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ABSTRACT

Purpose: Big data poses as a valuable opportunity to further improve decision-making in supply chain management (SCM). However, the understanding and application of big data seems rather elusive and partially explored. This paper intends to create further guidance in understanding big data and to explore applications from a business process perspective.

Design/methodology/approach: This paper is based on a sequential mixed-method. First, a Delphi study was designed to gain insights regarding the terminology of big data and later identify applications of big data in SCM using an adjusted SCOR process framework. This was followed by a questionnaire-survey among supply chain executives to elucidate the Delphi study findings and to assess the practical use of big data.

Findings: First, big data terminology seems to be more about data collection than of data management and data utilization. Second, the application of big data is most applicable for logistics, service and planning processes than of sourcing, manufacturing and return. Third, supply chain executives seem to have a slow adoption of big data.

Research limitations/implications: The Delphi study is explorative by nature and the questionnaire-survey rather small in scale; therefore, findings have limited generalizability.

Practical implications: The findings can help supply chain managers gain a clearer understanding of the domain of big data and guide them in where to deploy big data initiatives.

Originality/value: This study is the first to assess big data in the SCOR process framework and to rank applications of big data as a mean to guide the SCM community to where big data is most beneficial.

Key words: Big data, supply chain management, supply chain processes, decision-making, information technology, mixed-method

Article classification: Research paper

1. Introduction

The application of data and information flows in supply chain management (SCM) is not new, but as technologies has evolved, the practice of SCM is adopting big data and business analytics as a mean to improve information flows and decision-making, where high volumes of multidimensional data exceed traditional information technologies (George et al., 2014; Ramanathan et al., 2017). In SCM, interest has been devoted to big data and future research include several promising research directions (Fosso Wamba, Ngai, et al., 2017; Mishra et al., 2016; Mortenson et al., 2015; Wieland et al., 2016). Hitherto, the value of big data have been rather implicit and a recent Delphi study discovered that profound opportunities for big data exist on a corporate- and supply chain level, but also that several challenges exists (Kache and Seuring, 2017). Though, recent quantitative studies show a positive relation between big data, operational efficiency and firm performance (Côrte-Real et al., 2017; Fosso Wamba, Gunasekaran, et al., 2017; Gunasekaran et al., 2017), where existing operating models are to be affected by big data (Roden et al., 2017). In this regard, sustainable competitive advantages can be achieved through the application of big data (Matthias et al., 2017). The outcome of big data, from a business process perspective, is improved decision-making quality, but this often non-linear process varies dependent on the numerous data sources available (Janssen et al., 2017). With big data, information and communication technologies enable information to be readily accessible and improved analytic capabilities generates new insights, which are changing many supply chains by e.g. reconfiguring business processes (MacCarthy et al., 2016; Nudurupati et al., 2016). Therefore, existing analytic applications are to be improved and new applications arises which operations and SCM researchers need to further study (Hazen et al., 2016).

Despite valuable opportunities for big data, some of the fundamental questions are still unanswered. For example, Roden et al. (2017) questions what big data is? How big data can be used? And to what extend big data can affect processes and operating models? Thus, both academics and supply chain managers tend to be confused about the terminology of big data and unbiased managerial guidance on its application is currently weakly established (Richey et al., 2016). Studies on big data in business processes like plan, source, make, deliver, and return have only partially been explored (Sanders, 2016; Wang et al., 2016). Schoenherr and Speier-Pero (2015) stress that the application of big data in SCM is rather elusive and there is a need to understand what kind of supply chain questions can be addressed by big data. Furthermore, research questions are devoted to understand how big data can improve internal and external processes and its decision-making on a strategic, tactical and operational level (Fosso Wamba, Ngai, et al., 2017). Overall, the adoption and application of big data in operations and SCM are a relatively new area that misses empirical insights (Matthias et al., 2017; Tan et al., 2015). Therefore, an important first step is to create a better understanding of big data in a SCM context, while also guiding practitioners to where big data can best be applied. In the present study, the purpose is to further understand big data by exploring big data and its application in SCM from a business process perspective that can help the supply chain community in understanding, where the value of big data can be applied.

This paper intends to move the conversation on big data in a SCM context so it rests on empirical data in order to understand its application in practice. This paper advances the understanding of big data by deploying a sequential mixed method design, which includes a Delphi study and a questionnaire-survey. The Delphi study explores how the terminology of big data is understood in relation to data collection, data management and data utilization. The Delphi study, furthermore, explores and ranks possible applications of big data in the SCOR process framework. The questionnaire-survey further elucidates the Delphi study findings and assesses the practical use of big data by means of digital strategies and investments.

The article continues with the underlying theoretical foundation for this study, followed by an explanation and argument for our choice of method. Then the empirical findings are presented and discussed against existing theory. The paper ends with a conclusion that includes limitations, theoretical implications, practical implications and suggestions for future research directions.

2. Relevant literature

2.1 The big data terminology

Big data is related to business intelligence and business analytics and has emerged as a separate concept (Chen et al., 2012). From a management perspective, big data is a holistic approach for obtaining actionable insights to create a competitive advantage, which differs from business analytics in terms of the 5V's: volume, variety, velocity, veracity, and value (Fosso

Wamba et al., 2015). Generally, existing literature agree that information flows are to support decision-making having a data input, data processing and data output (Hazen et al., 2014), which in a big data setting is associated to a knowledge-discovery process (Philip Chen et al., 2014).

