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Framework for implementing big data analytics in Indian manufacturing: ISM-MICMAC and Fuzzy-AHP approach

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Abstract
Manufacturing firms generate a massive amount of data points because of higher than ever connected devices and sensor technology adoption. These data points could be from varied sources, ranging from flow time and cycle time through different machines in an assembly line to shop floor data collected from sensors viz. temperature, stress capability, pressure, etc. Analysis of this data can help manufacturers in many ways, viz. predict breakdown—reduction in downtime and waste, optimal inventory level—resource optimization, etc. The data may be highly voluminous, highly unstructured, coming from varied sources at a higher speed. Thus, big data analytics has become more critical than ever for the manufacturing industry to have the capability of effectively deriving business value from the vast amount of generated data. Manufacturing firms face hindrances and failures in the implementation of big data analytics. It is, therefore, necessary for the companies in the Indian manufacturing sector to identify and examine the reason and nature of barriers resisting the implementation of Big Data Analytics (BDA) to their organization. This paper explores the existing literature available to identify the barriers, categorized based on different functions of an organization. A total of 16 barriers are determined from the rigorous review of existing research. A survey is conducted on the industry experts from automobile, steel, automotive parts manufacturer, and electrical equipment industries to obtain a contextual relationship between the barriers. Interpretive Structural Modeling and MICMAC (Cross-impact matrix multiplication applied to classification) are the analytical techniques used in this research to classify the barriers into different impact levels and importance. Independent factors (barriers) have high driving power and are the key factors that were further analyzed using Fuzzy AHP to determine their comparative priority/importance. The result of this research shows that barriers related to Management and Infrastructure & Technology are the main hurdles in the implementation of big data analytics in the manufacturing industry. Six critical barriers (based on high driving power) are; lack of long-term vision, lack of commitment from top management, lack of infrastructure facility, lack of funding, lack of availability of specific data tools, and lack of training facility. Lack of commitment from top management is the most critical barrier. Research focuses on a comprehensive analysis of the barriers in implementing big data analytics (BDA) in manufacturing firms. The novelty lies in (a) finding an extensive list of barriers, (b) application domain and geography, and (c) the multi-criteria decision making technique used for finding the critical barriers to the implementation of big data analytics. The findings of this research will help industry leaders to formulate a better plan before the application of BDA in their organizations.

Keywords Big data analytics · Interpretive structural modeling(ISM) · MICMAC · FUZZY AHP

Abbreviations

BD	Big Data
BDA	Big Data Analytics
BI	Business Intelligence
IoT	Internet of Things
ISM	Interpretive Structural Technique
IT	Information Technology
MICMAC	Matriced' Impacts Croise's Multiplication Applique'e a UN Classement

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SSIM	Structural Self Interaction Matrix
SEM	Structural Equation Modeling

1 Introduction

As far as the depth and range of products are concerned, the manufacturing industry is one of the most complex. The manufacturing industry is categorized into two major segments, viz. discrete manufacturing and process manufacturing, based on the production processes they follow. It is further classified based on the product such as metal & mining, chemicals, aerospace, automotive, pharmaceuticals, etc. The industry is strongly affected by digitization, which has led to digital services like predictive maintenance and disruptive product innovations [1]. Today, one of the critical success factors for manufacturing companies is the efficient and effective management of data and its analysis [2]. With the advent of industry 4.0 technologies like IoT, blockchain, AI, and big data, it is becoming standard practice to support decision-making based on a comprehensive evaluation of data collected from varied sources viz. production equipment, sensors, and enterprise resource planning systems. Also, the advancement of industry 4.0, such as IoT, has resulted in an incremental increase in global data [3, 4]. These advancements create areas where big data analytics (BDA) tools and techniques can be applied in the manufacturing sector. BDA will revolutionize in making informed decisions, identify variables that affect production, monitor and mitigate risk, increase operational efficiency, carrying out market research, competitor analysis for any particular product, etc. [5, 6]. The concept of BDA was derived from internet giants like Amazon, Netflix, and Google, who analyze consumer activity data to provide customizable and personalized offerings [7].

There is colossal literature suggesting the importance of BDA and its possible revolutionary impact on operational and strategic decision making. Researchers are still investigating its application and decision-making impact in new business areas.

Despite the importance of BDA in revolutionizing the business operation and activities, most of the organization has failed at the implementation stage. A report suggested that around 80% of the organizations failed at the implementation stage [8–10]. Half of the big data projects implemented with high expectations failed to deliver [11]. In another report published in InfoWorld suggest 100% failure, even in the presence of mature Technology [12].

The majority of manufacturing industry leaders want to implement BDA for improving operational efficiency and have a competitive edge. But they are unable to because of a lack of awareness about BDA, related infrastructure, and many other organizational barriers. Thus, it is vital to investigate and analyze barriers to BDA implementation in today's technologically advanced world. It will help companies to formulate and plan better before implementing BDA in their organizations.

There is limited research on the barriers to BDA implementation [13, 14]) conducted a comprehensive review of the barriers and developed a framework on big data analytics throughout the product lifecycle [15] qualitatively investigated the drivers and barriers of industry 4.0. Still, there is limited literature available on barriers to the implementation of BDA in the manufacturing sector.

For an emerging economy like India, manufacturing is a critical driving force of the economic engine. It offers unparalleled job opportunities that transform societies and result in a high growth rate. Hence, developing countries like India must implement BDA for their rapidly expanding manufacturing sector and remain competitive. The implementation of BDA will help in uncovering new avenues to gain a competitive advantage through innovation. Manufacturing companies face an obstacle in the implementation of BDA. Hence, it is vital to conduct a quantitative analysis of the barriers in adopting BDA in the manufacturing sector focused on India. Such a study will guide and assist industry leaders in framing better policies for its implementation.

The problem statements of the study are:

1. What are the barriers to the implementation of BDA in the manufacturing sector?
2. How can industry leaders quantitatively examine the barriers?
3. Can the final result help industry leaders to formulate better strategies for BDA implementation?

Following are the objectives of this research for answering the above problem statements:

To determine the barriers to the implementation of Big data analytics in the manufacturing sector.
To quantitatively evaluate the barriers using analytical approach—ISM and MICMAC
To identify the most critical barrier using Fuzzy AHP

This paper explores the existing literature available to identify the barriers, categorized based on different functions of an organization. A total of 16 barriers are determined from the rigorous review of existing research. The opinion and judgment on these barriers are taken from industry experts from the automobile, steel, automotive parts manufacturer, and electrical equipment industries.

ISM and MICMAC are the analytical techniques used to classifies the barriers into different impact levels and importance. ISM helps to establish interrelationships among these barriers, and MICMAC is used to classify barriers into driving and dependence power. Independent factors (barriers) have high driving power and are the key factors that were further analyzed using Fuzzy AHP to find their comparative priority/importance.

The organization of this paper is as follows: Literature review on the topic is summarized in Sect. 2. Section 3 presents the research methodology, i.e., ISM-MICMAC. Section 4 discusses the final result and the Fuzzy AHP analysis. Section 5 concludes the outcome of the paper. Section 6 suggests future scope. The paper ends with references and an Appendix.

2 Literature review

This section reviews big data analytics concepts, its significance, application, and importance in the manufacturing industry. At the last, critical barriers to BDA implementation are identified.

2.1 Big data and big data analytics

Big data's technological development is considered the critical area of advancements in information and communication technology. It has evolved rapidly due to the ever-increasing affordability and availability of electronic devices and networks, driven mainly through social media and the increased presence of the Internet of Things (IoT). Firms can transform themselves into data-driven organizations due to technological advancements in big data awareness, infrastructure, analytics, and related services. Every firm wants to stay competitive; hence they need to build their future strategies surrounding big data owing to its potential of being a game-changer. Big data is usually used to describe a massive volume of datasets that are very complex and difficult to handle using conventional data analysis applications [16, 17]. In other words, the dataset size is so massive that current tools and storage systems are not capable enough to store, manage, and process it at an adequate time.

Organizations and practitioners may have different concepts on big data, but the definition introduced by [18] is widely used. According to the definition, big data has three dimensions, viz. volume, variety, and velocity (3 V). Several other definitions exist for big data like [19] describe it in three-part viz. high volume-velocity-variety that assists data-driven decision-making and can't be managed by conventional tools. The big data concept is further expanded by [20] when they claimed that it should have *Veracity* as a fourth dimension. Veracity refers to the unreliability and uncertainty in data sources, resulting from inaccuracy, inconsistency, incompleteness, and subjectivity in data. There are further additions to the above concepts by various organizations, but the general idea is the same.

We lack an integrated view of big data in the industry. Figure 1 clearly explains the interrelationship between different dimensions of big data [21]. Representation of the three dimensions of big data is done with the help of the triangular framework with the three edges representing them. Inside space is occupied by five more dimensions, i.e., complexity, decay, value, integrity, and variability, which are affected by the growth of three primary dimensions. Thus basic framework of 4 V is modified to a 7 V framework, which includes: volume-velocity-variety-veracity-value-variability-volatility [22–24]. The growth of the three dimensions negatively impacts Veracity but positively affects the other four dimensions. Traditional data is a subset of big data with the same three dimensions but with a smaller scope than big data. With the growth of three edge dimensions, the magnitude of big data also expands. The expansion of all three edge dimensions is interlinked to each other. Expansion of any one dimension will affect all the other seven dimensions.

