USING BIG DATA ANALYTICS IN SUPPLY CHAIN: LITERATURE REVIEW AND A PROPOSED FRAMEWORK

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Abstract - When supply chain management (SCM) meets Big Data Analytics (BDA), innumerable openings arise in academic research. Unfortunately, how analytics can be applied to supply chain processes is still unclear for both academics and industries. For that reason, the main goal of this study is to provide a clear understanding of the countless number of methods and techniques that are employed to analyze the using of BDA in SCM and help academics in mapping the newly available approaches to the real-world SCM issues. To better connect SC processes needs and what BDA offer, this paper provides a step-by-step approach in a wide-ranged overview of BDA-SCM. The review scrutinizes research works by using the supply chain operations reference (SCOR) model. This framework is based on three levels and will be used to perform a literature review of 805 academic publications from 2001 to 2017.

Index Terms - Big Data Analytics, supply chain management, SCOR matrix, Literature review.

I. INTRODUCTION

In recent years, the growing interest in Big Data has led organizations to develop Big Data Analytics (BDA) for their supply chains (SC) [1]. The primary goal of SC executives is to acquire meaningful information that allow them to better estimate, predict, uncover unseen patterns, and then improve competitiveness [2]. Analytics are altering the way supply chain management (SCM) processes this data, both internally through integration of transactional information systems, and externally through mobile devices, social media, and the Internet of Things (IoT) [3].

Considering many recent relevant publications in this field, suppliers and customers are using numerous products and services through unconventional forms of analytics in addition to traditional analytic tools. For that reason, the main goal of this study is to provide a clear understanding of the countless number of methods and techniques that are employed to study Big Data in SCM and help academics in mapping the newly available approaches to the real-world SCM issues.

The purpose of this research is double: First, it deals with the misalignment between data scientists and SC managers by creating a real cartographic assessment of how different BDA methods can be applied. Second, this study uses structured methodology to perform a literature review of 805 academic publications from January 2001 to December 2017.

The remainder of this paper is arranged as follows. Section 2 provides some background with an overview of BDA methods and the scope of review. Section 3 presents some SCM process-oriented Frameworks. Section 4 explains our research approach, followed by an analysis of the findings. Finally, section 5 includes a discussion of issues, and concluding arguments.

II. BIG DATA ANALYTICS AND SUPPLY CHAIN MANAGEMENT

A. What is 'Big Data'?

the definition of Big Data is not restricted to any quantifiable size of data storage. To be clearer, there is no rigorous conceptual definition of size, as noted in [4]. Otherwise, a definition broadly acknowledged by academicians and industry is that the paradigm of 'Big Data' is close to the base of the four Vs as illustrate in Figure 1 :

- volume—large quantities of data;
- velocity—speed of data acquisition;
- variety—multidimensional data fields;
- veracity—data quality and trustiness.

Figure 1: The Four V's of Big Data[5]

Following the literature that considers the application of Big Data in SCM, there is an increasing use for many of its derived benefits [1]. However, there are definitions that more or less differ in certain aspects, such as the one proposed in [2] where the term 'Big Data' describes the massive multi-faceted data

records that traditional tools are incapable of managing.

Furthermore, ‘value’ in the context of Big Data is a word that suggests mining for worthy information by investigating collected data [6] and so defines the term 'Big Data Analytics'.

B. What is 'Big Data Analytics' (BDA)?

As reported in [7], BDA are evolving as the ‘next big thing’ to handle and report substantial data that could not be analysed with traditional tools and convert it into new information [1]. Formally, BDA is the use of advanced analytic approaches for very large and unstructured data sets, including predictive methods, statistics, data mining, artificial intelligence (AI), and others [8]. Furthermore, major organizations in SCs like Amazon rely on predictive analysis through BDA to anticipate shipping from more than 200 distribution centres around the world [9]. Walmart processes order analytics from millions of customer transactions per hour, approximating 3 petabytes, including RFID data [10]. On the other hand, scholars are aware that decision makers progressively view BDA as a significant source of value-creation for competitiveness and business processes improvement [4]. An examination of bibliographies in the topic of BDA since the 2010s shows a growing number of publications more and more specialized and diversified: literature reviews [11]; [12]; etc.), original research ([6]; [1]; [13], etc.), and an assortment of case studies ([14]; [15]; etc.), and surveys ([1]; etc.).