Various conceptually defined big data frameworks and architectures are present in existing literature (Bi and Cochran, 2014; Biswas and Sen, 2016; Hofmann, 2017; Phillips-Wren et al., 2015; Rehman et al., 2016). To assess the practitioner view on big data, this study follows the framework provided by Bi and Cochran (2014) that includes data collection (DAC), data management (DAM) and data utilization (DAU). For data collection, the characteristics of data have become more diverse and include various data formats like numbers, text, images, and audio (Goes, 2014). Companies have been logging their transactions and activities resulting in large amounts of internal data. Combining this with the Internet of Things has enabled access to external data sources that can support the business even further, because it creates insights on the business environment at a more granular level (Bi and Cochran, 2014). Finally, the pace at which data are captured through advanced technologies, i.e., in real time, enables faster responses to changes as they occur (Davenport et al., 2012). For data management, the structured and unstructured data are to be stored in different systems in which a transparent IT-infrastructure enables data integrations and data sharing (Duan and Xiong, 2015). Here, various analytic techniques are to be applied, such as machine learning, data mining, and visualization methods (Philip Chen et al., 2014). Intra- and inter-organizational decision support systems rely on a network of systems for which governance procedures assure reliable data analytics (Demirkan and Delen, 2013). For data utilization, knowledge discovered is either to support decision-making or to make automated decision-making (Davenport and Kirby, 2016). The analytic insights derived can identify problems and opportunities within existing processes, discover explanatory and predictive patterns about what will happen and provide reasons for the occurrence, and determine the best possible outcome between alternatives based on accumulated knowledge (Wang et al., 2016).

2.2 Big data applications in SCM

The research domain of SCM is not new and has become an important capability for companies who seek to meet market and customer requirements in relation to cost, quality and time. SCM seeks to improve the long-term performance of the individual company and the supply chain as a whole by coordinating business functions (Mentzer, 2001, p. 22). In this regard, one company must seek a strategic supply chain orientation, where SCM is a necessary antecedent to effectively align supply chain strategy and supply chain structure within organizational design, human resources, information technology and organizational measurements (Esper et al., 2010). The use of data and information flows has long been a requirement in managing intra- and inter organizational business processes (Lambert et al., 1998). But as SCM has evolved, it has become a knowledge-based approach that relies on better use of information to make proactive decisions (Stevens and Johnson, 2016). Thus, big data has emerged as a paradigmatic shift on how organizations make decisions (Mortenson et al., 2015).

The application of big data in SCM has been referred to as SCM data science (Waller and Fawcett, 2013), predictive analytics (Schoenherr and Speier-Pero, 2015), business analytics, big data analytics and supply chain analytics (Wang et al., 2016), which are primarily similar terminologies for applying advanced qualitative and quantitative analytics for supply chain purposes by utilizing the vast amount of fast moving and diversified data available. From a supply chain analytics view point, data management resources are key building block in business analytics activities, thus enabling data-driven processes for operational performance (Chae et al., 2014). There is a common acceptance that big data can be adopted at strategic, tactical and operational levels, thus improving existing decision-making practices (Fosso Wamba, Ngai, et al., 2017; Kache and Seuring, 2017; Phillips-Wren et al., 2015).

In recent years, publications on the application of big data in operations and supply chain management have increased, where most emphasis has been given to manufacturing, procurement and logistics (Lamba and Singh, 2017). A literature search on "big data"-title and "supply chain*"-text was carried out in peer-reviewed databases to identify most prominent research conducted.

2.2.1 Main contributions so far

On a rather high-level themes and sub-themes for the application of big data in operations and SCM have been mapped in a literature review (Addo-Tenkorang and Helo, 2016). This study set forth that data-driven concepts are applied to achieve operational excellence, enhance customer experience and develop new business models, where also big data technologies relevant to SCM are identified. Furthermore, themes of big data acquisition, big data storage, big data analysis, big data application and big data value-adding are identified with regard to the 5V's.

Souza (Souza, 2014) provides a descriptive study on the application of supply chain analytics in the SCOR framework. Even though the study does not explicitly focus on big data, it still includes big data aspects. This work provides examples of decision-making at strategic, tactical and operational levels for each SCOR process, while also identifying relevant analytic techniques.

The work by Sanders (Sanders, 2016) identifies source, make, move, and sell as primary areas of application for big data. For "source" big data may be used to segment suppliers, evaluate sourcing channel options, integrate with suppliers, and support supplier negotiations. For "make" it involves granular performance reporting, mitigation of capacity constraints, inventory optimization, facility location/layout, and workforce analytics. For "move" the application of big data involves routing, scheduling, using transportation alternatives, optimizing, and maintaining vehicles. Finally, for "sell" and marketing purposes, big data enables micro- segmentation of customers, the capture and prediction of customer demand and behavior, and price and assortment optimizations. These applications are defined as conceptual, but also involve some empirical grounding.

A structured literature review based on 101 articles study big data and business analytics in a taxonomy for descriptive, predictive and prescriptive analytics and differentiates between strategic and operational applications (Wang et al., 2016); however the empirical basis for the included articles is not presented. Nonetheless, the work systematically introduces a range of applications for strategic sourcing; supply chain network design; product design and development; demand planning; procurement; production; inventory and logistics, which gives guidance to where big data may be applied. Furthermore, a five-stage analytic maturity framework is linked to the applications.

A conceptual study by Li et al. (Li et al., 2015) argues that big data can be applied at every stage of the product life-cycle: from the beginning, in the middle and towards the end of a product life. Beginning of the product life-cycle includes production aspects of procurement, manufacturing, equipment management, marketing and design. Middle of the product life-cycle contains the applications of warehouse management, transport, customer service, product support, corrective- and preventive maintenance. Lastly, end of the product life-cycle can use big data to enhance recycling in a product recovery system.

