presented at a scholarly conference about operations and SCM, where review and audience feedback concerned SCM theory and practitioner validation. In the second iteration, the manuscript and its framework were further developed and subjected to feedback in a publishing workshop. In the third iteration, the intuitive understanding of the framework was tested by presenting the framework for bachelor and master students of SCM. Moreover, presentations at two large Danish companies were conducted for their immediate feedback. Lastly, the review process of the paper also improved the framework and introduced business process theory and value theory as lenses for developing research propositions.

## **4. A big-data SCM framework**

To strengthen the current understanding of big data, a holistic big-data SCM framework is presented in Figure 2. A prerequisite for big data has been emphasized as value; however, a single dimension of value is too simplistic a view, and big data in SCM needs to be

understood with more granularities through the dimensions of value discovery, value creation and value capture:

- *Value discovery* represents the ability to generate, locate, collect, store and govern trustworthy data that relies on a transparent, yet complex, network of systems, platforms and databases embedded with multiple data sources, diverse data characteristics and various technologies enabling collection, management, processing and analysis of data.
- *Value creation* represents the use value of big data in domain-specific business processes and the ability to utilize the information generated from the big-data ecosystem for strategic and/or operational decision making by using decision (support) systems.
- *Value capture* represents the exchange value of big data and the strategic components enabling big-data-derived economic improvements, competitive gains, better performance or other incentives that are realized through value discovery and value creation activities.

## **INSERT FIGURE 2 ABOUT HERE**

Business processes are central to the value creation of big data. On one hand, business processes adopt strategic innovation through the exploration of data in order to implement more effective process configurations while, on the other hand, managing efficiency through exploiting existing data and systems in a faster way. The concepts of data first, problems first and business first represent different starting points for big-data initiatives. The data first and business first concepts are the tension of whether to start exploring data by discovering insights that can be utilized in the business processes or to initiate big-data projects as an outcome of business objectives (Vanauer et al., 2015). The aspect of problem first is adapted from Chen and Zhang (2014), who argue for big-data problems. Here, a specific function or decision maker realizes difficulties with a decision-making practice and starts using big data to solve a problem at hand. In the next sub-sections and in Tables 3–5, the constructs related to value discovery, value creation and value capture will be presented and defined by drawing on the most prevailing studies.

### *4.1. Constructs of value discovery*

As shown in Table 3, value discovery includes the constructs of big-data ecosystem, data characteristics, data sources, technology and analytics. The big-data ecosystem is a construct

of an interconnected network of systems, platforms and databases that enables collection, management and extraction of multifaceted data. Ecosystem networks and IT architectures facilitate the utilization of big data; however, various overlapping conceptual frameworks for a big-data ecosystem have been put forward in literature (Addo-Tenkorang and Helo, 2016; Demirkan and Delen, 2013; Hofmann, 2017; Phillips-Wren et al., 2015; Rehman et al., 2016; Zhong et al., 2017). The purpose of a big-data ecosystem is to have a platform that acts as a “single source of truth” by means of a shared platform of data integration for all key stakeholders (Fosso Wamba et al., 2015b), where isolated systems are found inappropriate (Demirkan and Delen, 2013). Embedded are several data disciplines such as data aggregation, data reduction, data verification, data disposal, data management and governance procedures (Phillips-Wren et al., 2015; Rehman et al., 2016). The frameworks for a big-data ecosystem have certain denominators:

- The creation and collection of data from multiple sources,
- Data are stored and integrated in operational data warehouses,
- Data are extracted from one or more data warehouses to which analytic techniques are applied for context-specific application and decision making,
- Data and system governance is an embedded part of every step in the process.

### **INSERT TABLE 3 ABOUT HERE**

Part of the big-data ecosystem is the constructs of data characteristics, data sources and technology. The data-characteristics construct is not fully defined by the features of volume, variety, velocity and veracity. Other Vs, such as variability, have been put forward to describe that big data brings more variance and uncertainty than traditional data sets (Li et al., 2015). Babiceanu and Seker (2016) introduce volatility, verification and validation as additional Vs and argue that big data has a shorter life-cycle, needs ensuring measurements and high-data transparency and that data generated should come from a purposeful process.

The data-source construct represents data from tiers of suppliers, different stand-alone and cross-functional internal processes to tiers of customers and consumers, where data can be created and gathered at different supply chain actors and used for a single company purpose (Hofmann, 2017). Thus, there is a variety of potential data sources upstream, internally and downstream. Examples of other key data sources are product and machine data (Li et al., 2015), customer data (Wang et al., 2016), supply chain event logs (Vera-Baquero et al.,

2015c), process performance data (Vera-Baquero et al., 2015a), environmental data (Dubey et al., 2016) and market data (Sanders, 2016).

The technology construct represents technologies that enable the collection, storage, processing and distribution of data. These technologies ensure automated data collection of high-quality, fast data-processing capabilities to store and integrate data, as well as the automation of administrative and repetitive tasks (Chen and Zhang 2014). The technological concepts frequently identified are cloud, sensor, RFID, communication technologies, computer power and the internet of things (Li et al., 2015).

