Effect of Big Data Analytics in Reverse Supply Chain:
An Indian Context

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ABSTRACT

The main purpose of this paper is to show the recent status of big data analytics (BDA) on various manufacturing and reverse supply chain levels (RSCL) in Indian industries. In particular, it emphasises understanding of the BDA concept in Indian industries and proposes a structure to examine industries' development in executing BDA extends in reverse supply chain management (RSCM). A survey was conducted through questionnaires on RSCM levels of 330 industries. Of the 330 surveys that were mailed, 125 completed surveys were returned, corresponding to a response rate of 37.87%, which was slightly greater than previous studies. The information of Indian industries with respect to BDA, the hurdles with boundaries to BDA-venture reception, and the connection with reverse supply chain levels and BDA learning were recognized. A structure was presented for the selection of BDA ventures in RSCM. This paper gives bits of knowledge to professionals to create activities including big data and RSCM and presents utilitarian and predictable direction through the BDA-RSCM triangle structure as extra device in the execution of BDA ventures in the RSCM factors. This paper does not provide outside legitimacy owing to limitations for the speculation of the outcomes even in the Indian surroundings, which originates from the present test. Future research ought to enhance the understanding in this area and spotlight the effect of big data on reverse supply chains in developed countries.

KEYWORDS

Big Data Analytics (BDA), Manufacturing Industries, Reverse Supply Chain Competences, Reverse Supply Chain Levels (RSCL)

1. INTRODUCTION

Big data analytics (BDA) has explored as a technique to achieve healthy advantage for manufacturing industries in current scenario(Tan *et al.*, 2015; Davenport, 2006).It has reflected more importance to research scholars and academicians(Dubey *et al.*, 2016).According to Strawn (2012), big data has great impact to industry 4.0 paradigm. Gobble (2013) considered BDA techniques as big innovation for remodelling in manufacturing industries. Currently, reverse supply chain management has received

DOI: 10.4018/IJISSCM.287128 *Corresponding Author

more attention by BDA (Jin *et al*., 2015; Hazen *et al*., 2016; Zhong *et al*., 2016; Fosso Wamba *et al*., 2017; Gunasekaran *et al*., 2017; Pauleen and Wang, 2017; Rothberg and Erickson, 2017;).

Data, process, and management challenges are three classifications of big data as per (Sivarajah *et al*. 2017). With the help of resource-based view (RBV) approach (Gunasekaran *et al*. 2017), it showed the importance and impact of resources and capabilities in supply chain costs and efficiency. RBV approach and model proposal were studied by Fosso Wamba *et al.* (2017) to have the impact of big data analytics capability (BDAC) on a industry performance. Industry performance and resources by BDAC are studied by Akter *et al*. (2016) and Gupta and George (2016) respectively.

Though a lot of achievements are reflected in recent research papers, various gaps are remained open and particularly in empirical research (Comuzzi and Patel, 2016; Strawn, 2012, Fosso Wamba *et al*., 2015; Kache and Seuring, 2017)..BDAC on industry performance and sustainable manufacturing were supported by(Fosso Wamba *et al.*, 2017; Gupta and George, 2016, Dubey *et al.*, 2016).However, a lot of gaps exist in reverse supply chain regarding BDA projects on development of frameworks and empirical research particularly in developing countries.

Manufacturing industries don't know about the development level of BDA or whether the industries' present abilities are adequate for directing an execution of a BDA venture in RSCM. The research on BDA isn't sufficiently wide and does not offer models as well as structures to examine the attainability of actualizing a big data venture. In this unique situation, Indian writings about BDA in reverse supply chain management (RSCM) can be comprehended to be moderately restricted.

To add to the progression of information and decrease perception flaws related with BDA in RSCM, this examination means to answer the accompanying inquiries:

Question 1: What are the troubles with boundaries for the reception of BDA in Indian reverse supply chains?

Question 2: What are the fundamental contrasts and effects of BDA on various manufacturing industries and reverse supply chain levels?