Other application specific studies are also published and include manufacturing in cyber-physical systems (Huang et al., 2015), service parts management (Boone et al., 2017), resource management (Braganza et al., 2017), sustainable supply chain (Kaur and Singh, 2017; Papadopoulos et al., 2017), shop floor scheduling and facility layout (Ji and Wang, 2017; Tayal and Singh, 2016), transport operations (Mehmood et al., 2017), servitization (Opresnik and Taisch, 2015), maintenance processes (Zhang et al., 2017) and process improvements (Vera-Baquero et al., 2015).

To summarize, the above mentioned studies have investigated the application of big data in SCM and clearly states that big data can be used for many purposes and in many business processes. However, existing literature falls short in empirical contributions, where conceptual frameworks and taxonomies on the application of big data dominate the current body of knowledge. Therefore, real-world insights on big data in SCM are necessary to understand its application in practice.

2.3 A process-oriented framework for analyzing big data

To empirically identify supply chain applications of big data this study draws upon the Supply Chain Operations Reference model (SCOR), which includes the cross-functional processes of plan, source, make, and deliver (Stewart, 1997), return, which was added later. The SCOR processes is widely used as a deductive framework to study supply chain topics (e.g. Sangari et al., 2015; Stavrulaki and Davis, 2010). SCOR as a framework have earlier been used to determine the effect of business analytics on supply chain performance (Oliveira et al., 2012; Trkman et al., 2010). The potential of big data is not limited to manufacturing companies; retailers, service providers and healthcare professionals, among others, also see big data potential (Fosso Wamba et al., 2015). In this regard, big data is also for service supply chains (Fosso Wamba et al., 2015; Opresnik and Taisch, 2015; Zhong et al., 2016), which is why the aspect of service processes has been added to this study as a supplement to the SCOR framework and represents the view of service supply chain as well as service processes in manufacturing settings.

3. Methodology

Big data in management research is in its initial phases and empirical studies are encouraged to further develop the research field (Frizzo-Barker et al., 2016). Existing studies on the application of big data in SCM falls short of empirical contributions, which leaves little insights towards how big data actually is applied in practice. In addition, the perception of big data among SCM professionals is not clear (Richey et al., 2016). Therefore, the present paper applies a mixed-method approach to explore experts understanding of big data and its applications in SCM and to further elucidate these findings among SCM executives. The mixed approach allows investigating big data in SCM among different samplings, which is an advantage when inadequate knowledge exists. Mixed-method is acknowledged in empirical driven research, because multiple perspectives of a problem can be explored (Choi et al., 2016). The design strategy for mixed-methods is to apply method triangulation that can eliminate the existing bias when just applying one method (Greene et al., 1989), which is found important to enhance research quality within SCM (Boyer and Swink, 2008). Mixed-methods can be combined in several ways and can contain both qualitative and quantitative approaches (Howick and Ackermann, 2011), where the methods can be applied concurrently or sequentially (Venkatesh et al., 2013).

This study adopts a sequential mixed-method design containing a Delphi study and questionnaire-survey, which combination previously have been adopted in SCM research (e.g. Cegielski et al., 2012). The first study applies Delphi method that is explorative in nature, which in turn, deals with uncertainty in an area with imperfect knowledge (Huscroft et al., 2013). Because of the confused perception of big data it has been found appropriate to use the Delphi study as the method consolidates expert knowledge. The aim of the Delphi study is to empirically explore the terminology and application of big data in supply chain management. The second study contains answers on a questionnaire-survey based on the Delphi study findings, which intend to further elucidate the Delphi study findings on a larger and different sample to see if any relationship exists among the various factors of interest.

3.1 Delphi study

Linstone and Turoff (2002) characterize the Delphi method as "a method for structuring a group communication process so that the process is effective in allowing a group of individuals, as a whole, to deal with a complex problem". The strength of the method is its ability to create consensus on an unexplored topic that lacks empirical evidence (Powell, 2003), which is the case of big data in SCM. With an end goal of ranking applications of big data in SCM, the method will be applied to identify the ways in which big data is applied in supply chain processes. The study has followed the traditional Delphi study approach of design, selection of experts, data collection rounds of brainstorming, narrowing down of factors and ranking, and finally analysis (Okoli and Pawlowski, 2004).

In a Delphi study, recruitment of appropriate experts is essential for the validity of the results (Rowe and Wright, 2011). As big data seems to be most applicable in larger companies (Frizzo-Barker et al., 2016), the sampling criteria was that the experts had to have practical experience with and knowledge about supply chain processes, business analytics, and big data, as well as experience working with big data in one of the larger organizations in Denmark. The sampling strategy was to have a diversified group of experts; therefore, experts represented larger Danish organizations of manufacturing, wholesalers, retailers, and service providers. Specifically, when contacting the organizations, we asked for the person responsible for supply chain, IT, and/or big data. Furthermore, experts from universities and consultancies were also chosen as they have a more context-free understanding of big data compared to industry experts. The experts were not asked to evaluate current organizational practices, but instead asked to share their overall knowledge of the field. Within the 100 largest companies in Denmark, 67 companies were contacted and 23 experts agreed to participate, which is the sample size considered appropriate for a Delphi study under typical circumstances (Worrell et al., 2013). In the expert panel, 17 hold a master degree, MBA or PhD and 17 have more than 5 years of experience with data usage in a supply chain perspective.