While most businesses strongly believe in applying BDA in their SCs, actual use is still limited, and many organizations struggle to extract valuable insights. Moreover, in most cases, companies and scholars do not know exactly which analytic methods and techniques to apply and to what business activities and purposes. This hypothesis is confirmed in a number of research works, such as ([7] and[16]). On the business side, Big Data projects today are considered significant investments because of the long preparation and research needed in the preliminary phase to identify the optimal BDA method for the particular SC process and the available collected data. Moreover, in the SCM context, analytic tools explore unusual information of business set-ups and customer interactions that rarely find their way into typical reports [17]. Due to the data’s complexity, BDA often involve advanced methods and techniques, as outdated statistical methods are only appropriate for structured and restricted data collections [1]. That is why, in most business and academic projects, data scientists and managers spend a great deal of time and effort analysing the applicable framework of analytic techniques through specifications and bibliographic reviews. In the next section, we describe our investigation of such reviews.

C. Scope of Review of BDA in SCM

Literature reviews areexpected to study published academic work, identify prospective research gaps, and highlight the limits of knowledge in the area [8]. In this study, we performed a detailed literature review of academic work that addresses BDA in SCM, beginning with early work in the field in an effort tothoroughly understand the trend.

First, we noticed there has been a progressively increasing number of publications over the past decade. Through our examination of the publications, we found a clear lack of a panoramic guide for capitalizing on BDA in SCM processes. We believe such a guide could assist academics and firms in focusing their efforts to identify the appropriate analytic methods for the business issue being dealt with. The literature review in this paper could be a powerful tool for providing this guidance. However, in consulting the bibliography, we found that the few existing review papers had restricted scopes of study, and in many cases, the study is strongly related to a specific issue in SCM (manufacturing, procurement, strategic decision-making, demand planning, etc.) and/or the application of a specific method of BDA (predictive analytics, statistical approaches, etc.) as illustrated and synthetized in Table I.

Table I. Scopes of the most relevant literature review that dealt with BDA on SCM

Ref	Covered topic	Scope of review	Description
[12]	E-commerce	Partial	Authors offered a framework of a systematic review to examine the BDA challenges in the e-commerce background.
[18]	Generic section about business management	Global but restricted	Authors conducted an extensive review journal publications about BDA in diverse perspectives and the business area of supply chain was a part in his spectra.
[19]	Smart manufacturing	Partial	Authors provided a comprehensive state-of-the-art including BDA applications to find the main challenges in multiple areas of application and tools regarding BDA where the smart manufacturing was a part of this analysis.
[20]	Governance	Partial	Authors studied a representative sample of publications in a form of a survey in the management and governance topics impacted by BDA.

[21]	Smart manufacturing	Partial	Authors proposed a broad literature review papers of conferences and journals in the area of smart manufacturing.
[22]	Generic section about business management	Global but restricted	Authors presented an overview of BDA applications and opportunities by benchmarking of papers from journals and conferences on different areas including business management.
[2]	Unstructured data and predictive analytics	Partial	Authors focused of the using of unstructured data (text, audio, video, and social media) with predictive analytics.
[11]	Levels of analytics in SCM	Global but restricted	The review proposed a new classification model but the study is focused on the question: Where BDA are applied in SCM more than why and how they are applied.
[4]	Strategic and Operational	Partial	Authors focused on strategy and operations in Logistics SCM (LSCM)

As Table I highlights, there is clearly a lack of a panoramic overview of literature that provides a macro-reading of the applicability of analytics to SC processes. This overview could be in the form of a synthesis study that answers the main question: Which BDA method/technique is applied and on which SCM process/activity? The main purpose of this research is to answer this question and thus fill the research gap between data science and SCM issues by linking data analytic methods to SC processes. To accomplish this, we need a process-oriented model that provides a granular grid on which we can match BDA methods. Using literature, the section below presents a case for the selection of a process-oriented framework among the existing models.

III. PROCESS-ORIENTED SCM FRAMEWORKS

In process-oriented SC models, there is a set of proposed models that includes : descriptive and normative models (DNM); global supply chain forum framework (GSCF), value reference model (VRM), sustainable balanced scorecard (SBS), and process classification framework (PCF). However, SCOR is considered by academics as the de facto standard and is used as a reference in the SCM field [23].

