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Big data analytics: Implementation challenges in Indian manufacturing supply chains

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ABSTRACT

Big Data Analytics (BDA) has attracted significant attention from both academicians and practitioners alike as it provides several ways to improve strategic, tactical and operational capabilities to eventually create a positive impact on the economic performance of organizations. In the present study, twelve significant barriers against BDA implementation are identified and assessed in the context of Indian manufacturing Supply Chains (SC). These barriers are modeled using an integrated two-stage approach, consisting of Interpretive Structural Modeling (ISM) in the first stage and Decision-Making Trial and Evaluation Laboratory (DEMATEL) in the second stage. The approach developed provides the interrelationships between the identified constructs and their intensities. Moreover, Fuzzy MICMAC technique is applied to analyze the high impact (i.e., high driving power) barriers. Results show that four constructs, namely lack of top management support, lack of financial support, lack of skills, and lack of techniques or procedures, are the most significant barriers. This study aids policy-makers in conceptualizing the mutual interaction of the barriers for developing policies and strategies to improve the penetration of BDA in manufacturing SC.

1. Introduction

Given the highly dynamic business environment, managers prefer taking data-driven decisions rather than trusting their intuitions (Davenport et al., 2001; Arunachalam et al., 2018). Firms are developing their organizational and technological capabilities for extracting value from the data, which will provide them a competitive edge over the other firms. However, analysts face significant challenges in understanding the potential of extracting value from the collected data/information. The value generated from the data depends on the capability of the organization for capturing, storing and analyzing data using advanced analytic tools/methods such as Big Data Analytics (BDA) (Hu et al., 2014). Indeed, in the last decade, there was significant interest in various information and communication technologies for the management of supply chains (SC), which are generating enormous amounts of data (Yesudas et al., 2014; Arunachalam et al., 2018).

Further, BDA has emerged from two sources, i.e., Big Data (BD) and Data Analytics (Russom, 2011; Waller and Fawcett, 2013). Big data refers to the storage and analysis of complex, voluminous data through the use of a series of technologies (Ward and Barker, 2013). These technologies include but are not limited to NoSQL, MapReduce, artificial intelligence and machine learning, which further make use of serious computing power to analyze massive datasets obtained from various sources (Russom, 2011). Data analytics refers to the science of examining raw data to derive useful information, using analytical tools such as mining/predictive analytics and descriptive analytics. Data analytics can help in identifying the trends and patterns from the data to support decision-making and includes processes such as data inspecting, cleansing, transforming and modeling. Thus, the combination of big data and data analytics

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forms the basis of BDA. It is worth mentioning that BDA can improve services, mass customization, digital marketing, and overall performance of the SC in highly competitive environments (Meredith et al., 2012; Tien, 2015). The detailed applications of BDA in supply chain could be seen in the review work of Tiwari et al. (2018) and Nguyen et al. (2018). Moreover, the future impacts of BDA in supply chains are discussed by Roßmann et al. (2018). It was found that BDA would improve the management of supplier performance, demand forecasts and reduce safety stocks. Moreover, big data may play a significant role in supply chain sustainability assessment (Belaud et al., 2019). Even though the big data phenomenon is believed to be the latest global sensation, its emergence has not been precipitated. Many organizations resist the implementation of BDA technologies due to behavioral and organizational issues, and ambivalence in understanding the potential benefits. Significant research in the BDA domain has focused on the perspective of technology for rationalizing its financial gains, social media, and its applications in supply chain management (SCM). However, the present literature lacks research on identifying the obstacles to BDA implementation in the context of developing countries like India. Thus, there is a need to address the following Research Questions (RQ):

RQ1: What are the barriers against BDA implementation in the Indian Manufacturing Supply Chains?

RQ2: How can the interrelationship between existing barriers be obtained?

RQ3: What is the intensity of these interrelationships?

The above information can be utilized to build suitable strategies for effective implementation of BDA. Furthermore, none of the past research studies have addressed the mutual influence of the critical barriers of BDA adoption using a multi-criteria decision-making (MCDM) approach in the Indian manufacturing SC. Hence, the present study fills a gap in the collective body of research; highlighting the identification of the barriers against BDA implementation from an exhaustive literature review and expert opinion analysis. This is followed by developing a hierarchical structural model of the barriers exploring the interrelationships between them by using ISM and fuzzy-MICMAC analysis. Further, DEMATEL is utilized to obtain the intensity of the interrelationships between the identified barriers.

The next section describes relevant literature, while the research methodology is explained in Section 3. The integrated model is developed in Section 4. Section 5 discusses the managerial implications of the proposed work, and finally, Section 6 details the conclusion and further scope of the study.

2. Literature review

BDA has emerged as one of the most interesting study areas for researchers, practitioners and industrialists in the recent times. There exist several publications that discuss the implementation of BDA and elaborate the various factors associated with its adoption. Addo-Tenkorang and Helo (2016) discussed the applications of big data in operations/SCM. Zhong et al. (2016) highlighted the opportunities, challenges, and future perspectives of big data for SCM in the manufacturing and service sectors. Waller and Fawcett (2013); Wang et al. (2016) and Cheikhrouhou et al. (2016) investigated the applications of BDA in SC and logistics management. (Yu et al., 2018) explored the influence of big data-driven capabilities of SC on the economic performance, in the context of the Chinese manufacturing sector, using structural equation modeling (SEM). It was concluded that there exists a positive correlation between data-driven SC and SC capabilities. Arunachalam et al. (2018) also studied BDA capabilities in the SCM with a focus on challenges, issues and implications for practitioners. Gangwar (2018) identified the drivers of big data adoption in the services and manufacturing sectors of India using SEM analysis. A significant change for acceptance of big data adoption was reported in this study. Yadegaridehkordi et al. (2018) also identified and sorted the adoption factors favoring big data and predicted the influence of big data adoption on the performance of manufacturing firms using a hybrid approach through "DEMATEL and adaptive fuzzy neuro inference systems (ANFIS). Lamba and Singh (2018) found that "management commitment, financial support for big data initiatives, big data competencies, organizational structure and change management program" are fundamental for the success of big data initiatives in Indian operations and SC management organizations. The authors used ISM, fuzzy Total Interpretive Structural Modeling (TISM) and DEMATEL. Moktadir et al. (2019) identified the main barriers against adopting BDA in the Bangladeshi manufacturing SCs through a Delphi-based Analytical Hierarchy Process (AHP). It emerged that the barriers are related to data and technology, i.e., "lack of infrastructure, the complexity of data integration, data confidentiality, and high cost of investments."

Few authors have studied big data for application in business activities. In this regard, Gunasekaran et al. (2018) interrogated the big data business analytics (BDBA) role in improving the level of agile manufacturing practices and deduced that market turmoil has a negative impact and that the gradual implementation of BDBA and helps to achieve better performance objectives. Hazen et al. (2016) proposed an agenda based on eight theories for examining the BDPA impact on supply chain sustainability in the USA. Dubey et al. (2019a) investigated BDPA's influence on "environmental performance (EP) and social performance (SP)" by employing a variance-based SEM approach and it was found that BDPA significantly influenced both EP and SP. Zhong et al. (2015) proposed a big data approach for investigating the logistics trajectory from RFID to enable logistics data in the Chinese context. Shukla and Mattar (2019) drafted a roadmap for interventions, prioritizing to facilitate the adoption of BDA in sustainable audit systems, using the ISM approach.

Several emerging voices are raising the need for integrating big data with other technologies to leverage the benefits of integration. Yang et al. (2017) reviewed the consequences and advantages of using cloud computing (CC) for analyzing big data in the digital earth and related science areas. It was highlighted that CC provides meaningful solutions for big data (BD). Hashem et al. (2015) reviewed the rise of big data in CC. The interrelationship between CC, BD, Hadoop technology and big data storage systems was detailed. Also, the research challenges were highlighted. Mishra et al. (2017) utilized social media big data to design a consumer-centric beef SC. Dubey et al. (2016) identified various factors for enabling world-class sustainable manufacturing through big data by developing a conceptual framework using confirmatory factor analysis. Zhong (2018) analyzed RFID datasets for intelligent manufacturing workshops with Python cleaning and classification algorithms. By introducing an integrative framework to improve the understanding of the circular economy (CE) and a relational matrix illustrating the complexity of large-scale data management, Jabbour et al. (2019) demonstrated the CE and BD applications. It may be noted that an efficient SC enables the efficient flow of data/information along with the finance and material flows, and due to ICT adoption. SC can monitor the flow of information for data analysis for extracting value from the same (Chae and Olson, 2013; Souza, 2014). 90 % of available data today has been generated in the last two years (Loechner, 2016), and 2.50 quintillion bytes data is being created per day (Jacobson, 2013). Furthermore, it is predicted that in a few years, such an exponential increase of data will reach zettabyte per year (Tiwari et al., 2018).

