Big Data Analytics for Supply Chain Transformation: A Systematic Literature Review using SCOR Framework

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Abstract

Recent developments in information technology generating massive amount of data is referred to as big data. Such data with variety and velocity pose a challenge to supply chain management (SCM) practitioners on how to deal with them to draw valued insights for enhanced decision-making. The analysis of big data can offer unique intuitions into supply and market dynamics like understanding the customer preferences, developing new products, demand forecasting, supplier selection and evaluation, process improvements, quality control, capacity planning, managing delivery schedules, order management, etc., to reduce the supply chain costs and improve product availability. Thus, this chapter reviews and classifies the literature on BDA application in SCM. We extracted and reviewed about 200 academic journal and conference articles from 2010 to 2017 from various research databases to know the extent of BDA applications in different supply chain domains (plan, source, make, deliver and return). The papers were also classified based on analytics (descriptive, predictive, and prescriptive) and the supply chain resources utilized (financial, human, technological, organizational, and intangibles). Based on the review results, we propose a supply chain (SC) visibility framework that identifies SC visibility as a key driving force for SC transformation, achieved through strong BDA capability. The findings of this review and future research directions will help the academics, researchers, and practitioners to focus on the BDA opportunities and challenges.

Keywords: Big data analytics, digital transformations, supply chain, SCOR model, systematic literature review (SLR)

1 Introduction

The BDA applications in SCM have received significant attention in the existing literature. Several reviews are published focusing on BDA on logistics and SCM listed in Table 1. Previous research has primarily focused on the classification of the BDA application areas based on the type of analytics used - descriptive, predictive, and prescriptive (Nguyen et al., 2017; Barbosa et al., 2017; Wang et al., 2016c; Souza, 2014; Gandomi Haider, 2015), operations and SCM functions (Lamba and Singh, 2017; Nguyen et al., 2017; Olson, 2015), logistics and SC strategy (Wang et al., 2016c), SCM resources and process (Barbosa et al., 2017), and BDA technologies (Zhong et al. 2016b). Souza (2014) categorized applications of SCA in terms of descriptive, predictive, and prescriptive analytics along with the supply chain operations reference (SCOR) model domains plan, source, make, deliver, and return. However, the focus of the study was more on how SCA may be applied across SCOR domains without explaining in detail the real-life applications in the context of SCOR domains. The researchers have not explored using the SCOR model domain classification scheme, viz., plan, procure, make, deliver, and return. In the literature, the SCOR model is a very well recognized SC model used by practitioners in different industries worldwide (Lockamy and McCormack, 2004; Theeranuphattana and Tang, 2008; Souza, 2014).

Classification of BDA applications across the SCOR domains will benefit SCM practitioners (Huang et al., 2005). BDA covers the comprehensive capability for the interface between IT assets and other firm resources and is considered an organizational capability (Cosic et al., 2015; Barbosa et al., 2017). SCM practitioners may be interested in understanding which resources BDA uses across the SCOR domains. A literature review focusing on BDA's role in the better use of SCM resources is scarce (Barbosa et al., 2017). So, this chapter uses a classification framework, which categorizes and connects the SCOR domains with the analytics and SCM resources level. The amount of investment to be made on BDA initiatives is difficult for an organization. An organization may not be able to invest equally in all the areas of the supply chain. Information about the latest BDA applications in SCM across the SCOR domains and the significant supply chain resources used for data collection, analysis, and data-driven decision-making will be beneficial for the organizations to make informed decisions, prioritizing the areas of BDA investment. Therefore, this review aims to provide useful insights on how BDA is applied in SCM by mapping BDA techniques and SCM resources to SCOR domains, viz., plan, source, make, deliver, and return.

Section 2 of this chapter describes the research methodology and process used in the study (i.e., systematic mapping). The results are presented in section 3. In section 4, an SC visibility and BDA capability framework is proposed based on the findings of the categorical structure used in the study. The areas identified for future research are presented in section 5. Section 6 offers the conclusions and limitations of the research.

Table 1: Literature reviews on BDA in SCM

Authors	#Articles	Time Range	Analysis/Categorization	Research objective
Arunachalam et al. (2017)	82	2008 to 2016	Bibliometric and thematic analysis	Development of BDA capabilities maturity model
Lamba and Singh (2017)	-	-	O&SCM functions	Identify future perspectives
Nguyen et al.(2017)	88	2011-2017	i. BDA application areas of SCM ii. Level of analytics (descriptive, predictive, and prescriptive) iii. BDA models iv. BDA techniques	Future research directions
Barbosa et al. (2017)	44	2005-2016	i. Level of analytics ii. Use of SCM resources iii. SCM processes	To identify how significant BDA is to support value achievement.
Wang et al. (2016c)	104	2004-2014	Level of analytics (descriptive, predictive, prescriptive)	To develop a supply chain analytics maturity framework of SCA based on functional, process-based, collaborative, agile SCA, and sustainable SCA capability levels.
Addo-Tenkorang and Helo (2016)		2010-2015	General classification based on BD technologies and BDA in SCM.	Identifying issues and proposal of a value-adding framework
Wamba et al.(2015)	62	2006-2012	Dimensions related to business value creation from BD	Assessment of the business value of BD
Olson (2015)	-	-	SCM functions	To observe recent trends and developments, problems and opportunities
Gandomi and Haider (2015)	-	-	Types of BD analytics	To describe, review, and reflect on BDA
Mishra et al. (2016)	57	2011-2015	Bibliometric analysis of BDA applications in SCM	To identify current trends and future directions for research
Souza (2014)	Nil	Nil	Level of BDA across SCOR model domains	Possible applications of advanced analytics
Zhong et al. (2016a)	-	-	Representative BDA applications in SCM	To review the current movement of BDA applications in SCM and identify current challenges, opportunities, and future perspectives.

2 Review methodology

The review methodology adopted in this chapter is based on the content analysis approach proposed by Mayring (2008). A similar review approach was used by Seuring and Muller (2008), Govindan et al. (2014), Gao et al. (2016) and Arunachalam et al. (2017). The review was systematically conducted using a four-step iterative process. The steps included: material collection, descriptive analysis, category selection, and materials evaluation.

Material collection

To have an all-inclusive coverage of all the possible applications of BDA in logistics and SCM, the following keywords were used: BD, data mining, analytics, business intelligence, data-driven, predictive analytics, real-time data, forecasting, product development, sourcing, procurement, production, logistics, SCM, inventory, maintenance, quality, operations, innovation, order picking, transportation, and manufacturing. The timeline starting from 2010 was selected for review as BDA has become a global phenomenon only after 2010, with significant research in this field regarding the volume and considerable contributions to theory and practices (Manyika et al., 2011; Nguyen et al., 2017). Further, this chapter reviews the significant developments in BDA applications in SCM through an eight-year analysis. The initial search generated 1657 papers, and 1021 were retained after removing the duplication and verifying in the Mendeley software. The inclusion criteria ensured that research from academic sources, such as peer-reviewed journals and reputed conference proceedings, was selected. The review did not include any publications in books, book chapters, doctoral work, white papers, editorial columns, etc. With the application of the inclusion criteria, the total number of papers dropped to 634. Upon meeting the inclusion criteria, the selected articles were subjected to exclusion criteria to reduce the number of papers by removing the publications that were not aligned with the scope of the present literature review. The exclusion criteria applied included reading the introduction and conclusion of each paper and removing those publications that do not deal with the application or benefits of the BDA in SCM (Lamba, Singh, 2017; Nguyen et al., 2017; Arunachalam et al., 2017). It was observed that many articles had the term BDA mentioned in the body of text or just pointed out potential benefits in the field of SCM without detailing how BDA is applied or how it can be implemented. Such papers were excluded from this study bringing the final count of publications to 220 for a full review.

Descriptive analysis

Figure 1 shows that the papers published on BDA applications in SCM have continuously increased over the last seven years. The trend has seen an enormous increase since 2014. The publication frequency distribution aligns with Gandomi and Haider (2015) and Nguyen et al. (2017). It indicates that the BDA application in SCM is gaining much attention from researchers. The selected 220 papers are from 87 different journals; only nine published more than five papers (Figure 2).

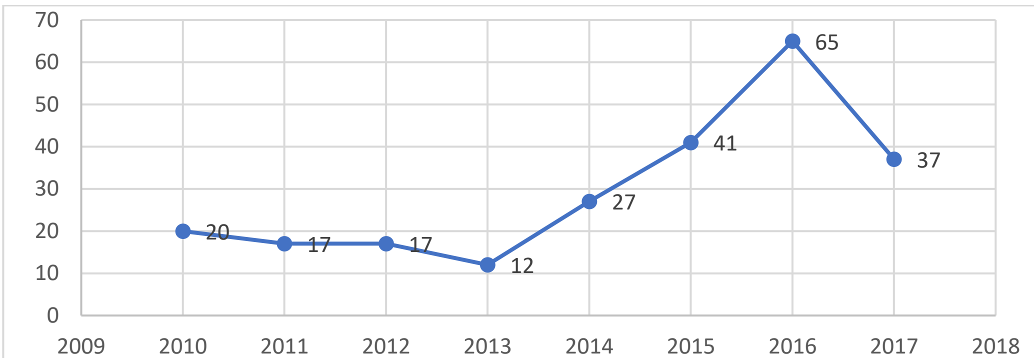


Figure 1: Articles published from 2010-2017

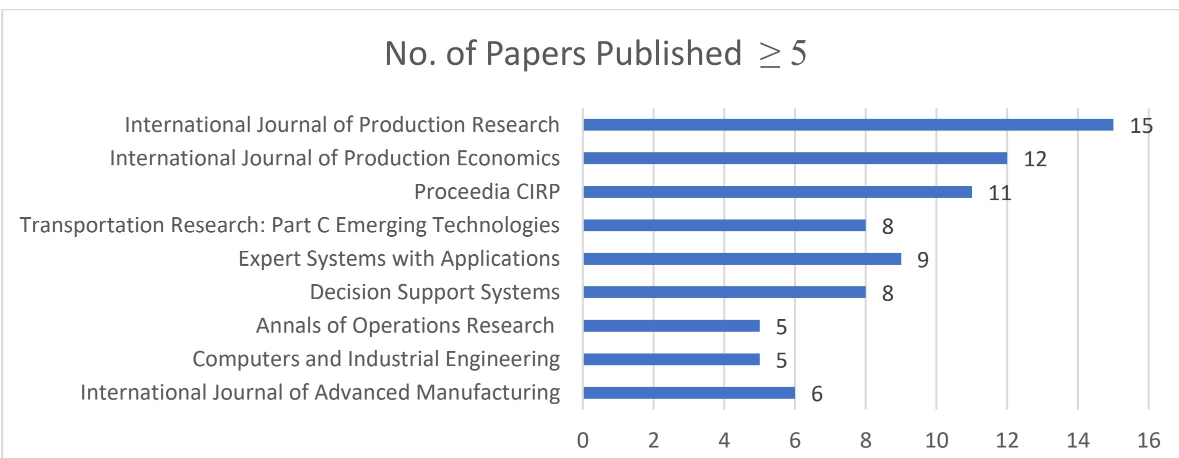


Figure 2: Distribution of Journals Publishing the Referred Articles

Article Classification

The classification step conceptualizes the framework through structural dimensions and analytics, i.e., SCOR domains, level of analytics, and SCM resources. The SCOR model developed by Supply Chain Council has five main processes: plan, source, make, deliver, and return.