The essential commitment of present paper is the distinguishing proof of the fundamental troubles and boundaries for execution of BDA techniques in RSCM conditions in Indian manufacturing industries. The second commitment is the proposition of a reference framework (BDA-RSCM triangle) to help researchers in BDA projects with regards to RSCM. Besides, this paper adds to the BDAC reverse supply chain literature (Akter et al., 2016; Fosso Wamba et al., 2017; Gupta and George, 2016) by researching segments of reverse supply chain partnerships (RSCP), human knowledge (HK), and innovation culture (IC) (BDA-RSCM triangle).

2. LITERATURE REVIEW

2.1 Big Data Analytics

Cox & Ellsworth (1997) suggested 'Big Data ' as the first term and found that data are very large to store in the computer. This type of problem is called as Big Data. Chen, Chiang, & Storey(2012) developed business intelligence and analytics (BI&A) framework in connection to Big Data. Data mining and statistical analysis are described by the application of (BI&A) technique (Chen et al., 2012).Recently industries face challenges to collect and store huge data in order to retrieve useful result(Bakshi, 2012).So industries should realise the importance of BDA regarding secured data and business advantage(Gobble, 2013; McAfee & Brynjolfsson, 2012). Reverse smart supply chain approach can be enhanced by Big Data Analytics in connection to industry 4.0 paradigms. Sensor data and data rise are achieved by Internet of Things (IoT) (Gobble, 2013 & Zhou *et al*., 2014). BDA is an important technique for gaining competitive advantage although other techniques in reverse supply chain are used to generate data.

2.2 Developments in BDA

BDA has lot of contribution to RSCM(Giannakis and Louis, 2016; Zhao *et al*., 2017; Zhong *et al*., 2015; Schoenherr and Speier-Pero, 2015).However, the keyword BDA is not available to all decision makers worldwide. Neverthless, it derived from the 3V approach (volume, velocity, and variety) (Watson, 2014) and 5V concepts (volume, velocity, variety, veracity, and value) (Jin *et al*., 2015; Kune *et al*., 2016; Fosso Wamba *et al*., 2017). Table 1 shows a sample of the data generated(unit time period) by different manufacturing industries in 2017 by taking complexity into consideration.

Table 1. Data generated in unit time period in 2017

organisation	source	data
ola	passengers	1,389
uber	passengers	1,389
YouTube	Video display	2,682,000
WhatsApp	Writings	20,700,000
Facebook	Users	216,302 photos
LinkedIn	Number of accounts	120
Emails	Sent messages	150,000,000
Google	Content views	68,500,000 words
Twitter	tweets	347,222
Instagram	Like users	2,430,555 posts

2.3 BDA Being Latest Tool for Reverse Supply Chain

A lot of papers have been published regarding big data after Davenport's publication (Davenport, 2006).Due to recent advancements in computations, the term analytics has been converted to BDA which is beneficial to industries and practitioners. The terms innovation, competition, and productivity are addressed by Manyika *et al*. (2011) and found that BDA has great impact on market framework. BDA is responsible for predictive analytics and data science in order to transform reverse supply chain. Big problems can be solved and innovation opportunities are found with the help of BDA (Marshall *et al*. 2015). Operational and strategic level are handled by BDA as it has great impact on industries. Richey Jr *et al*. (2016) investigated ten critical success factors (CSF).