Analytics as a construct extracts data from the big-data ecosystem and process the data into information. Generally, a large range of analytic tools exists (Frizzo-Barker et al., 2016). Wang et al. (2016) identify simulation, statistical and optimization models as groupings of analytic techniques. A further categorization represents descriptive, predictive and prescriptive analytics (Rehman et al., 2016; Wang et al., 2016). Other techniques, such as data mining, machine learning, social network analysis and algorithms, are more advanced techniques for big-data analytics (Chen and Zhang, 2014).

#### *4.2. Constructs of value creation*

As shown in Table 4, value creation includes the constructs of information utilization, decision systems, strategic decisions and operational decisions. The decision (support) system construct is a service-oriented information system enabling or supporting decision making that comes in different formats, i.e., data-as-a-service, information-as-a-service and analytics-as-a-service (Demirkan and Delen, 2013), or as infrastructure-as-a-service, platform as-a-service and software-as-a-service (Neaga et al., 2015). The decision systems have different functionalities, and the kind of decision system found appropriate for the specific process depends upon the application. Heterogeneous systems like ERP, CRM and business intelligence dashboards deal with standardized and structured data and have difficulties in dealing with unstructured data (Vera-Baquero et al., 2016). More customized systems are needed when dealing with the different data features embedded in big data.

### **INSERT TABLE 4 ABOUT HERE**

Information utilization as a construct is the application of information via a decision (support) system for domain specific purposes. In this regard, big data is being adopted to

domain-specific areas as business analytics, supply chain analytics, SCM data science or business process analytics (Phillips-Wren et al., 2015; Vera-Baquero et al., 2015a; Waller and Fawcett, 2013a; Wang et al., 2016). Information utilization determines knowledge, abstracts valuable information in rich data sets, and delivers business insights and actionable insights to specific supply-chain applications (Rehman et al., 2016; Schoenherr and Speier-Pero, 2015). The utilization of information results in decision making that is enabled through an information flow as an output of a knowledge-discovery process (Chen and Zhang, 2014) or as a data-manufacturing process (Hazen et al., 2014). Furthermore, information utilization can be differentiated as either functional, process-based, collaborative, agile or sustainable, representing different maturity levels (Wang et al., 2016).

The strategic-decision construct represents different application areas for effectively developing supply-chain strategies within strategic sourcing, supply-chain network design and product design and development (Wang et al., 2016). Examples of other applications span across various elements as part of the fully scoped product-life-cycle management (Li et al., 2015). The aim is to explore innovation possibilities that create a better supply-chain setup by integrating existing and new data sources (Tan et al., 2015), essentially, to develop the supply chain by means of process redesigns (Vera-Baquero et al., 2015a).

The operational-decision construct includes efficiently managing supply-chain operations at tactical and operational levels and can be applied within sales, demand planning, procurement, production, inventory and logistics (Sanders, 2016; Wang et al., 2016). The operational applications seek to incorporate big data into already existing processes by exploiting existing data for process optimizations, better management practices, and decision making on a continuous and standardized basis. Other application areas are enabled through the speed of data and information, where monitoring has been put to practice for, e.g., business-process improvements and logistics tracking (Vera-Baquero et al., 2015a; Zhong et al., 2015).

### *4.3. Constructs of value capture*

As shown in Table 5, value capture includes the constructs of incentives and strategy. Incentives as a construct represent a variety of motivational factors for the deployment and utilization of big data for SCM purposes. The high-level goal is to increase sales, reduce costs and maximize profits (Rehman et al., 2016; Richey et al., 2016), where data has become a valuable asset and resource to improve competitiveness, innovation and efficiency (Braganza

et al., 2017). Survey studies have documented a positive correlation between big data and performance (Côrte-Real et al., 2017; Fosso Wamba et al., 2017a; Gunasekaran et al., 2017). A Delphi study identified 23 different opportunities for big data on corporate and supply-chain levels, the highest rated being customer behavior, visibility and transparency, operation efficiency and maintenance, information management, logistics and integration and collaboration (Kache and Seuring, 2017). Some companies view big data as a survivability factor and required to keep up with the competitive environment (Rehman et al., 2016). In other cases, big data can be a market differentiator, where new services and new business models are introduced (Opresnik and Taisch, 2015). Furthermore, big data allow competitive priorities for different segments in either customer service, cost competition, quality, time or responsiveness, resulting in different supply-chain structures and strategies (Sanders, 2016).

### **INSERT TABLE 5 ABOUT HERE**

Strategy as a construct is the strategic components needed for the success of big-data implementations in SCM. First and foremost, big-data strategies are being realized as a mean to implement big-data initiatives (Fosso Wamba et al., 2015b) and big data has also been embraced as a component in supply-chain strategies (Richey et al., 2016). From a manufacturing perspective, big data adds new business models in terms of servitization through the procedures of big data-generation and big-data exploitation (Opresnik and Taisch, 2015). Studies emphasize that big-data initiatives should be integrated and aligned across business activities and processes to enable integrated-enterprise business analytics capabilities (Sanders, 2016; Wang et al., 2016). Dutta and Bose (2015) argue that big-data projects need to be managed differently as they involve a higher level of complexity than other analytic projects. Finally, Waller and Fawcett (2013b) find that new analytic competences are required to combine analytic techniques with domain-specific know-how.