(a) Plan: This process analyses the information and forecasts the market trends of goods and services.

(b) Source: This process deals with the procurement system. It includes the activities related to ordering and receiving materials and products. Major decisions include supplier selection, negotiations, vendor management, and evaluations.

(c) Make: This process in the model covers the manufacturing of goods. The related activities are scheduling, manufacturing, repairing, remanufacturing, and recycling materials and products.

(d) Deliver: In this process, the movement of the finished goods and services to reach planned or actual demand is covered. The related activities are receiving, scheduling, picking, packing, and shipping orders.

(e) Return: It is processed, returning the goods or receiving the product in a reversed loop. The related activities are to request, approve, and determine the disposal of products and assets.

(Lockamy, McCormack, 2004; Trkman et al., 2010; Delipinar and Kocaoglu, 2016; Souza, 2014).

The categories used for the level of analytics were descriptive, predictive, and prescriptive analytics. This classification is notable in literature (Wang et al., 2016c; Barbosa et al., 2017; Nguyen et al., 2017). The categorization suggested by Braganza et al. (2017) was used for the third layer, namely SCM resources. This classification scheme was used by Barbosa et al. (2017) to review the extent of using BDA to manage SCM resources. The descriptive statistics based on the classification scheme are presented below.

Classification by SCOR domains

The distribution of the selected papers for the review across the SCOR domains, viz., plan, source, make, deliver, and return, is presented in Figure 3. If any studies did not relate to one or more specific domains, they were classified under "Overall Supply Chain" (OSC). As seen from Figure 3, plan, make, and deliver domains have dominated the current literature, taking up to 76% of the publications.

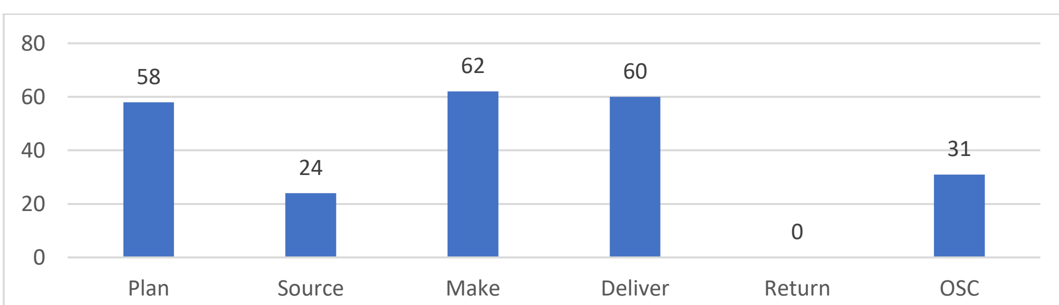


Figure 3: Classification of articles by SCOR domain

Research on the source domain is limited to 10% publications. However, the return domain has not received much attention from the researchers, with no publications from the selected list of articles. *Figure 4* presents the trend of research papers on how BDA is applied across the SCOR domains between 2010 to 2017. It is observed that there were very few papers before 2013. The real trend starts from 2013 onwards. There is an increased interest in the plan, make, and deliver domain from 2013 onwards, with high growth in the papers of making domain from 2015 surpassing other domains. The research in the source domain continues to grow at a steady rate.

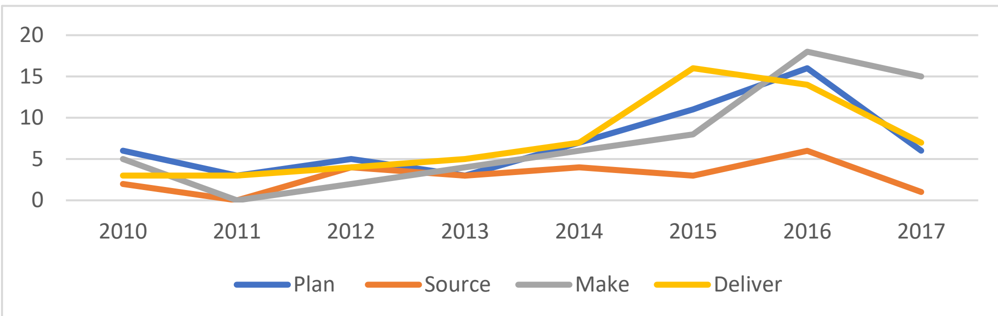


Figure 4: Trend of publications on SCOR domain

Classification by Level of Analytics

Figure 5 depicts the distribution of use of different levels of BDA in the literature. It is observed that predictive analytics is used in most of the studies (47%), followed by descriptive analytics (31%) and prescriptive analytics (27%). Figure 6 illustrates the popularity of each analytics type by year. The use of predictive analytics is seen to be dominating from 2010 to 2017, with all three types of analytics having an increasing trend.

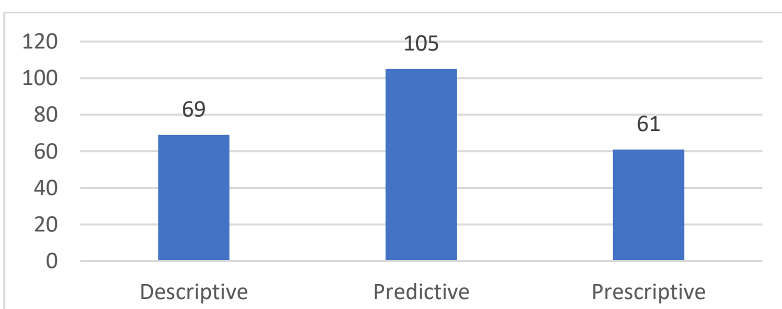


Figure 5: Classification of papers on level of analytics

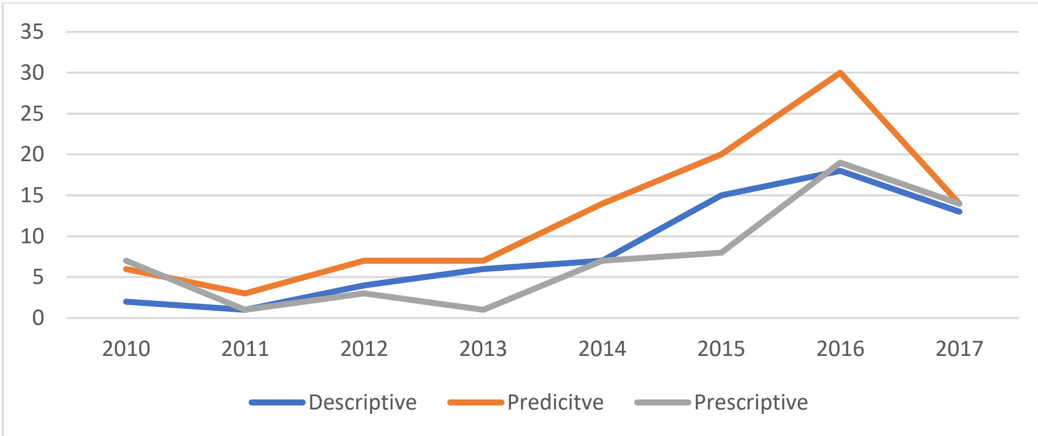


Figure 6: Trend of publications on level of analytics

Classification by SCM Resources

Figure 7 distributes the papers for SCM resources managed by BDA. Most papers address organisational and technological resources (56% and 54%, respectively) because BDA deals with a significant amount of data. Data, information, and knowledge considered organizational resources provide rich and valuable insights into decision-making.

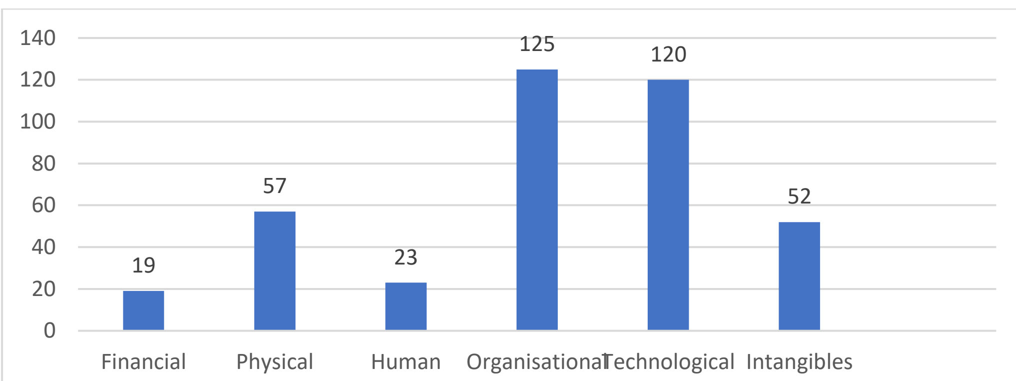


Figure 7: Categorization of articles on SCM Resources

The data are collected and stored from different sources in all the domains, and meaningful insights are extracted. Further, this voluminous data requires advanced storage and retrieval systems like ERP, RFID, Cloud servers, etc. Therefore, technological resources have comprehensive coverage in the BDA literature. The organizational resources with efficient data collection and storage technology are required to use BDA efficiently. Hence, we find that the technological resources are well spread across all the domains.

The physical resources have been studied in 25% of the studies. These studies include the processes that use physical resources such as physical manufacturing systems, movement of goods, order picking, storage, and transportation. Intangible resources are covered in 23% of the studies. These resources are primarily associated with the new product development and innovation process. These studies capture the BD from the customers through product feedback, complaints, preferences, etc., providing them with an opportunity to act as value co-creators. Human and financial resources are the least covered area, which is addressed in 10% and 8% of the studies. With the increase in the use of BDA for solving SCM issues, there are concerns about the availability of technical skills to manage and analyze the data (Richey et al., 2016; Schoenherr and Speier-Pero, 2015). Human resources also include the studies where the employee responses in the form of surveys are captured for decision making. Achieving financial performance is an objective of some of the studies. BDA applications in this area are not seen much. A few studies discuss optimizing the processes to reduce cost and increase profitability.