In the present scenario, the industry is recognizing the value of big data and the latest analytic tools to improve business, financial, and sustainability performance. Further, to improve costs, performance and consolidate the influence of big data; Dubey et al. (2019b) developed a model describing the importance of external resources and pressures using a pre-tested questionnaire. Badiezadeh et al. (2018) assessed the performance of sustainable SC in the presence of big data using "network data envelopment analysis" for estimating the efficiency of multistage processes. Yu et al. (2018) analyzed the effect of supply-driven SC capabilities on financial performance using SEM, and a significant positive effect and linkage were observed. Positive and significant coordination exists between responsiveness and financial performance too. With a Tactical Procurement Planning Model (TPPM), Oh and Jeong (2019) found an optimal trade-off between delay and profit, an optimal supply flow over a planning horizon, called "Smart Supply Chain Performance (SSCP)." Zaki et al. (2019) came up with a conceptual framework reflecting the emerging connections between big data and manufacturing by studying the patterns and manufacturing factors as well as the role and impact of big data. To understand big data and these applications, Brinch et al. (2018) implemented a sequential mixed technique along with the Delphi method, as well as a "Supply Chain Operations Reference (SCOR)" adjusted baseline process framework. They observed that data collection dominated the management and use of data, which was less relevant for procurement or manufacturing than for logistics, service and planning. Xu et al. (2019) analyzed the big data influence on assessing the quality of manufacturers' decisions on the manufacture/repackaging of a fixed collection fee mechanism and a discriminatory collection fee mechanism. It was found that the manufacturer values different charging mechanisms of the collection according to the levels of value perceived by consumers of the products used and the acquisition cost of big data.

3. Research methodology

The purpose of the paper is to identify and develop a structural model of the critical barriers against BDA implementation and to set up their interrelationship in the case of manufacturing supply chains using an ISM approach. Furthermore, MICMAC analysis was utilized to identify the driving and dependence power of each barrier. Moreover, DEMATEL was also used to overcome the limitation of ISM methodology in estimating the intensity of interrelationship between identified barriers. The research methodology is illustrated in Fig. 1.

3.1. Interpretive Structural Modeling

ISM is one of the well-known techniques for identifying the interrelationship between various linked parameters of a complex system (Warfield, 1974; Mudgal et al., 2009). ISM possesses the unique property of transferring unclear enunciated mental models into a well-defined structure. Thus, it helps in understanding inflicting order as well as the direction of complicated relationships (Gardas et al., 2015). For this, ISM makes use of the graph theory. The relationships of complex systems are analyzed by decomposing them into different levels. Thus, it may be seen as a "structural relationship diagram," which illustrates the simplified format of a complex system (Sage, 1977; Sagheer et al., 2009; Singh et al., 2003).

The ISM procedure can be explained through the following steps (Sagheer et al., 2009; Ravi, 2015; Faisal and Talib, 2016; Gardas et al., 2017; Raut et al., 2017):

Step 1: The construct of the system under study are identified and listed.

Step 2: Identified constructs are evaluated for the contextual relationship, which results in the formation of a "structural self–interaction matrix (SSIM)" to represent a pair-wise interrelationship amongst them.

Step 3: A binary matrix is developed from SSIM based on rules (explained later), and is called as "initial reachability matrix (IRM)."

Step 4: The transitivity is evaluated in IRM to obtain the "final reachability matrix (FRM)." This follows the relation "if a construct 'A' is linked to 'B' and 'B' is linked to 'C' then 'A' is certainly correlated to 'C'. The obtained FRM is partitioned into different levels.

Step 5: The level-wise constructs are connected graphically with the direct links and transitive is dropped to get "Digraph" and the final model is obtained by replacing with construct name.

Step 6: Finally, the obtained model is evaluated for any conceptual disagreements and modified accordingly.

3.2. Fuzzy MICMAC analysis

The steps for Fuzzy MICMAC are as follows (Bhosale and Kant, 2016):

Step 1: "Binary direct relationship matrix (BDRM)" is acquired by considering all diagonal elements as zero and rest are unchanged in the IRM matrix.

Step 2: Develop a "linguistic assessment direct reachability matrix."

Step 3: Develop a "Fuzzy MICMAC-stabilized matrix."

Step 4: Obtain the "driving and dependence powers" of each construct and draw the MICMAC plot.

3.3. DEMATEL

The Decision-Making Trial and Evaluation Laboratory (DEMATEL) technique was developed by the Geneva Research Centre of the Battelle Memorial Institute for understanding causal relationship structure of a complex system. DEMATEL not only evaluates the most critical factors of the studied system via an impact relation diagram but also transforms interdependency relationships into cause and effect groups through digraph and matrices.

Steps of DEMATEL:

Step1: Compute the "direct relationship matrix": For this, suppose there are m experts and n constructs to be studied. For each construct, the expert gives their opinion about the influence of construct i on construct j and similarly for all constructs using an integer scale of "no influence (0)," "low influence (1)," "medium influence (2)," "high influence (3)," and "very high influence (4)." Suppose each expert decision matrix is given by $\left[{x_{ij}}^{k}\right]_{n*n}$, then average "direct influence matrix" ($X = {x_{ij}}_{n*n}$) is given by Eq. 1:

$$x_{ij} = \frac{1}{m}\sum_{k=1}^{m} {x_{ij}}^{k}{}_{n^*n}\mathrm{i},\ \mathrm{j}\ =\ 1, 2, \ldots\ldots \mathrm{n} \tag{1}$$

Step 2: Normalize the "direct influence matrix": The normalized average "direct influence matrix" ($A = \left[a_{ij}\right]_{n*n}$) is given by Eq. 2:

$$A = \frac{X}{s} \tag{2}$$

Where $s = max\left(\max_{1\le i\le n}\sum_{j=1}^{n} x_{ij}, \max_{1\le i\le n}\sum_{i=1}^{n} x_{ij}\right)$

Every element in matrix A obeys the rule $0 \le a_{ij} \le 1$, $0 \le \sum_{j=1}^{n} a_{ij} \le 1$ and we have at least one i such that $\sum_{j=1}^{n} x_{ij} \le s$.

Step 3: Find the "total influence matrix": The "total influence matrix" $T = \left[t_{ij}\right]_{n^*n}$ is calculated by Eq. 3:

$$T = A + A^2 + A^3 + \ldots A^h = A(I-A)^{-1} \tag{3}$$

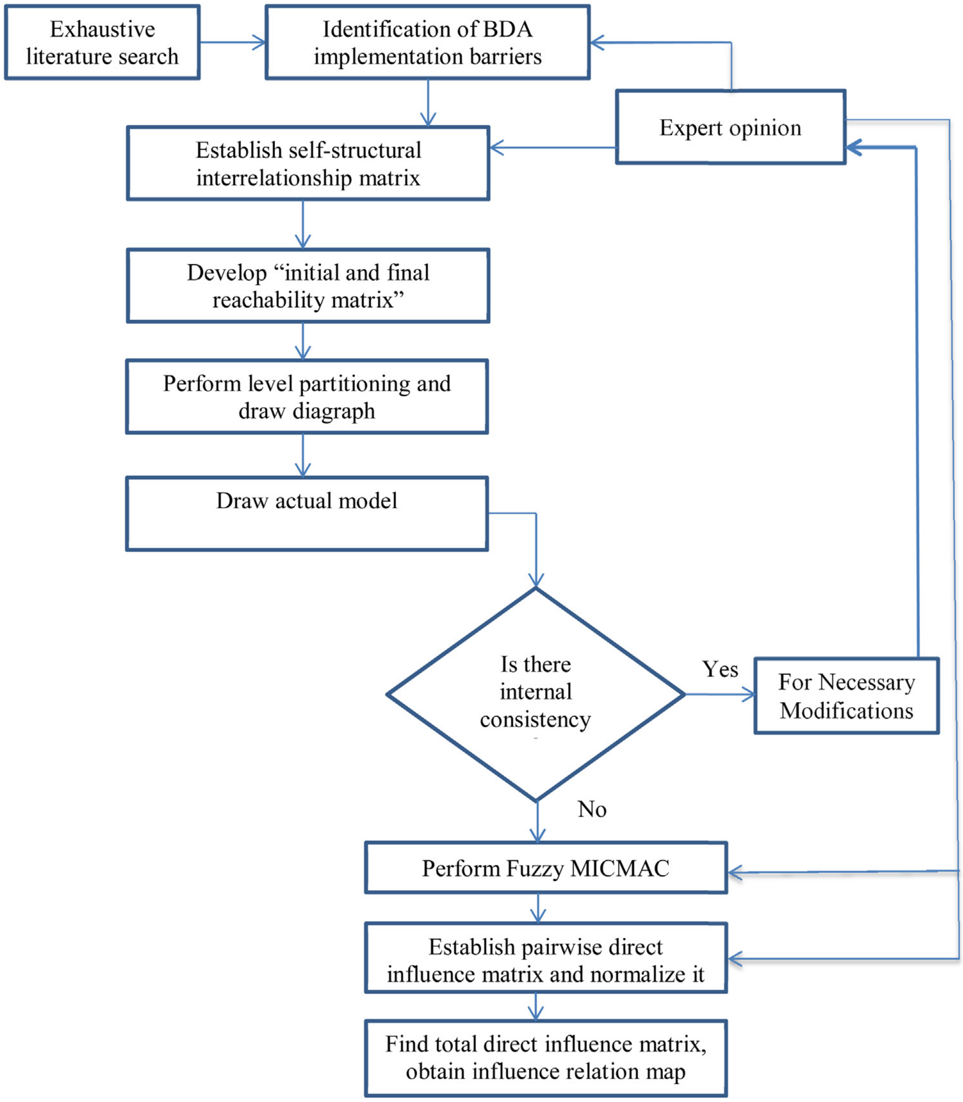

Fig. 1. Research methodology.

Where $h \to \infty$, and "*I* is denoted as identity matrix."

Step 4: Formulate the "influence relationship map": This is formed using two vectors R and C, where they are the sums of rows and columns, respectively, in the "total influence matrix" as shown in following Eq. 4 and 5:

$$R = [r_i]_{n^*1} = \left[\sum_{j=1}^{n} t_{ij}\right]_{n^*1} \tag{4}$$

$$C = [c_i]_{1^*n} = \left[\sum_{i=1}^{n} t_{ij}\right]_{1^*n} \tag{5}$$

Where "r_i is the sum of ith row in total influence matrix" T and depicts the total impacts of construct n_i on all other constructs. Similarly c_j is the sum of the jth column in "total influence matrix" T and depicts total impacts that construct n_i is getting from all other constructs. With the help of these two vectors, "influence relationship map" is drawn where $(R + C)$ is taken as *x axis* and $(R - C)$ as *y axis* for each construct. On the horizontal axis, $(R + C)$ value (also called as "Prominence") of a construct denotes its strength and is also the central part of the system. On the vertical axis, $(R - C)$ value (also known as "Relation") is the net effect of construct which it puts on the system. If $(r_i - c_j)$ value of a construct is positive, it shows that this construct has a net influence on the other constructs and can be clustered into the cause group. On the other hand, if $(r_i - c_j)$ is negative, the particular construct is influenced by another construct in the system and can be clustered into the effect group.

4. Application of the proposed approach and interpretations of results

The constructs used for developing the structural models were identified through an exhaustive literature review. The search keywords used were "challenges, hindrances, barriers, constraints, obstacles, big data, big data analytics, business analytics, manufacturing supply chains, and multi-criteria decision making (MCDM)." These keywords were found online in databases such as Scopus, Web of Science, ScienceDirect, Emerald insight and IEEE explorer. The search is limited to the English language articles only and omitted dissertations. After reviewing the articles from the above online databases and from the opinion of experts, 15 barriers were listed.

The expert team consisted of 47 members divided into two groups: the Internet of Things group and the SC group; three data analysts, two big data visualizers, two big data solution architects, three big data engineers, three big data researchers, two data ware-

Table 1
Identified barriers to BDA implementation.

S.N	Barrier	Explanation	References
1	Poor data quality and lack of trust in data	Data is intangible, and measuring its quality is a multi-dimensional problem. Poor quality of the data is a big barrier to the activities of the analytics, and it significantly affects the decisions of the management. The quality of the data can be categorized into two dimensions, namely intrinsic (completeness, consistency, timeliness, and accuracy), and contextual (data reputation, accessibility, believability, quantity, value-added, and relevancy). It may be noted that the trustworthiness of the data obtained from social media is a serious issue.	Wang and Strong (1996); Lee et al. (2002); Hazen et al. (2014); Hashem et al. (2015); Tan et al. (2015); Arunachalam et al. (2018)
2	Time-consuming activity	The activity of predictive analysis is a time-consuming initiative and comprises various phases of development, testing, and adoption. It is a long task to bring experts together from different sections with different mindsets. It may be noted that the commitment from the top management is required for the implementation of BDA, which may take one year to one and half years. Also, collecting data from various sections of the organizations, combining, validating, and cleansing the same and tracking the development together constitute a tedious activity.	Blackburn et al. (2015); Hashem et al. (2015); Arunachalam et al. (2018)
3	Lack of sufficient resources	In a supply chain network, the resource capabilities of the data and analytics vary significantly across organizations. Lack of sufficient IT capabilities for sharing information and data can cause considerable differences. For the effective implementation of BDA, formation of cross-functional teams and collaboration between the various elements within the firm is necessary. However, while forming the team, issues such as policies of data sharing, arrangements of incentives, etc. need to be taken care of. For the efficient utilization of BDA and business value creation, fact-based management and data-driven culture need to be motivated.	Seah et al. (2010); Dutta and Bose (2015); Hashem et al. (2015); Arunachalam et al. (2018)
4	Lack of security and privacy	There are various issues associated with the BDA systems implementation, i.e., ineffective data processing, unethical usage of data, security, and privacy, which could influence the final results of the investigation.	Tien (2012); Hu et al. (2014); Alfaro et al. (2015); Hashem et al. (2015); Richey et al. (2016); Arunachalam et al. (2018)
5	Lack of financial support	Lack of financial support influences the BDA implementation decision significantly. It may be noted that supporting and leveraging the capability of cloud computing for storing the data could add cost to the firm. Increasing data generation demands more cloud space, which further increases the financial burden on the organization.	Hashem et al. (2015); Rehman et al. (2016); Arunachalam et al. (2018)
6	Behavioral issues	BDA implementation may lead to some behavioral issues like over and underestimation due to real-time data and information availability. Here, over and underestimation refers to any deviation from the standard operating procedure. This may lead to increased inventory costs and SC risk. The employee may also fear job loss due to technology upgradation. These behavioral issues may sometime result in acceptance of statistically significant and unconnected correlations. Moreover, BDA implementation leads to behavioral issues due to culture change.	Hashem et al. (2015); Radke and Tseng (2015); Tachizawa et al. (2015); Arunachalam et al. (2018)
7	Return on investment (ROI) issues	Ambiguity and unclear benefits on ROI make stakeholders reluctant to implement big data. Further, fear of BDA implementation failure results in loss of confidence to recover the investment made.	Davenport et al. (2001); Hashem et al. (2015); Richey et al. (2016); Sanders (2016); Arunachalam et al. (2018)
8	Lack of top management support	The top management leadership should leverage and support BDA across the firm, as BDA implementation can improve the overall performance of SC. Lack of motivation from top management results in low momentum for BDA implementation.	Seah et al. (2010); Dutta and Bose (2015); Hashem et al. (2015); Wamba et al. (2015); Gunasekaran et al. (2017); Arunachalam et al. (2018)
9	Lack of skills	A recent investigation has highlighted that a lack of experts in the big data domain is a significant issue. The data scientist needs to have expertise in both analytical and domain skills. Due to insufficient professional skills, there could be an inability to identify appropriate data and develop adapted models.	Russom (2011); Waller and Fawcett (2013); Hashem et al. (2015); Schoenherr and Speier-Pero (2015); Richey et al. (2016); Arunachalam et al. (2018)
10	Data scalability	Data scalability refers to the ability or capacity to accommodate change in data sizes by using extra resources. It is often observed that data size keeps on increasing with time. After a particular period, the firms need to dump their data for storing newly generated data. For tackling the scalability issues, cloud computing capability may be considered.	Hu et al. (2014); Hashem et al. (2015); Kang et al. (2016); Richey et al. (2016); Rehman et al. (2016); Arunachalam et al. (2018)
11	Lack of techniques or procedures	Lack of efficient techniques or procedures leads to poor quality of obtained data. In BDA implementation, lousy data quality is a big problem.	Meixell and Wu (2001); Fildes et al. (2009); Blackburn et al. (2015); Hashem et al. (2015); Arunachalam et al. (2018)
12	Lack of data integration and management	Data integration management is the capability of the organization to utilize the techniques and tools for "collecting, integrating, transforming, and storing data from various data sources." Due to the complex nature of BD, the conventional database management systems such as RDBMS are not compatible. Therefore, cloud-based or web-based electronic data interchange systems may be employed for enhancing the data integration capability. The integration capability improves responsiveness and visibility.	Chae and Olson (2013); Ge and Jackson (2014); Hu et al. (2014); Radke and Tseng (2015); Stefanovic (2015); Tan et al. (2015); Wamba et al. (2015); Sanders (2016); Arunachalam et al. (2018)