From a broader perspective, big data also refers to the tools and advanced analytical techniques used for managing and processing this complex and massive dataset, which is evolving rapidly to extract valuable information and facilitate decision-making [25]. When it comes to the manufacturing industry, the data analytic process is more widely familiar as Business Intelligence (BI) due to some marked difference between BDA and BI based on the type of data and questions answered by its analysis. For example, a database about BI is finite to a particular timeline in an organizational data architecture. The data are accessed via a specialized data mart developed from a data warehouse in an offline mode, contrary to the real-time data format in BDA. Also, most of the time, data sources are limited to organizations' internal and external databases having low

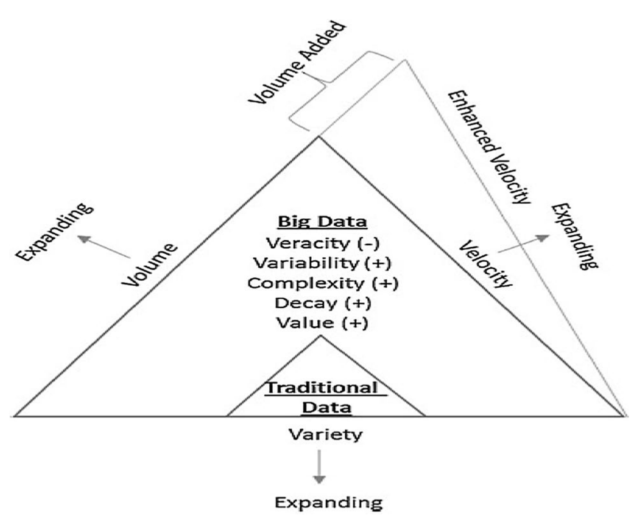

Fig. 1 An integrated view of big data [21]

Table 1 Business intelligence vs. Big data analytics

	Business intelligence	Big data analytics
Questions answered	What happened?	Why did it happen?
	When?	Will it happen again?
	Who?	What will happen if we change X?
	How many?	
Includes	Reporting (KPIs, metric)	Data mining
	Dashboards	Quantitative analysis
	Scorecards	Predictive modeling
	Ad hoc query	Text analytics
	OLAP	Multivariate modeling

complexity. Some marked differences between BI and BDA are listed in Table 1.

2.2 Big data analytics in the manufacturing industry

The manufacturing industry faces the wind of change with a more volatile and fragmented business environment than ever before. The industry must adapt to remain competitive or risk completely fading away. The next question firms face, where to start and how to stay competitive? The answers lie in BDA or BI as widely known in the industry, where the advanced analytical technique of data management is utilized to aggregate datasets in a structured way. These aggregated structured datasets help extract valuable information that aids in data-driven decision-making [7]. Many world-class firms in the manufacturing sector, i.e., automotive, steel, chemical, power, pharmaceutical, and garments industry, are using BDA tools to improve operational efficiency and minimize process flows, increase productivity, reduce downtime and enhance the quality of a product [26–28].

Business Intelligence refers to leveraging a range of tools that transform data to provide quick and actionable insights about an organization's current state. It offers detailed intelligence to business owners through reports, dashboards, graphs, charts, and summaries based on data visualization tools. As shown in Table1, BI tells you the current state of the business, i.e., what's happening now and what happened in the past, to lead us to the present state. BDA, on the contrary, is—predictive analytics, which tells what is going to happen in the future, and prescriptive analytics, which explain what one should do to have better outcomes. A review of the analytical methods employed on Big Data to extract the Hindsight, Insight, and Foresight from the data are summarized in [22, 23].

2.3 Importance of data analytics in the business environment

Significant contributions can be made to areas such as supply chain, distribution optimization, new product development, demand prediction, and customer relationship through big data analytics. The importance of data analytics is demonstrated by various researchers, such as [3]. They highlighted that the supply chain problem could be quantitatively resolved by making available useful quality data [29] mentions how manufacturing performance can be improved with the help of BDA [30] explored BD application in product lifecycle management [7] examined BD application for predictive analysis to measure the supply chain sustainability.

We can make the following inferences from the above scholarly articles: (1) the information from data points should be extracted and presented with the motive of helping end-users. (2) proper data integration and supply chain data analysis will help increase visibility upward and downward of the supply chain. (3) Spend analysis of data can reduce procurement costs by a strategic allocation of contracts among vendors. (4) product line profitability can be impacted by using sales data analytics. In other words, BDA is the natural evolution of big data in the manufacturing industry [31]. Numerous literature suggests the importance of BDA and its possible revolutionary impact on operational and strategic decision making. Owing to the BDA influence, more and more research is in progress. Table 2 compiles the current studies on the importance of BDA in different and new sectors or operational areas.

2.4 Barriers of data analytics in the manufacturing industry

In the BD era in this global market, companies in the manufacturing sector have begun to embrace BDA tools and techniques to sustain and remain competitive. Experts believe that India is one of the ideal countries to benefit from big data analytics. The government of India started the campaign of Make-In-India, Digital India, etc., to boost the

Table 2 List of recent studies on the importance of BDA

Author(s)	Analysis	Area
[32]	Opportunities and challenges	HRM, regulatory and ethical challenges
[33]	Employee-tourist encounter experiences	Tourism: creating positive tourist perceptions
[34]	High level of sustainable water supply	Sustainable water management in the smart city
[35]	Identification of factors of Cycle time	Electronics industries: Semiconductor wafer fabrication system
[36]	Innovative green product development and sustainable supply chain outcome	Mining industry supply chain
[22]	Potential implications and capabilities of BDA	Phosphate derivatives manufacturing process
[37]	Identifying the determinants to adopt Big data analytics	Construction industry
[38]	Understand possible safety risk combinations	Power infrastructure operations
[39]	Airline network planners	Aviation sector
[40]	A key factor in forecasting insurance customer profitability	Insurance industry
[41]	Decision-making for operations management of battle damage assessment and repair	Military-industrial logistics planning

manufacturing sector. These initiatives aim to help Indian industries strive for sustained business growth and development [42]. A study on Indian firms focused on the impact of BDA on social performance, environmental performance, and collaborative performance showed a positive effect [43, 44]. A recent survey done be [45] on Indian manufacturing industries indicated that 65% of the organization had set a top priority for BDA investment in the next couple of years. The study reflected predictive maintenance, connected supply chain, reduced energy consumption, production optimization, lower price of sensors and high computing needs, and connected customers as the key factors driving digital manufacturing in India. Still, the adoption of digital technologies in India is in its infancy. The top Indian Government office of the Department of Science & Technology expressed BDA as crucial for the Indian manufacturing sector. Polaris India Head and MD also pointed out the importance of BDA towards capturing, cleaning, and analyzing machine data to reveal insights that can improve performance [46].

Still, limited research exists on BDA implementation in the Indian manufacturing industry. Research article done in the Indian context are summarized in Table 3. It is observed that only the sales and marketing division is adopting data analytics to a certain extent for production based on sales over time. Manufacturers are reluctant to implement data analytics due to many hurdles and the myth they possess due to a lack of awareness. Hence it is of utmost importance to investigate these barriers faced in the implementation of big data analytics.

In this paper, the existing literature is examined using keywords like a *barrier in the implementation of BDA, BDA in the manufacturing industry, barriers in adoption of BDA, issues faced in the implementation of big data analytics, and BDA, barriers to adoption of BDA,* etc.

We could find a limited related article. Research by [6] has assessed challenges for the implementation of Industry 4.0 and its implication on process safety and environmental protection [14] explores the barriers to BDA in Bangladesh's manufacturing supply chain [51] investigated the barriers of BDA in the automotive sector through qualitative analysis [52] recommended specific tactics for addressing BD barriers by qualitative analysis [53] undertook an interpretive study to explore the adoption challenge of BDA in the South

Table 3 Summary of existing research in Indin context on BDA

Author(s)	Analysis	Method	Business environment
[47]	BDA	ISM-DEMATEL	Indian manufacturing supply chain
[48]	BDA	Conceptual	Challenges, issues, and implications in SCM
[49]	Big Data adoption	EFA, CFA, and SEM	Determinant in Indian service and manufacturing sector
[42]	BDA	EFA, CFA, and SEM	Linking BDA and operational sustainability
[43]	Big data and predictive analytics	PLS-SEM	Impact of BDPA on social performance (SP) and environmental performance (EP)
[44]	role of BDPA	PLS-SEM	Role of BDPA in a collaborative performance
[50]	BIG Data project	Conceptual	Framework for Big data project at a manufacturing company

African telecom industry. Table 4 summarizes the research related to BDA implementation.

3 Research methodology

This paper uses the ISM technique for identifying contextual relationships among 16 barriers in the implementation of data analytics in the manufacturing industry. MICMAC is further used to categorize the barriers into four groups based on driver and dependence power. Four groups are autonomous, dependent, linkage, and independent. Barriers in the independent group are further prioritized using Fuzzy AHP. Flow chart for research methods is shown in Fig. 2.

3.1 Barrier Identification, expert review and categorization

Sixteen most essential barriers in the implementation of BDA are identified through rigorous literature review. These barriers were validated through the interaction with the relevant industry experts (Appendix B Table 31). The barriers are further categorized under six broad groups (Fig. 3). The barriers identified are listed in Table 5, along with their references.

3.2 Interpretive structural modeling (ISM)

Warfield [64] was the first to propose the Interpretive Structural Modeling (ISM) approach to analyze and visualize the complex problem in a hierarchical structure and manage decision making. It is an interactive learning process that structures complex and directly related variables into a comprehensive and well-defined systematic model. It also helps in establishing interrelationships among identified variables. In ISM, practical experience and judgment of subject matter experts are used to decide whether the variables are connected or not and how they behave if connected [65]. Based on situations, the relationship between direct and indirect variables is discovered more precisely compared to seeing individual factors in isolation. Owing to this benefit, the researcher selects this approach for establishing the interrelationships between the identified barriers [66]. Moreover, [67] mentions that when the numbers of elements are large, it is a better approach for solving the complexity of relationships.