3 Results and discussions

This section discusses the status of extant research about BDA applications in SC and logistics management. The results of the SLR are shown in table 2, table 3, and table 4. Table 2 presents the categorization scheme applied to all the selected papers. Table 3 presents the summarized details of the level of analytics across the SCOR domains, and table 4 presents the resources managed by BDA across the SCOR domains. The SLR presented in table 2 classifies the selected 220 papers into three main categories, i.e., level of analytics, supply chain resources used for BDA in SCM (viz., financial, physical, human, organizational, technological and Intangibles) and the SCOR domain (viz., plan, source, make and deliver). Any paper that did not indicate one or more particular practices was classified under 'Overall SC" or 'OSC'.

Table 2: Systematic Literature Review

Sr. No.	Authors	Level of Analytics			SCM Resources Used						SCOR Domains				
		Descriptive	**Predictive**	**Prescriptive**	**Financial**	**Physical**	**Human**	**Organizational**	**Technological**	**Intangible**	**Plan**	**Source**	**Make**	**Deliver**	**OSC**
1	Addo-Tenkorang anf Helo (2016)	√						√	√						√
2	Ahiaga and Smith (2014)			√	√			√					√		
3	Akter et al. (2016)		√					√	√	√					√
4	Alkhalifah and Ansari (2016)			√					√			√			
5	Aloysius et al. (2016)			√				√	√		√				
6	Amarouche et al. (2015)	√							√	√	√				
7	Amos et al. (2016)			√		√							√		
8	Arias and Bae (2016)		√			√		√	√		√				
9	Arief et al. (2016)		√					√				√			
10	Arunachalam et al. (2017)	√	√	√				√	√						√
11	Azadnia et al. (2013)			√		√		√						√	
12	Babiceanu and Seker (2016)		√			√		√	√				√		
13	Bag, S. (2016)			√			√		√			√	√		
14	Bahrami et al. (2012)	√						√			√				
15	Balaban et al. (2015)	√				√			√					√	
16	Barbosa et al. (2017)	√	√	√	√	√	√	√	√						√
17	Bauer et al., (2016)			√				√					√		
18	Bendoly (2016)	√						√			√				
19	Bendoly et al. (2012)			√						√	√				
20	Berengueres and Efimov (2014)		√					√		√	√				
21	Bhattacharjya et al. (2016)	√								√	√				
22	Blackburn et al. (2017)	√						√			√				
23	Bradley et al. (2017)	√			√				√		√				
24	Brandenburger et al. (2016)		√						√				√		

Sr. No.	Authors	Level of Analytics			SCM Resources Used						SCOR Domains				
		Descriptive	Predictive	Prescriptive	Financial	Physical	Human	Organizational	Technological	Intangible	Plan	Source	Make	Deliver	OSC
25	Brinch et al (2017)	√						√	√						√
26	Butler and Bright (2014)			√									√		
27	Cárdenas et al. (2016)		√			√		√						√	
28	Chae (2015)		√			√				√	√				
29	Chae and Olson (2013)		√						√						√
30	Chae et al. (2014)		√					√							√
31	Charaniya et al. (2010)		√					√					√		
32	Chen and Blue (2010)		√					√			√				
33	Chen et al. (2010)			√	√			√	√		√				
34	Chen et al. (2016)		√					√	√				√		
35	Cheng et al. (2017)	√						√					√		
36	Chiang et al. (2011)		√			√		√						√	
37	Chien et al. (2013)		√										√		
38	Chien et al. (2017)		√					√					√		
39	Choi et al. (2016)	√						√				√			
40	Chong et al. (2016)		√					√	√	√	√				
41	Chuang et al. (2014)		√			√								√	
42	Chung and Tseng (2012)		√					√		√	√				
43	Chung and Tseng (2012)	√				√				√	√				
44	Çiflikli and Özyirmidokuz, (2010)			√				√					√		
45	Cochran et al., 2016)		√					√					√		
46	Cohen et al. (2017)			√	√								√		
47	Colace et al. (2014)	√							√	√	√				
48	Cristobal et al. (2015)		√			√		√						√	
49	Cui et al. (2016)		√			√		√	√					√	

Sr. No.	Authors	Level of Analytics			SCM Resources Used						SCOR Domains				
		Descriptive	Predictive	Prescriptive	Financial	Physical	Human	Organizational	Technological	Intangible	Plan	Source	Make	Deliver	OSC
50	Davis et al. (2012)		√					√					√	√	
51	Delen and Demirkan (2013)	√						√							√
52	Delen et al. (2011)		√					√	√	√	√			√	
53	Diana (2012)		√						√					√	
54	Dietrich et al. (2012)			√				√	√	√	√				
55	Djatna and Munichputranto (2015)		√		√			√	√				√		
56	Dobre and Xhafa (2014)		√					√	√	√					√
57	Dubey et al. (2016)	√			√		√	√	√				√		
58	Dudas et al. (2014)			√				√					√		
59	Durán et al. (2010)			√		√		√					√		
60	Ehmke et al. (2016)			√										√	
61	Eidizadeh et al. (2012)	√						√			√				
62	Fiosina et al. (2013)	√						√	√					√	
63	Gandomi and Haider (2015)	√	√					√	√						√
64	Gerunov (2016)	√							√	√	√				
65	Groves et al. (2014)			√				√				√			
66	Guo et al. (2014)			√				√						√	
67	Haberleitner et al. (2010)		√		√			√	√		√				
68	Hammer et al. (2017)			√					√				√		
69	Haverila and Ashill (2011)	√						√		√	√				
70	Hazen et al. (2014);		√					√							√
71	Hazen et al. (2016)	√	√	√				√	√						√
72	He et al. (2015)		√					√	√	√	√	√			
73	Ho and Shih (2014)		√						√			√			
74	Hofmann (2017)	√												√	

Sr. No.	Authors	Level of Analytics			SCM Resources Used						SCOR Domains				
		Descriptive	Predictive	Prescriptive	Financial	Physical	Human	Organizational	Technological	Intangible	Plan	Source	Make	Deliver	OSC
75	Hsu et al. (2015)		√					√	√	√				√	
76	Huang and Mieghem (2014)			√						√				√	
77	Ilie-Zudor et al. (2015)		√			√					√			√	
78	Ivanov (2017)			√				√	√			√			
79	Jain et al. (2014)	√						√				√			
80	Jain et al. (2017)			√					√				√		
81	Jeeva and Dickie (2012)	√				√						√			
82	Jelena and Fiosins (2017)		√					√	√		√				
83	Jeon and Hong (2016)			√		√			√	√	√				
84	Ji-fan Ren et al. (2016)			√	√			√	√						√
85	Jin et al. (2016)		√					√	√	√	√				
86	Jun et al. (2014)	√			√				√		√				
87	Kache and Seuring (2017)	√	√	√				√	√						√
88	Kargari and Sepehri (2012)		√			√		√						√	
89	Kemp et al. (2016)		√					√	√					√	
90	Kibira (2015)			√				√	√				√		
91	Kok and Shang (2014)			√	√	√			√					√	
92	Köksal et al., (2011)	√					√	√					√		
93	Koo et al. (2015)	√							√	√		√		√	
94	Kowalczyk and Buxmann (2015)			√			√	√			√				
95	Kretschmer et al. (2017)			√	√			√					√		
96	Krumeich et al. (2016)		√					√	√				√		
97	Kubac (2016)		√			√			√				√		
98	Kubáč (2016).		√			√				√				√	
99	Kuester and Rauch (2016)	√					√	√			√				

Sr. No.	Authors	Level of Analytics			SCM Resources Used						SCOR Domains				
		Descriptive	Predictive	Prescriptive	Financial	Physical	Human	Organizational	Technological	Intangible	Plan	Source	Make	Deliver	OSC
100	Kumar et al. (2016)			√				√	√				√		
101	Kumar et al. (2017)		√			√			√				√		
102	Kuo et al. (2015)			√	√			√				√			
103	Kwak and Kim (2012)			√					√				√		
104	Lade et al. (2017)		√				√		√				√		
105	Lanka and Jena (2014)		√						√					√	
106	Lau et al. (2014)		√						√	√	√				
107	Lee (2016)			√				√						√	
108	Lee and Chang (2010)	√					√	√		√	√				
109	Lee et al. (2013)		√					√	√				√		
110	Lee et al. (2017)			√		√			√					√	
111	Levner et al. (2011)		√					√	√					√	
112	Li et al. (2015)		√					√						√	
113	Li et al. (2016a)		√					√	√	√	√				
114	Li et al. (2016b)		√			√								√	
115	Li et al. (2016c)		√						√				√		
116	Li et al., (2014)		√			√			√				√		
117	Lin et al. (2010)			√	√			√				√			
118	Liu et al. (2016)	√						√	√	√			√		
119	Ma et al. (2014)		√					√	√		√				
120	Mariadoss et al. (2014)		√				√	√			√				
121	Marine-Roig, and Clavé (2015)		√						√	√	√				
122	Markham et al. (2015)	√							√	√	√				
123	Mason et al. (2017)		√					√	√				√		
124	Mehmood (2017)			√					√					√	

Sr. No.	Authors	Level of Analytics			SCM Resources Used						SCOR Domains				
		Descriptive	Predictive	Prescriptive	Financial	Physical	Human	Organizational	Technological	Intangible	Plan	Source	Make	Deliver	OSC
125	Min (2010)			√				√			√	√		√	
126	Miroslav et al. (2014)		√				√	√	√			√			
127	Mishra et al. (2016)	√	√	√					√						√
128	Miyaji (2015)	√				√	√							√	
129	Mori et al. (2012)		√				√	√	√			√			
130	Mourtzis et al. (2016)		√			√			√				√		
131	Moyne et al. (2016)	√							√				√		
132	Munro and Madan (2016)			√					√				√		
133	Nguyen et al. (2017)	√	√	√				√	√						√
134	O'Brien et al. (2014)	√				√	√							√	
135	Olson (2015)	√	√	√					√						√
136	Oruezabala and Rico (2012)	√							√	√		√			
137	Ostrowski et al. (2016)		√					√	√						√
138	Packianather et al. (2017)		√					√	√	√	√				
139	Pang et al. (2017)		√			√				√				√	
140	Papadopoulos et al. (2017)	√				√		√							√
141	Park et al. (2016)		√		√			√	√			√		√	
142	Peters and Link (2010)		√						√				√		
143	Petri et al. (2016)		√		√					√				√	
144	Prasad et al. (2016)	√					√		√		√				
145	Ralha and Silva (2012)		√			√		√				√			
146	Rehman et al. (2016)	√						√	√						√
147	Reuter et al. (2016)	√							√				√		
148	Richey et al. (2016)		√				√	√							√
149	Robinson et al. (2015)			√		√		√					√		