The Delphi study was designed as a three-round online questionnaire with two parts. The first part focused on understanding what characterizes big data in SCM, while the second part focused on exploring possible areas of application for big data in SCM. Each Delphi round can have the purpose of brainstorming to identify dominant factors in a particular domain and/or to rank/prioritize a seeded list (Worrell et al., 2013). In the first round seeding procedures were applied to reach consensus on the terminology of big data in SCM context. This step drew on existing big data definitions and theory related to data collection, data management and data utilization as already elaborated in the literature section. Furthermore, a brainstorming section about the areas of application for big data in supply chain processes was accomplished based on the SCOR. Prior to the second round, the brainstorming responses on the application of big data in each SCOR process were condensed by the authors to four to eight statements. These applications were then ranked in the second Delphi round, where answers for the big data terminology were re-evaluate based on the mean value achieved from the first round. In the final Delphi round, the experts re-evaluated the application scores based on the mean values achieved in the second Delphi round. For all ranking a five point Likert scale has been applied.

3.2 Questionnaire-survey

In a study carried out together with the Danish Purchasing and Logistics Forum (DILF) on the digital supply chain, an opportunity did rise to further elucidate the Delphi study findings. Thus, a questionnaire-survey has been conducted, where the application of big data has been studied in a new empirical context.

3.2.1 Data collection

DILF has together with university researchers established a supply chain panel containing supply chain executives in the Danish business environment. The panel members receive annually four mini-surveys per year, each focusing on a specific supply chain issue (e.g. big data in SCM, digital supply chains and supplier relationship management). Only one person per company can be panel member. Each survey consists of 10 to 15 questions. The basic idea with the panel is to obtain improve practical relevancy (Toffel, 2016) in terms of raising research questions (a problem of knowledge production) and relevancy in the communication with practice (a problem of knowledge transfer) (Carter, 2008). At the time where the survey was conducted the panel had 86 member companies that were contacted via personalized e-mail. 49 valid answers were received, resulting in a response rate at about 57%. All questions were measured on a five-point Likert scale with end points of ‘very low degree’ and ‘very high degree’. The findings is thus based on a rather small sample size and methodological issues of small samples are present, though, small samples are common in SCM and by relying on: a) extant literature, b) prior research results (Delphi study), c) not solely applied descriptive analytics and d) carefully drawing conclusions, the biases of small sample sizes is still mitigated (De Beuckelaer and Wagner, 2012).

3.2.2 Constructs

Overall, four questions was asked and these constructs are considered based on the literature review and the Delphi study findings. First, the constructs for big data terminology was selected based on highest scores for retrospectively data collection, data management and data utilization (Q1). Here, the questions concerning data-driven supply chain was asked related to the relevance and actual pursue. The selected constructs for the terminology of big data are:

- Integrate multiple data sources (DAC)
- Automated data collection methods (DAC)
- Store large amounts of data (DAC)
- Cross data and cross system analysis (DAM)
- Apply advanced data analysis methods (DAM)
- Apply visualization techniques making complex data simple to the decision maker (DAM)
- IT-enabled processes for fact-driven decision-making (DAU)
- Determine optimal decision (DAU)
- Identify problems and opportunities within existing processes (DAU)
- Discover explanatory and predictive patterns (DAU)

Second, the questionnaire-survey included questions related to digital strategies on a company level (Q2) and digital strategies within digital planning, digital services, digital logistics, digital supply, digital manufacturing, and digital return management (Q3). Subsequently, the questionnaire-survey also included questions relating to the actual need for big data analytics and current investment in big data analytics within logistics, service, manufacturing, planning, sourcing, and return processes (Q4).

3.2.3 Data analysis

The IBM© SPSS© statistics software v22.0 was used to evaluate the correlation among the questions of interest. This analysis explicitly recognizes the correlation among the various applications of big data within a business environment. In cases where no correlation is found, the findings will be descriptively reported. Correlation analysis was applied on:

- The correlation between Q1 and Q2
- The correlation between Q1 and Q3
- The correlation between Q1 and Q4
- The correlation between Q2 and Q3
- The correlation between Q2 and Q4
- The correlation between Q3 and Q4

4. Findings

4.1 Delphi study findings

Respondents have been questioned in regard to three aspects of the big data terminology. The questions asked, the mean values, and standard deviation (S.D.) are presented in Table 1. Overall, the three aspects received a score higher than 4, indicating that these are all considered important parts of big data in SCM, although the data collection (DAC) aspect was rated highest by the experts (mean score of 4.4). Here the respondents especially agree that big data in SCM involves different data sources, automated generation of data, and large amounts of data. In regard to the aspect of data management (DAM), the questions of cross-data and system analysis as well as advanced algorithms, tools, and applications for data analysis had the highest scores. The lowest rated statement for data management is that big data in SCM involves complex governance procedures. However, the answers revealed some disagreement on this statement. For data utilization (DAU), the questions achieved more or less equally distributed scores, although the statement of automated decision-making received the lowest scores. In addition, the data utilization scores reveal that the utilization of big data is more for operational purposes than strategic purposes.

-------------------------INSERT TABLE 1 HERE----------------------------

The brainstorming performed by the respondents on how big data may be applied in SCOR processes resulted in the identification of 39 potential areas of application of big data in SCM as listed in Table 2. Specifically, four to eight statements were provided for each process as defined by the SCOR ranging from the return (RET) process with only four to eight statements for service (SER) processes. The scores were distributed with service (SER) having the highest score, followed by return (RET), logistics (LOG), planning (PLA), sourcing (SOU), and manufacturing (MAN), in that order. For sourcing, big data will most likely be used as decision support for purchasing and information that can be utilized when negotiating with suppliers. For manufacturing, the respondents agreed that big data will have the greatest impact on identifying optimization possibilities, identifying root causes for manufacturing issues, as well as gaining insights to the manufacturing processes. For the application of big data in service, the respondents agree or strongly agree on all eight statements. The scores for service reveals that big data may especially be deployed to identify customer segments, gain customer insights, adjust/customize/develop service offerings, and to practice direct marketing. When it comes to logistics, the highest scores were assigned to the statement utilize big data for gaining logistical insights and to assess logistical performance. In planning, the scores show that big data will have the greatest impact on improving independent forecasting techniques and gaining insights about end-user consumption for existing products. Lastly, for return, big data will mainly enable learnings from customer complaints and the identification of root causes on defects (quality improvement).