house managers, two data architects, two database managers, three business intelligence analysts, two data warehouse analysts, two data modelers, two database developers, two business system analysts, two data mining analysts, two business data analysts, two data scientists, three professors from the department of computer engineering, three professors from the department of operations and SC management, and five supply chain and logistics managers from the manufacturing industries made up the team. According to Robbins (1994), the number of experts between 5 and 50 is statistically appropriate. Moreover, Murry and Hammons (1995) advocated the idea of 10–30 experts in the decision-making process. Two rounds of Delphi were carried out amongst the experts to reach consensus about the selection of the barriers against BDA

Table 2
"Structural self-interaction matrix" of barriers.

S. N	Barriers	12	11	10	9	8	7	6	5	4	3	2
1	Poor data quality and lack of trust in data	A	A	A	A	O	V	O	O	X	A	V
2	Time-consuming activity	A	A	A	A	O	V	V	A	O	A	
3	Lack of sufficient resources	V	O	O	O	A	O	O	A	V		
4	Lack of security and privacy	A	A	O	A	O	V	V	O			
5	Lack of financial support	O	O	O	O	X	X	V				
6	Behavioural issues	V	O	O	V	A	A					
7	Return on investment (ROI) issues	A	O	O	A	A						
8	Lack of top management support	O	O	O	V							
9	Lack of skills	V	X	V								
10	Data scalability	V	O									
11	Lack of techniques or procedures	V										
12	Lack of data integration and management	---										

implementation. This further reduced the number of barriers to 12. The final identified barriers are listed in Table 1.

After identifying the twelve critical barriers, the interrelationships between them are established in the "Structural Self-Interaction Matrix (SSIM)" in Table 2 by taking inputs from the experts. For interpretation of interrelationship, four types of symbols were utilized:

V- "Barrier i leads to barrier j."
A- "Barrier j leads to barrier i."
X- "Barrier i leads to barrier j and vice versa."
O- "No relationship between the barriers."

The SSIM is transformed into "Initial Reachability Matrix (IRM)" through the application of the following rules:

"If (i,j) entry in SSIM is V, then it is replaced by 1, and corresponding (j, i) entry becomes 0 in IRM.

If (i,j) entry in SSIM is A, then it is replaced by 0, and corresponding (j, i) entry becomes 1 in IRM.

If (i,j) entry in SSIM is X, then it is replaced by 1, and corresponding (j, i) entry also becomes 1 in IRM.

If (i,j) entry in SSIM is O, then it is replaced by 0, and corresponding (j, i) entry also becomes 0 in IRM."

The obtained IRM (Table 3) was checked for transitivity issues and the same was incorporated to get a FRM (Table 4). This procedure was followed by level partitioning which makes use of three sets i.e. "reachability, antecedent and intersection set." The reachability set contains itself and another construct on which it has an impact. However, the "antecedent set" contains itself and all other constructs that help in attaining it. The intersection of these two sets forms the intersection set. Also, for the construct whose reachability set and intersection set are the same are categorized as level 1 and form "the top level of ISM hierarchy" (Sage, 1977).

Further for the next iteration, these constructs were eliminated and a similar procedure was followed until the last level of the hierarchy was reached (Warfield, 1974; Raut et al., 2017; Jha et al., 2018). Table 5 shows "the reachability set, antecedent set, intersection set, and final levels" of all barriers. The level partitioning of all constructs was completed in six iterations. With the help of FRM and level partitioning, an initial diagraph was drawn. Transitivity was eliminated from the obtained diagraph to get a final diagraph and the final interpretive structural model (ISM) was obtained by replacing the construct name in the final diagraph. The interpretive structural model of the BDA implantation barriers is presented in Fig. 2, where BDABx denotes the Big Data Analytics Barriers number x.

A Fuzzy-MICMAC analysis was developed to identify the most critical barriers against BDA implementation in the manufacturing SC based on "the driving and dependence power." Traditional MICMAC considers an equal relationship between the identified constructs, which may or may not depict actual scenarios in real practice. For example, suppose there are three constructs A, B and C where A is associated with B as well as C. However, the extent of association of A with B and A with C may vary depending on an actual case of the system under study. In some cases, A might have a greater association with B as compared with C and vice-versa. Traditional MICMAC always considers an equal association between each associated constructs, which doesn't resemble actual circumstances. Thus, to increase the sensitivity of MICMAC, the use of fuzzy MICMAC is preferred over the traditional one (Bhosale and Kant, 2016).

Fuzzy MICMAC is a four-step methodology, where the first step consists of the construction of a "binary direct reachability matrix (BDRM)" and is obtained by making all diagonal elements as zero in IRM. The second step is the development of "linguistic assessment direct reachability matrix (LADRM)". We consider fuzzy "triangular membership function (TFN)" (shown in Fig. 3), which is defined by an upper limit u, a middle value m and lower value l, where $l < m < u$. The u, m and l are x-coordinate vertices of a membership function ($\mu_{\bar{A}}(x)$), which maps fuzzy set A input into real number interval [0,1]. The membership function ($\mu_{\bar{A}}(x)$) is given by the following Eq. 6:

$$\mu_{\bar{A}}(x) = \begin{bmatrix} 0\, x < l \\ \dfrac{x-l}{m-l}\, l \leq x \leq m \\ \dfrac{u-x}{u-m}\, m \leq x \leq u \\ 0\, x > u \end{bmatrix} \tag{6}$$

The linguistic scale for assessment is presented in Table 6. To rate the relationship between the considered constructs, the responses of the same experts who participated in an earlier phase of studies were considered. These responses were superimposed on BDRM to get LADRM, as shown in Table 7. The defuzzification method used is the "best non-fuzzy performance (BNP)." The formula to obtain BNP

Table 3
"Initial reachability matrix" of barriers.

S. N	Barriers	1	2	3	4	5	6	7	8	9	10	11	12
1	Poor data quality and lack of trust on data	1	1	0	1	0	0	1	0	0	0	0	0
2	Time consuming activity	0	1	0	0	0	1	1	0	0	0	0	0
3	Lack of sufficient resources	1	1	1	1	0	0	0	0	0	0	0	1
4	Lack of security and privacy	1	0	0	1	0	1	1	0	0	0	0	0
5	Lack of financial support	0	1	1	1	1	1	1	1	0	0	0	0
6	Behavioral issues	0	0	0	0	0	1	0	0	1	0	0	1
7	Return on investment (ROI) issues	0	0	0	0	1	1	1	0	0	0	0	0
8	Lack of top management support	0	0	1	0	1	1	1	1	1	0	0	0
9	Lack of skills	1	1	0	1	0	0	1	0	1	1	1	1
10	Data scalability	1	1	0	0	0	0	0	0	0	1	0	1
11	Lack of techniques or procedures	1	1	0	1	0	0	0	0	1	0	1	1
12	Lack of data integration and management	1	1	0	1	0	0	1	0	0	0	0	1

Table 4
"Final reachability matrix" of barriers.

