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Big data analytics application for sustainable manufacturing operations: analysis of strategic factors

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Abstract

In the present era of Industry 4.0, organizations are transforming from traditional production systems to digital production systems. This transformation is in terms of additional deployment of technologies that lead to digitization and integration of products and services, business processes and customers, etc. A high volume of unstructured data is being created across different processes due to digitization. The digitization captures the data that includes text, images, multimedia, etc., due to multiplicity of platforms, e.g., machine-to-machine communications, sensors networks, cyber-physical systems, and Internet of Things. Managing this huge data generated from different sources has become a challenging task. Big data analytics (BDA) may be helpful in managing this unstructured data for effective decision making and sustainable operations. Many organizations are struggling to integrate BDA with their manufacturing processes for sustainable operations. The application of BDA from a sustainability perspective is not extensively researched in the current literature. Therefore, firstly this study explores the contribution of BDA in sustainable manufacturing operations. It further identifies strategic factors for the successful application of BDA in manufacturing for sustainable operations. For a detailed analysis of strategic factors in manufacturing, a hybrid approach comprising the analytic hierarchy process, fuzzy TOPSIS and DEMATEL is used. Results revealed that development of contract agreement among all stakeholders, engagement of top management, capability to handle big data, availability of quality and reliable data, developing team of knowledgeable, and capable decision-makers have emerged as major strategic factors for the application of BDA in the manufacturing sector for sustainable operations. Major contribution of this study is in analyzing BDA benefits for manufacturing sector, identifying major strategic factors in implementation and categorization of these factors into cause and effect group. These findings may be used by managers as guidelines for successful implementation of BDA across different functions in their respective organization to achieve sustainable operations goal. The results of this study will also motivate industry professionals to integrate BDA with their manufacturing functions for effective decision making and sustainable operations.
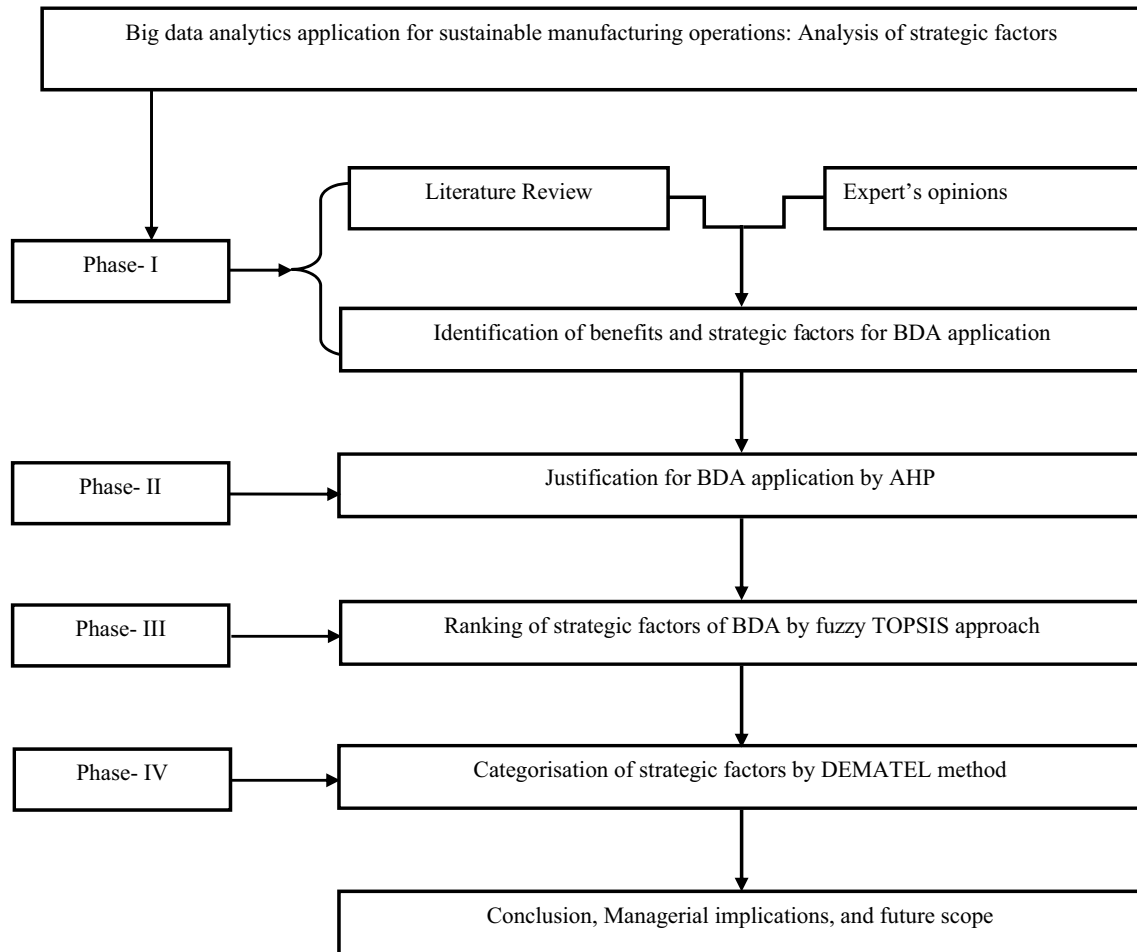

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Graphic abstract

| Big data analytics application for sustainable manufacturing operations: Analysis of strategic factors |

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Identification of benefits and strategic factors for BDA application

Phase- II → Justification for BDA application by AHP

Phase- III → Ranking of strategic factors of BDA by fuzzy TOPSIS approach

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Introduction

Manufacturing sector is generating a huge amount of unstructured data due to the use of various digital machines, electronic devices, and sensors on shop floors and production lines (Zhong et al. 2015). Managing this unstructured huge data is becoming a herculean task for industry professionals. Brinch et al. (2017) have observed that big data analytics can help in streamlining of this huge data for decision making and planning of operations. Gong et al. (2018) have found that BDA applications are getting popular across different functions of the supply chain. BDA is a new age technology to manage and integrate data to improve manufacturing performance (Bi and Cochran 2014). In addition, BDA can help plant automation in the era of the fourth industrial revolution (Telukdarie et al. 2018; Tseng et al. 2019). The term BDA refers to the use of advanced analytic techniques

such as applied mathematical analysis, predictive analytics, data processing, etc.. These techniques provide better insight about the processes that help in timely and right decision making and improving business processes. In the context of BDA, 5 V stands for the following characteristics of data: volume (dimension of data), velocity (flow rate of data), variety (different formats of data), veracity (uncertainty of data), and value (quality of data)" (Tao et al. 2018). In general, BDA is associated with typical data analysis and mining approaches, employed on a big volume of data. Data usually comes from various sources and needs to go through a sequence of procedures for meaningful analysis (Chen et al. 2014). BDA may be applied across the different functions of the supply chain, such as sourcing, manufacturing, distribution, and marketing (Sanders 2016).

