Big Valuable Data in Supply Chain: Deep Analysis of Current Trends and Coming Potential

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Abstract. Today, Big Data Analytics (BDA) are definitely the key basis of competitiveness for enterprises in their Supply Chains. The outburst of data captured, accumulated and analyzed is impacting the value-added-chain at all levels from manufacturers to customers. In this paper, we develop a structured methodology to provide a deep analysis of Big Data Analytics methods across the Supply-Chain Operations Reference (SCOR) model processes. An exhaustive literature review is illustrated to afford a comprehensive Mind-Map cartography with a BDA-SCOR matching matrix. The proposed approach points to a number of research concerns that need to be addressed by research community. Outcomes of this study may highlight relevant guidelines for upcoming works of both academics and industrials. It highlights the need for collaborative Big Data to manage SCM more intelligently. Our objective is to provide an effective analysis to understand how Big Data Analytics become even more valuable for better Supply Chain Management.

Keywords: Big valuable data · Analytics · Supply Chain Management · SCOR model · Mind-Map cartography

1 Introduction

There is no doubt; Big Data Analytics (BDA) is progressively becoming inevitable practice to extract more and more business values [1]. The main motive of Supply Chain (SC) managers is certainly to possess meaningful insights that allow them to better forecast, predict, reveal hidden patterns, and then to gain wider edge of competitiveness [2]. Henceforth, academics and industrials are aware that conventional databases are not capable to process such Big Data [3]. Analytics are reforming the way Supply Chain Management (SCM) handle acquired data internally; such as transactional information systems, and externally such as social networks, mobile devices, and IoT (Internet of Things) sensors [4].

Beyond considerate what Big Data earns, companies now are focusing on how analytics might be used to obtain business meaningful insights [5]. Given the variety and complexity of very large unstructured and high-dynamic datasets, this task is not trivial and may be very challenging [6].

Accordingly, we propose this paper with multifold purposes: (a) Foremost, it carried out a profound literature review across past and present patterns in academic publications. The bibliographical analysis is conducted by observing contributions, synthetizing knowledge, drawing tendencies, and making causality relationships by classifying intakes and highlighting further research opportunities. (b) Secondly, it provides a Mind-Map cartography of using BDA methods in Supply-Chain Operations Reference (SCOR) model as a clear synopsis of current research trends. (c) Lastly, this study draws future research trajectories and sheds light on the gaps that need to be overcome. Scholars can leverage this paper as a reference for future research opportunities, and SC specialists can use it as a methodology to benchmark BDA methods and measure impact in valuable information for SC.

This paper is structured as follows. We begin by introducing BDA methods and SCOR model reminder. We then develop the proposed methodology of bibliography analysis. Finally, we conclude by underlining the current trends of SCM-BDA researches, the untaken breaks, and the expected potential in the near future.

2   Related Works and Research Gaps

Analytics are ranged into several collections of methods, sub-methods and techniques that diverge in their objectives, prerequisites and applicability [7]. Hence, prior to hastily study applicability of these methods in SCM, there is a prerequisite to first understand their settings and features. The next sub-section offers a brief overview.

2.1   Big Data Analytics Methods and Techniques

The word 'value' in the context of BD denotes extraction of worthy information by investigating the accumulated data through transformation and processing. Aligned with [8], BDA are emerging as the 'next big thing' and is defined as a collection of technologies that handle, incorporate, and report massive data by transforming it into new insights not attainable with traditional technologies.

In one hand, academics are aware that decision makers progressively view in BDA an imperative driver of modernization and a substantial source of value creation for competitive benefit [9]. In fact, since 2014, there is an increasing emerging of research works: case studies ([10–12], etc.), original works ([13–15], etc.), surveys ([16, 17], etc.), and a variety of literature papers ([18–20], etc.). Likewise, industrials are attentive to the potential of analytics in management of SC. Indeed, the worldwide leader in research and advisory Gartner's® has mentioned in [21] that BDA appear among the Top 25 SC research topics for 2016. Forbes®, also, argued in [22] that no single research topic in the last decade has as much effect on incumbent investments for industrials.

Approaches of BDA are numerous and may be alienated into several methods and sub-methods; to be employed solely or combined jointly [17]. Each method/ sub-method uses one or a mixture of statistical or mathematical techniques, up on

the expected business value. According our literature review, the main root methods that concerned by SC are: Exploratory Data Analysis (EDA) [8], Confirmatory Data Analysis (CDA) [11], Qualitative Data Analysis (QDA) [23], and Real-Time Analysis (RTA) [24]. Based on the underlying methods, sub-methods and techniques can also be categorized into several groups, but given the breadth of these techniques, an exhaustive list exceeds the extent of a single paper. Though, a relevant sub-list which has already been used in the field of SC covers mainly: regression [25], optimization [26], induction [27], fuzzy logic [28], classification [10], aggregation [12], and so on.