## **5. Discussion**

Through this content-analysis-based literature review on big data in SCM, existing literature has been synthesized, and a big-data SCM framework has been provided. Pertinent constructs and measures are identified from a business-process perspective and related to the meta-categories of value discovery, value creation and value capture. In this discussion, the findings of the big-data SCM framework will be informed by business process theory and

value theory with the purpose of introducing research propositions. This section will be structured around value discovery, value creation and value capture.

For value discovery, there is a potential to extract information from the big-data ecosystem to be applied in various business-process applications. Sheng et al. (2017) argue for information retrieval, knowledge discovery and organizational change but without defining and explaining value discovery. As pointed out earlier, differences exist concerning what constitutes big data and what big data really means in a SCM context as opposed to just data (Roden et al., 2017). In SCM, there is a long history of using data and information to drive decisions and the focus on data and information flows is, therefore, not new to business processes. But, overall, the outset of big data in SCM is to take advantage of information to realize better decisions (Richey et al., 2016), and SCM frameworks have traditionally considered data and information as an input to the business processes. This literature review has showed that today's business processes can be part of a big-data environment that provides numerous opportunities to explore and exploit data in new ways. By this, the adoption of big data in SCM represents more emphasis on data as an input to a process than what has been considered earlier. Thus:

P1. The adoption of big data in SCM enables business processes to better utilize data and information as a new/enhanced resource and input to a specific process or activity.

Big data in SCM is regarded as disruptive. Addo-Tenkorang and Helo (2016) highlight this as a paradigm shift of the information age for more value-adding activities and note that different SCM areas collect diverse amounts of voluminous data. Business-process improvements are required to cope with the volume and speed of transactions across global supply chains, where decision support systems assist complex decision making (Vera-Baquero et al., 2015a). Business processes should adapt to the increasingly complex information flows to ensure that activities and process standards match the data environment. Consequently, business processes would need to change and adapt to this new contingency. Analytic infrastructures can facilitate supply-chain innovations within the supply-chain network, supply-chain technology or supply-chain processes (Tan et al., 2015). This would transform the configuration of inputs between tangible and intangible resources and require new process setups. Thus:



P2. The adoption of big data in SCM through exploitation and exploration of data will change business-process configurations.

Value-discovery capabilities are dependent on how well the big-data ecosystem is managed and governed. The digitization of internal operations leads to increasingly many databases to be integrated and aligned to support business-process activities and analytic applications. Moreover, external data sources are also to be governed, even though they are not within company control. The big-data ecosystem is dynamic and will scale in both volume and range, which makes it hard to control for its data quality. Thus, a data-quality problem exists, which requires methods for monitoring and controlling data quality (Hazen et al., 2014), and governance processes are a denominator for managing the big-data environment (Phillips-Wren et al., 2015). Following this logic, the more data and systems a company can govern as an input to the business processes, the more likely it is that business processes will adopt more information to their activities and decision-making practices. Therefore:

P3. An increase in size and scope of the governed big-data ecosystem has a positive effect on value-creating activities within the business processes and the utilization of data and information.

Value creation is associated with use value as a subjective measure (Bowman and Ambrosini, 2000). The use value of big data is the transition from value discovery to value creation, where analytic insights are transferred to and used by employees who thus become users of the data and information. Here, a range of requirements are put to the services-oriented decision support systems in order to secure efficient and effective decision-making processes (Demirkan and Delen, 2013). The users receive the information via decision support systems, and its information utilization gives big data in SCM a direct use-value effect on decision-making practices. However, the value adding of big data is difficult to measure because of the subjective nature of use value, and users of big-data-derived information determine the direct use value of big data. Lepak et al. (2007) note that use value refers to the quality of a new job, task, product or service. With this in mind, increasing big-data insights to decision-making practices should increase the accuracy, speed and quality of the tasks performed by the employees. Thus:

P4. An increase in big-data-derived decision making has a positive effect on use value by improving business-process outputs and the quality of a new job, task, product or service performed.

It has been argued that business processes need to adapt to the big-data ecosystem; however, several challenges are present in its realization and value creation (Kache and Seuring, 2017; Schoenherr and Speier-Pero, 2015). In this study, business processes have been a central construct to facilitate the use of big data, and the practices of BPM pose as an opportunity to mitigate and overcome these challenges. BPM follows process principles and seeks to standardize processes to control inputs and outputs with low variations to ensure constant value-adding activities to internal and external customers (Hammer, 2010). Standardizing processes across the company would establish data-collection procedures to help in the consistency and quality of data. In this regard, BPM would moderate the establishment of a single source of truth and improve information utilization. Furthermore, big data is also used for measuring performance and improving business processes (Vera-Baquero et al., 2015a, 2015b), which also are an integral part of BPM practices (Škrinjar and Trkman, 2013). Thus:

P5. An increase of BPM practices has a positive effect on the information utilization derived from the big-data ecosystem.