The ISM-MICMAC has been a trusted tool for researchers to conduct studies across various fields; however, this research paper creates a unique amalgamation of these tools concerning geography and area of study. The areas in which other researchers have used these tools are tabulated in Table 6.

The steps involved in ISM methodology are below [80]:

(1) List the barriers relevant to the study.
(2) Establish a contextual relationship between the listed barriers with the help of subject matter experts.
(3) A pairwise relationship matrix (self-interaction matrix (SSIM)) is developed for the barriers with the help of subject matter experts.
(4) The Reachability matrix is developed from the SSIM, and the matrix is checked for transitivity.
(5) The barriers are partitioned into different levels using the reachability matrix
(6) Develop a Conical matrix using levels and reachability matrix.
(7) Develop Digraph and remove the transitive links.
(8) ISM model is created from the final resultant Digraph.
(9) The ISM model developed is reviewed to check for conceptual inconsistency

3.2.1 Data collection

The ISM approach is based on the opinion of subject matter experts to develop contextual relationships among various variables. Industry experts from the manufacturing sectors were consulted for the study (Appendix B Table 31). All the individual responses were discussed with the particular respondent to understand their approach. All the different responses were then consolidated.

3.2.2 Structural self-interaction matrix (SSIM)

SSIM Matrix records all pairwise relationships between two barriers (i and j). Barriers in row *i* is compared with the barriers in column *j*. Responses are gathered by comparing barriers *i* leads to barriers *j*. The Symbols used for establishing

Table 4 Summary of existing research on the Barrier to BDA implementation

Author(s)	Analysis	Method	Business environment
[14]	BDA-critical barriers	Delphi-Based AHP	Bangladesh Manufacturing supply chains
[54]	BDA-critical barriers	ISM	Sustainable auditing system
[55]	BDA capability	IF-DEMATEL, ANP, and SAW	Business Performance
[52]	BDA Barriers	Qualitative, Factor identification	Domains of Technology, people, and organization

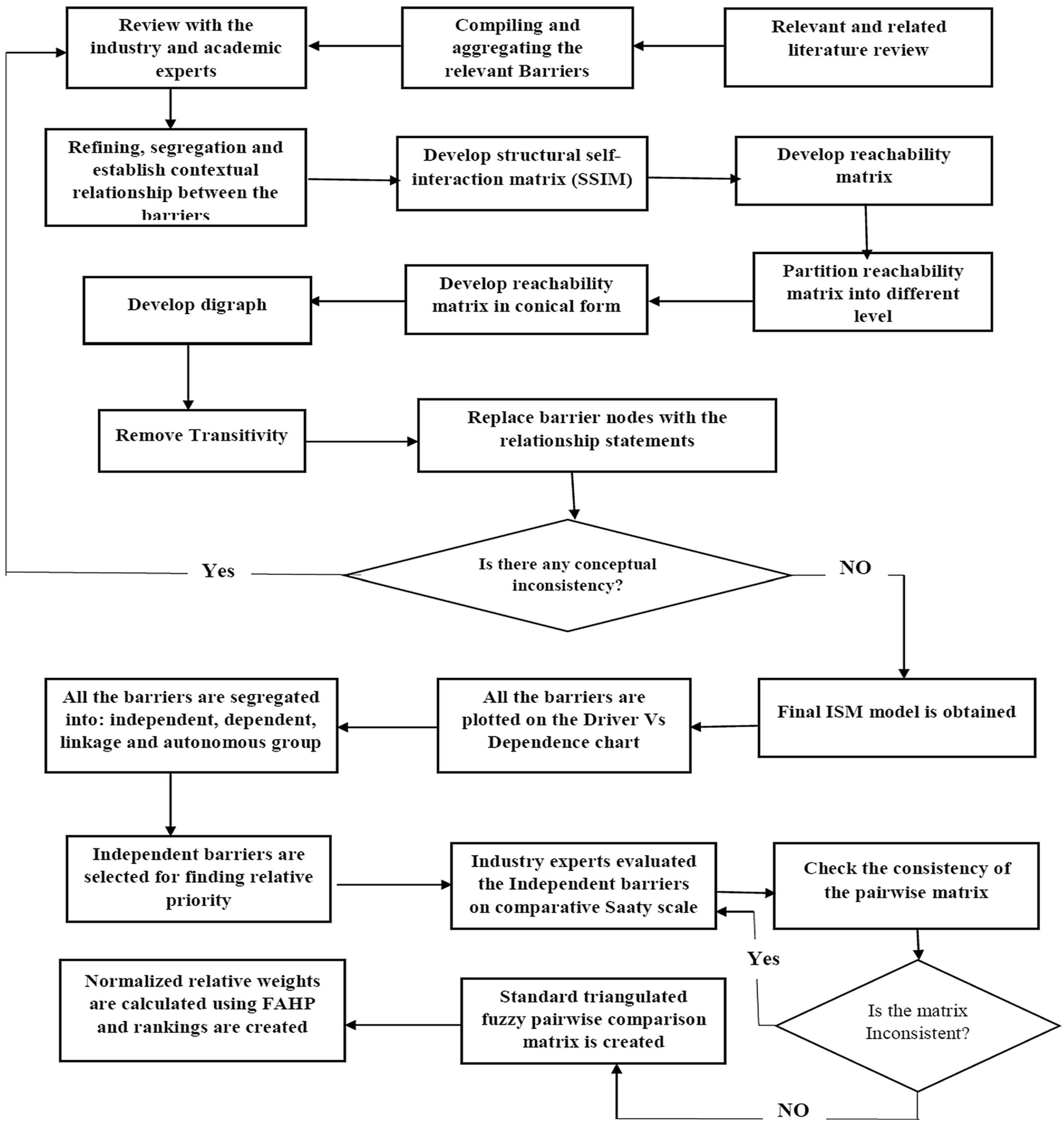

Fig. 2 Research method flow chart

the direction of relationships between the barriers (i and j) are as follows:

V: Barriers i will lead to barriers j;
A: Barriers j will lead to barriers i;
X: Barriers i and j will lead to each other; and
O: Barriers i and j are unrelated.

Explanation: Lack of infrastructure facility, unavailability of specific data tools, and training facility may lead to unskilled IT personnel, lack of awareness about DA, and higher investment. Similarly, lack of long-term vision, lack of management initiative, and top management commitment will lead to data security and privacy concerns, performance & scalability, poor data quality, absence of any policy to

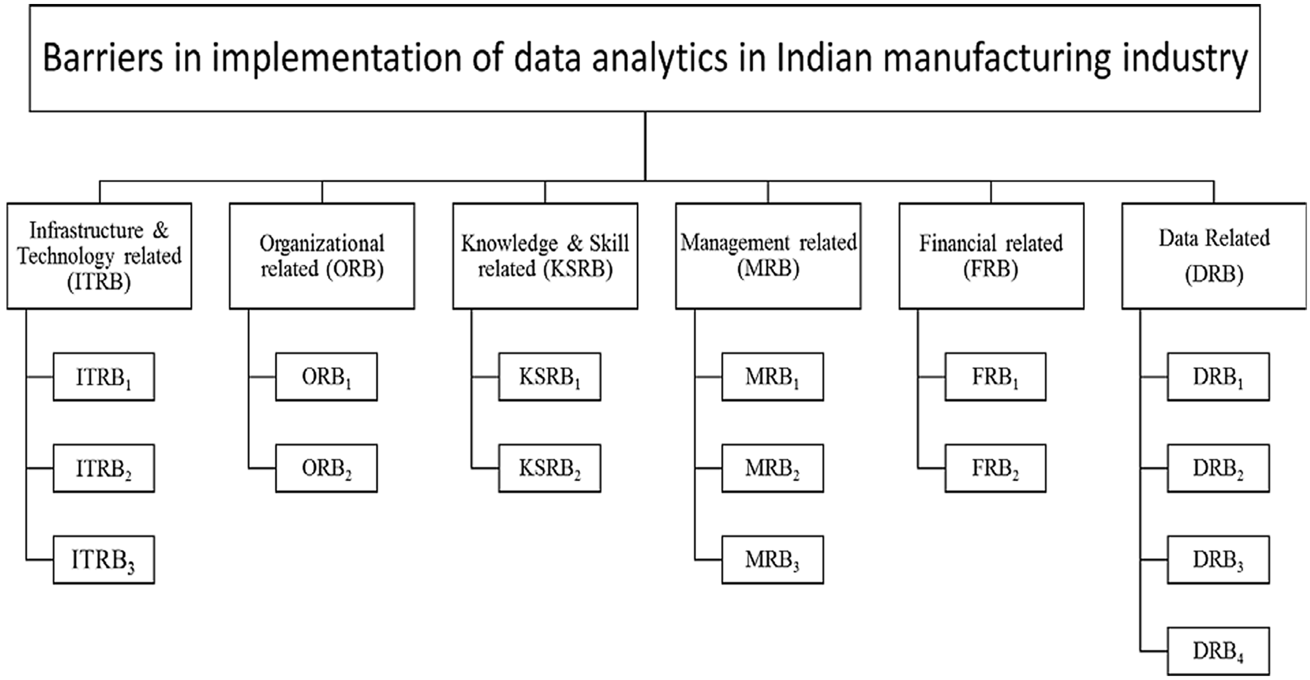

Fig. 3 Categorized barriers to BDA in the manufacturing industry

share data among the organization, and complexity of data integration. Lack of management initiative leads to a lack of funding and vice versa. The complexity of data integration leads to high-cost investment and performance issues, whereas it is affected by poor data quality. Insufficient funds will degrade the organizational performance and adaptability to change. Subsequently, it will degrade the quality, security, and privacy of data.