BDA plays a crucial role in improving business benefits and operational efficiency. A business benefit is a quantifiable outcome of an activity or decision that helps meet

business goals. For example: cost savings, revenue growth, improved quality, risk reduction, etc. Application of BDA in the manufacturing sector reduces processing defects to get better quality of items produced in a manufacturing firm, saves time and money, as it aids in better and real-time decision making. The real-time data capture and instant processing through advanced algorithms in BDA will help in better and real-time decision making. It has the ability to analyze equipment failures, production bottlenecks, supply chain deficiencies, etc., that enables better decision making. BDA also gives manufacturers a better insight by identifying patterns, measuring impact, and predicting outcomes. BDA is helpful to improve product lifecycle management (Li et al. 2015). In addition, BDA is useful to other areas such as performance management, health care, and governmental services (Elgendy and Elragal 2014). BDA provides improved data-driven decision making, which lead to deeper insight into business operations and as a result better performance management. In the health industry, a large amount of data is generated to control and monitor the various processes of treatment, protection, and management of patient's medical records, and regulatory requirements. BDA helps in health care as online patient scheduling, to prescribe treatments, and make clinical decisions with greater accuracy. BDA assists the government in fighting crime, enhancing transparency, improving transportation, etc. by applying predictive analytics and machine learning to big data and providing real-time access. In addition to this, with the high volume of data from sensors and satellite images, government can forecast in advance and quickly take action to minimize losses due to natural disaster. Higher productivity goals may be also achieved if predictive analytic tools are employed for monitoring and forecasting of workers' performance. Zhong et al. (2016) has observed that BDA plays a significant role in the efficient management of the health care industry and the digitization of records. Here, the digitalization of record means all the available data in a text-searchable format to retrieve the content easily for specific information. The data can be shared instantaneously to all the relevant parties, without managing a large volume of paper documents.

BDA reduces the processing time of structured and unstructured data (Barlow 2013). Overall business performance is getting impacted by BDA as BDA-enabled organizational activities assist to lower operating costs, improve product quality, and improve product delivery (Lin et al. 2018). It helps organizations for the better forecast; as a result, organizations realize operational process benefits in the form of cost reductions, better operations planning, lower inventory levels, and elimination of waste. Thus it improves the overall performance of the organization, i.e., profitability, productivity, efficiency, etc. (Gunasekaran et al. 2017). Wamba et al. (2020) have observed that BDA can improve supply chain agility, adaptability, and operational excellence.

For a manufacturing organization, BDA increases comparative advantage by strengthening the decision-making process making faster and better decisions, and increasing the capability of organizations (Dubey et al. 2016). It promotes innovation by providing the valuable information to improve the manufacturing operations and offers a means to manage environmental uncertainty; thus, it improves the overall performance of the organization.

Big data predictive analytics also facilitates in the sustainability of supply chains (Gandomi and Haider 2015). Predictive analytics tools of BDA help to get insights from data about what can happen in the future from available big data by discovering meaningful patterns of data using data mining tool like machine learning, artificial intelligence, and pattern repository system. Artificial intelligence and machine learning assist to identify inefficiencies, automate decision making, and improve the customer buying experience, which will improve sustainability of supply chain. Thus, big data predictive analysis assists in identifying and prioritizing the most important environmental and social challenges for improving the sustainability supply chain. According to Dubey et al. (2016), manufacturing organizations should adopt BDA for sustainable manufacturing operations. Continuous monitoring and analysis of operational data in real time helps in removing bottlenecks. Big data analytics helps in defect detection, predict machine failure, minimize risks, improve performance, and reduce downtime. BDA could help manufacturing firms to apply sustainable practices in more effective manner to enhance productivity. Big data support and improve sustainability measure in various operations by better management of sustainability practices of reduce, reuse and recycle. BDA also ensures lean and green manufacturing with resources optimization (Gunasekaran et al. 2017; Ji-fan Ren et al. 2017; Doolun et al. 2018). Sustainable manufacturing operations improve overall firm performance in terms of resources saving and reducing negative environmental impact (Braganza et al. 2017). Bag et al. (2020) have observed in context to the South Africa mining industry that big data analytics significantly contribute to green product development and sustainable supply chain outcomes. The environmental impact of manufacturing processes can influence the reputation of the organization in the long term (Wood et al. 2016).

The manufacturing organizations realize operational benefits in the form of cost reductions, better operations planning, lower inventory levels, better organization of the labor force and elimination of waste, while they leverage improvements in operations effectiveness and customer service as a result of BDA implementation. Popovič et al. (2018) established that the implementation of BDA reduces the consumption of materials (10–15%), energy (about 5%), scrap and rework (about 15%), and manual labor (about 20%). Also, their study revealed that implementation of BDA

reduced the maintenance and waste costs for about 12.5% on a year-to-year basis. On the other hand, particularly concerning the delivery of goods to the customer, it increases the satisfaction of customers. Companies incorporate effective decision-making process on the basis of meaningful information derived through data analytics which help them to run smarter, more agile and efficient businesses (Demirkan and Delen 2013).

Belhadi et al. (2019) have observed that researchers have not significantly explored the capabilities of BDA for sustainable manufacturing processes. Apart from it, studies on application of BDA in manufacturing sector in context to devloping countries like India are limited. Many organizastions are still working on silos and not automating their processes as per philosophy of Industry 4.0. This provides a research gap for the problem of current study, i.e., to investigate the strategic factors in implementation of I4.0 technologies such as BDA to achieve sustainable operations goal. The findings of this study will positively impact the successful implementation of BDA in manufacturing operations and will motivate the industry professionals to prioritize their resources to invest in BDA. Manufacturing organizations are facing severe challenges to adopt new technology for sustainable operations (Singh et al. 2019). Therefore, this study investigates strategic factors for implementing BDA in the manufacturing sector to make manufacturing operations more sustainable. The main objectives of this study are as follows:

- To justify the applications of BDA to ensure sustainable manufacturing operations.
- To identify strategic factors and rank them for implementing BDA in the manufacturing sector.
- To categories strategic factors in causes and effects from strategic perspective.

The structure of this paper is as follows: "Literature review" section deals with the literature review on big data applications for sustainable manufacturing operations, and the strategic factors for its implementation. In "Research methodology" section, the research methodology is discussed. "Results and discussion" section presents the obtained results and discussion. Finally, the conclusion, limitations, future scope, and managerial implications of the study are provided in "Conclusion, limitations, future scope, and managerial implications" section.

Literature review

In this section, literature review is presented on BDA applications for sustainable manufacturing operations and identification of strategic factors for BDA implementation in the manufacturing sector.