To succeed with big data, a cross-functional setup is required (Sanders, 2016; Wang et al., 2016), and integration and collaboration are required with key partners (Kache and Seuring, 2017). Companies with a functional-based process structure suffer from silo mentality, and their processes are poorly coordinated and poorly interconnected with internal departments and external stakeholders (Aparecida da Silva et al., 2012). Therefore, the functional structure suffers from the capability of identifying and utilizing data that originates from other functions and stakeholders. Gunasekaran et al. (2017) study big data as a technology; assimilation of big data is the extent to which technology diffuses across organizational processes, through its acceptance by stakeholders and its routinization along governance systems. Implementing horizontal processes across functional processes, or instead of functional processes, would improve the upstream and downstream integration between information systems and provide more options in utilizing data for cross-functional decision-making practices. Therefore:

P6. The setup and use of horizontal business processes have a positive effect on the information utilization derived from the big-data ecosystem.

It is being emphasized that big data is a strategic asset to be used for improving competitiveness, innovation and efficiencies (Braganza et al., 2017). Value capture represents the aim of achieving business value from big data through better profits and competitiveness. However, the ideal business cases for applying big data tend to be unclear (Kache and Seuring, 2017; Schoenherr and Speier-Pero, 2015). An explanation for this problem is that the exchange value of big data or other competitive incentives is difficult to quantify as a result of better decision making. Therefore, the value capture of big data has an indirect effect on the measures applied in SCM. By acknowledging this indirect effect, new measurements are needed to quantify the value of big data on a decision-making level. By utilizing big data, decisions could be made faster, more precisely and more informedly (Côte-Real et al., 2017; Hazen et al., 2014; Hofmann, 2017; Richey et al., 2016). Faster decisions can be quantified by measuring decision lead times, more precise decisions can be descriptively quantified by measuring the accuracy in the decisions itself, and more informed decisions can be quantified using perceptual data derived from the business users. Thus:

P7. Big data in SCM as a new asset has an indirect exchange-value effect on performance, with a strong potential to change supply-chain measures.

Building upon BPM practice' positive effect on the utilization of big data, innovation to the current process practices is required. Within BPM literature, maturity and capability models have paved the way for advances in process excellence to improve performance (Röglinger et al., 2012), and companies have different levels of maturity that effect the utilization of data, information and big data (Wang et al., 2016). In order to implement big-data solutions to SCM, innovation is required as part of the big-data strategy (Opresnik and Taisch, 2015). The degree of innovation required, though, would depend on the level of process maturity. A functional logic with limited BPM practices would require a larger degree of process innovations, and the fundamental structure of processes needs to be redefined. On the contrary, if the business processes are more mature, an incremental approach is more suitable, and smaller adjustments to the process configurations are needed. Therefore:

P8. Low levels of business-process maturity imply a focus on more radical process innovations to utilize big data (focus on effectiveness) whereas high levels of business-process maturity imply a greater focus on more managerial and incremental approaches (focus on efficiency).

Finally, value-capture capabilities depict how well the company can capture the profits as opposed to its competitors, and studies have identified a positive link between big data and performance (Côrte-Real et al., 2017; Gunasekaran et al., 2017). Thus, an increase in big-data-derived decision making has a positive effect on the captured exchange value. In the big-data implementation framework provided by Sanders (2016), the first step is to define optimal segments with clear attributes, which determines how the company intends to compete and align strategic priorities in relation to customer service, cost competition, quality, time or responsiveness. Therefore, the value disciplines of customer intimacy, operational excellence and product leadership (Treacy and Wiersema, 1993) need to be researched further in relation to big data in SCM because each value discipline would depict different process configurations and strategies as well as how the big-data ecosystem is managed and utilized. Thus:

P9. The level of alignment between the value disciplines of customer intimacy, operational excellence and product leadership with big-data SCM strategies impacts the level of captured exchange value.

## **6. Conclusions**

The hype surrounding big data is high, the perception of big data is somewhat confused and existing SCM literature has lacked a thorough understanding of big data and its value. By conducting a content-analysis-based literature review on big data in SCM, this study introduces a big-data SCM framework through the dimensions of value discovery, value creation and value capture. Pertinent constructs have been defined, including the assimilated measures. The study has been informed by business process theory and value theory through which research propositions are introduced as a basis for future theoretical improvements.