3.2.3 Initial reachability matrix

The initial reachability matrix is formed by replacing the value of V, A, X, and O in the SSIM matrix (Table 7), by binary digits 1 and 0. Rules followed for such transformation is outlined below [81, 82]:

- Cell (i, j) and cell (j, i) with value V in the SSIM matrix will be replaced by 1 and 0, respectively, in the initial reachability matrix.
- Cell (i, j) and cell (j, i) with value A in the SSIM matrix will be replaced by 0 and 1, respectively, in the initial reachability matrix.
- Cell (i, j) and cell (j, i) with value X in the SSIM matrix will be replaced by 1 and 1, respectively, in the initial reachability matrix.
- Cell (i, j) and cell (j, i) with value O in the SSIM matrix will be replaced by 0 and 0, respectively, in the initial reachability matrix.

The initial reachability matrix developed, as shown in Table 8. Note that a barrier affects itself so, the diagonals will have value as 1.

Transitivity is incorporated to make the expert opinion obtained on the contextual relationship consistent as per step 4. The transitivity matrix is obtained by replacing any inconsistency by 1* in an initial reachability matrix, as shown in Table 9.

Hence, the final reachability matrix is shown in Table 10. Table 10: Final Reachability Matrix contains pairwise relationships among barriers along with some inferred entries.

3.2.4 Level partitions

Reachability, antecedent, and interaction sets are obtained for each barrier from the final reachability matrix. The reachability set of a specific barrier consists of all the barriers in *j* columns with cell (*i,j*) value of 1. The antecedent set of a particular barrier includes all the barrier in *i* rows with cell (*i,j*) value of 1. common barriers between the reachability and antecedent set determines the intersection set. Subsequently, the barriers for which the reachability and the intersection sets are the same acquire higher levels in the ISM hierarchy. It signifies that the particular barrier at the highest level will not lead to the other barriers above their level in the ISM model. Once it is identified, the top-level barrier is removed from the other remaining variables [67]. The same iterative process is repeated until the level of each

Table 5 Barriers in implementation of data analytics in the manufacturing industry

Barriers	Description	References
Infrastructure & technology related barrier (ITRB)		
Lack of infrastructure facility (ITRB1)	There is an inadequate technological infrastructure to support the manufacturing companies' implementation of BDA	[52, 53, 56]
Lack of availability of specific data tools (ITRB2)	It can slow down the smooth implementation process in manufacturing facilities	[14]
Lack of training facility (ITRB3)	Lack of training facilities may obstruct the implementation of BDA in manufacturing firms	[53]
Organizational related barrier (ORB)		
Time constraints (ORB1)	The most significant problem in managing new projects	[53, 57]
No policy to share data among an organization (ORB2)	Multiple departments of the firm don't share data with each other due to the absence of a policy framework	[14]
Knowledge & skills related barrier (KSRB)		
Lack of skilled IT personnel (KSRB1)	It can lead to improper data handling, analysis, and interpretation	[14, 52]
Lack of awareness about data analytics (KSRB2)	Industry personnel are unaware of the latest technology in their field	Proposed
Management-related barrier (MRB)		
Lack of long term vision (MRB1)	Management is busy in the only day to day operation of the firm	Proposed
Lack of management initiative (MRB2)	Mgmt. is reluctant to take a risk and initiate new projects	[58]
Lack of commitment from top management (MRB3)	Management is not interested in the sustainable growth of the firm	[59, 60]
Financial related barrier (FRB)		
The high cost of investment (FRB1)	Infrastructure for BDA technology and tools may require substantial investment	[53]
Lack of funding (FRB2)	It hinders the availability of updated BDA software and tools	[14]
Data related barrier (DRB)		
Data security & privacy (DRB1)	It is essential for avoiding any nuisance in the competition and among the customers	[52, 61]
Performance & scalability (DRB2)	BDA requires massive performance and scalability	[53]
Data quality (DRB3)	Quality differs with the type of data sources, storage media, etc.,	[52]
The complexity of data integration (DRB4)	Data from multiple sources may create complexity in data integration	[62, 63]

Table 6 Summary of ISM-MICMAC used in the field of study

Author, Year	Technique used	Area of study
[59]	ISM, Fuzzy & MICMAC	Supply chain management
[68]	ISM	Electric mobility
[69, 70]	ISM, Fuzzy & MICMAC	Competitiveness in the Indian manufacturing sector
[71]	ISM, Fuzzy & MICMAC	Solar Energy
[72]	ISM & MICMAC	Designing the product life cycle
[73]	ISM-Fuzzy DEMATEL	Agri-food supply chains
[74]	DELPHI-ISM-ANP	Sustainable supplier selection process
[75]	ISM-MICMAC	End-of-life vehicle (ELV) recycling management
[76]	ISM-MICMAC	Green Lean Six Sigma implementation
[77]	ISM-MICMAC	m-commerce adoption in SMEs in the UK
[78]	ISM & MICMAC	Geology
[79]	ISM & TISM	Human Resource

barrier is found. The ISM model is developed using these identified levels. In this paper, it took ten iterations for the level identification process of 16 barriers.

Table 11 shows the level partition wherein barriers 9, 11, and 14 are grouped at the level I. Subsequent levels are determined through further iterations. Detailed level partitions from iteration I to iteration X are tabulated in Appendix A (Tables 21, 22, 23, 24, 25, 26, 27, 28, 29, and 30).

Table 7 Structural Self-Interaction Matrix (SSIM)

Barriers	Code	Barriers (i↓ & j→)	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
1	ITRB1	Lack of infrastructure facility	–	V	V	V	O	V	V	A	A	A	V	A	O	V	O	V
2	ITRB2	Lack of availability of specific data tools	–	–	O	V	O	V	V	A	A	A	V	A	O	V	O	V
3	ITRB3	Lack of training facility	–	–	–	V	O	V	V	A	A	A	V	A	O	V	O	O
4	ORB1	Time constraints	–	–	–	–	O	A	V	A	A	A	V	A	O	V	O	V
5	ORB2	No policy to share data among the organization	–	–	–	–	–	A	A	A	A	A	V	O	A	V	O	V
6	KSRB1	Lack of Skilled IT Personnel	–	–	–	–	–	–	V	A	A	A	V	A	O	V	O	V
7	KSRB2	Lack of awareness about data analytics	–	–	–	–	–	–	–	A	A	A	V	A	O	V	O	V
8	MRB1	Lack of long term vision	–	–	–	–	–	–	–	–	A	A	V	V	V	V	V	V
9	MRB2	Lack of management initiative	–	–	–	–	–	–	–	–	–	A	A	X	V	V	V	V
10	MRB3	Lack of commitment from top management	–	–	–	–	–	–	–	–	–	–	V	V	V	V	V	V
11	FRB1	High cost of investment	–	–	–	–	–	–	–	–	–	–	–	A	A	A	A	A
12	FRB2	Lack of funding	–	–	–	–	–	–	–	–	–	–	–	–	V	V	V	V
13	DRB1	Data security & privacy	–	–	–	–	–	–	–	–	–	–	–	–	–	V	O	V
14	DRB2	Performance & scalability	–	–	–	–	–	–	–	–	–	–	–	–	–	–	A	A
15	DRB3	Data quality	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	V
16	DRB4	Complexity of data integration	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–

Table 8 Initial reachability matrix

Barriers	Code	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
1	ITRB1	1	1	1	1	0	1	1	0	0	0	1	0	0	1	0	0
2	ITRB2	0	1	0	1	0	1	1	0	0	0	1	0	0	1	0	1
3	ITRB3	0	0	1	1	0	1	1	0	0	0	1	0	0	1	0	0
4	ORB1	0	0	0	1	0	0	1	0	0	0	1	0	0	1	0	1
5	ORB2	0	0	0	0	1	0	0	0	0	0	1	0	0	1	0	1
6	KSRB1	0	0	0	1	1	1	1	0	0	0	1	0	0	1	0	1
7	KSRB2	0	0	0	0	1	0	1	0	0	0	1	0	0	1	0	1
8	MRB1	1	1	1	1	1	1	1	1	0	0	1	1	1	1	1	1
9	MRB2	1	1	1	1	1	1	1	1	1	0	0	1	1	1	1	1
10	MRB3	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
11	FRB1	0	0	0	0	0	0	0	0	1	0	1	0	0	0	0	0
12	FRB2	1	1	1	1	0	1	1	0	1	0	1	1	1	1	1	1
13	DRB1	0	0	0	0	1	0	0	0	0	0	1	0	1	1	0	1
14	DRB2	0	0	0	0	0	0	0	0	0	0	1	0	0	1	0	0
15	DRB3	0	0	0	0	0	0	0	0	0	0	1	0	0	1	1	1
16	DRB4	0	0	0	0	0	0	0	0	0	0	1	0	0	1	0	1

3.2.5 Conical matrix

After obtaining the level of each barrier, a conical matrix is developed by rearranging barriers of the final reachability matrix at the same level across rows and columns. The value of driving and dependence power of the barriers is the sum of once in respective rows and columns [83, 84]. Next, the barriers are ranked on the driver and dependence power scale. Rank 1 is given to barriers with the highest value for respective power, i.e., dependence and driver.