Sr. No.	Authors	Level of Analytics			SCM Resources Used						SCOR Domains				
		Descriptive	Predictive	Prescriptive	Financial	Physical	Human	Organizational	Technological	Intangible	Plan	Source	Make	Deliver	OSC
150	Ronowicz et al. (2015)			√				√					√		
151	Salehan and Kim (2016)		√					√		√	√				
152	Sanders (2016)	√						√	√						√
153	Sangari and Razmi (2015)		√				√	√	√	√					√
154	Sann (2013)	√						√	√	√	√				
155	Schmidt et al. (2017)		√			√			√				√		
156	Schoenherr and Pero (2015)	√					√	√	√	√					√
157	Schoenherr and Swink (2015)		√							√	√				
158	Shafiq et al. (2017)	√						√	√				√		
159	Shan and Zhu (2015)		√			√			√					√	
160	Shanmugasundaram and Paramasivan (2016)		√							√	√				
161	Shi and Abdel (2015)		√			√			√					√	
162	Shin et al. (2014)		√		√			√					√		
163	Shukla and Kiridena (2016)			√				√			√			√	
164	Sivamani et al. (2014)		√			√	√		√					√	
165	Soban et al. (2016)			√				√					√		
166	Sodhi and Tang (2011)			√		√					√				
167	Soroka, 2017			√				√	√				√		
168	Souza (2014)	√	√	√					√						√
169	Spoel et al. (2017)	√					√	√						√	
170	Srinivasan and Swink (2017)		√		√	√	√	√	√	√					√
171	St. Aubin (2015)	√				√				√	√			√	
172	Stefanovic (2015)		√					√						√	
173	Tachizawa et al. (2015)			√		√									√

Sr. No.	Authors	Level of Analytics			SCM Resources Used						SCOR Domains				
		Descriptive	Predictive	Prescriptive	Financial	Physical	Human	Organizational	Technological	Intangible	Plan	Source	Make	Deliver	OSC
174	Tan et al. (2015)	√				√				√	√				
175	Tanev et al. (2015)	√				√		√		√	√				
176	Thiruverahan and Subramanian (2015)		√											√	
177	Thotappa and Ravindranath (2010)			√										√	
178	Toole et al. (2015)		√						√					√	
179	Trkman et al. (2010)		√						√						√
180	Tsai and Huang (2015)		√			√			√	√				√	
181	Tsao (2017)			√				√	√			√			
182	Tsuda et al. (2015)		√			√			√				√		
183	Tu et al. (2016)			√		√				√				√	
184	Ulrike et al. (2013)	√						√	√		√				
185	Unay and Zehir (2012)	√					√	√			√				
186	Veugelers et al. (2010)	√						√		√	√				
187	Walker and Brammer (2012)		√						√	√		√			
188	Walker and Strathie (2016)	√				√			√					√	
189	Wallander and Makitalo (2012)		√			√		√	√					√	
190	Waller and Fawcett (2013)		√				√				√			√	
191	Wamba et al. (2015)	√							√						√
192	Wang and Yang (2016)	√				√		√	√					√	
193	Wang and Zhang (2016)		√					√			√		√		
194	Wang et al. (2015)		√						√				√		
195	Wang et al. (2016a)		√					√					√		
196	Wang et al. (2016b)		√			√			√					√	
197	Wang et al. (2016c)	√	√	√				√	√						√
198	Wang et al., (2016d)			√		√		√	√				√		

Sr. No.	Authors	Level of Analytics			SCM Resources Used						SCOR Domains				
		Descriptive	Predictive	Prescriptive	Financial	Physical	Human	Organizational	Technological	Intangible	Plan	Source	Make	Deliver	OSC
199	Westerski et al. (2015)		√					√				√			
200	Wiener et al. (2010)		√					√					√		
201	Wu et al. (2013)	√				√		√				√		√	
202	Wu et al. (2017)		√	√				√	√						√
203	Xiao et al. (2016)	√							√	√	√			√	
204	Xie et al., 2016)		√						√					√	
205	Xu and Guting (2013)		√			√		√	√					√	
206	Xu et al. (2016)	√						√		√	√				
207	Yeniyurt et al. (2013)	√					√		√	√		√			
208	Zaki et al. (2017)			√				√	√				√		
209	Zangenehpour (2015)	√				√			√	√				√	
210	Zhan et al. (2017)	√			√			√		√	√				
211	Zhang et al. (2015)			√										√	
212	Zhao and Rosen (2017)		√						√				√		
213	Zhao et al. (2017)			√		√				√				√	
214	Zhong et al. (2013)		√					√	√				√		
215	Zhong et al. (2015a)	√				√							√		
216	Zhong et al. (2015b)	√				√							√		
217	Zhong et al. (2016)	√				√		√	√				√		
218	Zhong et al. (2017)		√			√		√	√				√		
219	Zhou et al. (2017)													√	
220	Zhu (2014)	√							√				√		

Table 3: Classification of papers on level of analytics used in different SCOR domains

SCOR Domain	Descriptive	Predictive	Prescriptive
Plan	26	23	9
Source	7	9	8
Make	11	29	22
Deliver	13	32	14
OSC	18	21	12

Table 4: SCM resources utilized in different SCOR domains

SCOR domains	Financial	Physical	Human	Org	Tech	Int.
Plan	5	9	7	36	26	33
Source	3	3	4	16	13	5
Make	6	15	4	36	36	1
Deliver	3	30	5	23	26	13
OSC	3	4	5	23	25	5

BDA applications in Plan Domain

The studies in this domain are further classified into two categories managing innovation-new product development and demand forecasting. Among five areas of SCOR domains, plan (58 out of 220 papers, 26%) is one of the most common areas where BDA supports decision making. It is observed from Figure 8 that 30 papers (or 51%) focus on using BDA for garnering innovation and new product development, while the remaining papers 28 papers (48 %) in this domain focus on using BDA for demand forecasting.

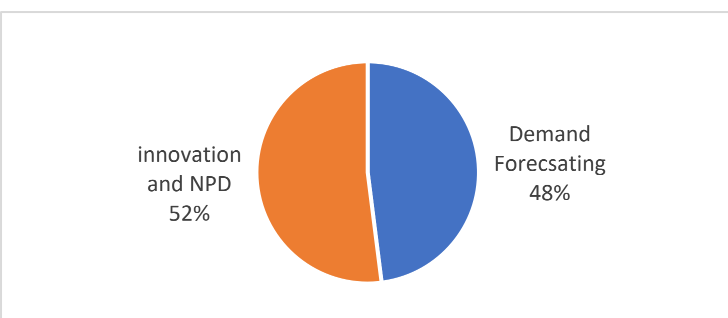


Figure 8: Distribution of papers in plan domain

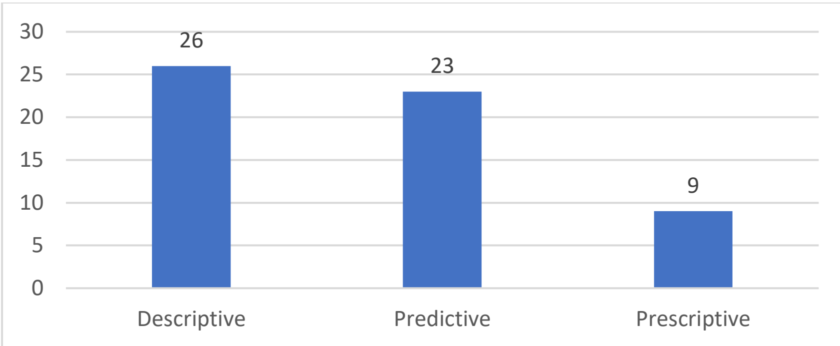


Figure 9: Level of analytics in plan domain

Figure 9 shows that descriptive (26 papers or 44%) and predictive (23 papers or 39%) analytics is widely used in the planning domain. Descriptive analytics is prominent in most studies on new product development and innovation. Out of the 28 papers on demand forecasting, 17 (or 60%) used predictive analytics, and nine (or 32%) used prescriptive approaches to BDA. The use of prescriptive analytics is primarily used in combination with predictive analytics.

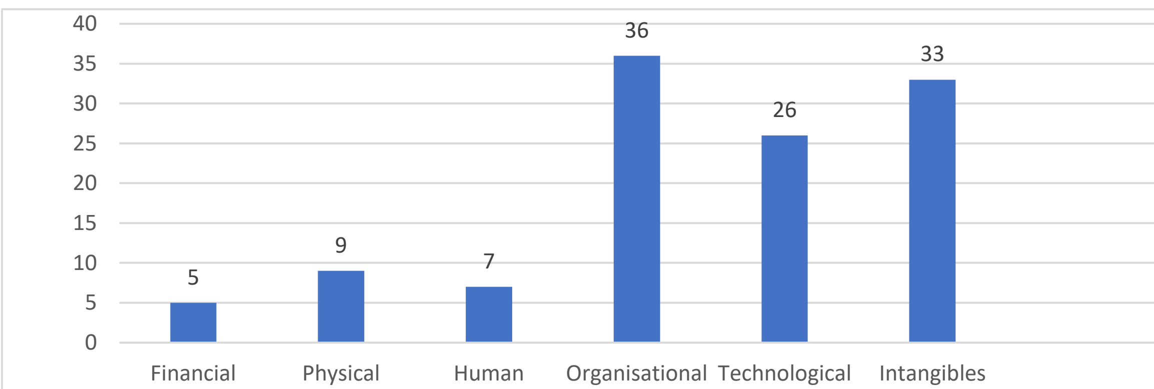


Figure 10: Distribution of papers on SCM resources in plan domain

Further, as seen in Figure 10, majorities of the studies manage organizational resources (36 papers or 62%), intangible resources (33 papers or 56%) and technological resources (26 papers or 44%). The intangible resources get prominence in the plan domain because of the involvement of the customers and the users in giving their feedback for product development and the innovation process. Human and financial resources have not received much prominence in the plan domain.

New Product development and Innovation

In online product reviews, BD is a major information source which helps managers and marketers realize their customers' concerns and interests (Xiao et al., 2016; Bendoly et al., 2012). Referred to as social and sentiment analysis, BDA helps design creative product strategies, launch new products to market as quickly as possible, and determine the product's weaknesses earlier in the development cycle (Zhan et al., 2017; Lee and Chang, 2010; Colace et al., 2014). Tanev et al. (2015), based on their work, observed that the value of product-enabled services in an online environment is dependent on various SCM parameters. Therefore being in touch with the customers for their valuable feedback and input is highly important. The different sources of BD used for NPD are online shopping sites, blogs, social network sites, and forums (Amarouche et al., 2015). A salesperson’s knowledge of marketing intelligence is also an important source of business intelligence (Kuester and Rauch, 2016; Mariadoss et al., 2014). It is proposed to combine the lead user intelligence with the voice of the customer techniques to lower the risk of an unreliable product (Sann et al., 2013). Jin et al. (2016) recommend that product designers analyze BD in customer opinion data, purchase records, and online behaviour using the Kalman filter and Bayesian method. Chung and Tseng (2012) suggest techniques for analyzing the qualitative and quantitative data available on the web.