The findings of the study contribute to the ongoing discussions concerning the value of big data in SCM and add a business-process perspective to how the value is discovered, created

and captured. Extant theory has predominantly focused on terminologies, i.e., supply-chain analytics, business analytics and SCM data science (Waller and Fawcett, 2013a; Wang et al., 2016); SCM applications (Lamba and Singh, 2017; Wang et al., 2016); big data tools and trends (Frizzo-Barker et al., 2016); assessing business value and performance (Côte-Real et al., 2017; Fosso Wamba et al., 2017a) and identifying challenges and opportunities (Kache and Seuring, 2017; Schoenherr and Speier-Peró, 2015). The big-data SCM framework and the embedded constructs further elucidate those contributions by adding further insights to the different value dimensions of big data in SCM, which expands the current view on big data in SCM and moves towards a more coherent and granular understanding of the concept. In addition, the identification of pertinent constructs and assimilated measures are among the first steps to understand big data's effect on business processes and its routes to business value. Literature reports on numerous research agendas related to big data (George et al., 2014; Phillips-Wren et al., 2015; Waller and Fawcett, 2013b), and there is a widespread need to study big data across SCM disciplines. The definition of value discovery, value creation and value capture, along with the embedded constructs, is an important step to guide future studies and research designs. Moreover, this study incorporates business process theory and value theory to introduce research propositions and provide theory-grounded explanations for how to understand the value of big data in SCM and how to realize its value.

It is reported that SCM practitioners adopt various understandings of big data (Richey et al., 2016) and that they find it hard to realize its value (Kache and Seuring, 2017; Schoenherr and Speier-Peró, 2015). SCM practitioners may adopt the big-data SCM framework in order to conceptualize strategies and for educational purposes to align and agree on a common understanding of big data among employees, departments, partners and other stakeholders. Moreover, companies are developing digitalization strategies in which the utilization of big data is a component in improving current supply-chain practices. The propositions introduced give some guidance on how to discover, create and capture big data's value, e.g., by establishing a governed big-data ecosystem, adopting BPM practices, increasing business-process maturity and reconsidering current supply-chain measures.

As a limitation, the study does not include drawbacks, risks and dangers of using big data in supply chains. Big data has proved a lasting concept, and there is a profound need to advance current knowledge to assist companies in utilizing big data for sustainable business value. In-depth and empirical studies, especially, are required to verify the framework and to understand how companies can successfully utilize big data to achieve both use and exchange value.

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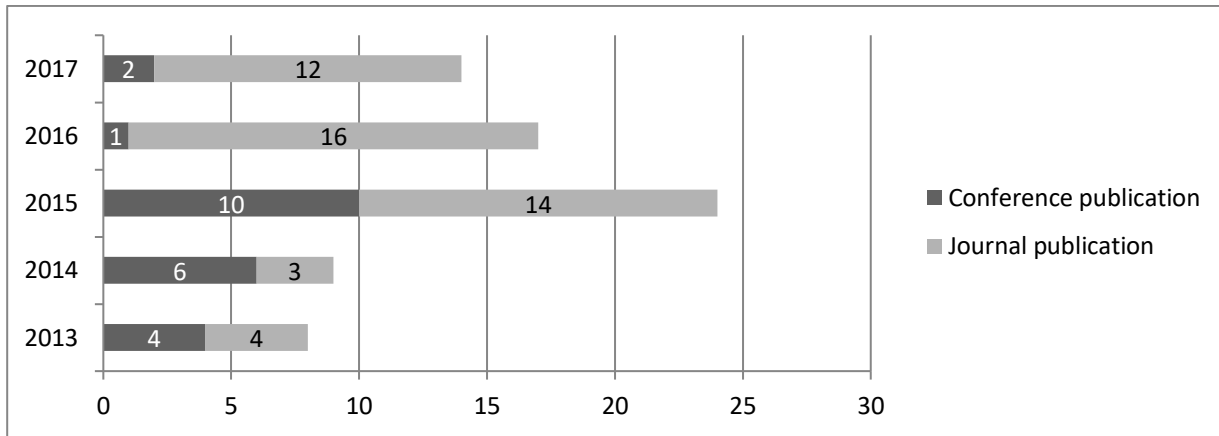
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# **Understanding the value of big data in supply chain management and its business processes: Towards a conceptual framework**

## **Figures & Tables**

**Table 1. Method and iteration overview**

		1 <sup>st</sup> iteration (jan-16)	2 <sup>nd</sup> iteration (may-16)	3 <sup>rd</sup> iteration (apr-17)
<b>Literature search procedure</b>				
EBSCO ( <i>Academic search premier &amp; Business source complete</i> )	<ul style="list-style-type: none"> <li>• Criteria 1: "big data"-title AND</li> <li>• Criteria 2: "supply chain*"-text</li> <li>• Filter: peer-reviewed, English, full text</li> </ul>	27	45	62
Science Direct	<ul style="list-style-type: none"> <li>• Criteria 1: "big data"-title AND</li> <li>• Criteria 2: "supply chain*"-all fields</li> <li>• Filter: journals</li> </ul>	29	42	82
Web of Science	<ul style="list-style-type: none"> <li>• Criteria 1: "big data"-title AND</li> <li>• Criteria 2: "Supply chain*"-topic</li> </ul>	29	37	86
IEEE Explore	<ul style="list-style-type: none"> <li>• Criteria 1: "big data"-document title AND</li> <li>• Criteria 2: "supply chain*"-abstract</li> </ul>	14	14	19
Engineering Village ( <i>Compendex &amp; Inspec</i> )	<ul style="list-style-type: none"> <li>• Criteria 1: "big data"-title AND</li> <li>• Criteria 2: "supply chain*"-all fields,</li> <li>• Filter: English</li> </ul>	67	82	142
Total search hits		166	220	391
<b>Analytic procedure</b>				
Inclusion and exclusion of articles incl. reading		x	x	x
Descriptive info documented		x	x	x
Identifying core sections and figures/tables		x	x	x
Coding of sections (all articles)		x	x	
Coding of sections (sample articles)				x
Draft constructs and framework		x		
Revise constructs and framework			x	x
Relate to business process theory and value theory				x
Proposition development				x
Academic / conference feedback		x	x	
Practitioner feedback			x	
Review feedback				x