BDA applications for sustainable manufacturing operations

In the prevailing business environment of economic slowdown, manufacturers are aiming to reduce waste and improve value. Customers are looking for high-quality and low-cost products (Dubey et al. 2016; Fercoq et al. 2016). Therefore, there is a challenge in front of manufacturing organizations to meet these expectations. BDA may be a possible solution to this problem due to its many benefits. In this subsection, the authors identify the various benefits of BDA applications in the manufacturing sector from a sustainability perspective from the existing literature which are summarized in Table 1. The main sustainability benefits of BDA application in manufacturing operations are enhanced production recovery/reuse, energy-efficient and safe processes, improved customer satisfaction, improvement in profit margin, waste minimization, resource optimization, developing sustainable capabilities. Here, developing sustainable capabilities means the ability of firms to respond to their short-term financial objectives as well as future goals for profound changes in the current production systems. These benefits are further classified into three aspects, i.e., economic, social, and environmental. The benefit "Enhanced production recovery/reuse" refers to the increase in the production rate of a manufacturing system that is achieved through the effective implementation of various techniques such as lean, Kaizen, six sigma, cloud-based enterprise resource planning, etc., with the help of BDA. Reuse infers that things are utilized by the second user without prior operations or as originally designed. The energy consumption, impact on the environment, and cost, would be reduced by accurate and timely decisions taken with the support of data analytics (Hazen et al. 2016; Raut et al. 2019). "Improved customer satisfaction" is the continuous change due to optimal forecast to meet organization targets and customer requirements. Utilizing BDA, the customer may be effectively involved with green purchasing practices, cleaner production, eco-labelling, and eco-design feedback (Raut et al. 2019). For instance, optimization and machine learning have been used to select suppliers with low carbon emissions and supply chain carbon maps are generated using BDA for identifying hot spots of carbon emission so that they can be reduced (Acquaye et al. 2014; Singh et al. 2018). Additionally, customer loyalty can be improved with BDA analysis of sentiment (Dubey et al. 2016). The firm should have a BDA-based data offering structure to its customers.

Tseng et al. (2019) stated that to build successful sustainable manufacturing operations, firms should upgrade the synchronization of financial-related decisions, obtain cost information, focus on service and quality of the product, and ensure improved customer satisfaction. BDA helps in reducing costs of manufacturing processes along with final

Table 1 Big data analytics sustainability benefits for manufacturing organizations

Benefits	Description	References	Sustainability aspects		
			Economic	Social	Environmental
Enhanced production recovery and reuse (EPRR)	Refers to increase in the production rate of a manufacturing system that is achieved through the implementation of various techniques	Amui et al. (2017), Lee et al. (2015), ElMaraghy et al. (2017)	√		√
Energy-efficient and safe processes (EESP)	Reduce the amount of energy required to provide products and services	Raut et al. (2019), Wang et al. (2019), Das et al. (2020)	√	√	√
Improved customer satisfaction (ICS)	Continuous change in expected performance by accurate forecast to meet organization targets	Dubey et al. (2016), Raut et al. (2019), Gawankar et al. (2020)		√	
Improvement in profit margin (IPM)	Refer to increasing the amount of profit made from the sale	Gawankar et al. (2020),Wang et al. (2019)	√		
Waste minimization (WM)	Systematic method for the minimization of waste within a manufacturing system without sacrificing productivity, which can cause problems	Song et al. (2019), Manavalan and Jayakrishna (2019), Cui et al. (2020)	√		√
Resources optimization (RO)	Refers capacity to intricate resources in an efficient way to accomplish a sustainable goal	Amui et al. (2017), Singh and El-Kassar (2019), Song et al. (2019)	√		√
Developing sustainable capabilities (DSC)	Ability of firms to respond to their short-term financial objectives as well as future goals	Singh and El-Kassar (2019), Amui et al. (2017)	√	√	√

costs of products and components. Using predictive analytics, the manufacturer can schedule predictive maintenance that allows manufacturers to prevent costly asset breakdowns and avoid unexpected downtime which lead to reduce operational costs.

Sustainable manufacturing focuses on resource optimization without compromising with the productivity or effectiveness of manufacturing operations. Resource optimization refers to the optimal usage of available resources and to reduce carbon dioxide emissions, harmful materials, etc., from different manufacturing processes (Piyathanavong et al. 2019). Sustainable natural resource management requires complete thought of different factors with the goal that available resources may meet the requirement of contemporary society along with future generations (Mustapha et al. 2017). Sustainable capability is the ability of firms to respond to their short-term financial objectives as well as future goals. The capacity to integrate intricate resources in a successful way to accomplish sustainable goals, convey sustained values to its stakeholders, and gain sustainable competitive advantage constitute a firm's sustainable capabilities. Subsequently, by coordinating green human resources management, and green supply chain management, etc., firms can develop such sustainable capabilities that lead to enhancing performance at the ecological, environmental and social levels (Amui et al. 2017). Singh and El-Kassar (2019) have

observed that organizations should have an environmental policy in place and their management should support implementing such environment-friendly practices.

Table 1 categorizes these sustainability benefits from three perspectives of the triple bottom line approach, i.e., social, economical and environmental. In manufacturing organization, minimization of manufacturing time and increasing reuse of components belong to social aspects of sustainability. Economic aspects include reduction of manufacturing cost, maintenance, and recycling. Environmental aspects refer to reduction in carbon dioxide emission, electric consumption, component packaging, and component weight (Raut et al. 2019).

Identification of strategic factors for big data analytics application

In this subsection, authors have reviewed the literature to identify strategic factors of BDA application for sustainable manufacturing. Strategic factors are defined as the attributes required to ensure overall success for an enterprise. In other words, strategic factors include issues vital to an organization's current activities. Based on the review of the literature, several strategic factors are identified. These strategic factors are listed in Table 2 with their brief description. Many organizations in developing countries are constrained with

limited access to technology, finances, infrastructure and skilled manpower. However, this is not the case with most of the organizations located in the developed countries (Kumar et al. 2020). Therefore, the strategic factors may be different for developing countries from the developed countries. The literature review reveals that a lot of work has been reported on the application of BDA particularly in developed countries (Mathias Kalema and Mokgadi 2017). Many organizations in developing countries are still struggling to leverage the benefits of BDA application for improving their performance from a sustainability perspective. Manufacturing organizations are showing reluctance for technological changes happening in the market with the same pace.

Research methodology

This study comprises four phases. The first phase is the identification of benefits and strategic factors for BDA application in the manufacturing sector. The second phase is the justification of BDA application in manufacturing, the third phase is the ranking of strategic factors, and the fourth phase is on the categorization of strategic factors into cause and effect. The research framework for all phases of the study is shown in Fig. 1. Based on the literature review, the benefits of BDA application and strategic factors for its implementation are identified. AHP is used for justification of the BDA application. Fuzzy TOPSIS and DEMATEL approaches are applied for the ranking and categorization of strategic factors for BDA application.

Analytic hierarchy process (AHP)

AHP-based methodology is proposed for justification of BDA application for sustainable manufacturing operations. It is a multi-criteria decision making (MCDM) approach used to solve complex decision making problems. The AHP approach was developed in 1972 (Saaty 1980). This is selected as it is easy to use and has high applicability in MCDM procedures. MCDM procedure is a methodology for decision making where various alternates are ranked on the basis of different criteria. Popular MCDM tools are AHP, TOPSIS,VIKOR, etc. AHP was used for decision making for flexible manufacturing system supply chain justification in Small and medium enterprises (SMEs), prioritizing the factors for coordinated supply chain and microalgae cultivation systems (Singh 2012, 2013; Tan et al. 2017).

As AHP is a hierarchical process, 3 levels are considered for this work. The goal of problem, benefits, and alternatives, i.e., big data-enabled manufacturing (BDM) and without big data-enabled manufacturing (WBDM). These are placed at the first, second, and third level of the hierarchy, respectively. The solution procedure passes through structural hierarchy development, construction and development of comparative judgments, and synthesis of priorities and consistency calculation.