Studies have proposed that the concept of BD has substantial implications for R&D and innovation management (Blackburn et al., 2017; Bradley et al., 2017; Lau et al., 2014). BD and BDA are not only used extensively for NPD but also ensure product success (Xu et al., 2016; Ünay, Zehir, 2012; Bahrami et al., 2012; Eidizadeh et al., 2017; Schoenherr and Swink, 2015). Haverila and Ashill (2011) found that technology-intensive managers conceptualize and recognize “intelligence” variables in successful and unsuccessful NPD projects. However, Tan et al. (2015) observed an absence of analytic data methods to support firms in capturing the innovation afforded by data and gaining a competitive advantage. Companies must develop a data analytic approach to utilize BD to gain a competitive advantage by boosting their SC innovation capabilities (Tan et al., 2015; Veugelers et al., 2010).

Demand Forecasting

BDA is used for obtaining an improved forecast, given that the company can identify the hidden trends and patterns from the data. Lamba and Singh (2017) supported that demand forecasting assists towards demand estimates. Process variations resulting from poor forecasts and demand predictions cause an imbalance leading to SC disruptions (Wang et al., 2016a; Souza, 2014; Chen and Blue, 2010; Chen et al., 2010). It is observed from the literature that the BD and BDA applications in demand forecasting are mainly for three purposes, viz., demand planning, demand sensing, and demand shaping. Demand planning deals with analyzing the different customer segments that help organizations create revenue plans (Chen and Blue, 2010; Haberleitner et al., 2010). Ulrike et al. (2013) proposed integrating sophisticated procedures to meet the data volume and complexity challenges. Automating analytics using adaptive forecasting time series benefit from performing forecasts of many variables with relatively high accuracy for a short period and few resources (Gerunov, 2016).

Demand sensing is a forecasting method performed on real-time information combined with new mathematical techniques to predict demand forecasts. With demand sensing and real-time analytical capabilities, organizations can analyze demand data with increasing real-time accuracy and reducing the bullwhip effect (Hofmann, 2017). Berengueres and Efimov (2014) used a linear extrapolation with GBM and other data mining techniques. The predicted information is recommended for CRM interactions between the airline and the passenger. Ma et al. (2014) developed an algorithm for predicting future sales by capturing hidden and upcoming product demand trends. The proposed analytics was an integration of three prediction techniques viz., i. Decision tree for large-scale data ii. Discrete choice analysis for demand modelling, and iii. Automatic time series forecasting for trend analysis. Packianather et al. (2017) recommended using k-means clustering, hierarchical clustering and time-series forecasting to determine associations between customer variables identifying the seasonal variations and trends to visualize the core characteristics of the firm's customers. Cluster analysis and decision trees were used to classify traffic patterns to predict the electric vehicle charging demand (Arias and Bae, 2016).

Customer opinions captured from social media are used for competitive analytics and sentiment benchmarks. The findings of such studies are used for identifying specific, actionable areas (Chong et al., 2016; He et al., 2015; Marine-Roig and Clavé, 2015; Salehan and Kim, 2016). The BDA techniques used for customer analytics include predictive analytics such as sentimental and neural networks used on online reviews (Chong et al., 2016), collected from amazon.com (Li et al., 2016a), and search traffic information using google insights (Jun et al., 2014), and Twitter hashtags (Chae, 2015).

BDA applications in Source Domain

The source domain has received very little interest from the researchers compared to the other SCOR domains (other than the return domain), with only 24 papers (or 16%). As seen in Figure 11 use of BDA in the procurement process (10 papers, 41%) has received more attention in the source domain. In comparison, the remaining papers in this domain are well distributed between supplier selection (6 papers, 25%), supplier performance (4 papers, 16%), and supplier risk management (4 papers or 16%).

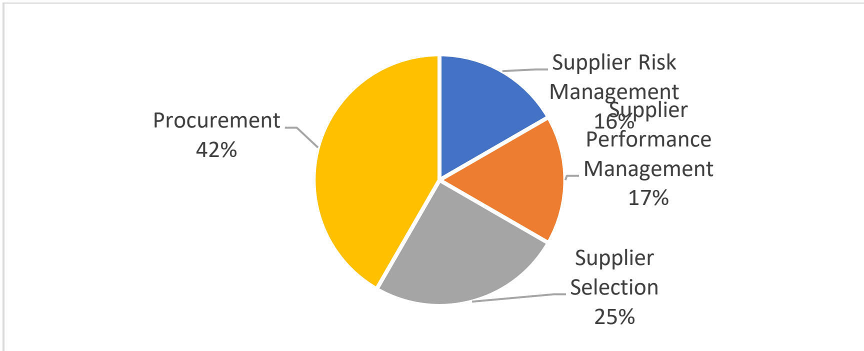


Figure 11: Distribution of papers in source domain

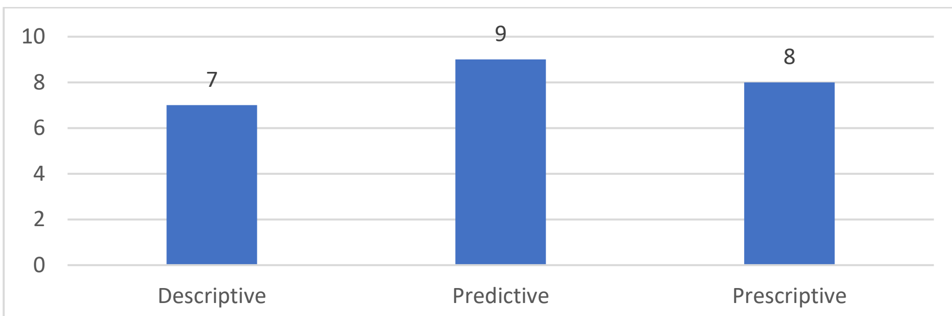


Figure 12: Level of analytics in source domain

It is observed from Figure 12 that all three-level analytics are almost equally balanced in their application in the source domain, with predictive analytics (9 papers or 37%) having a little higher edge over the other analytics. Prescriptive analytics is primarily used in the source domain to detect frauds and minimise supplier risks.

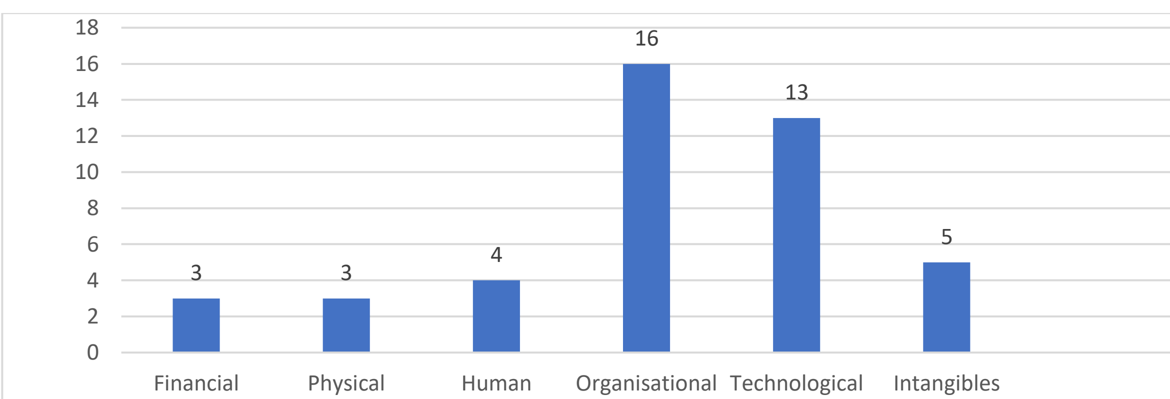


Figure 13: Distribution of papers on SCM resources in source domain

Figure 13 reveals that most studies focused on managing the organizational resources (16 papers or 66%) as the BDA application serves to find hidden trends and fault detection in the procurement process, optimize the supplier selection process, and minimize the risks. Technological resources were addressed in 13 papers (or 54%), followed by intangibles (five papers or 20%). The other resources, viz., financial (three papers or 12%), physical (three papers or 12%) and human (four papers or 16%), is least preferred in the literature.

Procurement

Many different types of data like spending details, supplier information, attribute criteria, etc., get generated during the procurement process from various sources. There is considerable scope for using BDA in procurement for beneficial info delivery (Westerski et al., 2015), understanding the procurement patterns of the customers (Mishra et al., 2017) and a variety of data-based analyses for business decisions that include quality problems and material availability (Souza, 2014; Min, 2010) not only in the traditional procurement system but also in the e-procurement environment (Wu et al., 2013). More and more enterprises are adopting e-procurement mode for purchase transactions, thereby generating a different combination of parameters increasing the difficulty level of the customer's choice. Identifying this substantial potential, Choi et al. (2016) recommend using BDA to exploit the full potential of BD availability. With the help of a case study on sound public decision-making regarding IT service procurement, the authors demonstrated sound public decision-making. The value of BDA is not only derived from private companies but also from public procurement (Choi et al., 2016; Mirsolav et al., 2014). Detection of the fraud in public procurement has also been one of the areas of research in procurement that has received attention. BDA techniques like semantic technologies (Miroslav et al., 2014), supervised learning (Arief et al., 2016), and association rules (Ralha and Silva, 2015) were proposed for early recognition of potentially irregular procurement. The fraud detection studies are performed by extracting useful information from procurement process databases. Groves (2014) performed the simulation for a one-product life cycle with six autonomous agents competing to procure parts and sell the finished products to customers. The use of simulation provides insights applicable to SC environments based on prescriptive analytics.

Supplier selection

A manufacturer or an assembler procures various raw materials, components, and subassemblies from different suppliers based in different locations, producing the final product. In most cases, these companies have many suppliers to select from, offering them to supply the required products. Supplier selection, therefore, becomes a critical decision for managing an efficient supply chain. The companies use different criteria to select the best supplier(s). As the supplier selection decision must be optimized, the decision-making techniques use the knowledge and experience of the decision-makers (Jain et al., 2014). BDA in supplier selection helps in discovering the hidden relationships. The same can be achieved by analyzing the supplier's pre-qualification data (Jain et al., 2014), firm profiles and transactional relationships (Mori et al., 2012), and historical data (AlKhalifah and Ansari, 2016) by using different techniques like association rule mining (Kuo et al., 2015; Lin et al., 2010), artificial intelligence, machine learning (Mori et al., 2012), and optimization techniques (Kuo et al., 2014). Two-stage supplier selection models with the first stage focusing on selecting the supplier and the second stage deciding on the quantity allocation for the key suppliers to minimize the purchasing cost is also recommended (Kuo et al., 2015; Lin et al., 2010).