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The scores show rather similar mean scores when evaluating the SCM processes where big data will be most applicable. In anticipation of these results, the respondents were asked to prioritize the different SCM processes in terms of which processes the application of big data would be most applicable. As Table 3 highlights, logistics (mean score of 5.3) had the highest score, which was then followed by service, planning, manufacturing, sourcing, and return processes (mean score of 1.4). These scores indicate that the mean values from Table 2, on a grouping level, are not fully consistent regarding the processes to which big data is most applicable. For example, return processes were initially scored as having greater importance than manufacturing and sourcing (Table 2), but when prioritized, return processes scored lowest (Table 3). Therefore, the prioritized list should be considered more reliable when evaluating on a group level.

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4.2 Questionnaire-survey findings

Table 4 contains the respondents' answers on pursuing a data-driven supply chain, where attributes of big data have been asked to identify their actual application and perception of relevance. The findings suggest a trend of medium to low scores, though, for its actual pursue all scores are below three. The highest actual scores are for IT-enabled fact-driven decision-making, identifying problems and opportunities within existing processes and to determine optimal decisions. For all cases, the actual application is lower than its perceived relevance, wherein, the largest gap exists to apply visualization techniques to complex data sets. An interesting finding is also that the storage of large volumes of data and applying the use of advanced data analysis methods has scored the lowest. No correlation was found for the terminology of big data to the other questions raised.

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Table 5 shows the correlation between digital strategies, where a significant correlation (significant level at 99%) was found between a digitalization strategy on a company level and a digital strategy on each business process area except for digital return management (significant level at 95%). The mean values are medium to low, where the highest scores are found on digital planning, digital service and digital logistics. Digital supply, digital manufacturing and digital return management are ranked the lowest. Additional correlation analyses were applied. The first was between digitalization strategy on corporate level and the actual need and degree of investments on big data analytics. The second on digital strategies on each business process area and the actual need and degree of investments on big data analytics. However, no significant correlation was found on either. This suggests that the digital strategies applied do not include big data analytics.

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Table 6 displays the actual and need investments in big data analytics. The scores are medium to low, showing a rather low adoption of big data. When asking specifically on big data, it shows that planning, logistics and service processes again have the highest scores, whereas sourcing, manufacturing and return processes have the lowest scores. For all processes it can be concluded that the actual need for big data is higher than its current investments, which indicates that supply chain managers see a potential to use big data but this is not a part of the digital strategy and the budgets for developing the supply chain.

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5. Discussion and analysis

This study has applied a mixed-method methodology containing a Delphi study and a questionnaire-survey on the terminology and application of big data in SCM. Based on the results three topics are up for discussion: terminology, application and adoption.

5.1 Terminology

There has been some confusion regarding the terminology of big data, for which extant publications have used similar terms such as SCM data science, predictive analytics, business analytics, supply chain analytics, and big data analytics (Sanders, 2016; Schoenherr and Speier-Pero, 2015; Waller and Fawcett, 2013; Wang et al., 2016). Variation in terminology usage makes it difficult to identify what big data is and what it is not. We have obtained some guidance about how big data may be understood in SCM by asking a group of experts how they perceive big data in relation to data collection, data management and data utilization (Bi and Cochran, 2014). The findings indicate that big data is more about data collection than data management or utilization, and big data is mostly focused on combining various datasets for cross-data and cross-system analysis. Chae et al. (2014) found that data management resources are key building block for supply chain analytics, which also can be stated in the context of big data because, all scores from the Delphi study related to the big data terminology in SCM are rather high. This could be an indication that big data is a term that incorporates terminologies like business analytics and business intelligence, but with additional perspectives. However, the questionnaire-survey revealed that the actual application and perceived relevance of applying big data analytics is considered less widespread among the supply chain executes than the hype suggests in extant literature (Frizzo-Barker et al., 2016). Furthermore, the fact that data collection is rated highest is an indication that companies have not yet been able to utilize their vast amount of data available, and, as a result, rate data management and utilization are having less importance when determining the terminology of big data. In addition, the supply chain executives responded in the questionnaire-survey that applying advanced analytic methods is not of highest relevance, rather it is to realize IT-enabled and fact-based decision-making and thus helping decision-makers through visualization.

5.2 Application

The applications listed for each process area via the Delphi study is the first study to address big data in the SCOR process framework equal to earlier studies on e.g. business analytics and supply chain analytics (Oliveira et al., 2012; Souza, 2014). The added aspects of service and return processes in SCM have been proved valid as its statements received significantly high scores. This empirical founded guidance has not been obtained in earlier studies. The applications already identified in literature cover a wide range of areas to which big data can be applied (Li et al., 2015; Sanders, 2016; Souza, 2014; Wang et al., 2016). This study mostly confirm existing applications, though, a few new applications are also identified. Examples of new applications would be supporting interaction with customers, learning from customer assessments, a differentiation between independent and dependent demand forecasting and all applications in return processes have previously not been covered. Although this study has identified some new areas of application, the applications listed should not be considered exhaustive. The Delphi approach has been guided by brainstorming and not by existing literature. For instance, some application areas related to sell, e.g., prize optimizations, were not identified (Sanders, 2016). Furthermore, the aspects of supply chain network design and decisions on the supply chain infrastructure (Wang et al., 2016) had very limited focus in our study. Aspects related to product life cycle were not fully identified, e.g., utility and maintenance aspects, and nor were product recovery decisions (Li et al., 2015). These missing, yet important, applications were not identified in our study, which indicate that the field of big data in SCM still is evolving and that many opportunities for utilizing big data exist for many business process purposes.