2.2   Supply Chain Operations Reference (SCOR) Model

In order to expand in competiveness of companies, SCOR model was developed by Supply Chain Council (SCC) for designing and enhancing SCs. It offers standard frame for deciding, organizing and fulfilling SC processes [29]. Nevertheless, it is traditionally used in benchmarking studies [30]. SCOR model governs five processes; they are consecutively named and briefly described in Table 1.

Table 1. Brief definition of processes in SCOR Model (SCOR model V.9.0 [29])

Plan	Process that includes planning activities
Source	Process that includes procurement activities
Make	Process that includes transformation of contents or services
Deliver	Process that includes fulfilment of customer orders
Return	Process that includes reverse movements of goods from customers

Based on pre-defined processes, SCOR can detect where action is required. It can also help to arrange more accurate projections. Accordingly, we base our study through SCOR processes. The next section describes step-by-step our methodology.

3   Proposed Methodology

3.1   Data Collection

By using Harzing's Publish or Purish V.5® [31], we queried out the more relevant and recent publications in the topic of BDA and SCM (from 2014 to 2017). Parameters of Harzing's search request are itemized in Table 2.

Once the information were sorted, we then cleansed and filtered the academic database by deleting unwanted columns (ranking, types, ISSN) and rows (programs, books, technical reports, white papers, patents, literature reviews, unrelated researches, etc.). We kept only used columns (cites, authors, title, year, source, publisher, URL, countries) and rows (journals).

Table 2. Search request in Harzing's Publish or Purish V.5® [31]

Query date	2017-03-22
Maximum papers number	100
Any of the words	{Big Data Analytics, Supply Chain, Management, Value}
Publication type	Journal
Since year	2014
Publisher	All
Search engine	Google Scholar Engine
Location	Title, abstract, key words

3.2 Analysis and Findings

By using the sorted list of last step, we reviewed each contribution and recorded a matrix that matched information with respect to BDA methods and SCOR processes. Discussion of our relevant findings and empirical results are in following sections.

Finding1: SCOR-BDA matching matrix. For each row (reference), we analyzed BDA methods, sub-methods and techniques (Sect. 2.1), and then recorded matching cells with regard to SCOR processes according to Table 1. Table 3 below illustrates the SCOR-BDA matrix as applied to the collected bibliographical dataset.

Finding 2: Mind-Map Cartography of SCOR-BDA. We constructed cartography by using Mind-Mapping technique [32] with Coggle® tool [33]. The branching out in (Appendix, Fig. 3) illustrates that all defined methods are employed in all SCOR processes but not with the same techniques. For instance, the FUzzy Logic technique (FUL) is used in Data Statistical-inference Methods (DSM) in 'Make' process but not in 'Source' process. Another ascertainment; the process 'Deliver' is the most prolific branch regard to methods and techniques already addressed in literature.

Finding 3: Overview of SCOR-BDA evolution. Bars diagrams in Fig. 1; summarize the total number of publications for each process in SCOR, in the current three years (2014–2017).

As seen in Fig. 1, there is an exponential increase in the number of contributions for all SCOR processes with an overall exponential variation of +0.064 ($R^2 = \sim 0,90$). A few publications was issued in early 2014 (equal and less than 11%), and at the end of 2015 ($\sim 11\%-\sim 23\%$). However, in just two consecutive years later (2016 and 2017), publication rates have almost doubled for each year and each process (for instance; in plan process, the rate jumped from 11% to 26%, and then to 53%). This demonstrates that BDA tools have emerged as one of the fastest growing fields in SCM in recent years. On the other hand, as we observe an unequal growing interest for processes, we then broke down the total numbers by processes.

Finding 4: Detailed view of SCOR-BDA evolution. Figure 2 sorts the number of contributions for each process in the matrix BDA-SCOR of the selected dataset.
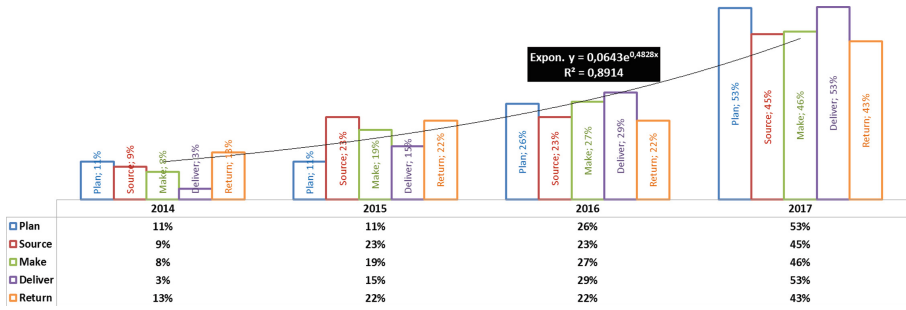
Table 3. SCOR-BDA matching matrix according to the bibliographical dataset.