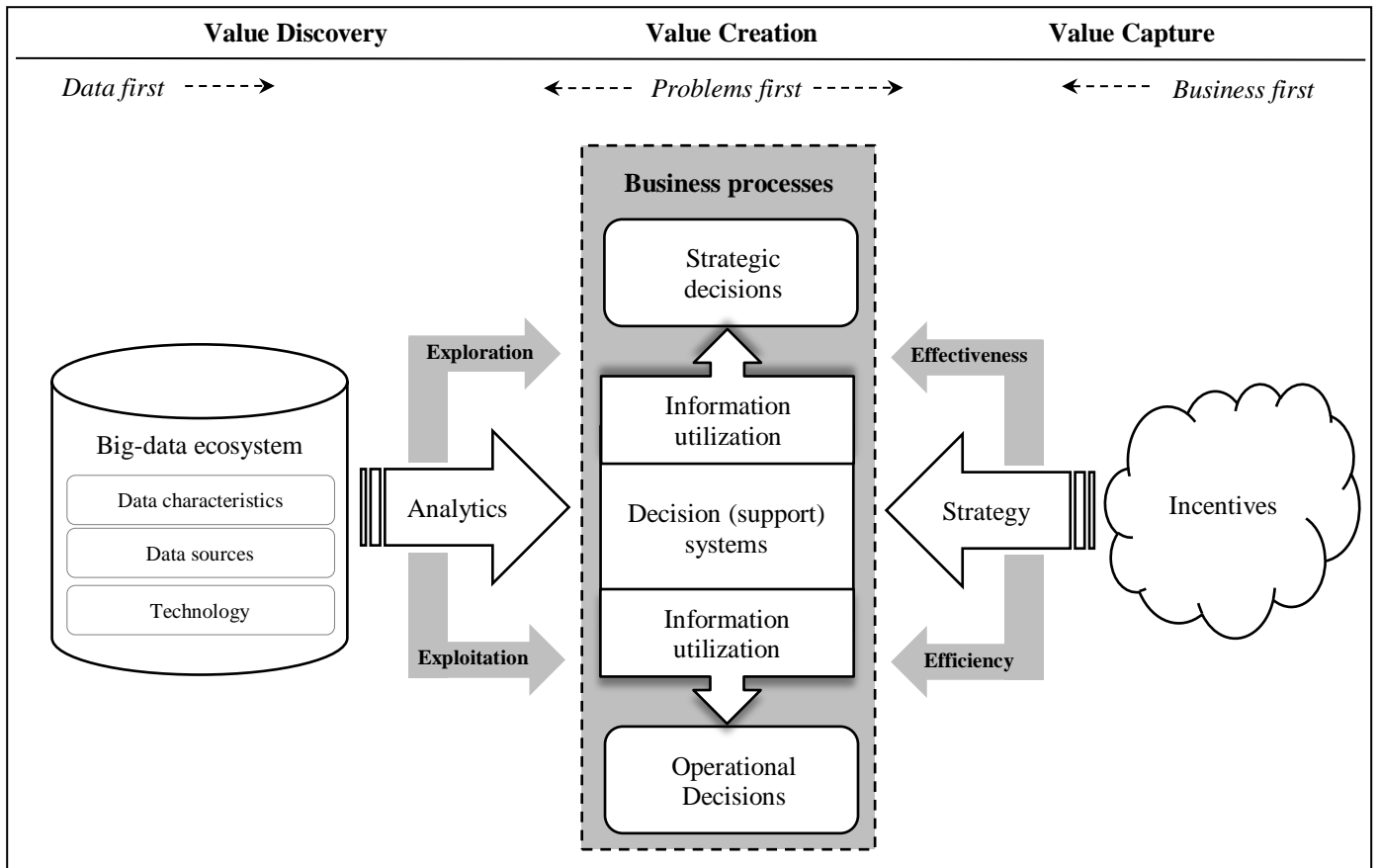


**Figure 1.** Yearly distribution of publications

**Table 2.** Distribution between research methods

<b>Research design</b>	<b>Reference</b>	<b>Total</b>
Conceptual	(Amudhavel et al., 2015; Biswas and Sen, 2016; Bohlouli et al., 2014; Choi et al., 2017; Fan et al., 2015; George et al., 2014; Ghosh, 2015; Gölzer et al., 2015; Hazen et al., 2016; He et al., 2013; Ittmann, 2015; Leveling et al., 2014; Li et al., 2015; Lu et al., 2013; Neaga et al., 2015; Opresnik and Taisch, 2015; Rehman et al., 2016; Robak and Zielonogórski, 2013; Vanauer et al., 2015; Vera-Baquero, et al., 2015a, 2015b, Waller and Fawcett, 2013a, 2013b; Witkowski, 2017; Zhong, Newman, et al., 2016)	25
Case study	(Braganza et al., 2017; Chircu et al., 2014; Dutta and Bose, 2015; Hazen et al., 2014; Jin and Ji, 2013; Lee et al., 2014, 2015; Ma et al., 2015; Tan et al., 2015; Vera-Baquero et al., 2015c; Vera-Baquero et al., 2014; Zhang et al., 2017; Zhao et al., 2017; Zhong, Lan, et al., 2016)	14
Experiments	(Hofmann, 2017; Hseush et al., 2013; Ji and Wang, 2017; Liu and Yi, 2016; Liu and Wang, 2016; Mehmood et al., 2017; Vera-Baquero et al., 2016; Zage et al., 2013; Zhong et al., 2015, 2017)	10
Survey	(Bughin, 2016; Chen et al., 2015; Chen and Zhang, 2014; Côte-Real et al., 2017; Dubey et al., 2016; Fosso Wamba et al., 2017; Gunasekaran et al., 2017; Zhang and Cheng, 2016)	8
Literature reviews	(Addo-Tenkorang and Helo, 2016; Babiceanu and Seker, 2016; Demirkan and Delen, 2013; Fosso Wamba and Akter, 2015; Frizzo-Barker et al., 2016; Wang et al., 2016)	6
Mixed methods	(Fosso Wamba et al., 2015; Papadopoulos et al., 2017; Phillips-Wren et al., 2015; Sanders, 2016; Schoenherr and Speier-Pero, 2015; Wu et al., 2017)	6
Grounded methods	(Boone et al., 2017; Kache and Seuring, 2017; Richey et al., 2016)	3





**Figure 2.** Big-data SCM framework

**Table 3.** Constructs of value discovery

<b>Construct (second order themes)</b>	<b>Definition</b>	<b>Measures (first order concepts)</b>	