In structural hierarchy development, the authors built analytic hierarchy model for a given problem as shown in Fig. 2. The goal of this problem is to justify the application of BDA in manufacturing sector, and it is placed at top level. The main factors in the present context are benefits of BDA application in manufacturing sector are placed on second level of hierarchy. The justification of BDA is analyzed on the basis of its benefits. At level 3 which is the last level of hierarchy, two alternatives namely big data-enabled manufacturing (BDM) and without big data-enabled manufacturing (WBDM) are positioned as these are the final outcome.

In the construction and development of comparative judgments, the priorities of elements are determined at every level. The pairwise comparisons are done in terms of which benefit dominates the other. For this purpose, responses from experts are obtained in linguistic terms and converted into crip values. A pairwise comparison matrix (nxn), P_1 for all benefits of BDA is constructed on the basis of Satty's nine-point scale (1994) as given in Appendix 1, and it is expressed as: $P_1 = \left[a_{ij} \right]_{nxn}$, where the matrix element a_{ij} represents the relative importance ith factor w.r.t. jth factor and $a_{ij*}a_{ji} = 1$ when $i \neq j$(symmetric elements are reciprocal) and $a_{ij} = 1$ when $i \equiv j$(diagonal elements are reciprocal).

Next, the matrix P_1 is normalized by dividing each entry in a column by the sum of column entries. Let b_{ij} be the normalized value of ith criteria with respect to jth criteria, and it is expressed as: $b_{ij} = \frac{a_{ij}}{\sum_{i=1}^{n} a_{ij}}$ for all $j = 1$ to n. Further, the normalized matrix (n X n) is used to obtain a priority vector matrix (principal matrix), P_2 (n X 1) by taking the average of each row elements. The matrix, P_2 is expressed as: $P_2 = [c_{ij}]_{nx1}$ where $c_{ij} = \frac{\sum_{j=1}^{n} b_{ij}}{n}$ for all $i = 1-n$. The matrix P_2 is a column vector where the element indicates the weight of each benefit.

The consistency ratio (CR) of the pairwise comparison matrix is determined to check whether the expert responses are consistent. To find the consistency ratio, P_3 and P_4 column vectors are evaluated using the matrices P_1 and P_2 as per Eq. (1) (Singh 2012).

$$P_3 = P_1*P_2 \text{ and } P_4 = P_3/P_2 \tag{1}$$

Next, λ_{max} is evaluated by taking average of the P_4 vector, i.e., $\lambda_{max} = \frac{\sum_{j=1}^{n} p_j}{n}$ where p_j is the element of column vector P_4. Finally, consistency index (CI) is calculated as:

$$CI = \frac{\lambda \max - n}{n - 1}$$

where n is the size of the matrix.

Table 2 Strategic factors for big data analytics application

| Strategic factors	Description	Reference
Development of contract agreement among all stakeholders	Ensures confidence of big data usage among stakeholders and defines responsibilities and procedures for better communication	Janssen et al. (2017), de Camargo Fiorini et al. (2018)
Commitment and engagement of top management	Top management will guarantee resource mobilization and its attention in BDA implementation	Gupta et al. (2018), de Camargo Fiorini et al. (2018), Dubey et al. (2016), Ivanov et al. (2019)
Development of capability for handling big data	Deployment of accurate tool and techniques for analysis, visualization, and processing of big data	Janssen et al. (2017), Yaqoob et al. (2016), Dubey et al. (2019a), Wilcox et al. (2019)
Robust cybersecurity system	Refers to the maintenance of privacy and security of big data. Its absence may lead to financial loss and damage to a firm's reputation	Lee (2017), Ivanov et al. (2019)
Coordination among big data stakeholders	Cooperation is needed to change the mindset of all stakeholders against the notions that BDA tools require huge investment and extra efforts	de Camargo Fiorini et al. (2018), Wilcox et al. (2019)
Problem identification and solving capacity	Capabilities in terms of resources including human, technology, capital, etc., to ensure conversion of inputs into higher value outputs	Janssen et al. (2017), Dubey et al. (2019a)
Process integration and institutionalization	Capacity to coordinate procedures to institutionalize assignments/information that brings improvement in the big data chain. In other words, this is an imperative condition for institutionalizing and reutilizing the utilization of big data	Janssen et al. (2017), Gupta et al. (2018)
Flexible digital infrastructure	In-house resources for data acquisition, data processes, and data analysis	Cui et al. (2020), Duan et al. (2019), Ivanov et al. (2019)
Strategy development for BDA	The process or activities that ensure the strategic planning is actually executed	Janssen et al. (2017), Gupta et al. (2018), Gupta et al. (2020)
Availability of quality and reliable big data	Ensuring adequate and correct data for the intended purpose	Janssen et al. (2017), Duan et al. (2019), Wilcox et al. (2019)
Knowledgeable and capable decision-makers	For quick and better decision, the experienced decision-makers are required, who easily understand and analyze the big data	Del Fabbro and Santarossa (2016), Cui et al. (2020)
Data-driven organization culture	Changing a culture is a vast scale undertaking, and in the end, the majority of the authoritative apparatuses for changing personalities should be placed in play	Janssen et al. (2017), Duan et al. (2019), Weerakkody et al. (2017), Cui et al. (2020)
Process monitoring and control	Hardware and software system related to data processing	Dubey et al. (2019b), Duan et al. (2019)
Integrating customers' requirements with performance framework	Data help to improve the customer relationship with the performance of the industry, decision making capability and reduce fraud	Dubey et al. (2019a), Janssen et al. (2017), Gupta et al. (2020)
Responsive information sharing framework	The relation between information system framework and industry performance is an evaluation of the roundabout advantages of information technology	Duan et al. (2019), Dubey et al. (2019b)
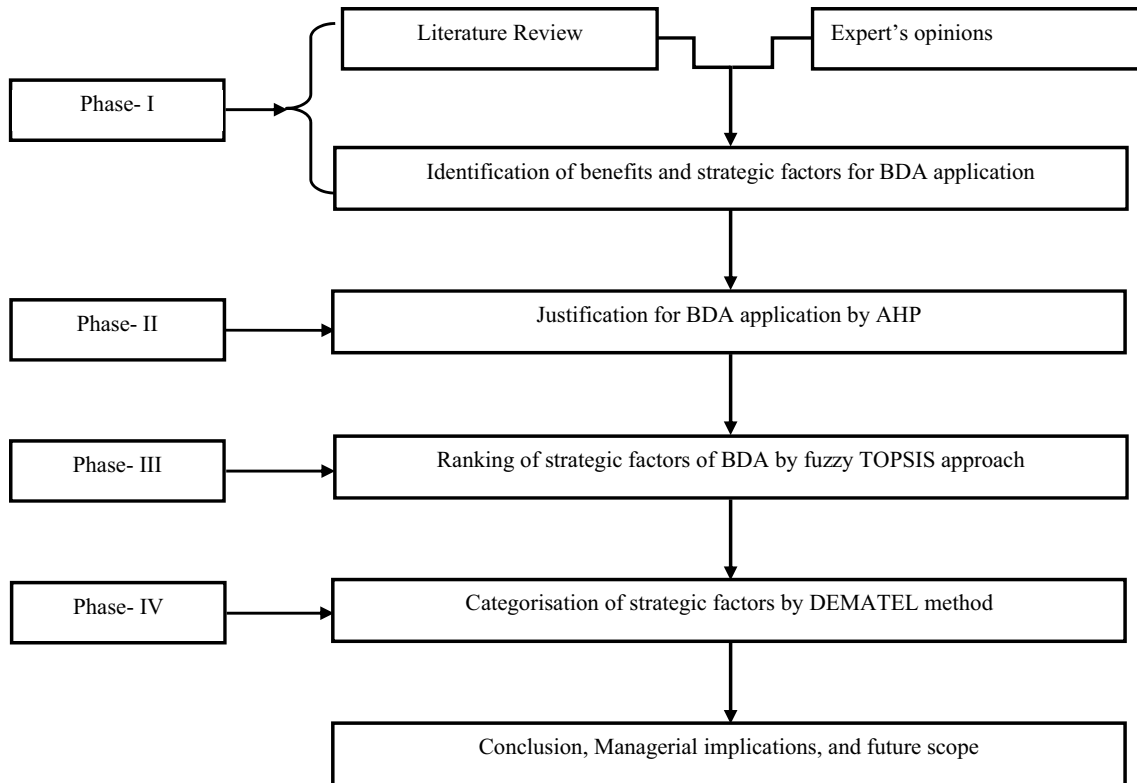
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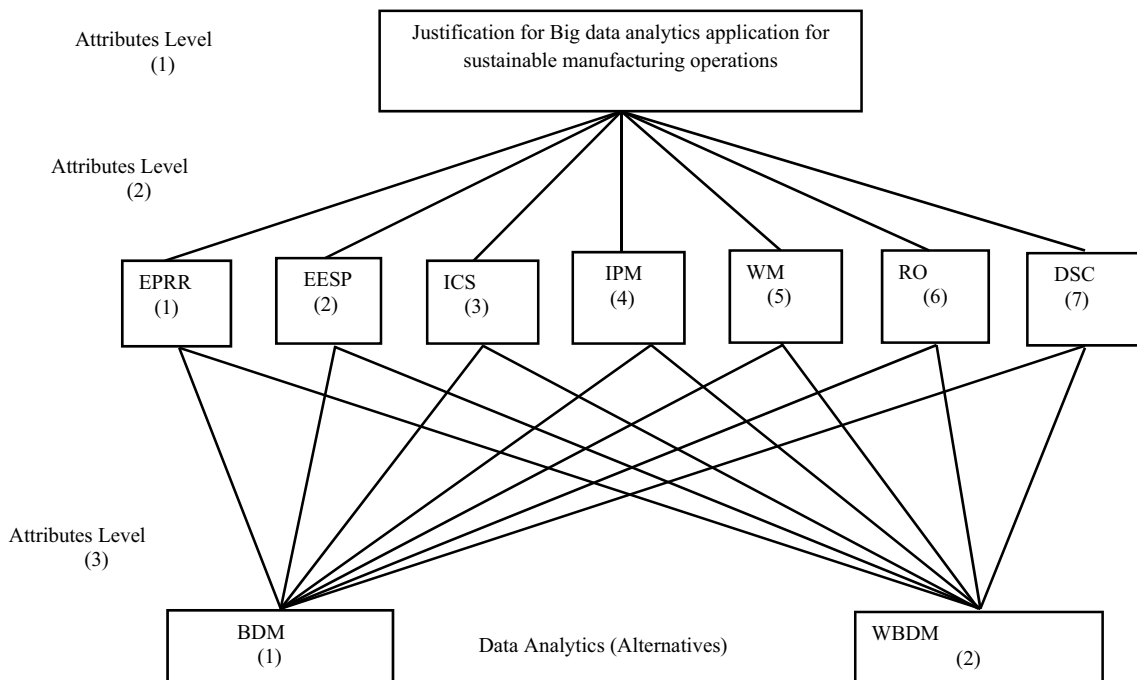
Fig. 2 Schematic of the analytic hierarchy process