2.4 Conceptual Structure for BDA-RSCM

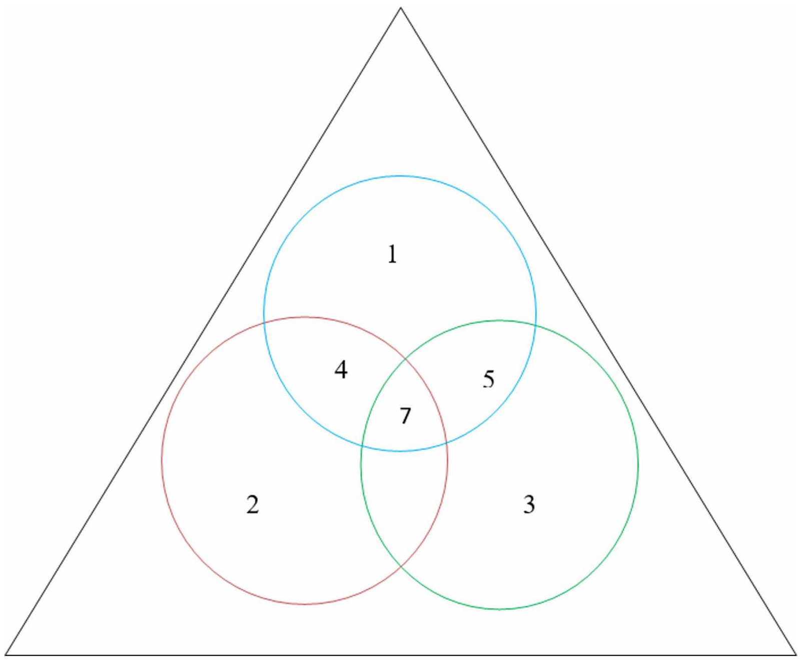
Structures are needful perspectives to BDA (Chae, 2015; Addo-Tenkorang and Helo, 2016; Kache and Seuring, 2017). The framework of this research is retrieved from new developments in the BDAC theory (Akter *et al.,* 2016; Gupta and George, 2016; Fosso Wamba *et al.,* 2017). Various constructs were located after a lot of reviews of BDA and BDAC. Due to conjoint analysis of corresponding interactions, BDA-RSCM triangle can be better explained. The elements of BDA-RSCM triangle are nearer to the segmentation of Big Data availability (Gupta and George, 2016). The proposed structure is shown in Figure 1 .

The current structure has three vital elements: (a) RSCP, (b) HK, and (c) IC. Sustainability is an important criteria for any industry by using BDA. The BDA-RSCM triangle explains about human knowledge, innovation culture and RSCP. Human knowledge explains about monitoring the BDA projects, Innovation culture reflects about the maturity level of industry and RSCP manages all about reverse supply chain data flow.

It is obvious that the BDA-RSCM triangle is assumed as the introductory technique for industries to initiate a BDA-RSCM project. To acquire positive results and successful on BDA projects, it is vital to execute above three elements.

1-Reverse supply chain partnership, 2- Human Knowledge, 3-Innovation culture
4- RSCP – HK interaction, 5- IC-SCP interaction, 6-BDA-RSCM critical triangle
7- HK-IC interaction

Figure 1. BDA-RSCM Triangle



3. RESEARCH METHODOLOGY

A survey-method is conducted in this study. It is vastly related to reverse supply chain analysis (Aggestam, *et al*., 2017; Gunasekaran *et al*., 2017; Dubey *et al*., 2016; Schoenherr *et al*., 2015; Larson, 2005). By using a 1-7 Likert scale, the importance of each element (RSCP, HK, IC) was measured which ranged from strongly disagree (1) to strongly agree (7) (Papadopoulos *et al.*, 2017).

3.1. Data Collection

125 replies are collected from 330 surveys that were sent by using various social network sites, with a 37.87 percent response rate, which was satisfactory compared to previous reverse supply chain studies(George and Gupta, 2016; Dubey *et al*., 2016). Units having less than 50 employees had response of 16%, less than 100 employees had 32%, and more than 200 employees were the major respondents from the sample. The potential respondents are Chief Executive officers (10%), Executives (15%), Chief Executives (10%), Junior managers (20%), and analysts (45%).

A questionnaire was developed using the total design method [Gunasekaran *et al*., 2017]. Different items were collected from earlier published studies. The questionnaire at the initial stage was sent to selected persons for pretesting. questionnaire was sent to selected person after Pilot test. Modifications were made wherever necessary and unreliable items were eliminated [Zelbst *et al*.,2012; Gunasekaran *et al*., 2017]. Then, the final version of the questionnaire was designed. A database was created by selecting all leading manufacturing industries. The sample firms defined in the database are randomly selected. multiple regression analysis was performed. Reliability test was done having Cronbach's alpha exceeded 0.70 (Fosso Wamba *et al.,* 2017; Gunasekaran *et al.,* 2017).