Big-data ecosystem	An environment of interconnected systems, platforms and databases	<ul style="list-style-type: none"> <li>– Data collection</li> <li>– Data storage</li> <li>– Data aggregation</li> <li>– Data reduction</li> <li>– Data verification</li> <li>– Data quality</li> <li>– Data disposal</li> <li>– Data update</li> <li>– Data processing</li> <li>– Data standardization</li> <li>– Data management</li> <li>– Data ownership</li> <li>– Data sharing</li> </ul>	<ul style="list-style-type: none"> <li>– Data dissemination</li> <li>– Database</li> <li>– System infrastructure</li> <li>– System architecture</li> <li>– System design</li> <li>– System integration</li> <li>– Big data eco system</li> <li>– Information system</li> <li>– Governance</li> <li>– Knowledge management</li> <li>– Security</li> <li>– Privacy</li> </ul>
Data characteristics	The nature of data features	<ul style="list-style-type: none"> <li>– Volume</li> <li>– Variety</li> <li>– Velocity</li> <li>– Veracity</li> <li>– Variability</li> <li>– Volatility</li> <li>– Validation</li> </ul>	<ul style="list-style-type: none"> <li>– Complexity</li> <li>– Structured data</li> <li>– Unstructured data</li> <li>– Internal data</li> <li>– External data</li> <li>– Open data</li> <li>– Closed data</li> </ul>
Data sources	Generic sources for data collection	<ul style="list-style-type: none"> <li>– Product and machine data</li> <li>– Customer data</li> <li>– Supplier data</li> <li>– Performance data</li> <li>– Supply chain event data</li> </ul>	<ul style="list-style-type: none"> <li>– Environmental data</li> <li>– Internet data</li> <li>– Market data</li> <li>– Financial data</li> </ul>
Technology	Technologies that enable the collection, storage, processing and distribution of data	<ul style="list-style-type: none"> <li>– Information technology</li> <li>– Cloud</li> <li>– Sensor</li> <li>– RFID</li> <li>– Computer power / Hardware</li> <li>– Track &amp; trace</li> </ul>	<ul style="list-style-type: none"> <li>– Internet of things</li> <li>– 3D printing</li> <li>– Communication technologies</li> <li>– Physical internet</li> <li>– Wireless</li> </ul>
Analytics	The processing of data into information	<ul style="list-style-type: none"> <li>– Simulation models</li> <li>– Statistical models</li> <li>– Optimization models</li> <li>– Descriptive analytics</li> <li>– Predictive analytics</li> <li>– Prescriptive analytics</li> <li>– Screening methods</li> </ul>	<ul style="list-style-type: none"> <li>– Data mining</li> <li>– Validation</li> <li>– Quantitative methods</li> <li>– Business intelligence</li> <li>– Big data analytics</li> <li>– Algorithms</li> <li>– Machine learning</li> </ul>