3.2.6 Digraph and ISM model

An initial digraph with transitive links is drawn from the conical form (Table 12) of the reachability matrix. It is used to represent the barriers and their interdependencies by nodes and lines of edges. In one way, a digraph is a visual representation of all the barriers and their interdependencies [85]. After removing transitivity, a final digraph is obtained. Barriers at the level I are kept at the top of the hierarchy, meaning they won't lead to any other barrier. The barriers

Table 9 Transitivity matrix

Barriers	Code	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
1	ITRB1	1	1	1	1	1*	1	1	0	1*	0	1	0	0	1	0	1*
2	ITRB2	0	1	0	1	1*	1	1	0	1*	0	1	0	0	1	0	1
3	ITRB3	0	0	1	1	1*	1	1	0	1*	0	1	0	0	1	0	1*
4	ORB1	0	0	0	1	1*	0	1	0	1*	0	1	0	0	1	0	1
5	ORB2	0	0	0	0	1	0	0	0	1*	0	1	0	0	1	0	1
6	KSRB1	0	0	0	1	1	1	1	0	1*	0	1	0	0	1	0	1
7	KSRB2	0	0	0	0	1	0	1	0	1*	0	1	0	0	1	0	1
8	MRB1	1	1	1	1	1	1	1	1	1*	0	1	1	1	1	1	1
9	MRB2	1	1	1	1	1	1	1	1	1	0	1*	1	1	1	1	1
10	MRB3	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
11	FRB1	1*	1*	1*	1*	1*	1*	1*	1*	1	0	1	1*	1*	1*	1*	1*
12	FRB2	1	1	1	1	1*	1	1	1*	1	0	1	1	1	1	1	1
13	DRB1	0	0	0	0	1	0	0	0	1*	0	1	0	1	1	0	1
14	DRB2	0	0	0	0	0	0	0	0	1*	0	1	0	0	1	0	0
15	DRB3	0	0	0	0	0	0	0	0	1*	0	1	0	0	1	1	1
16	DRB4	0	0	0	0	0	0	0	0	1*	0	1	0	0	1	0	1

Table 10 Final reachability matrix

Barriers	Code	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
1	ITRB1	1	1	1	1	1	1	1	0	1	0	1	0	0	1	0	1
2	ITRB2	0	1	0	1	1	1	1	0	1	0	1	0	0	1	0	1
3	ITRB3	0	0	1	1	1	1	1	0	1	0	1	0	0	1	0	1
4	ORB1	0	0	0	1	1	0	1	0	1	0	1	0	0	1	0	1
5	ORB2	0	0	0	0	1	0	0	0	1	0	1	0	0	1	0	1
6	KSRB1	0	0	0	1	1	1	1	0	1	0	1	0	0	1	0	1
7	KSRB2	0	0	0	0	1	0	1	0	1	0	1	0	0	1	0	1
8	MRB1	1	1	1	1	1	1	1	1	1	0	1	1	1	1	1	1
9	MRB2	1	1	1	1	1	1	1	1	1	0	1	1	1	1	1	1
10	MRB3	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
11	FRB1	1	1	1	1	1	1	1	1	1	0	1	1	1	1	1	1
12	FRB2	1	1	1	1	1	1	1	1	1	0	1	1	1	1	1	1
13	DRB1	0	0	0	0	1	0	0	0	1	0	1	0	1	1	0	1
14	DRB2	0	0	0	0	0	0	0	0	1	0	1	0	0	1	0	0
15	DRB3	0	0	0	0	0	0	0	0	1	0	1	0	0	1	1	1
16	DRB4	0	0	0	0	0	0	0	0	1	0	1	0	0	1	0	1

having the same level are grouped on the same level of the hierarchy.

Finally, a digraph is changed into an ISM model (Fig. 4) by replacing nodes of the barriers with statements. The model depicts how various barriers impact the implementation of data analytics. It shows that lack of commitment from top management being the most critical barrier (based on high driving power) cause in the implementation of data analytics in the manufacturing industry.

3.3 MICMAC analysis

MICMAC (Cross-impact matrix multiplication applied to classification) is based on the multiplication properties of matrices [86]. The purpose of MICMAC analysis is to identify and analyze the key barriers that drive the model. For this purpose, all the barriers are categorized into four quadrants (Fig. 5) according to their dependence and driving power: Independent, Linkages, Autonomous, and Dependent

Table 11 Level partition table: Iteration I–Iteration X

Code	Reachability set	Antecedent set	Intersection set	Level
ITRB1	1,2,3,4,5,6,7,9,11,14,16	1,8,9,10,11,12	1,9,11	VIII
ITRB2	2,4,5,6,7,9,11,14,16	1,2,8,9,10,11,12	2,9,11	VII
ITRB3	3,4,5,6,7,9,11,14,16	1,3,8,9,10,11,12	3,9,11	VII
ORB1	4,5,7,9,11,14,16	1,2,3,4,6,8,9,10,11,12,13	4,9,11	V
ORB2	5,9,11,14,16	1,2,3,4,5,6,7,8,9,10,11,12,13	5,9,11	III
KSRB1	4,5,6,7,9,11,14,16	1,2,3,6,8,9,10,11,12	6,9,11	VI
KSRB2	5,7,9,11,14,16	1,2,3,4,6,7,8,9,10,11,12	7,9,11	IV
MRB1	1,2,3,4,5,6,7,8,9,11,12,13,14,15,16	8,9,10,11,12	8,9,11,12	IX
MRB2	1,2,3,4,5,6,7,8,9,11,12,13,14,15,16	1,2,3,4,5,6,7,8,9,10,11,12,13,14,15,16	1,2,3,4,5,6,7,8,9,11,12,13,14,15,16	I
MRB3	1,2,3,4,5,6,7,8,9,10,11,12,13,14,15,16	10	10	X
FRB1	1,2,3,4,5,6,7,8,9,11,12,13,14,15,16	1,2,3,4,5,6,7,8,9,10,11,12,13,14,15,16	1,2,3,4,5,6,7,8,9,11,12,13,14,15,16	I
FRB2	1,2,3,4,5,6,7,8,9,11,12,13,14,15,16	8,9,10,11,12	8,9,11,12	IX
DRB1	5,9,11,13,14,16	8,9,10,11,12,13	9,11,13	IV
DRB2	9,11,14	1,2,3,4,5,6,7,8,9,10,11,12,13,14,15,16	9,11,14	I
DRB3	9,11,14,15,16	8,9,10,11,12,15	9,11,15	III
DRB4	9,11,14,16	1,2,3,4,5,6,7,8,9,10,11,12,13,15,16	9,11,16	II

Table 12 Conical matrix

Barriers	Code	9	11	14	16	5	15	7	13	4	6	2	3	1	8	12	10	Driving power	Rank
9	MRB2	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0	15	2
11	FRB1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0	15	2
14	DRB2	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	3	10
16	DRB4	1	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0	4	9
5	ORB2	1	1	1	1	1	0	0	0	0	0	0	0	0	0	0	0	5	8
15	DRB3	1	1	1	1	0	1	0	0	0	0	0	0	0	0	0	0	5	8
7	KSRB2	1	1	1	1	1	0	1	0	0	0	0	0	0	0	0	0	6	7
13	DRB1	1	1	1	1	1	0	0	1	0	0	0	0	0	0	0	0	6	7
4	ORB1	1	1	1	1	1	0	1	0	1	0	0	0	0	0	0	0	7	6
6	KSRB1	1	1	1	1	1	0	1	0	1	1	0	0	0	0	0	0	8	5
2	ITRB2	1	1	1	1	1	0	1	0	1	1	1	0	0	0	0	0	9	4
3	ITRB3	1	1	1	1	1	0	1	0	1	1	0	1	0	0	0	0	9	4
1	ITRB1	1	1	1	1	1	0	1	0	1	1	1	1	1	0	0	0	11	3
8	MRB1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0	15	2
12	FRB2	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0	15	2
10	MRB3	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	16	1
Dependence Power		16	16	16	15	13	6	11	6	10	9	7	7	6	5	5	1	149	
Rank		1	1	1	2	3	8	4	8	5	6	7	7	8	9	9	10		

[87, 88]. The first quadrant is of the barrier with weak driving and weak dependence power. These barriers are relatively disconnected from the system; hence they are called autonomous or excluded barriers. The second quadrant comprises those barriers which have weak driving power but strong dependence power. They are called dependent barriers. The third quadrant is of those barriers which have strong driving as well as dependence power. These barriers are unstable compared to others; hence, any effect on them leads to an impact on other barriers. They are called linkage variables. The fourth quadrant barriers are those that have strong driving power but weak dependence power. They are called independent barriers. The position coordinates of barriers, as derived from the reachability matrix, as shown in Table 13.