4. DATA AND RESULT ANALYSIS

4.1. Descriptive Statistics

The response rate was 37.87% and Likert scale of 7- point was used (Gunasekaran *et al*., 2017; Chen and Paulraj, 2004). The value of cronbach's alpha was 0.71 after the reliability test of data (Landis and Koch, 1977). Table 2 reflects the response rate by different industries.

Table 2. Response rate by manufacturing industries

Industries	N	%
Aluminium	40	32.0
Copper	20	16.0
Automotive	11	8.8
Steel Industry	10	8.0
Oil and Gas	6	4.8
Heavy Industries	6	4.8
Machines and Equipment	6	4.8
Food/Beverage	6	4.8
Plastics	6	4.8
Leather	5	4.0
Wood	3	2.4
Computer and Electronics	3	2.4
Textiles	3	2.4
Total	125	100

One third of the response rate was achieved by Aluminium industries followed by copper, automotive and steel industries with 16.0%, 8.8%, and 8.0%, respectively. The other industries such as Oil and Gas, Heavy Industries, Machines and Equipment, Food/Beverage and Plastics achieved 4.8% of the response rate. The leather company, the conventional Indian industry, achieved 4.0% .Wood, computer and electronics, textiles have achieved 2.4%.

Table 3 lists the industry sizes and Table 4 shows respondents' profession.

Reverse Supply chain Analyst, Intra trade analyst and Data Analyst represent more than 50% of the respondents. It is evident that there is a positive correlation with the aluminium industries. The respondents like CEOs participations were very lucrative as compared to other respondents.

Table 3. Response rate by industry size

Size of industry(employee wise)	N	%
Less than 50	20	16.0
Less than 100	40	32.0
Less than 500	5	4.0
Less than 1000	5	4.0
≥ 1000	55	44.0
Total	**125**	**100**

Table 4. Response rate by Profession

Profession	N	%
Reverse Supply chain Analyst	50	40.0
Intra trade analyst	10	8.0
Data Analyst	5	4.0
Chief Executive officers	15	12.0
Executives	5	4.0
Chief Executives	20	16.0
Junior managers	20	16.0
Total	**125**	**100**

The mean average of professionals having BDA knowledge is 3.58, but it is observed that there is a huge gap when BDA utilisation in reverse supply chain. The circumstance deteriorates when BDA ventures are accounted for the short time period.

The principle hindrances in the utilisation of BDA in RSCM ventures are principally connected with the absence of affirmation of the advantages of utilizing BDA and access and expenses related with capital speculations. Different boundaries that have been accounted for are the absence of capable experts in associations and a business opportunity for the advancement of BDA ventures. These outcomes can be translated as per the grouping of RSCM(Gupta and George, 2016).

Table 5 demonstrates the connection among Profession and BDA knowledge. It may be noticed that there is a relation between BDA knowledge and reverse supply chain levels. In this way, Executives and Chief Executive officers have more BDA knowledge than other practitioners. Then again, Junior managers achieved just the fourth rank.

What's more, it is imperative to look at BDA knowledge in various industries. Table 6 analyzes industries and their BDA knowledge. Copper, Food/Beverage, and Steel Industry showed high BDA knowledge. Then again, the Wood and Leather industry has sound information about BDA.

4.2. Skewness and Kurtosis

This data used as skewness and kurtosis technique (Gunasekaran et al., 2017; Dubey et al., 2016; Curran et al., 1996). As detailed in Table 7, the most extreme total estimation of skewness was 0.753 and 1.540 for kurtosis. The numerical values are well inside for skewness (< 2) and kurtosis (< 7) (Gunasekaran et al., 2017; Curran et al., 1996).