**Table 4. Constructs of value creation**

<b>Construct (second order themes)</b>	<b>Definition</b>	<b>Measures (first order concepts)</b>	
Decision (support) systems	A service oriented information system enabling or supporting decision making	<ul style="list-style-type: none"> <li>– Data-as-a-service</li> <li>– Information-as-a-service</li> <li>– Analytics-as-a-service</li> <li>– Infrastructure-as-a-service</li> <li>– Platform-as-a-service</li> <li>– Software-as-a-service</li> <li>– Automated decision-making</li> <li>– Human decision-making</li> <li>– Communication platform</li> </ul>	<ul style="list-style-type: none"> <li>– Information interfaces</li> <li>– Software</li> <li>– Data presentation / visualization</li> <li>– Centralized decision making</li> <li>– Decentralized decision making</li> <li>– System users</li> <li>– Decision database</li> <li>– Information platform</li> </ul>
Information utilization	The application of information for domain-specific purposes	<ul style="list-style-type: none"> <li>– Knowledge discovery process</li> <li>– Data manufacturing process</li> <li>– Actionable insights</li> <li>– Real time actions</li> <li>– Business analytics</li> <li>– Supply chain analytics</li> <li>– SCM data science</li> </ul>	<ul style="list-style-type: none"> <li>– Business process analytics</li> <li>– Determining hidden knowledge</li> <li>– Business performance information</li> <li>– Analytic maturity applications</li> <li>– Deliver business insights</li> <li>– Abstracting valuable information</li> </ul>
Strategic decisions	Strategic SCM applications that develop effective solutions	<ul style="list-style-type: none"> <li>– Problem detection</li> <li>– Problem solving</li> <li>– Supply chain design</li> <li>– Supply chain network design</li> <li>– Supplier relationship management</li> <li>– Customer relationship management</li> <li>– Supply chain innovation</li> <li>– Process redesign</li> <li>– Disaster resilience</li> </ul>	<ul style="list-style-type: none"> <li>– Human resources</li> <li>– Business model development</li> <li>– Product design &amp; development</li> <li>– Informing strategic direction</li> <li>– Partner choice</li> <li>– Servitization</li> <li>– Product lifecycle management</li> <li>– Market penetration</li> <li>– Green supply chain management</li> </ul>
Operational decisions	Operational SCM applications that leverage efficient decision making	<ul style="list-style-type: none"> <li>– Performance management</li> <li>– Risk management</li> <li>– Inventory management</li> <li>– Logistics</li> <li>– Procurement</li> <li>– Manufacturing</li> <li>– Customer service</li> <li>– Sustainability</li> </ul>	<ul style="list-style-type: none"> <li>– Maintenance</li> <li>– Planning</li> <li>– Monitoring</li> <li>– Sales and marketing</li> <li>– Business process improvement</li> <li>– Control tower</li> <li>– Resource management</li> </ul>

**Table 5.** Constructs of value capture

<b>Construct (second order themes)</b>	<b>Definition</b>	<b>Measures (first order concepts)</b>	
Incentives	Motivational factors for the deployment of big data in SCM	<ul style="list-style-type: none"> <li>– Competitiveness</li> <li>– Profit maximization</li> <li>– Cost reduction</li> <li>– Meeting market and customer demand</li> <li>– Better customer service &amp; experience</li> <li>– Stay-in-business</li> <li>– Innovation</li> <li>– New revenue streams</li> <li>– Growth</li> <li>– Understanding products, markets and customers</li> </ul>	<ul style="list-style-type: none"> <li>– Operational efficiency</li> <li>– Market differentiation</li> <li>– Process transparency</li> <li>– Visible and flexible processes</li> <li>– Bargaining power</li> <li>– Responsiveness</li> <li>– Identify improvement opportunities</li> <li>– Value propositions</li> <li>– Exploit captured data</li> <li>– Better strategy execution</li> <li>– New business models</li> <li>– Market and industry evolution</li> <li>– Better and faster decision-making</li> </ul>
Strategy	Strategic components for the success of big data implementations	<ul style="list-style-type: none"> <li>– Project management</li> <li>– Holistic approach across functions</li> <li>– Strategic emphasis</li> <li>– Big data strategy</li> <li>– Big data generation</li> <li>– Big data exploitation</li> <li>– Supply chain strategy</li> <li>– Stakeholder management</li> <li>– Data analytic capabilities</li> <li>– Investments</li> </ul>	<ul style="list-style-type: none"> <li>– Servitization</li> <li>– Organizational change</li> <li>– Business first vs. data first</li> <li>– Data scientists</li> <li>– Dynamic capabilities</li> <li>– Leadership commitment</li> <li>– Create and realize solutions</li> <li>– Analytics as a core competence</li> <li>– Data/Knowledge as an asset</li> <li>– Data-driven culture</li> </ul>

## **Appendix 1: Reference list of the included articles in the content-analysis based literature review**

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