S. N	Barriers	1	2	3	4	5	6	7	8	9	10	11	12	Driving Power
1	Poor data quality and lack of trust on data	1	1	0	1	1*	1*	1	0	0	0	0	0	**6**
2	Time consuming activity	0	1	0	0	1*	1	1	0	1*	0	0	0	**5**
3	Lack of sufficient resources	1	1	1	1	0	1*	1*	0	0	0	0	1	**7**
4	Lack of security and privacy	1	1*	1*	1	1*	1	1	0	1*	0	0	0	**8**
5	Lack of financial support	1*	1	1	1	1	1	1	1	1*	0	0	1*	**10**
6	Behavioural issues	1*	1*	0	1*	0	1	1*	0	1	1*	1*	1	**9**
7	Return on investment (ROI) issues	0	1*	1*	1*	1	1	1	1*	1*	0	0	1*	**9**
8	Lack of top management support	1*	1*	1	1*	1	1	1	1	1	0	0	1*	**10**
9	Lack of skills	1	1	0	1	1*	1*	1	0	1	1	1	1	**10**
10	Data scalability	1	1	0	1*	0	1*	1*	0	0	1	0	1	**7**
11	Lack of techniques or procedures	1	1	0	1	0	1*	1*	0	1	1*	1	1	**9**
12	Lack of data integration and management	1	1	0	1	1*	1*	1	0	0	0	0	1	**7**
	Dependence Power	**10**	**12**	**5**	**11**	**8**	**12**	**12**	**3**	**8**	**4**	**3**	**9**	**95**

*transitive links.

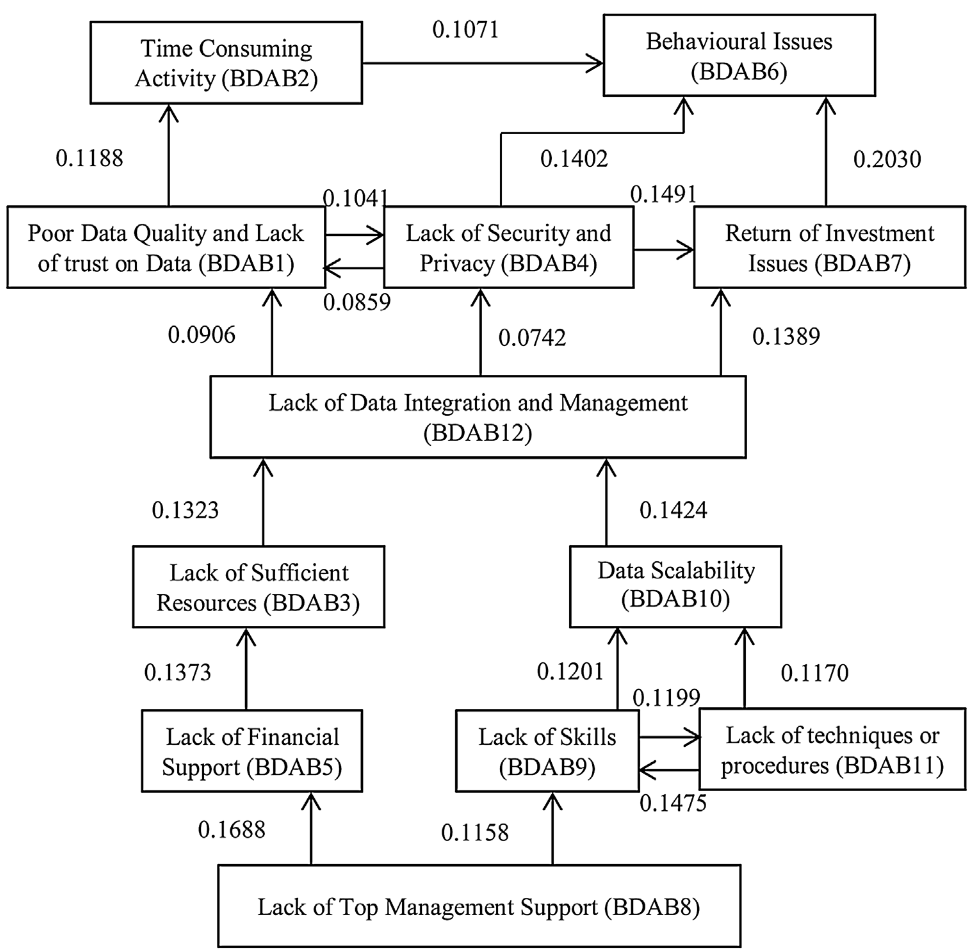

Fig. 2. The ISM model for BDA implantation barriers.

Table 5
Level partitions of the "final reachability matrix" **(Iteration I to VI).**

Iteration No.	Reachability Set	Antecedent Set	Interaction Set	Level
1.	1,2,4,5,6,7	1,3,4,5,7,8,9,10,11,12	1,4,5,7	
2.	2,5,6,7,9	1,2,3,4,5,6,7,8,9,10,11,12	2,5,6,7,9	I
3.	1,2,3,4,6,7,12	3,4,5,7,8	3,4,7	
4.	1,2,3,4,5,6,7,9	1,3,4,5,6,7,8,9,10,11,12	1,3,4,5,6,7,9	
5.	1,2,3,4,5,6,7,8,9,12	1,2,4,5,7,8,9,10,11,12	1,2,4,5,7,8,9,12	
6.	1,2,4,6,7,9,10,11,12	1,2,3,4,5,6,7,8,9,10,11,12	1,2,4,6,7,9,10,11,12	I
7.	2,3,4,5,6,7,8,9,12	1,3,4,5,7,8,9,10,11,12	3,4,5,7,8,9,12	
8.	1,2,3,4,5,6,7,8,9,12	5,7,8	5,7,8	
9.	1,2,4,5,6,7,9,10,11,12	2,4,5,6,7,8,9,11	2,4,5,6,7,9,11	
10.	1,2,4,6,7,10,12	6,9,10,11	10	
11.	1,2,4,6,7,9,10,11,12	6,9,11	6,9,11	
12.	1,2,4,5,6,7,12	3,5,6,7,8,9,11,12	5,6,7,12	
1.	1,4,5,7	1,3,4,5,7,8,9,10,11,12	1,4,5,7	II
3.	1,3,4,7,12	3,4,5,7,8	3,4,7	
4.	1,3,4,5,7,9	1,3,4,5,7,8,9,10,11,12	1,3,4,5,7,9	II
5.	1,3,4,5,7,8,9,12	1,4,5,7,8,9,10,11,12	1,4,5,7,8,9,12	
7.	3,4,5,7,8,9,12	1,3,4,5,7,8,9,10,11,12	3,4,5,7,8,9,12	II
8.	1,3,4,5,7,8,9,12	5,7,8	5,7,8	
9.	1,4,5,7,9,10,11,12	4,5,7,8,9,11	4,5,7,9,11	
10.	1,4,7,10,12	9,10,11	10	
11.	1,4,7,9,10,11,12	9,11	9,11	
12.	1,4,5,7,12	3,5,7,8,9,11,12	5,7,12	
3.	3,12	3,5,8	3	
5.	3,5,8,9,12	5,8,9,10,11,12	5,8,9,12	
8.	3,5,8,9,12	5,8	5,8	
9.	5,9,10,11,12	5,8,9,11	5,9,11	
10.	10,12	9,10,11	10	
11.	9,10,11,12	9,11	9,11	
12.	5,12	3,5,8,9,11,12	5,12	III
3.	3	3,5,8	3	IV
5.	3,5,8,9	5,8,9,10,11	5,8,9	
8.	3,5,8,9	5,8	5,8	
9.	5,9,10,11	5,8,9,11	5,9,11	
10.	10	10	10	IV
11.	9,10,11	9,11	9,11	
5.	5,8,9	5,8,9,10	5,8,9	V
8.	5,8,9	5,8	5,8	
9.	5,9,11	5,8,9,11	5,9,11	V
11.	9,11	9,11	9,11	V
8.	8	8	8	VI

Table 6
Linguistic scale.