Table 5. Profession versus BDA knowledge

Profession	Mean	N	Standard Deviation
Chief Executives	4.5652	20	0.50687
VP Executives	4.0000	5	0.00000
Chief Executive officers	3.5625	15	0.51235
Junior managers	3.5455	20	0.50876
Reverse Supply chain analyst	3.5222	50	1.04517
Intra trade analyst	2.9999	10	0.00000
Data Analyst	2.9999	5	0.00000
Total	**3.5836**	**125**	**0.89513**

Table 6. Industry versus BDA knowledge

Industries	Mean	N	Standard Deviation
Aluminium	4.0345	40	0.94426
Copper	4.0000	20	0.00001
Automotive	3.9999	11	0.64357
Steel Industry	3.9256	10	0.27759
Oil and Gas	3.9352	6	0.36585
Heavy Industries	3.8400	6	0.51000
Machines and Equipment	3.5401	6	0.93933
Food/Beverage	3.2747	6	0.74492
Plastics	3.1328	6	0.36695
Leather	2.9999	5	1.40420
Wood	2.9999	3	0.00001
Computer and Electronics	2.6400	3	1.24721
Textiles	2.0001	3	0.00001
Total	**3.5836**	125	**0.88412**

4.3. Multiple Regression Analysis

This research used various multiple regression analysis (Gunasekaran et al., 2017; Eckstein et al., 2015) to investigate the connections among dependent and independent variables.

Our hypotheses to support the BDA-RSCM triangle are:

H1. HK → IC - *HK has significant positive effect on Reliability* and represents a boundaries to BDA adoption in Reverse supply chains.
H2. RSCP → HK - RSCP *has significant positive effect on HK* and represent a hurdles to BDA adoption in reverse supply chains.
H3. IC → RSCP – *IC has significant positive effect on RSCP* and varies in organisational and reverse supply chain levels.

Table 7. Skewness and kurtosis analysis

	N	SKEWNESS		KURTOSIS	
	STATISTIC	STATISTIC	STD. ERROR	STATISTIC	STD. ERROR
BDA_PRO	125	0.307	0.194	-1.261	0.377
BDA_RSCM	125	0.705	0.194	-0.688	0.377
RSCM_INN	125	-0.131	0.194	-1.525	0.377
BDA_KNO	125	-0.752	0.194	1.072	0.377
G_OTP	125	-0.211	0.194	-1.345	0.377
G_MTP	125	-0.275	0.194	-0.913	0.377
G_BDAB	125	-0.632	0.194	-1.092	0.377
H_INV	125	-0.288	0.194	-1.354	0.377
IT_ADP	125	0.481	0.194	-1.541	0.377
IT_SEC	125	0.375	0.194	-0.883	0.377

BDA_PRO = ventures to use BDA in unit period; BDA_RSCM = BDA application in RSCM; RSCM_INN = R SCM innovation; BDA_KNO = BDA knowledge; G_OTP = Gap of talented people in the industry; G_MTP = Gap of talented people in the market; G_BDAB = Gap of BDA benefits; H_INV = High investments; IT_ADP = IT adaption; IT_SEC = IT security.

Regression analysis has been used to have the hypothesis testing. HK and IC are considered as dependent variable and independent variable in hypothesis-1 respectively (i.e. HK → IC) where HK is positively related to innovation culture and represents a boundary to BDA adoption in reverse supply chains (β=0.533; *t*=7.787; *p*=0.000). HK and RSCP are considered as independent variable and dependent variable respectively in hypothesis-2(i.e. RSCP → HK) where RSCPs are positively related to HK and represent a hurdle to BDA adoption in Indian reverse supply chains (β=0.473; *t*=6.641; *p*=0.000). Similarly IC and RSCP are taken as independent and dependent variable in hypothesis-3(i.e. IC → RSCP).Hypothesis-3 stated that IC *has significant positive effect on RSCP* and varies in organisational and reverse supply chain levels. This hypothesis was supported as well (β=0.470; *t*=6.578; *p*=0.000). The results support the critical triangle, suggesting model strength and recommending these structures as a initial tool for practioners to analyse an industry capabilities regarding BDA venture.

4.3. Correlation Analysis

Table 8 shows the Pearson correlation coefficients. The coefficients show the relations between various elements.

5. DISCUSSION AND CONCLUSION

This paper reflects to an exact research in BDA in context to reverse supply chain of Indian manufacturing industries. It makes a profitable commitment to short out the gaps in empirical research including BDA in RSCM (Fosso Wamba et al., 2015). Since BDA can be utilized in companies which are irrespective of size (Addo-Tenkorang and Helo, 2016), it is important to comprehend the diverse ideal models as well as methodologies created.