The ratio of consistency index (CI) to random consistency index (RCI) is known as the consistency ratio which is expressed as:

$$CR = CI/RCI \tag{3}$$

where RCI is random consistency index and RCI value taken as per Appendix 2.

If CI is less than 0.1 decisions are considered as consistent. For CR value more than 0.1, the nature of decisions ought to be revised till CR value reaches in a consistent range.

The acceptable CR depends on the size of the matrix, and it is 0.1 for matrix size 4×4 and larger (Saaty 2000). If the value of consistency ratio is equal to or less than the permissible value, it suggests that the assessment within the matrix is satisfactory or shows a good level of consistency in the relative decisions. Similar procedure is followed for last hierarchy for computing the weights of BDM and WBDM for each benefit. The list of variables/symbols used in the expressions/ equations in this work is given in Appendix 9.

Fuzzy TOPSIS approach

Fuzzy TOPSIS is used for the ranking of strategic factors for BDA application for sustainable manufacturing operations. Fuzzy TOPSIS was employed for analyzing disposition strategies in reverse supply chains, disposition decision in reverse logistics, prioritizing strategic factors for reverse logistics, and environmental sustainability (Agrawal et al. 2016; Singh and Agrawal 2018; Samaie et al. 2020). This approach was also implemented to support outsourcing of logistics service, evaluation of 3PL in a supply chain, and supplier selection (Kumar and Singh 2012; Lima Junior et al. 2014).

In the fuzzy TOPSIS method, the data is collected in linguistic terms (later converted on a fuzzy scale) for selected alternatives for the chosen criteria, unlike the TOPSIS approach where crisp values are gathered. Fuzzy TOPSIS is a simple, realistic form of modeling and compensatory method which includes and excludes alternative solutions based on hard cutoff (Singh and Agrawal 2018). Additionally, it is a computation process that can be easily programmed into a spreadsheet that contains a data on a scalar value that represents both the best and worst alternatives at the same time, a sound logic that represents the rationale of human choice and the performance measures of all alternatives can be visualized on polyhedron (Kim et al. 1997). Moreover, the integration of fuzzy will further increases its strength as it is capable of handling vague and uncertain information (Zimmermann 1985). These benefits of fuzzy TOPSIS make it a better choice among MCDM

approaches. Therefore, this approach is employed for this work, and the step-by-step procedure of fuzzy TOPSIS is detailed below:

Step 1 Collect the data through the survey method in the form of linguistics terms. The experts should be asked to select the best option. The options are expressed in linguistic terms for a given question. A 5-point scale with the linguistic terms low (L), fairly low (FL), medium (M), fairly high (FH), and high (H) is generally used in the questionnaire. Once the data is collected in linguistic terms, the same is converted into fuzzy numbers.