BDA applications in Make Domain

It is observed from Figure 14 that the making domain takes up 28% (62 out of 220 papers) of the total publications. The majority of research papers in this area (36 papers, 58%) focus on using BDA for improving the manufacturing environment and achieving process improvements, followed by application in quality management (10 papers, 16%), maintenance management (7 papers, 11%), and scheduling and production control (7 papers, 11%).

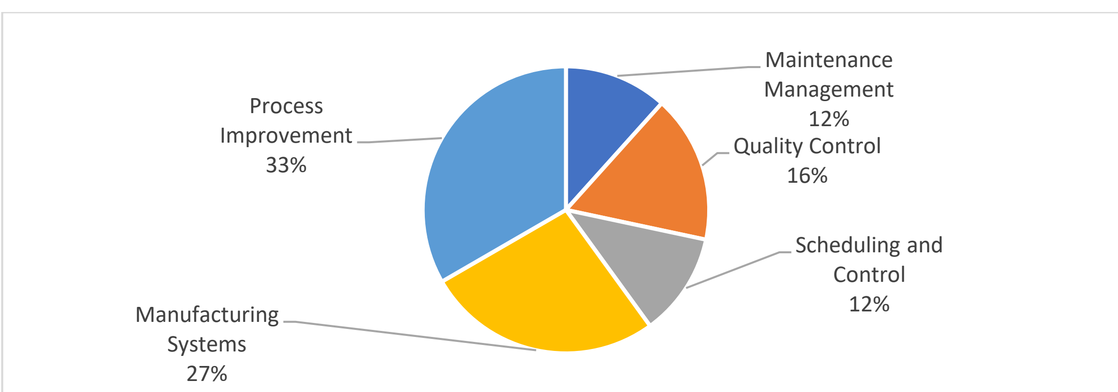


Figure 14: Distribution of papers in make domain

Figure 15 reveals that the level of analytics is more inclined towards predictive (29 papers or 46%) and prescriptive analytics (22 papers or 35%). Descriptive analytics is used to a lesser extent (11 papers or 17%).

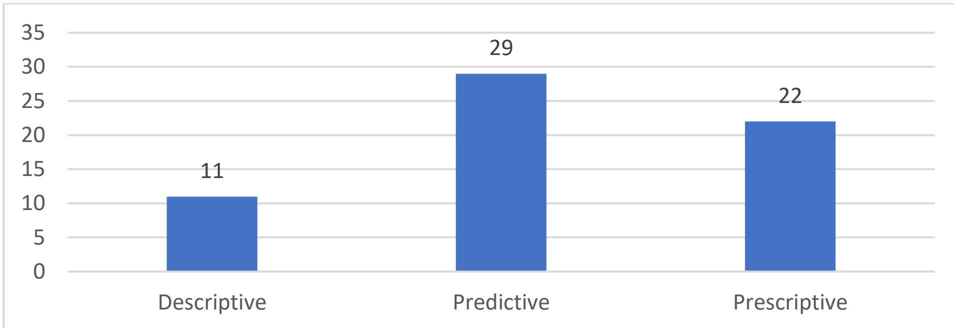


Figure 15: Level of analytics in make domain

Further, the focus of all the studies was to use the BDA to manage and use data for organizational decision-making. Therefore, we find that most studies dealt with managing the technological and organizational resources (36 papers each or 58% each). Physical resources were the focus of the study in 15 papers (or 24%). Managing the financial resources (six papers or 9%), human resources (three papers or 4%), and intangible resources (two papers or 3%) have received very little attention in the make domain. (See Figure 16).

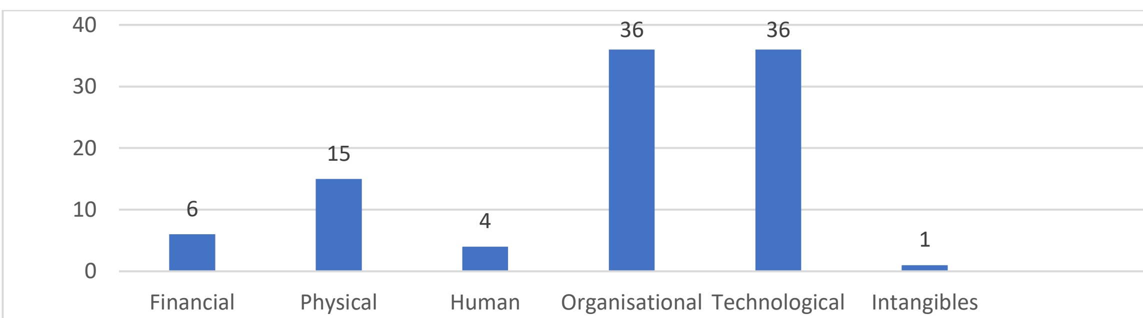


Figure 16: Distribution of papers on SCM resources in make domain

Manufacturing Systems

There is increasing pressure on the manufacturing enterprises to improve their efficiency and productivity due to the increasing and changing customer demands. Many factors, including various complex products, uncertainties, capacity constraints, and labour shortages, make production management face more and more significant challenges. (Butler and Bright, 2014; Cheng et al., 2017; Zaki, 2017). Internet of Things (IoT) is the organic evolution of the internet that creates a smart environment (Mourtzis et al., 2016; Davis, 2012; Lade et al., 2017), giving scope for the intensive use of BDA (Babiceanu and Seker, 2016; Cheng et al., 2017; Lee et al., 2013). With the increasing connectivity of devices, the rapid growth of data recorded and ready for analysis is growing correspondingly (Zhu et al. 2014). Liu et al. (2016) found that customized manufacturing tasks could be finished more reliably and efficiently if all participants exchanged the data through a cloud platform in real-time.

Prescriptive analytics, like multi-objective optimization, has been identified as a robust approach for generating a set of optimal trade-off design alternatives (Dudas et al., 2014; Munro and Madan, 2016.) in manufacturing. Few authors have proposed using a combination of computational intelligence approaches combining optimization, simulation, and data mining to optimize the manufacturing systems (Amos et al., 2016, Jain et al., 2017). The use of simulation as a BDA technique in manufacturing is used as a tool for data generator and model validation. Kibira et al. (2015) recommend using BDA to extract significant parameters that affect the system performance, using these parameters as input values for simulation and then using the simulation output to optimise the system. Virtual manufacturing environments are proposed to be developed to capture, store, reuse, and share manufacturing knowledge (Shafiq et al., 2017). The virtual environments are reported to provide for the collective intelligence of a factory and enhance effective decision-making (Kretschmer, 2017). Soroka et al. (2017) find that BDA in redistributed manufacturing (RdM) may help small-scale manufacturing companies to manufacture tailored products satisfying the specific needs of consumers (Zaki, 2017; Soroka, 2017).

Process improvement

A typically processed lot in manufacturing generates huge data, which needs proper analysis for process troubleshooting (Cochran et al., 2016 Charaniya et al., 2010). Djatna and Munichputranto (2015) used overall equipment effectiveness as a quantitative productivity measurement for continuous improvement and evaluation. Using the android-based mobile BI system, they identified the critical production line effectiveness measurement and machine utilization parameters. Apart from process analytics, manufacturing process modelling (Çiflikli and Özyirmidokuz, 2010; Kwak and Kim, 2012; Robinson, 2015) and process simulation (Soban, 2016) are also observed to be an area of interest for BDA application. Çiflikli and Özyirmidokuz (2010) suggest that the nonlinearities between process parameters, which are not inevitable in manufacturing processes, can also be addressed by process modelling. Energy consumption (Shin et al., 2014), energy costs (Hammer et al.; 2017) and reduction of the greenhouse gas emissions (Wang et al., 2016c) are optimized using BDA for attaining sustainable manufacturing. The process optimization technique proposed by Kwak and Kim (2012) addresses the issue of handling a significant amount of missing values due to the data discarded by gross measurement errors. The IoT and wireless technologies like RFID found their application in the shop floor environment, referred to as intelligent shop floors (Zhong et al., 2017). Charaniya et al. (2016) developed a kernel-based methodology to integrate all the process parameters. Li et al. (2017) proposed using a Genetic Algorithm - Support Vector Machines method to identify the input process variables for a cleaner production environment.

Maintenance Management

Predictive maintenance represents one area where BD solutions benefit various process types. Predictive analytics enables immediate data collection for analysis by the data aggregation and merging functions which extract keys correlating to yield from the equipment's parameter for detecting the root cause (Tsuda et al., 2015; Moyne et al., 2016). Wang et al. (2015 discussed predictive analytics where the schedules may be optimized using the linguistic interval-valued fuzzy reasoning method (Kumar et al., 2017). The decision tree model as a predictive mining technique was used for detecting and isolating machine breakdowns (Cochran et al., 2016).

Scheduling and Production Control

The exposure of the manufacturing companies to volatile market conditions causes wide variations and discrepancies in executing production plans and schedules. Using real-time shop floor data about men, machines, materials, and orders captured through RFID technology can be an important source for developing the standard operating times on which the advanced production plan and schedules are prepared (Zhong et al., 2013). BDA has a huge potential for production planning and control (Krumeich et al., (2016), control engineering analyses (Hoffman, 2017) and managing the dynamically changing production circumstances and huge varieties in production programs (Reuter et al., 2016). Prescriptive analytics was used to optimise the scheduling problem, which is usually NP-hard (Cohen et al., 2017) and the performance of industrial manufacturing systems (Hammer et al., 2017) to maximise the enterprise profit.

BDA applications in Deliver Domain

Another domain for BDA applications is delivered with 60 out of 220 papers (or 27%). Figure 17 shows that transport and traffic management (26 papers, 43%) and inventory management (16 papers or 26%) are the most prominent application areas of BDA in this domain. BDA use for logistics network management (10 papers, 16%) and order picking (8 papers, 13%) is also gaining importance in the recent past.