5.3 Adoption

The Delphi study findings have shown high scores for the application of big data and the expected value that resides in the utilization of big data is high (Addo-Tenkorang and Helo, 2016). However, the results from the 49 supply chain executives reveal another perspective. Extant literature acknowledges big data as an emerging phenomenon that still has to prove its value (Matthias et al., 2017). The questionnaire-survey findings suggests that digital strategies are weak on the agenda both on a company and a supply chain level, where also the actual need and current investments on big data receive medium to low scores. Furthermore, a significant correlation was found between digital strategy on a company level and digital strategy on process levels, but when doing a correlation analysis on big data analytics there was no significant correlation found. This finding may be biased by a small sample size, but this initial finding suggests that big data is weakly on the digital agenda for supply chain executives, emphasizing that big data still is in its emerging phase.

6. Conclusions

This study has deployed a sequential mixed-method design to further understand big data and its application in SCM. The first study was explorative, where a three round Delphi study assessed and ranked 22 statements on the terminology of big data and identified 39 applications of big data using an adjusted SCOR process framework. The second study was a questionnaire-survey among supply chain executives to further elucidate the findings found in the Delphi study and to assess the practical use of big data for supply chain purposes. The foremost finding of this mixed-method study is that the processes of logistics, service and planning have been found most beneficial for big data, whereas the process of sourcing, manufacturing and return management are found less beneficial. Furthermore, the Delphi study suggests that big data is more about data collection than of data management and data utilization. Finally, a correlation analysis did not show a relationship between digital strategies and big data analytics, where both digitalization and big data seems to have a slow adoption into SCM practices.

6.1 Limitations

This study has sought to enhance the construction validity through method triangulation by using a sequential mixed method approach. But given the exploratory nature of this research limitations still exist. In general, the findings have limited generalizability for two reasons. One being that the Delphi study is explorative, where the expert knowledge may not fully capture the general perception and application of big data. Therefore, the applications listed should not be considered exhaustive. The other being that the questionnaire-survey includes a small sample size and was only carried out in a Danish context. Furthermore, Richey et al. (2016) points that many perceptions of big data exist among SCM managers, which is a potential bias for this study.

6.2 Theoretical implications

Extant research has lacked empirical contributions, where big data's application in SCM is rather elusive and that proper guidance to practitioners currently are weakly established (Matthias et al., 2017; Richey et al., 2016; Schoenherr and Speier-Pero, 2015); therefore, a central contribution of this paper is its movement of the big data conversation based on empirical insights. Big data have been a rather confused concept in SCM (Richey et al., 2016) and this study adds practitioners' point of view to the discussion in regard to the terminology and application of big data. Extant research has sought to further understand big data, where the volume, variety, velocity, veracity and value characteristics seems to be agreed upon (Fosso Wamba et al., 2015) and several data value chains and architectures have been developed (Bi and Cochran, 2014; Biswas and Sen, 2016; Hofmann, 2017; Phillips-Wren et al., 2015; Rehman et al., 2016). Though, these do not take practitioners point of view into account. This study contributes by adding practitioners perception related to data collection, data management and data utilization, which can enrich the ongoing to discussion on the concept of big data.

Earlier studies have identified a variety of applications of big data in SCM (Li et al., 2015; Sanders, 2016; Wang et al., 2016), but all applications identified have been not been ranked against each other to allow priorities. Furthermore, existing literature have put most emphasis on manufacturing, procurement and logistics (Lamba and Singh, 2017). Though, when asking SCM practitioners, this study finds that big data is most beneficial in the processes of logistics, planning and service; the processes of manufacturing, sourcing and return management is found less beneficial for big data. This contribution is rather profound as the Delphi study and the questionnaire-survey confirms each other findings on this question. Therefore, existing literature may not properly address SCM practitioners focus areas for applying big data. Most applications identified have been covered by existing studies; the contribution resides that the Delphi panel has ranked specific application areas for big data, thus suggesting most beneficial applications within each business process. Applications for return processes have not before been treated in literature, which is a contribution by itself.

Finally, even though the hype of big data seems rather high with many promising research directions (Frizzo-Barker et al., 2016; Mishra et al., 2016) the actual application of big data and the current investments indicates a rather slow adoption of big data, where big data is weakly in the strategic agenda for the digitalization of supply chain management practices.

6.3 Practical implications

The findings of the present study can hopefully help supply chain managers and executive officers to better understand big data and its potential applications. The study findings are based on experts and SCM executives who have shed light on the terminology of big data from a SCM perspective. This study highlight that big data is not well understood and that the adoption of big data is limited, thus by providing empirical insights and guidance towards where big data may be most beneficial can potentially enable big data as an integral part of the supply chain and digitalization strategy. In this regard, the findings provided can be used as a guidance to discuss potential focus areas and investments of big data. The applications are not exhaustive and supply chain managers should also seek inspiration from earlier studies on the application of big data. Furthermore, the findings are generic and not context specific and managers should also take their industry, maturity, role in the supply chain and other company specific aspects into account.