SCOR was developed and established in 1996 by the Supply Chain Council (SCC) as a reference model for design and enhancement of SCs. The model provides a common setting for determining, unifying, and accomplishing SC processes [24]. SCOR provides standard guidelines for companies to aid in examination of SC configuration, identification and measurement of metrics, and continuous application of best practices. It is considered a diagnostic tool that gathers performance processes, metrics, best practices, and people into an integrated structure. Furthermore, SCOR is commonly used as a deductive framework to study SC topics as mentioned by [25], and can also be categorized as a powerful normative approach to benchmarking process-oriented analysis in SCM [24]. Besides, SCOR has been used as a process-oriented framework for academic SCM analysis in a number of works such as [17]and [8], while other studies are literature review papers like [23]. Likewise, the proposed comprehensive cross-operational review in this study is also based on SCOR. Our second motivation for the use of SCOR lies in the granularity of the levels within the SCOR structure. Each process level can be split into several sub-levels according to the desired level of detail.

The SCOR model is structured around five basic processes—plan, source, make, deliver, and return—that are further sub-sectioned into processes, sub-processes, activities, and tasks [23]as listed in Figure 2.

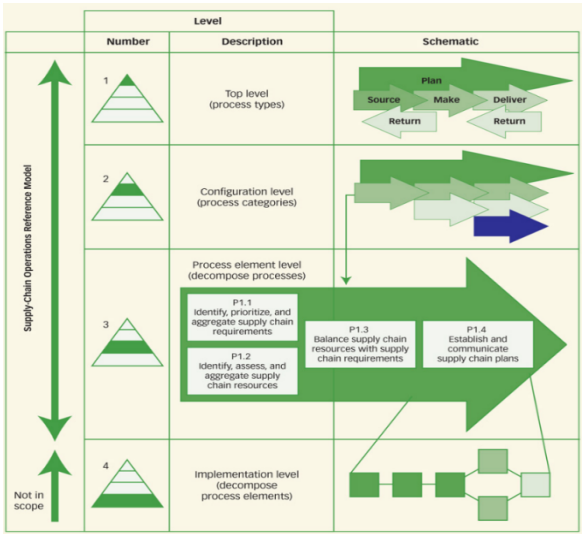


Figure 2. The SCOR structure [24].

To be clearer about our second motivation, we acknowledge that our main research project aims to conduct a detailed study by levels from both perspectives: on one hand, to explore the methods and sub-methods/techniques of BDA by levels, and on the other hand, to delve into SCOR processes and sub-processes/activities/tasks by levels. The tableII illustrates some possible examples of uses of analytics that were extracted from the literature studied.

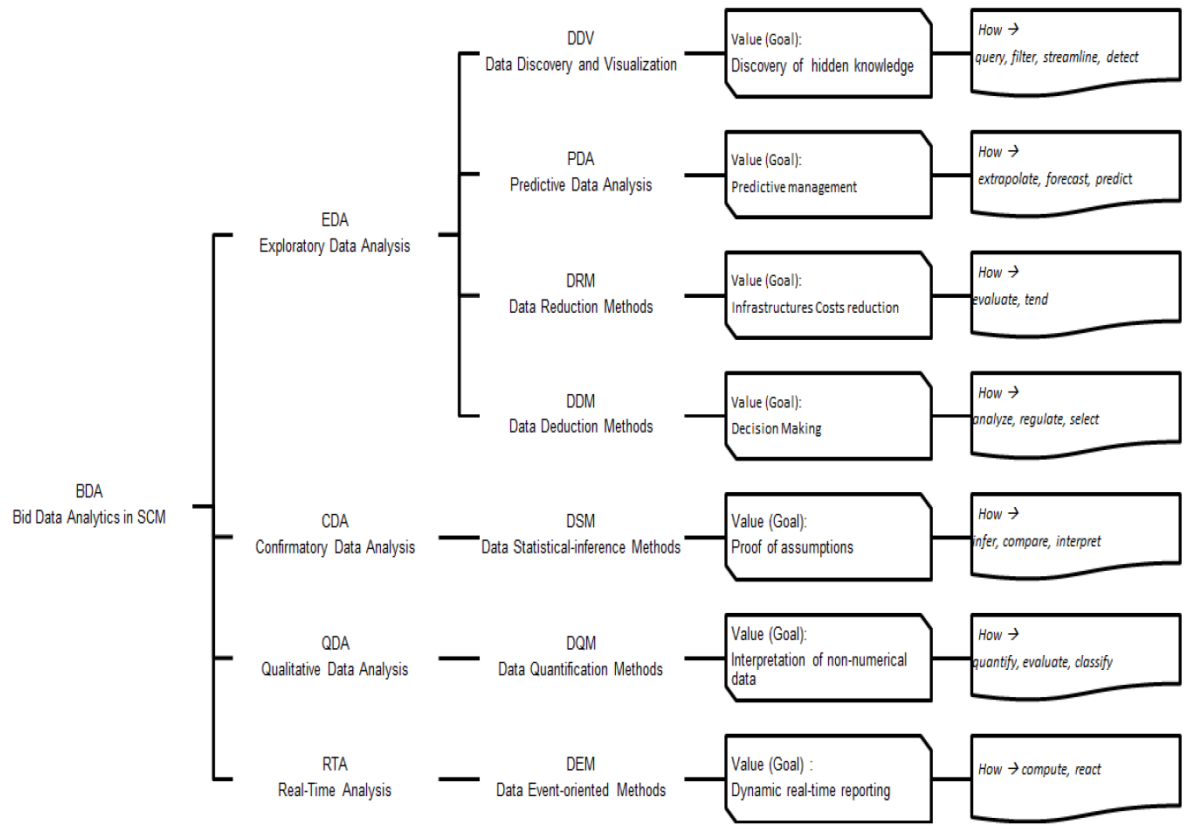
Table II. The five main processes of SCOR [24]with examples