References	Method-Data Discovery and Visualization	Method-Predictive Data Analysis	Method-Data Reduction Methods	Method-Data Deduction Methods	Method-Data Statistical-inference Methods	Method-Data Quantification Methods	Method-Data Event-oriented Methods	Technique-Optimization	Technique-Regression	Technique-Classification	Technique-Association rules learning	Technique-Dimensional reduction	Technique-Aggregation	Technique-Operations Research	Technique-Fuzzy logic	Technique-Real-Time reporting score	Technique-Sequential Analysis	Technique-Rules Induction	Streamlining and modeling	SCOR-Plan Process	SCOR-Source Process	SCOR-Make Process	SCOR-Deliver Process	SCOR-Return Process
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	2014	2015	2016	2017
Plan	11%	11%	26%	53%
Source	9%	23%	23%	45%
Make	8%	19%	27%	46%
Deliver	3%	15%	29%	53%
Return	13%	22%	22%	43%

Fig. 1. Normalized total numbers of publications in BDA-SCOR matrix according to the bibliographical dataset (2014–2017)
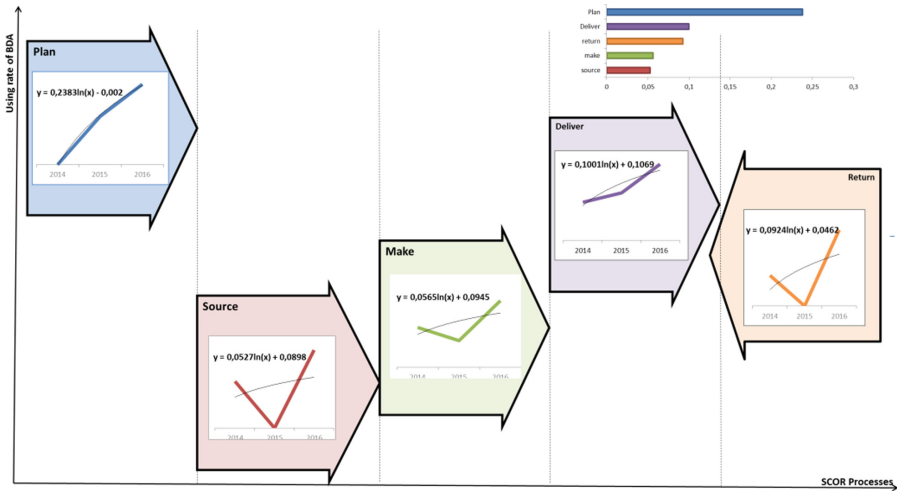

Fig. 2. Variations of BDA in SCOR processes according to the collected dataset (2014–2017)

As we observe in Fig. 2, all SCOR processes have adopted BDA, however with mixed paces. The evolution rate is sorted to make processes in a consecutive order: (1) Plan (+0,238), (2) Deliver (+0,100), (3) Return (+0,092), (4) Make (+0,056) and lastly (5) Source (+0,052).

Subsequently, we assume that: the more operations are oriented inside the company (manufacturer), the less analytics are exploited. In other words, researchers need valuation of the data that are positioned at company's connectivity with the outside (mainly Deliver, Return and Plan). This indicates a lack of collaboration between companies in the process of valuing their data. We can explain this by the fact that these companies compete to extract as much value from data, but unfortunately each company acts separately. This point is very significant as it raises the need for collaborative Big Data to exploit it intelligently in SCM.

Furthermore, from a rational point of view, BDA are applied to processes differently because of the nature of these processes themselves. In instance, it seems normal to use analytics in Plan process as it is the most uncertain activity and then which necessities advanced techniques to obtain pertinent results. While for Make process, which is less unstable and better setup and maintained, analytics are less pertinent.

4   Conclusion: Discussion and Future Trends

It is true that the proposed approach may have some limits such as restriction in dataset collection. Indeed, we have collected data by the way of Harzing's Publish or Purish® tool which is itself limited in search queries and cannot combine searching engines. Despite this, the study allowed us to have a deep overview of the BDAs and their positioning in the SC processes.

The proposed approach offers a matching matrix and a Mind-Map cartography for BDA-SCOR benchmarking. Both tools can be largely taken up by academics and SC specialists to intuitively integrate them in orienting understanding. Furthermore, the empirical results presented in this paper argue that future researches should embrace more largely BDA, to continue redefining the focus of the contemporary management of SC. However, as the relevant literature shows, using BDA must not be hastily due to a fashion effect. SC specialists must establish a comprehensive schema to identify the objective of using analytics, the reason to expand volumes of exploited data and expressly the expected business value by using analytics.