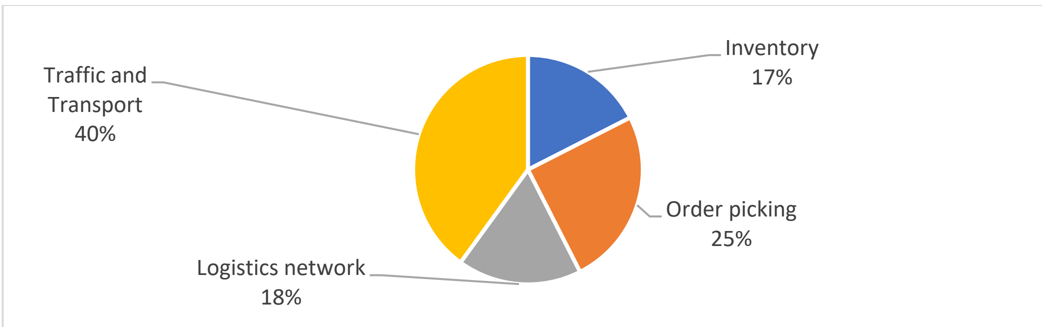


Figure 17: Distribution of papers in deliver domain

Predictive analytics has been the most popular technique, with 32 papers (or 53%) out of 62 papers in the deliver domain, followed by prescriptive analytics with 14 papers (or 23%). BDA using descriptive studies has attracted less attention from the researchers, with only 11 papers (or 21%) using them. (See Figure 18).

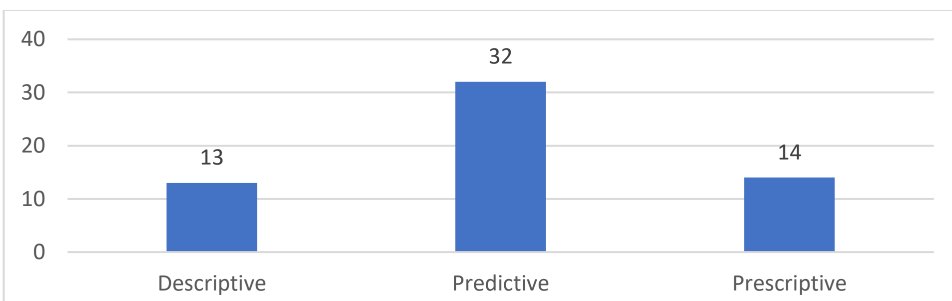


Figure 18: Level of analytics in deliver domain

It is observed from Figure 19 that the use of BDA for managing physical resources has been observed to find high visibility in the delivery domain, with the majority of the studies (30 papers or 50%) focusing on them. This was followed by studies also focusing on the issues of data collection (technological resources, 26 papers or 43%) and using the data for improving the organizational capabilities (23 papers, 38%). Managing the financial resources (3 papers or 5%), human resources (five papers or 8%), and intangible resources (13 papers or 21%) have received very little attention in the deliver domain.

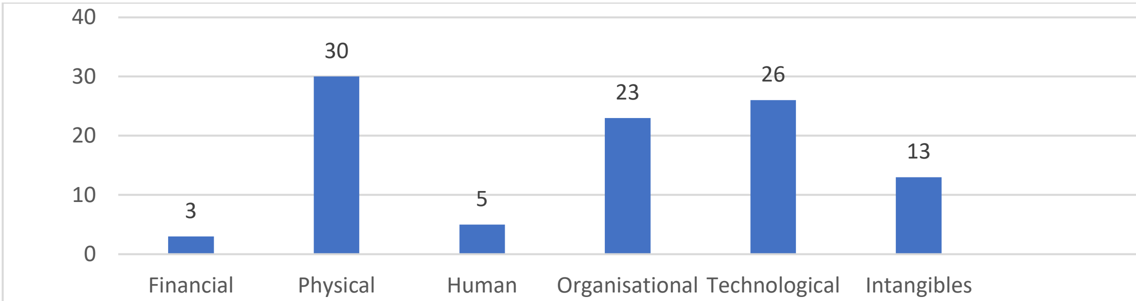


Figure 19: Distribution of papers on SCM resources in make domain

SC Network management

Park et al. (2016) implemented an interactive web-based visual analytic system to provide detailed information about supply network activities on demand management. The proposed system enables the decision-makers to interactively use visual encodings to match the demand gaps between the network nodes (Davis et al., 2012; Ilie et al., 2015). Shukla & Kiridena (2017) developed an advanced analytics framework for configuring SC networks using historical sales data, including network node-related information. The primary focus of most of the studies on BDA in the supply network area has been sustainability and green SCM (Papadopoulos et al., 2017; Shukla & Kiridena, 2017; Zhao et al., 2017; Davis et al., 2012, Wu et al., 2017). Wireless sensor network (WSN) technologies connecting to IoT and Automated Meter Reading (AMR) systems were used to collect the BD.

Order picking

Many solution methodologies minimize the travelling distance for order picking (Chuang et al., (2014); Li et al. (2016b; Pang et al., (2017); Azadnia et al., (2013). Chuang et al. (2014) explored how an effective layout zoning following class-based storage can enhance order picking efficiency using association web statistics and association rule mining. Li et al. (2016b) also proposed improvement in order picking time in stores using an integrated mechanism based on the ABC categorization. BDA is used for the shelf space allocation strategy, leading to increased store profitability (Tsai and Huang, 2015) and reduced travel times (Chiang et al., 2014). The proposed solution captured customers' purchasing behaviour from records of previous transactions captured through RFID (Tsai and Huang, 2015) and analyzed using association rule mining (Chiang et al., 2014).

Inventory Management

Maintaining an optimal inventory level in the organization is one of the most significant requirements for a competitive supply chain. Automation and integration of warehousing systems are inevitable for more efficient and centralized distribution (Alyahya et al., 2016). The various inventory control techniques and methodologies aim to reduce the overall SC costs by efficiently controlling the inventory. BD and BDA have been applied in this area to minimize the shortages and avoid overstocking of the products (Guo et al., 2014), as a variety of data in the form of historical demands, forecasts, etc., are readily available to the organizations. Therefore, inventory management requires particular attention in the field of SCM. The BDA must provide accurate and up-to-date information for better user-friendly inventory management decisions (Lee et al., 2016; Stefanovic, 2015). This is done by tracking the inventory levels, orders and sales by implementing intelligent inventory management solutions to reveal hidden relations with integrated data-driven analysis (Zhou et al., 2017), predicting inventory level requirements based on average consumptions over a period, using machine learning algorithms (Thiruverahan and Subramanian, 2015), Back-propagation neural network to train the prediction model (Guo et al., 2014; Hsu et al. (2015) and Genetic Algorithm (Thotappa and Ravindranath, 2010). BDA has a high potential for the improvement of the various SC processes that include mitigation of the bullwhip effect, demand variability at various nodes in the SC network (Hoffman, 2017; He and Zhao, 2012) and determination of optimum safety stock at various storage points in the SC (Guo et al., 2014). Integrated analytics based on operations research, data mining, and geographic information can be used for in-transit inventory (Delen et al., 2011). Huang and Meighem (2014) propose a dynamic decision support model that takes orders offline to reduce the inventory holding and back-ordering costs. Consideration of the green aspects of the SC for reducing the environmental risks due to the sediment storage, transport, and deposition of BDA using satellite imagery and elevation data captured through GIS (Balaban et al., (2015) is also studied.

Transportation and logistics

Transportation and logistics planning is an emerging field in which the organizations can have an improved business sense and SC decisions by taking advantage of BD-enabled by the popularization of Intelligent Transportation Systems (Shi and Abdel, 2015; Wang et al., 2016b; Kemp et al., 2016; Kubac, 2016). Many moving objects in the supply chain can be traced and tracked using precise transportation modes to model the BD (Xu & Güting, 2013). The research studies have focussed more on developing a smart logistics environment with an ITS with the objective of prompt delivery aligning just-in-time standards (Dobre and Xhafa, 2014); Sivamani, 2014; Miyaji (2015).

The sensed data needs formatting and standardizing for further deployment (Zhong et al., 2015). As one of the data collection sources, RFID technology helps capture real-time data used for different purposes, including keeping the inventory records, as any inaccuracies in these records will affect the SC performance (Kok and Shang, 2014). The collected data can be temperature and humidity data during storage, transportation, event files, and geographic and demographic data for efficient trip management (Cristobal et al., 2015). Human or organizational factors data clubbed with real-time traffic and weather data were used to predict truck arrival times (Spoel et al., (2017). Ergonomics methods applied to BD collected from On-Train Data Recorders (OTDR) can help address the risk issues and improve human performance (Walker and Strathie, 2016). Wallander and Makitalo (2012) used passenger train traffic data to analyse the transport delay chains, which can be used to develop rail traffic punctuality and the whole railway system to improve the rail network system.

Cui et al. (2016) used GPS devices as a data source to minimise the difference between travel demand and transport services, leading to a sustainable urban transport system. Critical traffic data were captured by the devices installed on the vehicles. Many research studies felt the need to integrate new BD resources into customary transportation demand modeling so that the increasing stress on already burdened transportation infrastructure, waiting time, congestion and accidents happening due to rapid urbanization are reduced through proactive real-time traffic monitoring (Toole et al., 2015; Cristobal et al., 2015; Xiao et al., 2016; Zangenehpour et al., 2015; Shi and Abdel, 2015; Wang et al., 2016b).

It has been found that transitionary technologies are presently leading the way in capturing the wealth of information for intelligent transportation systems (Shan Zhu, 2015; Zangenehpour et al., 2015). St.-Aubin et al. (2015) provide a functional framework for implementing an automated, high-resolution, video-based traffic-analysis system to conduct a road safety analysis and validate traffic flow models. Another significant application of BDA techniques that were observed in the literature included techniques such as granular computing (Xie et al., 2016), multiresolution data aggregation & visual data mining (Wang et al., 2016c), association rule mining (Lanka and Jena, 2014; Diana, 2012; Kargari and Sepehri (2012)), neural networks (Li et al., 2014), network routing, scheduling, real-time control algorithms (Levner et al., 2011). Kargari and Sepehri (2012) suggested clustering retail stores in a distribution network considering the available information to reduce distribution and transportation costs, such as store location, order, goods, vehicles, and road and traffic information.

To select a route according to the user's requirement, the model uses necessary delivery information, including location, delivery vehicle, user, etc. With the increased internet usage, companies can gather real-time situations to develop a more reliable relationship as an outcome of the Internet of Things. Sustainable and green transportation systems have also been the focus of the research studies (Zhao et al., 2017; Lee et al., 2017; Tu et al., 2016). Ehmke et al. (2016) introduced the shortest path algorithm that incorporated flexibility in travel speeds and estimated arrival time distributions at nodes on a path to reduce emissions relative to minimum distance and time-dependent paths. Tu et al. (2016) addressed the issue of the absence of charging stations as a limiting factor for the penetration of electric vehicles. Mehmood (2017) studied the transport operations to deal with lowering CO2 footprint (O'Brien et al., (2014). However, most models developed are deterministic Petri et al. (2016).