Step 2 A fuzzy decision matrix is derived based on the data collected in step 1 and converted into triangular fuzzy numbers.

$$D = \begin{bmatrix} Y_{11} & Y_{12} & \dots & Y_{1j} & \dots & Y_{1n} \\ Y_{21} & Y_{22} & \dots & Y_{2j} & \dots & Y_{21} \\ \dots & \dots & \dots & \dots & \dots & \dots \\ Y_{i1} & Y_{i2} & \dots & Y_{ij} & \dots & Y_{in} \\ \dots & \dots & \dots & \dots & \dots & \dots \\ Y_{m1} & Y_{m2} & \dots & Y_{mj} & \dots & Y_{mn} \end{bmatrix}$$

where $Y_{ij} = (d_{ij}, e_{ij}, f_{ij})$ is a triangular fuzzy number for the linguistic term allocated by the ith respondent to the jth factor. i = 1, 2, …, m are the number of respondents, and j = 1, 2, …, n are the number of factors (Strategic factors). Table 3 shows the scale in terms of triangular fuzzy numbers used for each linguistic term.

Step 3 A fuzzy decision matrix (D) is converted into a fuzzy un-weighted matrix (R) using the following relationship (Singh and Agrawal 2018).

$$R = \left[r_{ij}\right]_{m \times n;} = \left(\frac{d_{ij}}{c_{j*}^*}, \frac{e_{ij}}{c_j^*}, \frac{f_{ij}}{c_j^*} \right) \text{ and } R = \left[r_{ij}\right]_{m \times n;} = \left(\frac{d_j^-}{d_{ij}}, \frac{d_j^-}{e_{ij}}, \frac{d_j^-}{f_{ij}} \right) \tag{4}$$

For benefit criteria, $c_{j*}^* = \max_i c$ and for cost criteria, $d_j^- = \min_i d_{ij}$.

Step 4 Evaluate the weighted normalized decision matrix (V) using Eq. 5 (Singh and Agrawal 2018).

$$V = R * W \tag{5}$$

where W is the weight of vector criteria as evaluated with AHP and $V = \left[v_{ij}\right]_{m \times n;}$ i = 1, 2,… m; j = 1,2,…n

Table 3 Scale for Linguistic terms

Linguistic terms	Fuzzy numbers
Very low	(0.0, 0.1, 0.3)
Low	(0.1, 0.3, 0.5)
Medium	(0.3, 0.5, 0.7)
High	(0.5, 0.7, 0.9)
Very high	(0.7, 0.9, 1)

Step 5 Generate the ideal and negative ideal solution for the strategic factors using Eq. 6 (Singh and Agrawal 2018).

$$A^+ = \{V^*_{w1}, V^*_{w2} \dots V^*_{wn}\} \text{ and } A^- = \{V^-_{w1}, V^-_{w2} \dots V^-_{wn}\} \tag{6}$$

The values as per Eq. 7 are considered for the ideal and negative ideal solution.

$$V^* = (1, 1, 1) \text{ and } V^- = (0, 0, 0) \tag{7}$$

Step 6 Compute the total of distances from fuzzy positive ideal solution (FPIS) and fuzzy negative ideal solution (FNIS) for each factor using Eq. 8 (Singh and Agrawal 2018).

$$D^+ = \frac{\sum_{i=1}^{m} d(V - V^+)}{m} \tag{8}$$

$d(V - V^*)$ is the distance between two fuzzy numbers which is determined using Eq. 9

$$d(V_1 - V_2) = \sqrt{\frac{1}{3}[(g_2 - g_1)^2 + (h_2 - h_1)^2 + (i_2 - i_1)^2]} \tag{9}$$

On the similar lines, the distance from the negative ideal solution is evaluated using Eq. 10

$$D^- = \frac{\sum_{i=1}^{m} d(v - v^-)}{m} \tag{10}$$

Step 7 Compute the relative closeness to the ideal solution using Eq. 11

$$C = D^- / D^+ + D^- \tag{11}$$

Step 8 Rank the strategic factors based on the order of the values of C.

DEMATEL approach

DEMATEL method was applied for evaluating direct and indirect influences among criteria in multi-criteria decision scenarios (Gandhi et al. 2015). DEMATEL was applied for prioritizing of investment projects portfolio, agri-food supply chains for sustainable initiatives, and analysis of cloud adoption determinants (Hidayanto et al. 2015; Altuntas and Dereli 2015; Mangla et al. 2018). This method was also applied to evaluate green supply chain management practices and enablers in solar power developments (Lin 2013; Luthra et al. 2016). Singh et al. (2019) have used DEMATEL for analyzing the application of ICT in SMEs from the food industry. The steps used in AHP, Fuzzy TOPSIS and DEMATEL approach are described in the following

subsection. The step by step process of DEMATEL approach is given below:

Step 1 Collect expert response and evaluate their average to obtain average matrix Z.

Consider '*m*' experts and '*n*' factors for the analysis. Expert opinion is taken based on pairwise comparison to get the degree of direct influence between two factors. x_{ij} denotes the degree of influence of factor ion factor *j* as per expert view. The integer scores of 0, 1, 2, 3, and 4 denote no influence, low influence, medium influence, high influence, and very high influence, respectively. An *n x n* nonnegative matrix, $X^k = [x^k_{ij}]$ is obtained from each expert. The average matrix $Z = [zij]$ is obtained as per Eq. 12 and represents the aggregate of all responses.

$$Z_{ij} = \frac{1}{m} \sum_{i=1}^{m} x^k_{ij} \tag{12}$$

Step 2 Generate the normalized initial direct-relation matrix, N

The matrix, $N = [nij]$, where the value of each element in matrix N is ranged between [0, 1], and it is evaluated using Eq. 13.

$$N = \lambda * Z, \text{ or} [n_{ij}]_{nxn} = \lambda [z_{ij}]_{nxn} \tag{13}$$

where $\lambda = Min\left[\frac{1}{\max 1 \leq i \leq n \sum_{j=1}^{m} |Z_{ij}|}, \frac{1}{\max 1 \leq i \leq n \sum_{j=1}^{n} |Z_{ij}|}\right]$.

Step 3 Develop the total relation matrix Y.

Total relation matrix *Y* is derived using Eq. 14 and its individual element represents the indirect effect of factor *i* on factor *j*. Matrix Y shows the total relationship between each pair of strategic factors.

$$Y = N(I - N)^{-1} \tag{14}$$

where I is the Identity matrix.

Step 4: Determine the sums of rows and columns of Total relation matrix Y.

The sums of rows and columns of matrix Y are denoted by vectors S_R and S_C, and these are evaluated using Eq. 15.

$$S_R = [r_i]_{nx1} = \left(\sum_{j=1}^{n} y_{ij}\right)_{nx1} \text{ and } S_C = [c_j]'_{1xn} = \left(\sum_{j=1}^{n} y_{ij}\right)'_{1xn} \tag{15}$$

The values of S_R and S_C indicate the total given and received both, directly and indirectly, effects that factor i has on the other factors.

Step 5 Develop a cause and effect relationship.

The cause and effect diagram is constructed in a coordinate plane using the values of $S_R + S_C$ and $S_R - S_C$ as abscissa and ordinate, respectively. Interrelationships among system factors are established using the cause and effect diagram. Based on the values of ($S_R - S_C$), strategic factors

are classified into cause and effect group. If the score of $(S_R—S_C)$ is positive, strategic factors fall in cause group and directly affect other strategic factors. On the other hand, if the score of $(S_R—S_C)$, is negative, such strategic factors belong to the effect group, and these are influenced by the other strategic factors.