Plan	Balances the demand and supply to meet the sourcing, manufacturing and supplying requirements. Example: examining the volumes of synchronous input data instantly to adjust and predict the schedules; where this have often been performed monthly and/or annually [26],
Source	Includes the procurement activities to acquire goods/services aligning planned and actual demand. Example: analytics can be used in supplier selection and assessment [4],
Make	Is related to the transformation of products and services to meet planned and actual orders. Example: manufacturing in plants can be improved by using analytics in smart manufacturing [27]
Deliver	Comprises the fulfilment of customer demand as requested in the planned and actual orders. Example: optimized transportation system can be processed by analytics to improve logistics [28].
Return	Is associated to all reverse movements of goods and services from customers for any reason. Example: analytic methods can contribute in managing smartly the reverse logistics by predicting the information flow from retailers to producer companies [29].

Accordingly, considering these motivations, our review of BDA-SCM literature is based on the SCOR framework. The next section presents a step-wise description of the research approach used for the literature review.

IV. RESEARCH APPROACH: PROPOSED BDA TAXONOMY

Analytic methods are categorized into several sub-methods and techniques that differ in their purposes, prerequisites, and applicability [9]. Therefore, prior to hastily analysing the applicability of analytic methods, a taxonomy framework must first be chosen for those methods. The next sub-section describes our proposed BDA taxonomy based on our review.



For our goal of analysing existing academic work, the literature review provides us with many possible ways to classify BDA approaches. We found three main categories: (1) a taxonomy based on the nature of and objective for using BDA with three classes: descriptive, predictive, and prescriptive as found in [4]; (2) a taxonomy based on the scope of using analytics in SCM issues, where eight classes were identified: architecture, framework, theory, methodology, model, platform, process, and tool, as in [21]; and (3) a taxonomy based on the technological aspects of BDA as in the technology

organization environment (TOE) framework used in [1]. None of these three types of taxonomy frameworks can provide a comprehensive and complete grid for our study because our goal is to follow a detailed model of all BDA techniques, as mentioned in the previous section. Alternatively, we propose a new taxonomy based on classifying the literature into several levels related to the nature of the analytic algorithm.

Analytic approaches are plentiful and may be classified into methods and sub-methods, and combined or employed separately [30]. A method or sub-method usually uses one or a combination of statistical or mathematical techniques, depending on the desired business value and/or business context. Because of our extended literature review, we found numerous methods that concern SCM. Based on these methods, there are several related sub-methods and techniques that can also be classified into categories and sub-categories.

However, the extent and diversity of these techniques makes it difficult to provide a complete list and is beyond the scope of this unique study. Relevant sub-methods include optimization, classification, fuzzy logic, and regression, as well as others. Figure 3 presents a hierarchy of the most relevant, as also detailed in the following description.

D. Exploratory data analysis (EDA)

EDA is the stage of analysis dealing with determining what to make of the data and how to frame it, and then finding the best way to present and manipulate it based on a business insight [31]. EDA includes a set of sub-methods, we cluster them into four main categories:

(a) Data discovery and visualization (DDV) : In SCM, a set of techniques are used such as regression (REG) algorithms in green SCM, dimensional reduction (DRE) heuristics in logistics optimization, and rules induction (RIN) heuristics in customer segmentation.