Moreover, this work outlines the ongoing progress achieved in studies with respect to BDA and BDAC. Besides, it portrays the upper hand that BDA can give to industries and the enthusiasm for KM with respect to this point.

Till now, there have been no arguments that talk about BDA-RSCM ventures in developing regions. This topic gave brief direction to sort out this flaw. At last, our study based on survey

Table 8. Pearson's correlation coefficients

	BDA_ PRO	BDA_ RSCM	RSCM_ INN	BDA_ KNO	G_ OTP	G_ MTP	G_ BDAB	H_ INV	IT_ ADP	IT_ SEC
BDA_PRO	1									
BDA_ RSCM	0.7187	1								
RSCM_ INN	0.540	0.483	1							
BDA_ KNO	0.524	0.434	0.028	1						
G_OTP	0.365	0.147	0.031	0.340	1					
G_MTP	0.651	0.380	0.234	0.493	0.754	1				
G_BDAB	0.482	0.095	0.432	0.061	0.425	0.695	1			
H_INV	0.351	0.310	-0,036	0.417	0.563	0.665	0.357	1		
IT_ADP	0.416	0.410	0.332	-0.022	0.324	0.308	0.147	0.341	1	
IT_SEC	0.395	0.293	0.413	0.131	0.264	0.511	0.344	0.631	0.470	1

BDA_PRO = ventures to use BDA in unit period; BDA_RSCM = BDA application in RSCM; RSCM_INN = R SCM innovation; BDA_KNO = BDA knowledge; G_OTP = Gap of talented people in the industry; G_MTP = Gap of talented people in the market; G_BDAB = Gap of BDA benefits; H_INV = High investments; IT_ADP = IT adaption; IT_SEC = IT security.

added to develop a structure for BDA ventures. The BDA-RSCM triangle can be utilized as a initial methodology for industries to start BDA- RSCM projects. HK, IC, and RSCP are three basic elements of constructs. For industries to be fruitful in BDA reverse supply chain ventures, it is essential for them to have clear approaches actualized in these elements.

This study offers the open door for professionals to discuss the commitment that BDA can make to their industries, particularly in the reverse supply chain. The proposed system can economically affect industries that execute BDA ventures as it features the need of a basic on asset usage and effective administration . This work gives experiences to reverse supply chain organizations and organizations that are occupied with executing BDA ventures.

Additionally, BDA can be a basic way to deal with enhancing the level of reverse logistic services. Besides, attainment is required to deal with the BDA fundamentals (Fosso Wamba et al., 2017) and to accomplish better outcomes. The BDA-RSCM triangle has a few ramifications for experts. Apex administration requires a high level of attention to the advantages of BDA and the basic elements of human knowledge, innovation culture, and RSCM networks. As stated, the BDA-RSCM triangle ought to be utilized as an essential instrument for BDA ventures. In the event that all elements of the triangle are not fulfilled, a BDA project can't be executed.

This paper makes a hypothetical and in addition pragmatic commitment. From the perspective of a professional, the basic triangle fills in as a structure for practioners to analyze if the industry is prepared to execute a BDA venture. The BDA-RSCM triangle provides directions for researchers to test experimentally its strength in different countries.

This research has a few constraints. The first is that the examination was restricted to manufacturing industries in India. In light of the discoveries of this research, the learning of reverse supply chain organizations in BDA is beginning as the organizations are in the primary stage. Second, this study does not include service industries. Third, top executives should give suggestions to help industries.

Future investigations utilizing the structure proposed by the BDA-RSCM triangle can be an opportunity for researchers to propel this theme. Different studies that expand this exploration field could be with respect to the effect of reverse supply chain network in developing countries. It is important to extend this subject with studies that give knowledge about the elements that accelerate the procedure with the end goal to fulfill the BDA-SCM triangle. At long last, a recommendation to the network of scientists and professionals is to recognize other key achievement factors in BDA-RSCM in developing nations. It may be profitable to execute the BDA-RSCM triangle structure in manufacturing industries and check whether there are contrasts with respect to BDA execution.

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