4 SC Visibility, BDA Capability, and SC Transformation

The findings of the SLR indicate that SC decision-makers are required to process voluminous data for decision-making to reduce SC costs and increase product availability, meeting the customer demands. For providing the required assistance to the decision-makers with rich and quality data, they must be available to the organization along with organizational infrastructure in terms of technological resources, physical systems and processes, human expertise and financial resources for collection of data, storage of data and performing the data analysis for extracting meaningful information leading to successful supply chain transformation.

SC visibility framework

The SLR reveals that BDA provides an excellent opportunity for strategic and operational improvements in the supply chains (Wang et al., 2016c). However, firms must be able to grab these opportunities and convert them into actions (Srinivasan and Swink, 2017). In SCM, the managers must collect and analyze information from stakeholders across the SCOR dimensions discussed in this chapter to drive better decision-making. Our proposed framework uses SC visibility (Williams et al., 2013) as the primary driving force that leads to successful SC transformation through a robust BDA capability, as shown in Figure 20.

SC visibility

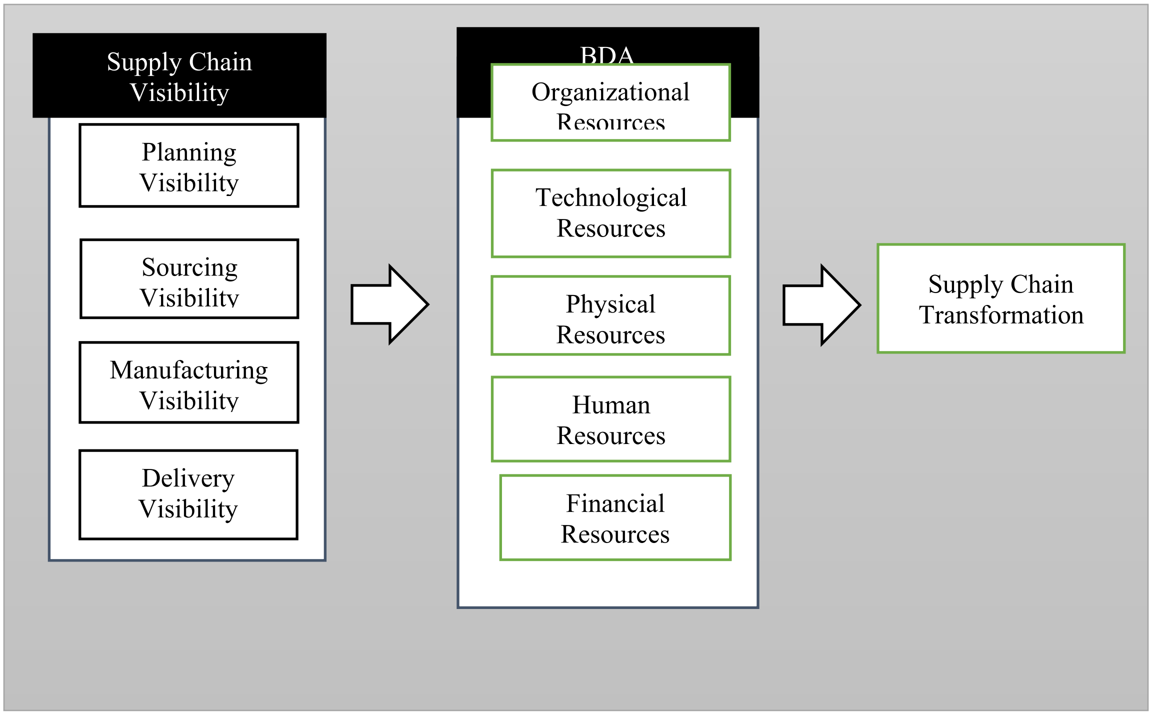
Srinivasan and Swink (2017) define SC visibility as the availability of appropriate and precise data from external partners, enabling the firms to build systems to process and acquire insights and synchronized decision-making between the SC partners (Baratt and Baratt, 2011; Gabraith, 1973). The SC visibility is required across all the domains of SC, viz., plan, source, make, deliver, and return. The demand data enables the firms to sense the changing customer patterns, competitor actions, promotion actions, pricing strategies, demand forecasting, delivery planning, inventory decisions, NPD, etc. The supply data generated from the suppliers enables the firms to recognize the changes, costs, shipping notifications, delivery schedules, managing inventory, etc.

BDA capability

In this study, we conceptualize the BDA on the organizational facility with technological tools and techniques, physical systems, human analytical skills and financial resources that enable the firms to collect, process, organize, visualize, analyze the data and use the derived information for enabling a big-data-driven efficient supply chain.

SC Transformation

Usually, a firm investing in achieving high SC visibility will also ensure well-developed resources that build their BDA capability. SC visibility will be useless if the firm has not developed its BDA capability or vice-versa. To achieve an efficient SC, SC visibility and BDA capability must co-exist. The availability of rich information for operational and strategic decision-making will help the SC managers to reduce operational costs and improve product delivery performance.



5 Future research directions

The future directions to capitalize on the research development of BDA applications in the SCM context are discussed in this section.

Future investigations on BDA applications in the SCOR Domains

Plan Domain

BDA in NPD helps to reduce the risk and market uncertainties as the data is acquired through different sources at the early phases of product development (Wamba et al., 2015), which can be used to identify the previously unrecognized customer needs (Tsai et al., 2013), for generating new product ideas (Trkman et al. 2012), in the process developing a long-term relationship with customers acting as co-creators of the product lending customer loyalty and retention. (Gantz and Reinsel 2012). It is found from the literature that most studies on NPD and innovation focus on the sources of BD and different approaches for analyzing the data. Further studies should be undertaken on improving customer involvement by using BD and organizations' cooperation with the customers and their involvement in the NPD process (Zhan et al., 2016).

Source domain

The review suggests that the source domain has received the least attention from the researchers. More studies in this domain on different aspects of BDA applications in procurement modes, supplier selection and evaluation, supplier risk management, supplier contracts management, etc., must be taken in the future.

Make domain

In the make domain, the Internet of Things (IoT) and smart manufacturing have started gaining importance and are expected to bring voluminous data regarding quantity and category, providing an opportunity for the application and development of BD. It is believed that the BDA in the IoT space will accelerate research advancements and business models (Min, 2014). BDA enables data set and comprehensive assessment from different sources and customers towards decision-making, improving customer service and manufacturing flexibility, optimize production quality, save energy, and improve equipment service (Ilie-Zudor, 2017). Presently BDA in the make domain is used for process monitoring, fault finding and process optimisations, mainly based on the predictive and prescriptive analytics (Moyne et al., 2017). The real challenge in the future will be implementing BDA in smart manufacturing systems. Therefore the experts in the make domain must identify the critical tasks/processes for a more manageable outcome. Further, these IoT-based smart manufacturing systems are connected with embedded sensors and communications devices.

Deliver domain

Supply chains have become more reliable, efficient and predictable with digital technologies in transportation and warehousing functions. The review reveals that the supply chains are accessing real-time data and analytics with the extended use of RFID and other IoT sensors that provide a live view of their machinery, vehicles, and operators. Future studies should focus on ensuring a safe and pleasant working environment for the drivers and reducing traffic accidents and fatalities. Future studies may also focus on the impact of BDA on the potential use of autonomous vehicles. Studies on exploring how 3D printing can help to eliminate the transportation costs as it is expected that the 3D printing will help the manufacturing facilities to be moving closer to the customers hence reducing the distance and also the need for stocking inventories as the products can be manufactured whenever the demand is received. Further studies should focus on how the supply chains can adopt or adapt to new business models to stay on course, compete in today's digital market, and ultimately embrace the transformative capabilities of BD for the industry.

The other research gaps which are required to be addressed in the future studies on BDA applications in deliver domain include in-plant logistics movement of raw materials, products, and vehicles, just-in-time inventory management with the use of IoT and smart manufacturing systems, use of BDA for efficient use of robots in the warehouse and order picking management.

Return domain

The review did not identify any significant applications of BDA in the return domain. The results are in sync with the past studies (Nguyen et al., 2017; Barbosa et al., 2017). There is a high research potential to fill this gap in future studies. Further studies may focus on how the companies may learn from customer complaints while returning a defective product in the supply chain, identify root causes for defects, use predictive analytics to predict return rates, and conduct assessments of the return process performance. Presently, the research in the return domain may be lacking because of difficulty obtaining the field's information. Still, new technologies such as IoT and intelligent systems will soon overcome this barrier.

Levels of analytics across the SCOR domains

In the plan domain, the descriptive and predictive level dominates over the prescriptive level of analytics. In the source domain, the level of analytics seems to be equally balanced within the limited number of articles available in this domain. In make domain, the studies are dominated by predictive and prescriptive analytics. Predictive analytics dominates the deliver domain, focusing less on deploying descriptive and prescriptive analytics. Nguyen et al. (2017) suggest that BDA application is a linear process to catalyze rapid progression. Future studies should balance the emphasis on all three levels of analytics. The findings of this review will be useful guidance for future studies on identifying the relevant level of analytics in a given domain.

5.4. SCM resources

Most studies on BDA applications in SCM focus on utilizing organizational and technological resources. Studies utilizing the intangible resources for managing NPD and product innovations were observed in the plan domain, and studies utilizing the physical resources were observed in deliver and make domain. Very few studies focused on the utilization of financial and human resources. The BDA capabilities of organizations depend on how best the various resources are utilized within the supply chains. It is evident from the review that although enough attention has been given to the technological resources in the literature, the future studies will still have to address the challenges of utilizing the technological resources due to the increased generation of real-time data with the use of the IoT devices, sensors and embedded technology. More studies will be required to address the challenges of utilizing human resources. With the increased complexities in the data, there is a considerable demand for experts to handle the technology and perform the BDA (Chen et al., 2012; Richey et al., 2016; Schoenherr and Speier-Pero 2015; Barbosa et al., 2017). These skills may be categorized as technical skills for collecting, storing, and retrieving data and analytical skills for analyzing the qualitative and quantitative data generated from different domains.

6 Conclusions and Limitations

This chapter offers a holistic view of BDA applications in the SC context. This SLR's findings will guide academicians and practitioners working in the BDA area to build for such challenges. Based on the study results, we propose an SC visibility framework that identifies SC visibility as the main driving force for successful SC transformation, achieved through strong BDA capability. The findings of this SLR and future research directions will help the academics, researchers and practitioners to focus on the BDA challenges. The authors recognize that our study has limitations. While the authors have conducted a thorough literature search through different research databases like Scopus, Web of Science, Emerald Insights, etc., to identify all possible relevant articles, it is possible that some research articles could have been missed in this review and may be further explored.

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