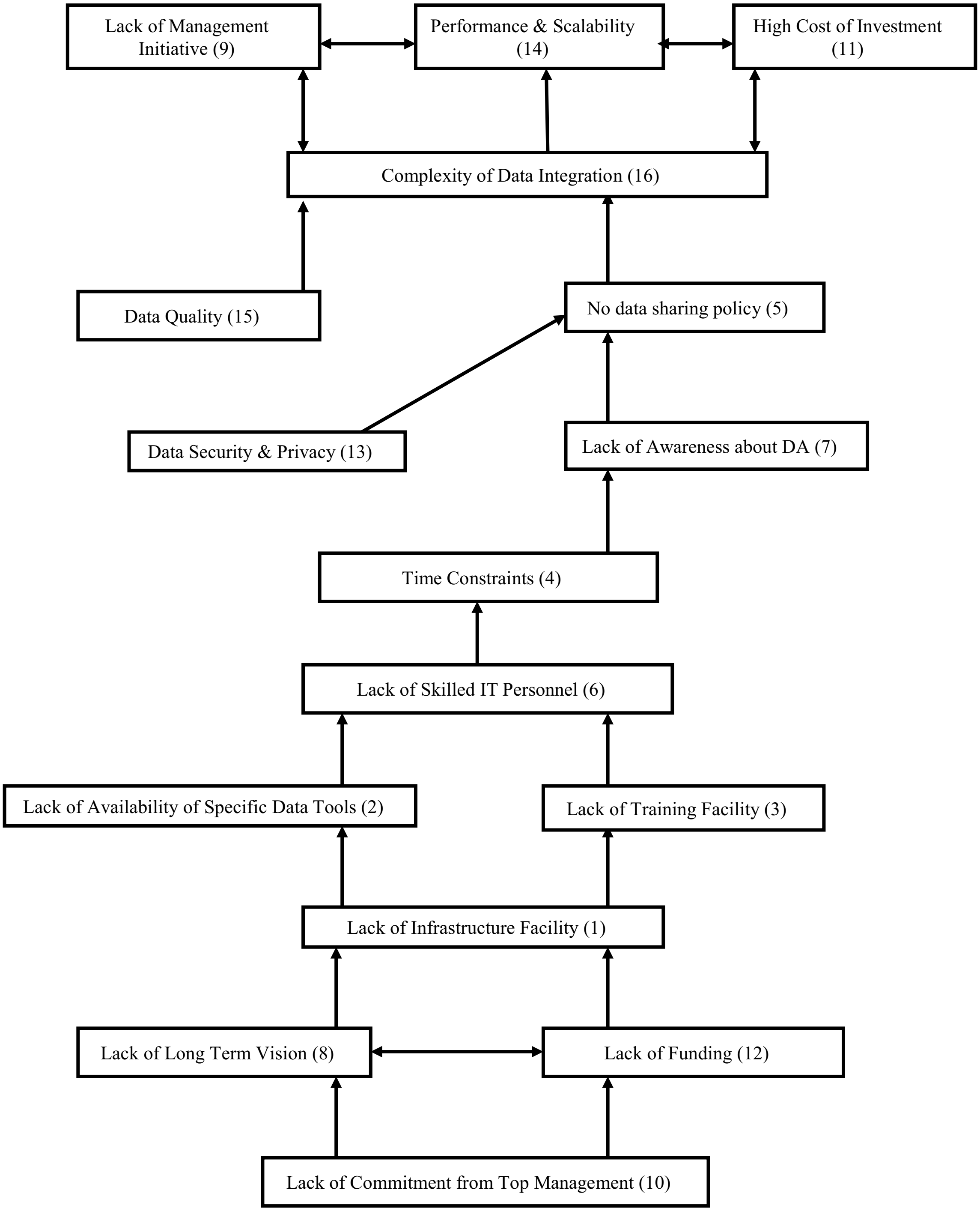

Fig. 4 ISM based model for barriers

4 Results and discussion on the outcome of ISM-MICMAC

This paper identifies sixteen barriers that create hindrances in the implementation of data analytics in the manufacturing industry from the literature review. ISM Modelling is used to structure and analyze these barriers. Figure 4 depicts the 16 barriers into ten levels through the ISM model. From the values of Table 13, a driving-dependence power graph (Fig. 5) is obtained from MICMAC analysis. MICMAC gives insights into the interdependencies among the 16 barriers. Significant findings of this study are summarized into four clusters:

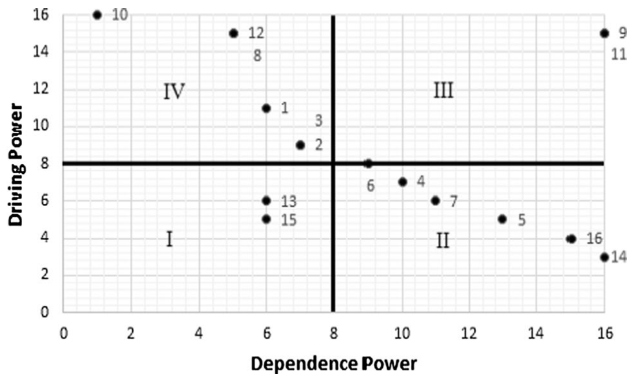

Fig. 5 MICMAC Analysis

Table 13 Position coordinates of identified barriers

Barriers	Code	Dependence power	Driving power
1	ITRB1	6	11
2	ITRB2	7	9
3	ITRB3	7	9
4	ORB1	10	7
5	ORB2	13	5
6	KSRB1	9	8
7	KSRB2	11	6
8	MRB1	5	15
9	MRB2	16	15
10	MRB3	1	16
11	FRB1	16	15
12	FRB2	5	15
13	DRB1	6	6
14	DRB2	16	3
15	DRB3	6	5
16	DRB4	15	4

First quadrant (Q-I): This is an autonomous quadrant. Barriers in this quadrant have weak driving and weak dependence power. These factors are generally disconnected and rarely influence the system. From the result of this study, poor data quality (DRB3) and data security & privacy (DRB1) appear in this quadrant, respectively, at levels III and IV in the ISM model. They may be essential but, compared to other barriers, are least connected with the system. These barriers are shown not to be against the implementation of data analytics. Data quality plays a critical role in Big data analytical techniques for extracting Hindsight, Insight, and Foresight [22, 23, 89].

Second quadrant (Q-II): This is a dependent quadrant. The barriers in this quadrant have weak driving power but strong dependence power. According to this study, the following barriers appear in this quadrant viz. time constraints (ORB1), no policy to share data among organization (ORB2), lack of awareness about data analytics (KSRB2), performance & scalability (DRB2), and complexity of data integration (DRB4). The absence of policy to share data among various departments in an organization creates a major hurdle in any data analytics project. It is also coupled with the complexity of data integration at the level I and II in the ISM model, which creates resistance to the implementation of data analytics.

Third quadrant (Q-III): This is a linkage quadrant. The barriers in this quadrant have both strong driving and dependence power. In this study, lack of management initiative (MRB2) and high cost of investment (FRB1) appear in this quadrant. Both of these barriers are positioned at level I in the ISM model. They play an important role in the implementation of data analytics in the manufacturing industry.

Fourth quadrant (Q-IV): This is an independent quadrant. Barriers in this quadrant have strong driving power and weak dependence power**.** As per this study, the following barriers appear in this quadrant: lack of infrastructure facility (ITRB1), unavailability of specific data tools (ITRB2), lack of training facility (ITRB3), lack of long term vision (MRB1), lack of commitment from top management (MRB3) and lack of funding (FRB2). Due to high driving power, these are the key barriers that impact the implementation of data analytics projects. All three barriers related to information technology positioned at level VII, and VIII in the ISM model, appear in this quadrant. While management-related barriers (MRB1, MRB3) are at level IX and X in the ISM model, it shows that targeting them can lead to the successful implementation of data analytics.

Manufacturing firms to implement BDA may require an expert to use, which is barrier 6 "Lack of skilled IT personal.". Does it mean that hiring skilled IT personal will solve the problem of BDA implementation? The answer may be "NO." Even if skilled IT personal are hired, the pressure will mount on "Lack of Availability of Specific Data Tools (barrier 2) and "Lack of Training Facility (barrier 3) because these are linked and have higher driving power thus need to ensure their availability else the implementation may face pressure.

Similarly, merely thinking about developing IT infrastructure facilities (barrier 1) may not help if sufficient funding is not available, and most importantly, the management must have the vision (barrier 8) and commitments (barrier 10). Management commitments and long-term vision have the highest driving power and can drive to remove all the obstacles in implementing BDA in manufacturing.

Table 14 Fuzzy triangular nos for criteria

Equal	1	(1,1,1)
Moderate	3	(2,3,4)
Strong	5	(4,5,6)
Very strong	7	(6,7,8)
Extremely strong	9	(9,9,9)
Intermediate value	2	(1,2,3)
	4	(3,4,5)
	6	(5,6,7)
	8	(7,8,9)

Table 17 Fuzzy geometrical mean

	Fuzzy geometrical mean (r_i)
ITRB1	0.371, 0.459, 0.589
ITRB2	0.22, 0.252, 0.302
ITRB3	0.833, 0.9983, 1.201
MRB1	1.698, 2.168, 2.70
MRB3	3.302, 3.95, 4.53
FRB2	0.818, 0.998, 1.22

4.1 Prioritization of drivers using Fuzzy AHP

The ISM-MICMAC analysis produced six barriers into the fourth quadrant. The indicators grouped in this quadrant are most important in terms of drivers and independence. These are the indicators that drive all other indicators. In this section, our motive is to prioritize these indicators and find the most prominent barrier. Subsequently, it will also help in establishing the relative criticality of the obtained critical barriers (high driving power) through the ISM-MICMAC model. These barriers will help management in framing the BDA strategies.

Fuzzy MCDM refers to the fuzzy objective requirement and fuzzy decision making [90, 91]. The steps of fuzzy AHP for finding out the weights of each criterion are as follows [92].

Step 1: Make a pairwise comparison matrix and determine the fuzzy triangular values using standard fuzzification as in Table 14.

Pairwise comparison matrix: Five experts from the manufacturing industry were asked to evaluate the barriers on [93, 94] comparative scale. The combined outcome is shown in Table 15.