Results and discussion

As discussed in the research methodology framework (Fig. 1), this study is carried out in four phases. The first phase of identification of BDA benefits and strategic factors for its implementation has been done through literature review. The remaining three phases are analyzed based on using different MCDM techniques as discussed in the preceding section. AHP method is used for the justification of the application of BDA. Fuzzy TOPSIS approach is employed for the ranking of strategic factors, and the DEMATEL tool is utilized for the analysis of cause and effect of strategic factors. This study is applicable to the Indian manufacturing sector. The findings of this work will help the managers to take decision for BDA application for sustainable manufacturing operations in different fields under manufacturing sector. Therefore, the study will motivate to industry professionals to invest in BDA applications across different functions to achieve the goal of sustainable manufacturing operations. Results are discussed in the following subsections.

Justification of BDA application for sustainable manufacturing operations

This subsection evaluates the priority vector in terms of relative weights for the applications identified and the global desirability index (GDI) for two alternatives. The first alternative is big data-enabled manufacturing (BDM), and the second alternative is without big data-enabled manufacturing (WBDM). A higher value of GDI indicates a better alternative. Justification of BDA in the manufacturing sector is analyzed based on the framework developed in "Analytic hierarchy process" section (Fig. 2) using AHP. Initially, a pairwise comparison matrix (P_1) for seven applications of BDA at level 2 of the AHP model is developed as shown in Table 4. Each element of this matrix signifies the relative importance. For example, $p_{23} = 5$ signifies benefit at second row (Energy efficient and safe processes) has strong importance over benefit at the third column (Improved customer satisfaction). Element p_{32} is the reciprocal of p_{23} and interpreted accordingly as per the Saaty scale (refer to Appendix 1). Further, the priority vector is determined as per the procedure in "Analytic hierarchy process" section for all seven benefits and it signifies the relative weight of each benefit. The priority vector is shown in the last column of Table 4. Also, the CR is evaluated following the procedure given in "Analytic hierarchy process" section to examine the degree of consistency in the pairwise comparison of seven applications (Appendix 3), Results of the pairwise comparison are shown in Table 4. The evaluated value of CR is 0.0923 which is less than 0.1. This signifies the good level of consistency in the relative decision about applications.

Subsequently, priority vector is evaluated for both the alternatives, i.e,. big data-enabled manufacturing (BDM) and without big data-enabled manufacturing (WBDM) for each sustainability benefit. The results are shown in Table 5. For example, for benefit, PF the value of PV is 0.889 and 0.111 for BDM and WBDM, respectively. A higher value of PV in the case of BDM shows that big data-enabled manufacturing is justified when performance forecasting benefit is considered. It is observed from results (Table 5) that in terms of all seven benefits, manufacturing organizations with BDA have more priority vector value in comparison with manufacturing organizations without BDA.

Global weight for each alternative is calculated by multiplying the local weight of each alternative to the weight of each benefit, and these evaluated global weights for each alternative are shown in Table 6. Subsequently, the global

Table 4 Pairwise comparison matrix of sustainability benefits (Level 2)

	EPRR	EESP	ICS	IPM	WM	RO	DSC	Priority Vector (PV)
EPRR	1	0.143	0.25	0.2	0.2	0.33	0.12	0.025
EESP	7	1	5	3	2	6	0.33	0.2260
ICS	4	0.2	1	0.33	0.2	5	0.25	0.0765
IPM	5	0.33	3	1	0.33	4	0.2	0.1030
WM	5	0.5	5	3	1	7	0.5	0.1940
RO	3	0.167	0.2	0.25	0.14	1	0.16	0.0395
DSC	8	3	4	5	2	6	1	0.3360
Total	33	5.34	18.45	12.8	5.87	29.33	2.5	

Table 5 Pairwise comparison judgment matrices

Applications	Alternative investigation	BDM	WBDM	Total
EPRR	BDM	1	0.125	1.125
	WBDM	8	1	9
	PV	0.889	0.111	
EESP	BDM	1	0.125	1.125
	WBDM	8	1	9
	PV	0.889	0.111	
ICS	BDM	1	0.1429	1.1429
	WBDM	7	1	8
	PV	0.875	0.125	
IPM	BDM	1	0.1429	1.1429
	WBDM	7	1	8
	PV	0.875	0.125	
WM	BDM	1	0.125	1.125
	WBDM	8	1	9
	PV	0.889	0.111	
RO	BDM	1	0.1667	1.1667
	WBDM	6	1	7
	PV	0.857	0.143	
DSC	BDM	1	0.1429	1.1429
	WBDM	7	1	8
	PV	0.875	0.125	

desirability index (GDI) is obtained by summing the all values of corresponding alternatives. The GDI value for BDM and WBDM is 0.8811 and 0.1189, respectively, as given in Table 6. A higher value of GDI justifies the application of BDA for sustainable manufacturing operations.

Ranking of strategic factors for the application of BDA

Strategic factors for BDA application in the manufacturing sector are identified through literature. After discussion with experts, fifteen factors are finalized for their ranking from a strategic perspective. These factors are listed in Table 2. A questionnaire-based survey was conducted in the context of big data analytics application for sustainable manufacturing operations in the Indian manufacturing sector, and the experts were selected from industry and academia. The experts from industries and academia were requested to give the responses in the questionnaire designed for this study. The experts team comprises two production managers, one marketing manager, one operation engineer, one logistics manager, and two academicians. The experts from industries have more than ten years of experience in their domain, whereas the experts from academia have more than fifteen years of experience in teaching and research. In total, seven experts were requested to provide their responses for rating of all 15 strategic factors in linguistic terms. A 5-point scale having the linguistic terms as very low (VL), low (L), medium (M), high (H), and very high (VH) was used for this purpose. The procedure described in "Fuzzy TOPSIS approach" section is applied here for ranking. The authors collected the responses from the experts in linguistic terms and converted them into crisp values by referring scale given in Table 3. Thus, the matrix so obtained is called fuzzy decision matrix D, and it is shown in Appendix 4. Then matrix D is converted into an un-weighted fuzzy matrix, R using Eq. 4, and the same is given in Appendix 5. Further the weighted normalized matrix is evaluated using Eq. 5. This evolves the product of un-weighted fuzzy decision matrix R (Appendix 5) and PV value for sustainability benefits given in Table 4. The same is shown in Table 7.