6.4 Future directions

Five areas for future research are suggested to be further pursued. First, extant research has sought to establish overviews of the application of big data, including this study, which covers SCM as a broad discipline. These overviews provide only initial guidance because the application of big data is context dependent. Therefore, future research on the application of big data should include factors like industries, market dynamics and maturity levels, while considering the companies' role in the supply chain. Second, future research should seek more in-depth studies on specific applications that can guide practitioners on what data sources are needed, what analytic techniques to apply and how each specific application can be implemented and integrated into existing business practices. Third, the questionnaire-survey of this study represents a small sample and could contain bias; therefore, large-scale surveys would be valuable to further quantify the adoption and application of big data. Fourth, existing research on big data seems to focus mostly on large companies (Frizzo-Barker et al., 2016), but big data can also be for smaller small and medium sized companies. In this regard, the practice among different firm sizes could be included in future research. Fifth, this study has also indicated a slow adoption of digitalization and big data in SCM, which should be further investigated. It is known that severe barriers exists for implementing big data (Kache and Seuring, 2017), but little seems to be known on how to overcome these barriers. Therefore, future research is encouraged to help supply chain executives in developing data-driven supply chains that incorporates big data into the larger digitalization agenda, where other emerging technologies also are affecting the adoption of big data.

7. References

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Table 1. Scores for the big data terminology in SCM

Factor		Big data in SCM involves?	First answer Mean	First answer S.D.	Second answer Mean	Second answer S.D.
Data collection (DAC)	DAC1	Different data sources (e.g. product-, market-, supply chain- and financial data)?	4.7	.54	4.8	.42
	DAC2	Automated technologies to collect data (e.g. sensors, RFID, internet, GPS)?	4.7	.57	4.6	.58
	DAC3	Large amounts of data?	4.4	.71	4.4	.71
	DAC4	Different types of data (e.g. numbers, text, audio and video)?	4.1	.90	4.2	.83
	DAC5	High speed collection of data (e.g. real time data)?	4.1	.90	4.0	.88
		Overall	**4.4**	**.43**	**4.4**	**.42**
Data management (DAM)	DAM1	Cross data and cross system analysis?	4.3	.75	4.3	.70
	DAM2	Advanced algorithms, tools and applications for data analysis (e.g. optimization-, statistical- and simulation software)?	4.3	.77	4.3	.77
	DAM3	Advanced visualization techniques to support decision-making?	4.1	.75	4.1	.75
	DAM4	Advanced system infrastructure for data acquisition, data storage and data access?	4.1	.77	4.1	.75
	DAM5	Establishing and maintaining an integrated data- and system network?	4.0	.64	4.0	.64
	DAM6	Complex governance procedures of harmonizing, cleaning and sharing of data?	3.6	1.20	3.7	1.11
		Overall	**4.0**	**.45**	**4.1**	**.44**
Data utilization (DAU)	DAU1	Determines optimal decision by utilizing accumulated knowledge?	4.1	.63	4.2	.58
	DAU2	IT-enabled processes for fact-driven decision-making?	4.2	.73	4.2	.74
	DAU3	Operational decision-making (e.g. short term, focus on efficiency)?	4.2	.89	4.2	.89
	DAU4	Discovers explanatory and predictive patterns about what will happen and reasons why so?	4.2	.95	4.2	.95
	DAU5	Identifies problems & opportunities within existing processes and functions?	4.1	.85	4.1	.82
	DAU6	Supporting business processes with actionable insights?	4.0	.64	4.0	.60
	DAU7	Strategical decision-making (e.g. long term, focus on effectiveness)?	4.0	.71	4.0	.71
	DAU8	Automated decision systems?	3.6	.95	3.5	.90
		Overall	**4.1**	**.47**	**4.1**	**.48**

Note: First answer (N=23), second answer (N=19)