(b) **Predictive data analysis (PDA):** In SC predictive management, the main techniques include algorithms of optimization (OPT) in SCM modelling, aggregation (AGG) in SCM sustainability, and classification (CLA) in operational SCM, in addition to operational research (ORE) approaches in logistics.

(c) Data reduction methods (DRM): In SCM research, the DRM used specific techniques such as fuzzy logic (FLO), real-time reporting score (RRS) [32], and regression (REG).

(d) Data deduction methods (DDM) are concerned with establishing hypotheses based on existing models [16]. Techniques used in DDM have the ability of explaining causality relationships or applying inductive reasoning rules such as association rules learning (ARL).

E. Confirmatory data analysis (CDA)

CDA is the evaluation stage where statistical tools are used, such as inference, causality, and coordination. At this point, the model is built and CDA questions it through challenging suppositions, constructing estimation precision, regression investigation, and variance scrutiny [1]. The main sub-methods in this category is data statistical-inference (DSM) [33]used to interpret, infer, compare, and draw suitable proofs of assumptions. Regression (REG) models are the most usually applied technique in SCM issues such as stepwise regressionand linear regression algorithms [5].

F. Qualitative data analysis (QDA)

QDA is concerned with non-numeric data, such as notes, videos, audio files, images, and other transcoded data sourced from different sensors [34]. The main sub-category in QDA is the set of data quantification methods (DQM) that gather the quantification approaches and the qualitative analysis and interpretation of data. These methods are used in various fields of SCM such as marketing surveys analysis by using the technique of aggregation, opinion mining algorithms (OMA) to extract products features from textual or visual data by techniques like association rules learning (ARL), and some applications in product lifecycle management (PLM) by using classification (CLA) techniques [35].

G. Real-time analysis (RTA)

RTA involves using data dynamically as soon as they arrive in the system in immediate or nearly immediate modes with high responsiveness [13]. Data event-oriented methods (DEM) are the most important sub-category in RTA [15]; [28] by using adapted techniques to reactive-analysis such as sequential analysis (SAN) and streamlining and modelling (SMO) in [36] for interconnected sensors in manufacturing.

V. PROPOSED SEARCH STRATEGY

In this paper, we provide a step-by-step approach to conduct a well-structured review approach to afford a wide-ranging overview of BDA-SCM research evolutionbased on three stages:

1. Raw Extraction Stage
2. Cleansing and Preparation Stage

- **Step 1:** Distribution of Raw Collection by Type
- **Step 2:** Distribution of Journal Papers by Topic
- **Step 3:** Distribution of BDA-SCM Journal Papers by Approach

3. Analysis and Findings Stage

The Figure 4illustrates and summarizes the steps of the search process used to select papers for review,

including figures and rates. The following sub-sections provide the detail of the first two stages of our research approach.