Consistency indices, CI, RI, and CR values, respectively obtained, are 0.048, 1.24, and 0.039. These indices indicate responses received are consistent.

The standard triangulated fuzzy pairwise comparison matrix is created by converting expert opinion in Table 15 using the standard triangulated criteria in Table 14. The resulting Fuzzy matrix is shown in Table 16.

Step 2: Calculated Fuzzy geometrical mean value (r_i):

Obtained by fuzzy number multiplication: $A_1 \times A_2 = (l_1, m_1, u_1) \times (l_2, m_2, u_2) = (l_1 * l_2, m_1 * m_2, u_1 * u_2)$

$$r_i = (l_{i1} * l_{i2} \cdots l_{in})^{1/n}, (m_{i1} * m_{i2} \cdots m_{in})^{1/n}, (u_{i1} * u_{i2} \cdots u_{in})^{1/n}$$

where ***l*, *m*,** and ***u*** represents a lower, middle, and upper fuzzy number. ***n*** represents the number of columns.

Ex. For the first row: geometrical mean would be.

r_1 = [{(1*2*1/4*1/6*1/8*1/4)^(1/6)},{(1*3*1/3*1/5*1/7*1/3)^(1/6)}, {(1*4*1/2*1/4*1/6*1/2)^(1/6)}].

Table 15 Expert relative opinion on the barriers

	ITRB1	ITRB2	ITRB3	MRB1	MRB3	FRB2
ITRB1	1.00	3.00	1/3	1/5	1/7	1/3
ITRB2	1/3	1.00	1/5	1/7	1/9	1/4
ITRB3	3.00	5.00	1.00	1/3	1/5	1.00
MRB1	5.00	7.00	3.00	1.00	1/3	3.00
MRB3	7.00	9.00	5.00	3.00	1.00	4.00
FRB2	3.00	4.00	1.00	1/3	1/4	1.00

Table 16 Fuzzy pairwise matrix

	ITRB1	ITRB2	ITRB3	MRB1	MRB3	FRB2
ITRB1	1,1,1	2,3,4	1/4,1/3,1/2	1/6,1/5,1/4	1/8,1/7,1/6	1/4,1/3,1/2
ITRB2	1/4,1/3,1/2	1,1,1	1/6,1/5,1/4	1/8,1/7,1/6	1/9,1/9,1/9	1/5,1/4,1/3
ITRB3	2,3,4	4,5,6	1,1,1	1/4,1/3,1/2	1/6,1/5,1/4	1,1,1
MRB1	4,5,6	6,7,8	2,3,4	1,1,1	1/4,1/3,1/2	2,3,4
MRB3	6,7,8	9,9,9	4,5,6	2,3,4	1,1,1	3,4,5
FRB2	2,3,4	3,4,5	1,1,1	1/4,1/3,1/2	1/5,1/4,1/3	1,1,1

The computed r_i values for the six high impact barriers are shown in Table 17.

Step 3: Evaluate Fuzzy weights

The formula used for getting weight is:

$$w_i = r_i * \left(r_1 + r_2 + \cdots + r_m\right)^{-1}$$

where "***m***" represents the number of rows.

$$\left(r_1 + r_2 + r_3 + r_4 + r_5 + r_6\right) = (7.243, 8.8234, 10.54)$$

$$\left(r_1 + r_2 + \cdots + r_m\right)^{-1} = (0.095,\ 0.1133,\ 0.138)$$

Fuzzy weights obtained using the formula for w_i are displayed in Table 18.

Step 4: De-Fuzzification

Now, De-Fuzzify the number using the center of area method (COA) using the expression given below

$$w_i = \left(\frac{l + m + u}{3}\right)$$

Fuzzy weights in Table 18 are Defuzzified as in Table 19, using the above expression.

Step 5: Normalized weights

The De-fuzzified weights obtained as in Table 19 are normalized in 0–1 and 0–100% scales as in Table 20.

Therefore, the priority of the independent barriers are as follows: MRB3 > MRB1 > FRB2 > ITRB3 > ITRB1 > ITRB2.

Table 18 Fuzzy weights

	Fuzzy weights (w_i)
ITRB1	0.035, 0.052, 0.081
ITRB2	0.021, 0.0286, 0.042
ITRB3	0.079, 0.1131, 0.166
MRB1	0.161, 0.2458, 0.372
MRB3	0.313, 0.4473, 0.625
FRB2	0.078, 0.1131, 0.168

Table 19 De-Fuzzify weights

	De-Fuzzify weights
ITRB1	0.056
ITRB2	0.030
ITRB3	0.119
MRB1	0.260
MRB3	0.462
FRB2	0.120

Table 20 Normalized weights

Barriers	Code	Normalized weights	
Lack of commitment from top management	MRB3	0.441	44.10%
Lack of long term vision	MRB1	0.248	24.80%
Lack of training facilities	ITRB3	0.114	11.40%
Lack of funding	FRB2	0.114	11.40%
Lack of infrastructure facility	ITRB1	0.054	5.40%
Lack of availability of specific data tools	ITRB2	0.029	2.90%

4.2 Consistency check for FAHP

A modified method for calculating λmax (relative weight), consistency index (CI), and consistency ratio(CR) is developed.

λmax = average (λlmax, λmmax, λumax); where l, m and u are suffix representing matrix formed by lower, medium, and upper values respectively.

λmax= average (5.147, 6.231, 7.60) = 6.327

CI = (λmax-n)/(n−1); n= matrix order = 6

CI = (6.327−6)/(6−1) = 0.0654;

CR = CI/RI, RI for corresponding "n=6" is 1.24 [93].

Condition for consistency: CR<0.1

CR = 0.0654/1.24 = 0.0527 <0.1 hence consistent.

5 Conclusion

Manufacturing firms in emerging economies are eager to implement BDA techniques and tools to remain competitive and maintain sustained firms' operations and performance. The adoption of BDA technology is at a nascent stage in manufacturing industries. The Indian manufacturing firms, in particular, are facing barriers to the implementation of BDA. Therefore, this paper is instrumental to the BDA literature concerning the manufacturing landscape by evaluating the importance of each barrier by using the ISM-MICMAC and Fuzzy AHP analytical approaches.

Sixteen barriers were obtained through literature study, and subject-related experts categorized the barriers into six groups. These barriers were analyzed using ISM. Barriers were structured in the ISM model and ranked based on their driving and dependence power to understand where they lie in MICMAC analysis. The research concludes that Management, Infrastructure & Technology related barriers are critical barriers (High driving power) to BDA implementation. Six sub-barriers, namely lack of commitment from top management (MRB3), lack of long term vision (MRB1), lack of funding (FRB2), lack of infrastructure facility (ITRB1), lack of availability of specific data tools (ITRB2), and lack of training facilities (ITRB3), are the critical barriers in driving for the implementation of BDA in the manufacturing industry. Lack of commitment from top management (MRB3), lack of long-term vision (MRB1) are management-related and are at Xth and IXth level in the ISM model. These levels depict the highest driving power. Lack of funding (FRB2) is related to finance while, lack of infrastructure facility (ITRB1), lack of availability of specific data tools (ITRB2), and lack of training facilities (ITRB3) are related to IT infrastructure & Technology.

Six sub-barriers are further investigated using Fuzzy-AHP for finding their relative criticality. The Sub-barrier lack of commitment from top management (MRB3) is the most critical driver, which confirms the outcome of the ISM model. The top two critical Drivers are management-related.

A similar study done in Bangladesh's manufacturing supply chain found IT infrastructure as a vital barrier followed by data privacy [14]. A study on the green lean six sigma implementation issue found that IT infrastructure and management are prominent factors [76], while Knowledge of Technology was a critical barrier to m-commerce adaptation SME's in the UK [77]. Our findings are supported by the study done previously in different domains and geography, at least on critical barriers; Management and Infrastructure & Technology. This paper will help decision-makers in manufacturing companies formulate strategies related to BDA in their respective firms.

5.1 ISM MICMAC for academia

In this era of digitization, the absorbing power of students and researchers has increased tremendously. Thus, academic professionals can use this technique to figure out an active classroom pedagogical approach for application-based teaching to be better equipped to handle real-life scenarios in the business context. Work on trapezoidal fuzzification version of ISM-MICMAC may be developed and tested for its accuracy and reliability.

5.2 ISM MICMAC for industry

This methodology has varied applications across the industry. For example, it can be used for long-range planning. This methodology can also be used for designing processes, planning of career, strategic planning, solution of complex engineering enablers, design of products, re-engineering, financial decision making, Strategic human resource management (HRM), and e-commerce.

6 Limitations and future scope

This paper shows that 16 barriers have been identified, posing a hindrance to the implementation of data analytics in the manufacturing industry. Using ISM and MICMAC analysis, a model is developed. First, enough literature related to the topic of this study is not available. For this paper, literature related to sustainable supply chain management, reverse logistics, and remanufacturing is found, but there are hardly any research papers focused on India attempting linkages between barriers that impact the implementation of data analytics in the manufacturing sector. The barriers are identified through the literature review of journals and discussed with subject matter experts from the industry. The present study is entirely based on the subjective judgments of experts from the industry. This study can be expanded by identifying and incorporating the most significant barriers which are related to the implementation of data analytics in different sectors of the manufacturing firms in India. Some more factors like Data governance issues, Aligning BDA with corporate strategy, Ethical uses of BDA, Legislative and regulatory compliance, etc., can also be explored before finalizing the framework. The study was focused on the Indian manufacturing sector. The study may be extended to explore cross-country and cross-sector impact.