Table 2. Scores for big data's application in SCM

Factor		**Big data's application is, especially, useful in?**	**First answer** Mean	S.D.	**Second answer** Mean	S.D.
Sourcing processes (SOU)	SOU1	Decision support for purchasing?	4.3	.72	4.3	.72
	SOU2	Providing information for supplier negotiations?	4.1	.57	4.1	.57
	SOU3	Assessing supplier performance?	3.9	.70	3.9	.66
	SOU4	Supplier integration and data sharing?	3.9	.73	3.9	.70
	SOU5	Identifying and evaluating sourcing options for products and suppliers?	3.6	.76	3.7	.65
	SOU6	Automated purchasing decisions?	3.7	1.08	3.7	1.08
	SOU7	Benchmarking the sourcing process?	3.6	.59	3.6	.59
		Overall	**3.9**	**.37**	**3.9**	**.38**
Manufacturing processes (MAN)	MAN1	Identifying optimization possibilities?	4.4	.50	4.4	.50
	MAN2	Identifying root causes regarding manufacturing issues?	4.1	.54	4.1	.54
	MAN3	Gaining insights about manufacturing processes?	4.0	.85	4.0	.85
	MAN4	Assessing manufacturing performance?	3.9	.85	3.9	.85
	MAN5	Digitalizing manufacturing processes?	3.7	.87	3.7	.73
	MAN6	Understanding manufacturing cost structures and product profitability?	3.7	.99	3.7	.99
	MAN7	Designing flexible manufacturing setups?	3.4	.68	3.3	.67
		Overall	**3.9**	**.46**	**3.9**	**.46**
Service processes (SER)	SER1	Identifying customer segments?	4.6	.75	4.7	.66
	SER2	Gaining customer insights?	4.6	.51	4.6	.50
	SER3	Adjusting existing service offerings?	4.4	.51	4.4	.51
	SER4	Customizing service offerings?	4.4	.51	4.4	.51
	SER5	Practicing direct marketing to specific customers?	4.4	.68	4.4	.68
	SER6	Developing new service offerings?	4.3	.57	4.3	.57
	SER7	Learning from and reacting to customer assessments?	4.1	.77	4.1	.77
	SER8	Supporting interaction with customers?	4.1	.77	4.1	.79
		Overall	**4.4**	**.41**	**4.4**	**.42**
Logistics processes (LOG)	LOG1	Gaining logistical insights (e.g. by tracking movement and identifying waste)?	4.4	.51	4.4	.51
	LOG2	Assessing logistical performance	4.1	.79	4.2	.60
	LOG3	Informing suppliers and customers on operational logistical performance (e.g. delays)?	4.2	.70	4.1	.67
	LOG4	Scheduling transportation (e.g. products and employees)?	4.1	.76	4.1	.76
	LOG5	Designing logistics networks?	3.9	.72	3.9	.72
	LOG6	Identifying and evaluating logistical options?	4.0	.89	3.9	.85
		Overall	**4.1**	**.47**	**4.1**	**.48**
Planning processes (PLA)	PLA1	Forecasting independent demand (e.g. finished goods)?	4.4	.51	4.4	.51
	PLA2	Gaining insights about end-user consumption for existing products?	4.3	.47	4.3	.47
	PLA3	Determining appropriate demand and supply strategy?	4.1	.55	4.1	.55
	PLA4	Assessing planning performance?	4.1	.77	4.1	.77
	PLA5	Planning dependent demand (e.g. raw materials)?	4.0	.83	4.0	.73
	PLA6	Gaining insights about end-user consumption for new product releases?	3.9	1.02	4.0	.92
	PLA7	Conducting scenario and contingency planning?	3.8	.94	3.8	.86
		Overall	**4.1**	**.53**	**4.1**	**.50**
Return processes (RET)	RET1	Learning from customer complaints?	4.3	.64	4.4	.59
	RET2	Identifying root causes for defects?	4.2	.95	4.3	.87
	RET3	Predicting return rates?	4.1	.79	4.2	.67
	RET4	Assessing return process performance?	3.8	.70	3.7	.64
		Overall	**4.1**	**.51**	**4.1**	**.43**

Note: First answer (N=19), second answer (N=21)

Table 3. Prioritization of big data's application in SCM

To which processes is big data most applicable?		First answers		Second answers	
		Mean	S.D.	Mean	S.D.
LOG	Logistics	4.5	1.37	5.3	1.20
SER	Service	4.3	1.68	4.7	1.20
PLA	Planning	4.1	1.60	4.1	.91
MAN	Manufacturing	3.6	1.32	3.2	.89
SOU	Sourcing	2.9	1.42	2.2	1.18
RET	Return	1.6	.87	1.4	.81

Note: A score of 6 indicates that the respondents consider the application most important, whereas a score of 1 is least important.
Note: First answer (N=19), second answer (N=21)

Table 4. Degree of pursuing a data-driven supply chain and its relevance

Big data attribute		Mean	S.D.
Apply visualization techniques making complex data simple to the decision maker (DAM)	Relevance	3.14	1.16
	Actual	2.49	1.18
IT-enabled processes for fact-driven decision-making (DAU)	Relevance	3.12	1.00
	Actual	2.63	.92
Determine optimal decision (DAU)	Relevance	3.12	1.02
	Actual	2.51	.99
Identify problems and opportunities within existing processes (DAU)	Relevance	3.08	1.05
	Actual	2.59	1.01
Automated data collection methods (DAC)	Relevance	2.92	1.31
	Actual	2.35	1.12
Cross data and cross system analysis (DAM)	Relevance	2.90	1.15
	Actual	2.41	1.14
Integrate multiple data sources (DAC)	Relevance	2.88	1.17
	Actual	2.35	1.04
Discover explanatory and predictive patterns (DAU)	Relevance	2.84	1.09
	Actual	2.33	1.02
Apply advanced data analysis methods (DAM)	Relevance	2.76	1.08
	Actual	2.37	1.00
Store large amounts of data (DAC)	Relevance	2.59	1.12
	Actual	2.35	1.00

Note: N=49 for all questions

Table 5. Correlation between digital strategies

To which degree does your company pursue digital strategies within:	Mean	S.D.	Factor	To which degree does your company have an explicit digitalization strategy?	
Digital planning	3.02	1.12	Digital planning	Correlation	,490**
				P-value	0
Digital services	2.96	1.09	Digital services	Correlation	,439**
				P-value	0,002
Digital logistics	2.92	1.03	Digital logistics	Correlation	,563**
				P-value	0
Digital supply	2.76	1.08	Digital supply	Correlation	,539**
				P-value	0
Digital manufacturing	2.59	1.19	Digital manufacturing	Correlation	,456**
				P-value	0,001
Digital return management	2.27	1.01	Digital return management	Correlation	,340*
				P-value	0,017

**. Correlation is significant at the 0.01 level (2-tailed).
*. Correlation is significant at the 0.05 level (2-tailed).
Note: N=49 for all questions

Table 6. Actual need and current investments in big data analytics

Factor		N	Mean	S.D.
Planning (PLA)	Actual need	43	3.19	1.04
	Current investments	44	2.82	1.09
Logistics (LOG)	Actual need	42	3.07	.86
	Current investments	43	2.79	.98
Service (SER)	Actual need	43	2.84	1.01
	Current investments	43	2.65	1.01
Sourcing (SOU)	Actual need	40	2.50	1.16
	Current investments	41	2.27	1.10
Manufacturing (MAN)	Actual need	36	2.44	1.04
	Current investments	35	2.29	1.11
Return (RET)	Actual need	38	2.16	.93
	Current investments	38	2.08	.96