Linguistic construct	TFN
"No influence (No)"	"(0,0,0)"
"Very low influence (VL)"	"(0, 0.1, 0.3)"
"Low influence (L)"	"(0.1, 0.3, 0.5)"
"Medium influence (M)"	"(0.3, 0.5, 0.7)"
"High influence (H)"	"(0.5, 0.7, 0.9)"
"Very high influence (VH)"	"(0.7, 0.9, 1)"
"Complete influence (C)"	"(1, 1, 1)"

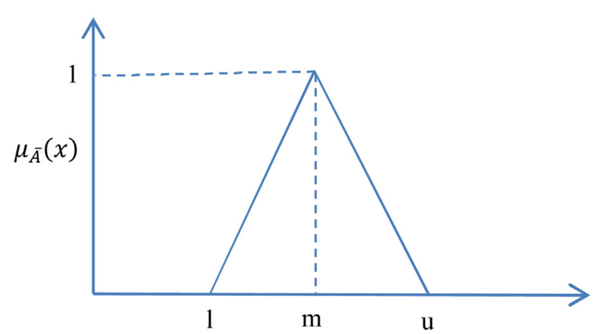

Fig. 3. Triangular Fuzzy Number (TFN).

is given in Eq. 7. The defuzzified "Fuzzy direct reachability matrix (FDRM)" is presented in Table 8.

$$BNP_{ij} = \frac{(u-l)+(m-l)}{3} + l \tag{7}$$

The third step is to obtain the fuzzy-stabilized matrix, which follows the rule as given in Eq. 8.

$$C = A, B = \max k \left[\left(\min(a_{ik}, b_{kj}) \right) \right] \; where\, A = [a_{ik}] \; and\, B = \left[b_{kj} \right] \tag{8}$$

Where A is the BDRM, B is the defuzzified LADRM and C is the resultant stabilized matrix. Finally, each row and column is summed to obtain the driving and dependence power, respectively, of each constructs, as shown in Table 9. The fourth step is to use this information to plot Fuzzy MICMAC diagram as dependence on x-axis and driving on y-axis, which is further divided into four clusters, i.e. autonomous, dependence, linkages and driving cluster as illustrated in Fig. 4.

The output of the ISM model in the form of FRM was utilized for considering direct influence for the DEMATEL case. The responses of experts were gathered for the constructs where interrelationship existed in FRM of the ISM model using an integer scale (see the first step of DEMATEL in the research methodology section). The "average direct influence matrix" is illustrated in Table 10, while the "normalized direct matrix" is presented in Table 11. Moreover, the "total influence matrix" is shown in Table 12, which presents the details about the casual and effect clusters. Based on these data, the influence relationship plot was drawn showing prominence (R + C) on the x-axis and relation (R-C) on the y-axis (Fig. 5). For evaluating the significant relationship between the identified constructs, the

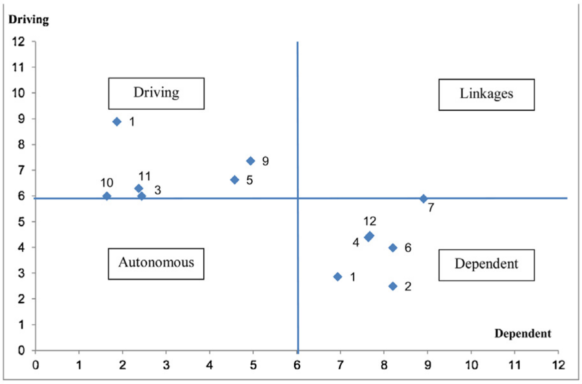

Fig. 4. "Fuzzy MICMAC Plot".

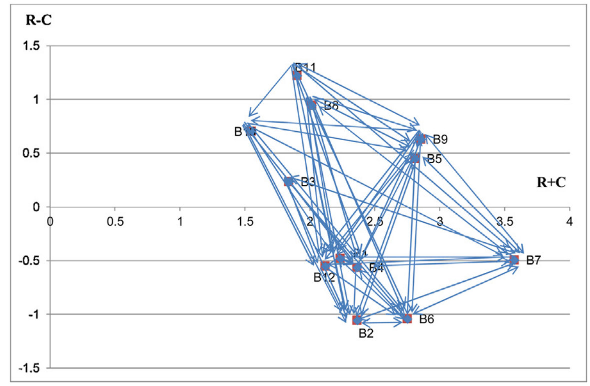

Fig. 5. DEMATEL Relationship Map.

threshold value concept was adopted from the work of (Gardas et al., 2019).

4.1. ISM results

Fig. 2 shows the ISM model of BDA implementation barriers in manufacturing SC. The obtained ISM hierarchy is a six-level structure, which demonstrates the various interrelationships between the identified barriers. Fig. 2 is also embedded with the result obtained from DEMATEL, in the form of intensities between the different barriers. For instance, the relationship intensity of BDAB1 with BDAB2 is 0.1188. The barriers in the ISM model can be categorized into three groups, i.e., most significant, medium significant and least significant barriers. The barriers at the bottom two levels are most significant, followed by medium significant barriers in the next two levels. The top two levels are the least significant barriers. Thus, it is evident that the "Lack of Top Management Support (BDAB8)" at the sixth level and "Lack of financial support (BDAB5)", "Lack of skills (BDAB9)" and "Lack of techniques or procedures (BDB11)" at the fifth level is the most critical barriers against BDA implementation in manufacturing firms. Thus, these barriers demand the maximum attention of the decision and policymakers for their successful elimination and improving the performance of the entire supply chain. Moreover, these barriers drive the other barriers present in the above levels. The fourth level of the ISM model consists of the barriers "Lack of Sufficient Resources (BDAB3)" and "Data Scalability (BDAB10)," which further drives the other top three level barriers. The third level consists of a single barrier i.e., "Lack of Data Integration and Management (BDAB12)" that drives the barriers present in the top two levels. "Poor Data Quality and Lack of trust on Data (BDAB1)", "Lack of Security and Privacy (BDAB4)" and "Return of Investment Issues (BDAB7)" are at the second level drives the barriers at the first level, i.e., "Time Consuming Activity (BDAB2)" and "Behavioral Issues (BDAB6)."

4.2. Fuzzy MICMAC analysis

The BDA implementation barriers in manufacturing SC in the Indian context were clustered into four groups as presented in

Table 7
"Linguistic Assessment Direct Reachability Matrix".

	B1	B2	B3	B4	B5	B6	B7	B8	B9	B10	B11	B12
B1	0	H	0	VL	0	0	M	0	0	0	0	0
B2	0	0	0	0	0	M	M	0	0	0	0	0
B3	C	C	0	VH	0	0	0	0	0	0	0	C
B4	VL	0	0	0	0	VH	H	0	0	0	0	0
B5	0	L	VH	M	0	M	M	L	0	0	0	0
B6	0	0	0	0	0	0	0	0	M	0	0	L
B7	0	0	0	0	H	M	0	0	0	0	0	0
B8	0	0	VH	0	VH	M	VH	0	L	0	0	0
B9	H	VH	0	VH	0	0	L	0	0	VL	VH	H
B10	VH	C	0	0	0	0	0	0	0	0	0	C
B11	M	M	0	H	0	0	0	0	H	0	0	H
B12	VH	L	0	M	0	0	M	0	0	0	0	0

Table 8
"Defuzzified FDRM".

	B1	B2	B3	B4	B5	B6	B7	B8	B9	B10	B11	B12
B1	0	0.7	0	0.1333	0	0	0.5	0	0	0	0	0
B2	0	0	0	0	0	0.5	0.5	0	0	0	0	0
B3	1	1	0	0.8667	0	0	0	0	0	0	0	1
B4	0.1333	0	0	0	0	0.8667	0.7	0	0	0	0	0
B5	0	0.3	0.8667	0.5	0	0.5	0.5	0.3	0	0	0	0
B6	0	0	0	0	0	0	0	0	0.5	0	0	0.3
B7	0	0	0	0	0.7	0.5	0	0	0	0	0	0
B8	0	0	0.8667	0	0.8667	0.5	0.8667	0	0.3	0	0	0
B9	0.7	0.8667	0	0.8667	0	0	0.3	0	0	0.1333	0.8667	0.7
B10	0.8667	1	0	0	0	0	0	0	0	0	0	1
B11	0.5	0.5	0	0.7	0	0	0	0	0.7	0	0	0.7
B12	0.8667	0.3	0	0.5	0	0	0.5	0	0	0	0	0

Fig. 4. The figure has four quadrants; each one forms a cluster as follows:

1. Autonomous: These barriers do not have any significance, are disconnected from the observed system, and have low dependence and driving power. In our case, no construct (i.e., barriers) was reported in this category.
2. Dependence: Such barriers have relatively low driving power but are highly dependent on other barriers. These barriers are found on the top of the hierarchy level as others drive them. These barriers are often considered as performance-oriented factors. In our case, “Poor Data Quality and Lack of trust on Data (BDAB1), Time Consuming Activity (BDAB2), Lack of Security and Privacy (BDAB4), Behavioural Issues (BDAB6), Return of Investment Issues (BDAB7) and Lack of Data Integration and Management (BDAB12)” fell in the dependence category.
3. Linkages: These barriers are highly sensitive as they have very high driving as well as dependence power. These barriers are not easy to handle due to their nature and hence, need extra care and effort to manage.
4. Driving: These barriers possess primary importance as they have very high driving power and have the least dependence on the others. These barriers aid in the occurrence of other barriers. Hence, they need to be eliminated to avoid challenges. In our case, “Lack of Sufficient Resources (BDAB3), Lack of financial support (BDAB5), Lack of Top Management Support (BDAB8), Lack of skills (BDAB9), Data Scalability (BDAB10) and Lack of techniques or procedures (BDB11)” fell under the driving category.