Appendix A

See Tables 21, 22, 23, 24, 25, 26, 27, 28, 29, and 30.

Table 21 Level partition–Iteration I

Barriers	Reachability set	Antecedent set	Intersection set	Level
1	1,2,3,4,5,6,7,9,11,14,16	1,8,9,10,11,12	1,9,11	
2	2,4,5,6,7,9,11,14,16	1,2,8,9,10,11,12	2,9,11	
3	3,4,5,6,7,9,11,14,16	1,3,8,9,10,11,12	3,9,11	
4	4,5,7,9,11,14,16	1,2,3,4,6,8,9,10,11,12,13	4,9,11	
5	5,9,11,14,16	1,2,3,4,5,6,7,8,9,10,11,12,13	5,9,11	
6	4,5,6,7,9,11,14,16	1,2,3,6,8,9,10,11,12	6,9,11	
7	5,7,9,11,14,16	1,2,3,4,6,7,8,9,10,11,12	7,9,11	
8	1,2,3,4,5,6,7,8,9,11,12,13,14,15,16	8,9,10,11,12	8,9,11,12	
9	**1,2,3,4,5,6,7,8,9,11,12,13,14,15,16**	**1,2,3,4,5,6,7,8,9,10,11,12,13,14,15,16**	**1,2,3,4,5,6,7,8,9,11,12,13,14,15,16**	**I**
10	1,2,3,4,5,6,7,8,9,10,11,12,13,14,15,16	10	10	
11	**1,2,3,4,5,6,7,8,9,11,12,13,14,15,16**	**1,2,3,4,5,6,7,8,9,10,11,12,13,14,15,16**	**1,2,3,4,5,6,7,8,9,11,12,13,14,15,16**	**I**
12	1,2,3,4,5,6,7,8,9,11,12,13,14,15,16	8,9,10,11,12	8,9,11,12	
13	5,9,11,13,14,16	8,9,10,11,12,13	9,11,13	
14	**9,11,14**	**1,2,3,4,5,6,7,8,9,10,11,12,13,14,15,16**	**9,11,14**	**I**
15	9,11,14,15,16	8,9,10,11,12,15	9,11,15	
16	9,11,14,16	1,2,3,4,5,6,7,8,9,10,11,12,13,15,16	9,11,16	

The bold signifies the barriers entering into the partitioning level during iteration

Table 22 Level partition–Iteration II

Barriers	Reachability set	Antecedent set	Intersection sset	Level
1	1,2,3,4,5,6,7,16	1,8,10,12	1	
2	2,4,5,6,7,16	1,2,8,10,12	2	
3	3,4,5,6,7,16	1,3,8,10,12	3	
4	4,5,7,16	1,2,3,4,6,8,10,12,13	4	
5	5,16	1,2,3,4,5,6,7,8,10,12,13	5	
6	4,5,6,7,16	1,2,3,6,8,10,12	6	
7	5,7,16	1,2,3,4,6,7,8,10,12	7	
8	1,2,3,4,5,6,7,8,12,13,15,16	8,10,12	8,12	
10	1,2,3,4,5,6,7,8,10,12,13,15,16	10	10	
12	1,2,3,4,5,6,7,8,12,13,15,16	8,10,12	8,12	
13	5,13,16	8,10,12,13	13	
15	15,16	8,10,12,15	15	
16	**16**	**1,2,3,4,5,6,7,8,10,12,13,15,16**	**16**	**II**

The bold signifies the barriers entering into the partitioning level during iteration

Table 23 Level partition–Iteration III

Barriers	Reachability set	Antecedent set	Intersection set	Level
1	1,2,3,4,5,6,7	1,8,10,12	1	
2	2,4,5,6,7	1,2,8,10,12	2	
3	3,4,5,6,7	1,3,8,10,12	3	
4	4,5,7	1,2,3,4,6,8,10,12,13	4	
5	**5**	**1,2,3,4,5,6,7,8,10,12,13**	**5**	**III**
6	4,5,6,7	1,2,3,6,8,10,12	6	
7	5,7	1,2,3,4,6,7,8,10,12	7	
8	1,2,3,4,5,6,7,8,12,13,15	8,10,12	8,12	
10	1,2,3,4,5,6,7,8,10,12,13,15	10	10	
12	1,2,3,4,5,6,7,8,12,13,15	8,10,12	8,12	
13	5,13	8,10,12,13	13	
15	**15**	**8,10,12,15**	**15**	**III**

The bold signifies the barriers entering into the partitioning level during iteration

Table 24 Level partition–Iteration IV

Barriers	Reachability set	Antecedent set	Intersection set	Level
1	1,2,3,4,6,7	1,8,10,12	1	
2	2,4,6,7	1,2,8,10,12	2	
3	3,4,6,7	1,3,8,10,12	3	
4	4,7	1,2,3,4,6,8,10,12,13	4	
6	4,6,7	1,2,3,6,8,10,12	6	
7	**7**	**1,2,3,4,6,7,8,10,12**	**7**	**IV**
8	1,2,3,4,6,7,8,12,13	8,10,12	8,12	
10	1,2,3,4,6,7,8,10,12,13	10	10	
12	1,2,3,4,6,7,8,12,13	8,10,12	8,12	
13	**13**	**8,10,12,13**	**13**	**IV**

The bold signifies the barriers entering into the partitioning level during iteration

Table 25 Level partition–Iteration V

Barriers	Reachability set	Antecedent set	Intersection set	Level
1	1,2,3,4,6	1,8,10,12	1	
2	2,4,6	1,2,8,10,12	2	
3	3,4,6	1,3,8,10,12	3	
4	**4**	**1,2,3,4,6,8,10,12**	**4**	**V**
6	4,6	1,2,3,6,8,10,12	6	
8	1,2,3,4,6,8,12	8,10,12	8,12	
10	1,2,3,4,6,8,10,12	10	10	
12	1,2,3,4,6,8,12	8,10,12	8,12	

The bold signifies the barriers entering into the partitioning level during iteration

Table 26 Level partition–Iteration VI

Barriers	Reachability set	Antecedent set	Intersection set	Level
1	1,2,3,6	1,8,10,12	1	
2	2,6	1,2,8,10,12	2	
3	3,6	1,3,8,10,12	3	
6	**6**	**1,2,3,6,8,10,12**	**6**	**VI**
8	1,2,3,6,8,12	8,10,12	8,12	
10	1,2,3,6,8,10,12	10	10	
12	1,2,3,6,8,12	8,10,12	8,12	

The bold signifies the barriers entering into the partitioning level during iteration

Table 27 Level partition–Iteration VII

Barriers	Reachability set	Antecedent set	Intersection set	Level
1	1,2,3	1,8,10,12	1	
2	**2**	**1,2,8,10,12**	**2**	**VII**
3	**3**	**1,3,8,10,12**	**3**	**VII**
8	1,2,3,8,12	8,10,12	8,12	
10	1,2,3,8,10,12	10	10	
12	1,2,3,8,12	8,10,12	8,12	

The bold signifies the barriers entering into the partitioning level during iteration

Table 28 Level partition–Iteration VIII

Barriers	Reachability set	Antecedent set	Intersection set	Level
1	**1**	**1,8,10,12**	**1**	**VIII**
8	1,8,12	8,10,12	8,12	
10	1,8,10,12	10	10	
12	1,8,12	8,10,12	8,12	

The bold signifies the barriers entering into the partitioning level during iteration

Table 29 Level partition–Iteration IX

Barriers	Reachability set	Antecedent set	Intersection set	Level
8	**8,12**	**8,10,12**	**8,12**	**IX**
10	8,10,12	10	10	
12	**8,12**	**8,10,12**	**8,12**	**IX**

The bold signifies the barriers entering into the partitioning level during iteration

Table 30 Level partition–Iteration X

Barriers	Reachability set	Antecedent set	Intersection set	Level
10	**10**	**10**	**10**	**X**

The bold signifies the barriers entering into the partitioning level during iteration

Appendix B

See Table 31.

Table 31 Details of expert profile and related company

Company-name	Type of product	Company size (Turnover/Employee strength)	Respondent expertise	Expert-Mgt position	Year of experience
A: Automotive company	Four wheelers: Multi-segment cars	Turnover: approx Rs. 80 thousand crore	Production and operations	General manager	Approx 20 years
		Employee: 15,945	Procurement and sourcing	Senior manager	12 years
			Logistics and supply chains	Assistant general manager	17 years
B: Automotive company	Two wheelers: different ranges of bykes	Turnover: approx Rs. 19 thousand crore	Production and operations	Manager	10 years
		Employee: 8599	R&D	Senior manager	13 years
			Sales and marketing	Senior manager	13 years
			Product development and new initiatives	Assistant general manager	17 years
C: Steel industry	Sheets, Rods, bars	Turnover: approx Rs. 1.4 trillion	Plant operations, quality	Senior Manager	12 years
		Employee: 32,364	Quality assurance and control	quality expert	15 years
			Boiler, Process expert, production	Manager	11 years
D: Electrical equipment company	Consumer products (Appliances, Fans, Lighting), Exports, and EPC (Illumination, Transmission Towers and Power Distribution)	Turnover: approx Rs. 3000 crores	Procurement and sourcing	Chief manager	17 years
		Employee: 3007	Production and operations	Manager	12 years
			R&D	Senior Manager	14 years
E: Atomotive parts manufacturer	Pistons, cylinders, piston rings, engine values	Turnover: approx Rs. 1850 crores	Logistic and supply chains	Manager	12 years
		Employee: 4285	Plant operations and quality assurance	Plant head	17 years
			business development	Senior manager	15 years

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