Otherwise, the usage of BDA methods and techniques in the field of SC can still be significantly improved in at least three aspects: (a) more attention needs to be focused to BDA in manufacturing (Make process) and procurement (Source process). (b) A faultless and feasible deployment of BDA should be set up between all SC actors, thus, valuation of massive data would be conducted more accurately in terms of collaboration with decreasing of underlying costs, and timely truthful information can be provided for decision-makers (c) Upstream of the data processing step, this data should be collected, arranged, grouped, and summarized jointly by all SC actors. Rather than just accumulating and processing data, managers need to structure, and link their efforts to create a coherent picture of valuable data across overall the chain. This leads us to scrutinize more collaborative and intelligent Big Data utilization.

Appendix

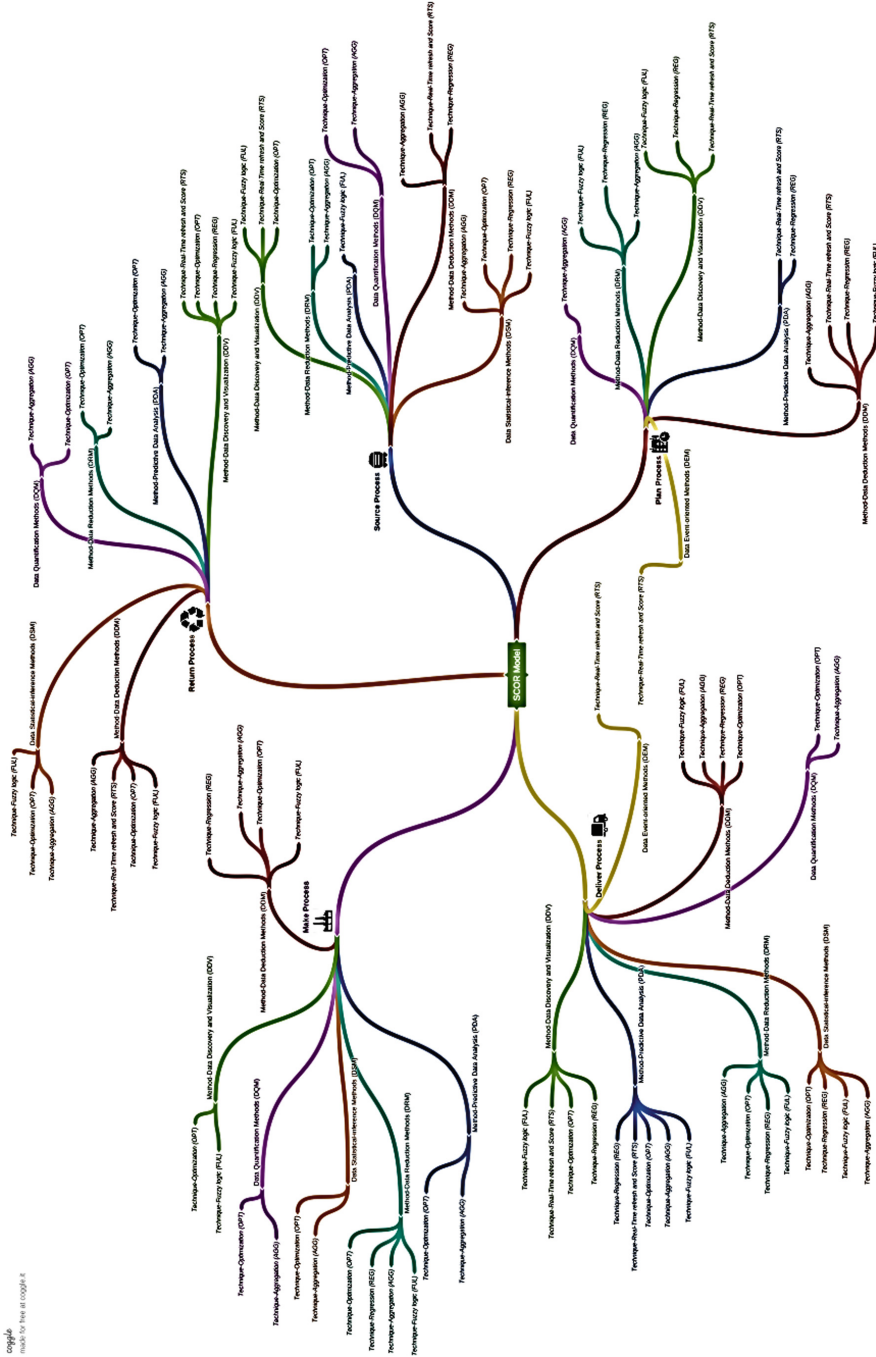Figure 3 bellow illustrates the Mind-Map cartography according the collected dataset.

Fig. 3. MindMap of BDA- SCOR according to the bibliographical dataset (available under public access on [67])

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