4.3. DEMATEL results

The intensity of interrelationship was estimated through DEMATEL, which complemented the ISM model. DEMATEL is used to get the two main clusters of causal and effect groups. Causal group factors have high potential to drive other constructs, while effect group constructs are dependent on causal factors. It was observed that “Lack of Sufficient Resources (BDAB3), Lack of financial support (BDAB5), Lack of Top Management Support (BDAB8), Lack of skills (BDAB9), Data Scalability (BDAB10) and Lack of techniques or procedures (BDB11)” were categorized as causal factors, which

Table 9
“Fuzzy MICMAC Stabilized Matrix”.

	B1	B2	B3	B4	B5	B6	B7	B8	B9	B10	B11	B12	Rsum
B1	0.1333	0.7	0	0.1333	0.5	0.7	0.7	0	0	0	0	0	2.8666
B2	0	0	0	0	0.5	0.5	0.5	0	0.5	0	0	0.5	2.5
B3	1	1	0	1	0	1	1	0	0	0	0	1	6
B4	0.1333	0.1333	0	0.1333	0.7	0.8667	0.7	0	0.8667	0	0	0.8667	4.4
B5	0.8667	0.8667	0.8667	0.8667	0.5	0.5	0.5	0.3	0.5	0	0	0.8667	6.6335
B6	0.5	0.5	0	0.5	0	0	0.5	0	0.5	0.5	0.5	0.5	4
B7	0	0.7	0.7	0.7	0.7	0.7	0.7	0.7	0.5	0	0	0.5	5.9
B8	0.8667	0.8667	0.8667	0.8667	0.8667	0.8667	0.8667	0.8667	0.5	0.3	0.3	0.8667	8.9003
B9	0.8667	0.8667	0	0.8667	0.3	0.8667	0.8667	0	0.8667	0.1333	0.8667	0.8667	7.3669
B10	1	1	0	1	0	1	1	0	0	0	0	1	6
B11	0.7	0.7	0	0.7	0	0.7	0.7	0	0.7	0.7	0.7	0.7	6.3
B12	0.8667	0.8667	0	0.8667	0.5	0.5	0.8667	0	0	0	0	0	4.4668
Csum	0.1333	0.7	0	0.1333	0.5	0.7	0.7	0	0	0	0	0	

Table 10
“Average Direct Influence Matrix”.

	B1	B2	B3	B4	B5	B6	B7	B8	B9	B10	B11	B12
B1	0.0000	2.6667	0.0000	2.3333	3.6667	3.0000	4.0000	0.0000	0.0000	0.0000	0.0000	0.0000
B2	0.0000	0.0000	0.0000	0.0000	2.0000	2.3333	2.6667	0.0000	3.3333	0.0000	0.0000	0.0000
B3	4.0000	3.0000	0.0000	2.6667	0.0000	3.3333	4.0000	0.0000	0.0000	0.0000	0.0000	3.6667
B4	1.6667	2.0000	2.3333	0.0000	1.6667	3.0000	3.3333	0.0000	2.0000	0.0000	0.0000	0.0000
B5	3.6667	2.6667	3.3333	1.6667	0.0000	4.0000	4.0000	4.0000	3.6667	0.0000	0.0000	2.6667
B6	2.3333	2.3333	0.0000	2.3333	0.0000	0.0000	2.0000	0.0000	2.0000	1.3333	1.6667	1.6667
B7	0.0000	2.3333	4.0000	3.6667	4.0000	3.6667	0.0000	4.0000	2.6667	0.0000	0.0000	3.6667
B8	2.0000	3.0000	4.0000	2.0000	4.0000	3.0000	4.0000	0.0000	2.0000	0.0000	0.0000	3.0000
B9	3.6667	3.6667	0.0000	4.0000	2.3333	3.6667	3.6667	0.0000	0.0000	3.6667	4.0000	4.0000
B10	4.0000	4.0000	0.0000	4.0000	0.0000	2.6667	4.0000	0.0000	0.0000	0.0000	0.0000	4.0000
B11	3.6667	4.0000	0.0000	3.6667	0.0000	3.6667	4.0000	0.0000	3.3333	3.6667	0.0000	3.6667
B12	2.3333	3.0000	0.0000	1.3333	2.0000	2.6667	3.3333	0.0000	0.0000	0.0000	0.0000	0.0000

Table 11
“Normalized Direct Influence Matrix”.

	B1	B2	B3	B4	B5	B6	B7	B8	B9	B10	B11	B12
B1	0.0000	0.0684	0.0000	0.0598	0.0940	0.0769	0.1026	0.0000	0.0000	0.0000	0.0000	0.0000
B2	0.0000	0.0000	0.0000	0.0000	0.0513	0.0598	0.0684	0.0000	0.0855	0.0000	0.0000	0.0000
B3	0.1026	0.0769	0.0000	0.0684	0.0000	0.0855	0.1026	0.0000	0.0000	0.0000	0.0000	0.0940
B4	0.0427	0.0513	0.0598	0.0000	0.0427	0.0769	0.0855	0.0000	0.0513	0.0000	0.0000	0.0000
B5	0.0940	0.0684	0.0855	0.0427	0.0000	0.1026	0.1026	0.1026	0.0940	0.0000	0.0000	0.0684
B6	0.0598	0.0598	0.0000	0.0598	0.0000	0.0000	0.0513	0.0000	0.0513	0.0342	0.0427	0.0427
B7	0.0000	0.0598	0.1026	0.0940	0.1026	0.0940	0.0000	0.1026	0.0684	0.0000	0.0000	0.0940
B8	0.0513	0.0769	0.1026	0.0513	0.1026	0.0769	0.1026	0.0000	0.0513	0.0000	0.0000	0.0769
B9	0.0940	0.0940	0.0000	0.1026	0.0598	0.0940	0.0940	0.0000	0.0000	0.0940	0.1026	0.1026
B10	0.1026	0.1026	0.0000	0.1026	0.0000	0.0684	0.1026	0.0000	0.0000	0.0000	0.0000	0.1026
B11	0.0940	0.1026	0.0000	0.0940	0.0000	0.0940	0.1026	0.0000	0.0855	0.0940	0.0000	0.0940
B12	0.0598	0.0769	0.0000	0.0342	0.0513	0.0684	0.0855	0.0000	0.0000	0.0000	0.0000	0.0000

Table 12
"Total Influence Matrix".

	B1	B2	B3	B4	B5	B6	B7	B8	B9	B10	B11	B12	Rsum	R + C	R-C	Group
B1	0.0399	0.1188	0.0373	0.1041	0.1331	0.1388	0.1618	0.0303	0.0487	0.0103	0.0109	0.0432	0.8771	2.2344	−0.4802	Effect
B2	0.0356	0.0439	0.0232	0.0417	0.0813	0.1071	0.1144	0.0201	0.1147	0.0160	0.0163	0.0396	0.6539	2.3635	−1.0557	Effect
B3	0.1409	0.1371	0.0321	0.1195	0.0551	0.1553	0.1737	0.0235	0.0450	0.0106	0.0113	0.1323	1.0363	1.8386	0.2340	Cause
B4	0.0859	0.1069	0.0879	0.0523	0.0842	0.1402	0.1491	0.0239	0.0909	0.0148	0.0153	0.0482	0.8996	2.3627	−0.5634	Effect
B5	0.1704	0.1714	0.1373	0.1332	0.0843	0.2171	0.2236	0.1341	0.1589	0.0248	0.0256	0.1489	1.6297	2.8101	0.4493	Cause
B6	0.0987	0.1139	0.0236	0.1066	0.0427	0.0635	0.1159	0.0163	0.0872	0.0497	0.0544	0.0819	0.8542	2.7496	−1.0411	Effect
B7	0.0848	0.1575	0.1534	0.1711	0.1687	0.2030	0.1226	0.1324	0.1340	0.0216	0.0224	0.1684	1.5401	3.5735	−0.4934	Effect
B8	0.1248	0.1682	0.1505	0.1299	0.1688	0.1839	0.2117	0.0390	0.1158	0.0190	0.0197	0.1491	1.4805	2.0152	0.9457	Cause
B9	0.1771	0.2046	0.0502	0.1963	0.1362	0.2165	0.2245	0.0370	0.0790	0.1201	0.1199	0.1815	1.7429	2.8550	0.6308	Cause
B10	0.1439	0.1666	0.0355	0.1553	0.0601	0.1457	0.1809	0.0247	0.0499	0.0107	0.0113	0.1424	1.1272	1.5508	0.7036	Cause
B11	0.1647	0.1997	0.0424	0.1789	0.0758	0.2017	0.2163	0.0300	0.1475	0.1170	0.0238	0.1638	1.5616	1.9020	1.2213	Cause
B12	0.0906	0.1211	0.0288	0.0742	0.0900	0.1225	0.1389	0.0235	0.0404	0.0089	0.0094	0.0349	0.7832	2.1174	−0.5510	Effect
Csum	1.3573	1.7096	0.8023	1.4630	1.1804	1.8954	2.0335	0.5348	1.1121	0.4236	0.3404	1.3342	λ = 0.0985			