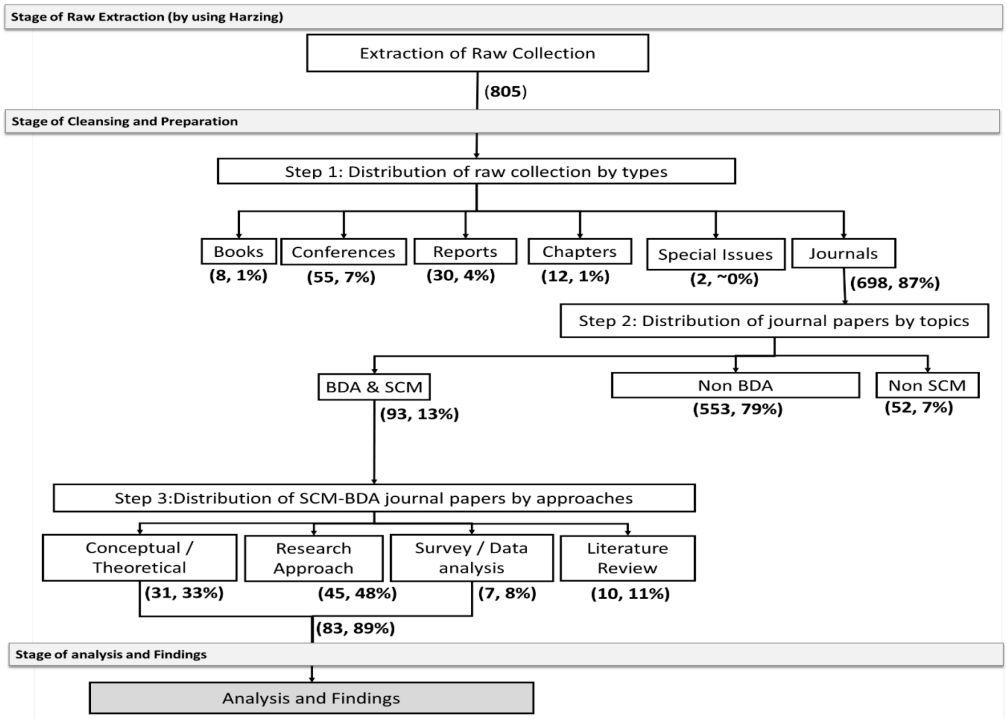


Figure 4. Step-wise chart of the proposed review strategy with

A. Raw Extraction Stage

To get a broader base of literature, we conducted the search from 2001 to December 2017 using the Harzing request itemized in Table 4. Our raw results included a total of 805 papers and used CSV format (one row per paper with multiple columns such as cites, authors, title, year, source, publisher, URL, countries).

Table 3. The query of research in Harzing[37]

Query Parameters	Field value
Query Date	2018-02-20
Maximum number	1000
Any of the words	{Big Data Analytics, Supply Chain, Management, Value}
Since year	2001
Publisher	All
Location	Title, abstract, key words

B. Cleansing and Preparation Stage

To get a broader base of literature, we conducted the search from 2001 to December 2017 using the Harzing request itemized in Table

1) Step 1: Distribution of Raw Collection by Type

After analytically reading the abstract, introduction, and discussion sections of each of the 805 papers, the following rule was applied: conference papers, repeated records, work reports, introductions to special issues, chapters, and books were excluded. We kept only journal papers to retain the highest quality publications in our study. This resulted in 698 papers with a retention rate of 87%.

2) Step 2: Distribution of Journal Papers by Topic

Based on the journal papers selected in the previous step (698), we conducted a quick analysis based on the core text of each publication, and then separated the papers into those related to BDA and those not related to BDA but that dealt with an analytic approach. This step identified 553 (79%) non-BDA papers to be reviewed later and 93 (13%) BDA papers to be classified in the next step. The remaining 52 (7%) papers were not related to an SCM topic, but to close topics such as organization of enterprises, macro-economics, and globalization.

3) Step 3: Distribution of BDA-SCM Journal Papers by Approach

In this step, we continued cleansing the dataset consisting of the 93 SCM-BDA papers. All literature review papers, a total of 10 (11%), were dropped, leaving a final sample for review of 83 papers (89%) mainly published between 2014 and 2017 and distributed as following: 31 papers (33%) in conceptual and theoretical studies, 7 papers (8%) as surveys and practical data analysis works, and 45 research approaches papers (48%). This distribution shows a minor ratio of surveys and practical data analysis and that is probably due to the fact that implementation of BDA-based solutions is still in its early stages in SCM. The previous stage narrowed the list of full-length peer-reviewed journal papers to 83 (89%) that deal with the use of analytics and Big

Data. The current stage focuses on a meticulous examination of those papers by conceptualizing the taxonomy framework established in previous sections.

CONCLUSION AND FUTURE INSIGHTS

Through a process-oriented analysis, this research proposed a deep understanding of academic implications in determining BDA adoption in SCM. Furthermore, this structured literature review provides a taxonomy for BDA methods and techniques based on a matching matrix that uses a BDA-SCOR model.

Arguing the whole details about all the stages in the proposed approach exceed the scope and limits of this paper. Therefore, we provided only the application of the two first stages and summarized briefly the outcomes of third stage. The extension of this research (3rd stage) will be published in another paper with the study of 83 selected papers following the described BDA-SCOR matrix. We will also highlights upcoming research paths and the main gaps that need to be overcome. Academics can use the results to orient their future research opportunities, and SC professionals can employ them to benchmark BDA and measure their impacts on the SCM.

In spite of the given insights, some limitations exist. First, since use of BDA in SCM is still in the early stages, there might be different opinions among firms about BDA's business value for SCM. Additionally, in this study, we tried to depict the applicability of BDA using one macro-level of SCOR, which might be unsatisfactory for accurate understanding. Therefore, in future research, we will integrate the multiple overlapping levels of SCOR.

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