λ = threshold value.

corresponded with the driving cluster in Fuzzy-MICMAC Analysis; hence, this validates the results. The effect group cluster consisted of "Poor Data Quality and Lack of trust on Data (BDAB1), Time Consuming Activity (BDAB2), Lack of Security and Privacy (BDAB4), Behavioral Issues (BDAB6), Return of Investment Issues (BDAB7) and Lack of Data Integration and Management (BDAB12)" which are resonating with the dependent cluster in Fuzzy-MICMAC Analysis, verifying the Fuzzy-MICMAC results. The barriers could be ranked based on their prominence (i.e. R + C values) which follows the relation as follows: BDBA7 > BDBA9 > BDBA5 > BDBA6 > BDBA2 > BDBA4 > BDBA1 > BDBA12 > BDBA8 > BDBA11 > BDBA3 > BDBA10.

4.4. Discussion

The theme of the present study is oriented towards three research questions, as discussed in the introduction. To answer the first question, the present study identified the barriers against BDA implementation through exhaustive literature search and was validated through the opinion of domain experts. These experts were from a wide variety of stakeholders (including industry and academia). Thus the barriers list is comprehensive. Further, to answer the second question, an ISM model was developed, showing the significant interrelationships between the barriers. Fuzzy MICMAC analysis was also carried out, which not only clusters the barriers into suitable categories but also identifies the barriers' strength through their driving and dependence potential. Moreover, to answer the third question, the DEMATEL approach was integrated into the ISM model to assess the intensity of the interrelationship among the barriers.

In this study, not only barriers against BDA implementation in manufacturing SCs are addressed, but also several mitigating strategies are listed in the next section. These strategies are carefully drafted based on the findings of this study and in consultation with various stakeholders and domain experts to eliminate the existing identified barriers. Thus, this study is a complete package to address BDA implementation issues. The new contribution of this work to the body of literature is as follows:

- Identification of comprehensive list of barriers against BDA implementation in Indian manufacturing SC.
- Modelling the contextual interrelationship between identified barriers through a novel integrated approach of ISM-DEMATEL.
- Preparation of strategies to eliminate the identified barriers.

5. Managerial implications

The findings of this study indicate a clear need for development of data generation capabilities and improvement of the infrastructure. The companies that handle huge amounts of data need to perform data audit operations on the data sources such as sensors and RFID to ensure that unrelated data is not getting generated due to faulty devices. Establishment of metrics based on the rules of business, appropriately defining variables for the purpose of measurement, and employing policies and strategies of data reduction, help the companies to reduce the volume of data at source (Rehman et al., 2016; Arunachalam et al., 2018). Streamlining of the customer reviews (unstructured data) helps in the reduction of unusable data generation, improves the quality of the data, and decreases the cost of infrastructure and storage. In the implementation of the BDA technologies, top management has an important role to play in adopting the analytic tools as practical decision-making approaches. Experts' opinions should be considered before communicating the data insights to the management. The understanding of statistics and the excellent thinking ability of the analysts help in making correct decisions (Blackburn et al., 2015; Markham et al., 2015). BDA implementation can boost and enhance the performance of conventional SC management. The outcome of the study will aid policymakers in the manufacturing industry to identify the barriers against BDA adoption and their mutual influence. The policymakers may alter the existing policies and strategies, so the newly updated strategies may help in eliminating the most significant barriers identified in this work. Some strategies in this regards are discussed below:

1. The top management of organisations should form assessment teams for BDA implementation. The team should be responsible for facilitating the BDA implementation process by providing required resources and eliminating any roadblocks.
2. The organisations should form a consortium that can assist in bringing financial investments through fundraising and other action plans. The members of the consortium should share their expertise and seek external help for developing the skillsets of human resources. In such regard, building research infrastructure is most desired.
3. A legal mechanism could be drafted between organisation for sharing of resources so that it aids in the BDA implementation process and simultaneously doesn't lose anything through such collaboration.
4. Investment in technologies should be made to make the system secure from any cyber-attack. Further, the technologies could also help in obtaining a better quality of data, which may be enriched with powerful information.
5. For acquiring the competitive advantage and profits, there is a need for efficient data integration strategies/policies to standardize information-sharing procedures. The adoption of cloud computing may be considered for secured and access-controlled information sharing.

6. To improve the capabilities of the analytics, organizations with low-level analytics ability may start from the development of descriptive analytics (primary) and gradually shift towards sophisticated (prescriptive or predictive) analytics. The developed models should be periodically monitored to ensure their performance (Radke and Tseng, 2015; Arunachalam et al., 2018).
7. The change of culture should be continuously monitored for behavioral issues. For this, various training and counseling session may be organized from time to time. Moreover, the grievance desk for employees may be established to settle related issues.

6. Conclusion and future scope of the study

This study contributes to the scientific literature in supply chain management with the identification of significant barriers for BDA implementation in the Indian manufacturing supply chain context. Twelve barriers were identified through a methodology using exhaustive literature search and expert opinion analysis. To evaluate the contextual interrelationship, an ISM model was constructed, which showed the different hierarchy levels. Then, a Fuzzy-MICMAC analysis was carried out to identify and cluster the factors with the most significant driving power. Moreover, DEMATEL was utilized to estimate the intensity of interrelationship between the identified constructs and to identify the causal interrelations. The barriers were grouped into cause and effect clusters. "Lack of Top Management Support (BDAB8), Lack of financial support (BDAB5), Lack of skills (BDAB9), and Lack of techniques or procedures (BDB11)" emerged as the most critical barriers against BDA adoption in manufacturing firms. Furthermore, barriers like "Lack of Sufficient Resources (BDAB3), "Data Scalability (BDAB10), and Lack of Data Integration and Management (BDAB12)" were medium significant barriers, while barriers such as Poor Data Quality and Lack of trust on Data (BDAB1), Lack of Security and Privacy (BDAB4), Return of Investment Issues (BDAB7), Time Consuming Activity (BDAB2) and Behavioral Issues (BDAB6) were identified as being the least significant barriers. It was also observed that the constructs falling under the driving cluster in the Fuzzy-MICMAC analysis were in the casual group in DEMATEL analysis. Similar instances were observed between the dependence cluster in the Fuzzy-MICMAC and the effect group of DEMATEL analysis, which validates the results obtained in Fuzzy-MICMAC and DEMATEL analysis.

A few limitations of the work are identified and will be considered for future research directions such as the ambiguity in the opinion formulated by the experts. In that case, a fuzzy form of the input may be considered to leverage the ambiguity and the vagueness of the assessment. Moreover, the study is carried out in the Indian scenario and cannot be generalized to other countries with varying contexts or to other production sectors. Future studies may focus on the comparison between the results of our work with empirical evidence from other activity sectors or manufacturing activity in other countries.

CRediT authorship contribution statement

Rakesh D. Raut: Conceptualization, Methodology, Validation. **Vinay Surendra Yadav:** Conceptualization, Methodology, Validation. **Naoufel Cheikhrouhou:** Conceptualization, Methodology, Validation. **Vaibhav S. Narwane:** Conceptualization, Methodology, Validation. **Balkrishna E. Narkhede:** Conceptualization, Methodology, Validation.

Declaration of Competing Interest

Authors declare no competing of interest.

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