Next, the distance of the rating of each factor from a positive ideal solution is evaluated using Eq. 8. This is given in

Table 6 Weights of applications for alternatives and global desirability index

Sr. no	Applications	Weight of each benefit	Alternatives			
			BDM local weight	WBDM local weight	BDM global weight	WBDM global weight
1	EPRR	0.025	0.889	0.111	0.0223	0.0027
2	EESP	0.2260	0.889	0.111	0.2009	0.0251
3	ICS	0.0765	0.875	0.125	0.0669	0.0094
4	IPM	0.1030	0.875	0.125	0.0901	0.0127
5	WM	0.1940	0.889	0.111	0.1724	0.0214
6	RO	0.0395	0.875	0.143	0.0345	0.0056
7	DSC	0.3360	0.875	0.125	0.294	0.0420
Total global weight (GDI)					0.8811	0.1189

Appendix 6. Similarly, the distance of the rating of each factor from a negative ideal solution is evaluated using Eq. 10 and shown in Appendix 7. Further, the total distance of each factor is calculated from the positive and negative ideal solution. These are represented by D^+ and D^-, and the same is given in Appendices 6 and 7. Subsequently, the relative closeness with respect to ideal solution A^+ is evaluated using Eq. 11, and the same is used in the ranking of performance. The biggest value of closeness is ranked "1" and the lowest value of closeness is ranked "15." By following this closeness value, all the strategic factors are ranked and tabulated in Table 8. Commitment and engagement of top management, strategy development for BDA, and development of capability for handling big data are prioritized as 1st, 2nd, and 3rd in their relative importance, and these are very crucial for BDA implementation. Without commitment and support from top management, such kind of high-cost initiatives cannot be successful. Management should also develop a trained workforce to manage huge data through BDA. Responsive information sharing framework and development of contract agreement among all stakeholders are ranked 14th and 15th, respectively, and these factors have relatively less impact on the implementation of BDA.

Categorization of strategic factors in terms of cause and effect

As mentioned earlier, the DEMATEL approach is applied to categorize the strategic factors into two classes, viz. cause and effect. This is implemented by the evaluation of direct and indirect influences among strategic factors. Following the procedure given in "DEMATEL approach" section, the influence matrix data is recorded in terms of the 15 strategic factors from 7 experts and an average influence matrix, Z, is constructed using Eq. 12 (Appendices 3, 4, 5, 6, 7, and 8). Further, a normalized initial direct-influence matrix, N, is derived using Eq. 13. Average influence matrix, Z, and normalized initial direct-influence matrix, N, are given in Table 9. The steps of the DEMATEL approach were evaluated according to the above-mentioned procedure in "DEMATEL approach" section.

Subsequently in the DEMATEL approach the total influence matrix, Y, is calculated using Eq. 14, and results are shown in Table 10. Further, the rows sum vector (S_R), columns sum vector (S_C), $S_R + S_C$ vector, and S_R—S_C vector of matrix Y are calculated using Eq. 15 and these are shown in Table 11. Finally, the ranking of strategic factors is obtained on the basis of their (S_R–S_C) values and this is also presented in Table 11. Further, the results of the DEMATEL approach are also summarized in Fig. 3 in cause and effect groups.

Following the criteria of the positive score of (S_R–S_C), eight strategic factors falling in the category of cause group are identified, which directly affect other strategic factors in

Table 7 Weighted normalized fuzzy matrix

	1			2			3			4			5			6			7		
C-1	0.016	0.02	0.022	0.02	0.06	0.1	0.047	0.06	0.067	0.027	0.045	0.063	0.017	0.052	0.086	0.003	0.01	0.017	0.029	0.088	0.147
C-2	0.016	0.02	0.022	0.141	0.181	0.201	0.047	0.06	0.067	0.045	0.063	0.081	0.052	0.086	0.121	0.017	0.024	0.031	0.147	0.206	0.265
C-3	0.016	0.02	0.022	0.141	0.181	0.201	0.02	0.033	0.047	0.045	0.063	0.081	0.052	0.086	0.121	0.017	0.024	0.031	0.147	0.206	0.265
C-4	0.007	0.011	0.016	0.06	0.1	0.141	0.007	0.02	0.033	0.045	0.063	0.081	0.017	0.052	0.086	0.01	0.017	0.024	0.088	0.147	0.206
C-5	0.007	0.011	0.016	0.1	0.141	0.181	0.047	0.06	0.067	0.009	0.027	0.045	0.052	0.086	0.121	0.01	0.017	0.024	0.029	0.088	0.147
C-6	0.011	0.016	0.02	0.1	0.141	0.181	0.047	0.06	0.067	0.045	0.063	0.081	0.121	0.155	0.172	0.017	0.024	0.031	0.206	0.265	0.294
C-7	0.016	0.02	0.022	0.1	0.141	0.181	0.047	0.06	0.067	0.045	0.063	0.081	0.052	0.086	0.121	0.017	0.024	0.031	0.088	0.147	0.206
C-8	0.011	0.016	0.02	0.1	0.141	0.181	0.033	0.047	0.06	0.027	0.045	0.063	0.017	0.052	0.086	0.024	0.031	0.035	0.088	0.147	0.206
C-9	0.016	0.02	0.022	0.141	0.181	0.201	0.033	0.047	0.06	0.027	0.045	0.063	0.121	0.155	0.172	0.017	0.024	0.031	0.147	0.206	0.265
C-10	0.011	0.016	0.02	0.141	0.181	0.201	0.02	0.033	0.047	0.027	0.045	0.063	0.017	0.052	0.086	0.017	0.024	0.031	0.147	0.206	0.265
C-11	0.011	0.016	0.02	0.141	0.181	0.201	0.007	0.02	0.033	0.045	0.063	0.081	0.052	0.086	0.121	0.017	0.024	0.031	0.088	0.147	0.206
C-12	0.007	0.011	0.016	0.1	0.141	0.181	0.033	0.047	0.06	0.027	0.045	0.063	0.052	0.086	0.121	0.01	0.017	0.024	0.088	0.147	0.206
C-13	0.011	0.016	0.02	0.06	0.1	0.141	0.033	0.047	0.06	0.045	0.063	0.081	0.086	0.121	0.155	0.01	0.017	0.024	0.088	0.147	0.206
C-14	0.011	0.016	0.02	0.06	0.1	0.141	0.02	0.033	0.047	0.027	0.045	0.063	0.052	0.086	0.121	0.01	0.017	0.024	0.088	0.147	0.206
C-15	0.002	0.007	0.011	0.06	0.1	0.141	0.007	0.02	0.033	0.027	0.045	0.063	0.017	0.052	0.086	0.003	0.01	0.017	0.088	0.147	0.206

Table 8 Closeness coefficient matrix and ranking of strategic factors

Strategic factors	Strategic factors for BDA implementation	D^+	D^-	C	Ranking
C-1	Development of contract agreement among all stakeholders	6.67038	0.3521	0.050139	15
C-2	Commitment and engagement of top management	6.33759	0.75235	0.106115	1
C-3	Development of capability for handling big data	6.39095	0.72115	0.101398	3
C-4	Robust cybersecurity system	6.64735	0.42696	0.060353	13
C-5	Coordination among big data stakeholders	6.4504	0.62222	0.087976	8
C-6	Problems identification and solving capabilities	6.44129	0.62757	0.088779	7
C-7	Process Integration and institutionalization	6.43448	0.63192	0.089427	6
C-8	Flexible digital infrastructure	6.46666	0.612	0.086457	9
C-9	Strategy development for BDA	6.36313	0.73731	0.10384	2
C-10	Availability of quality and reliable big data	6.39781	0.71702	0.100779	4
C-11	Knowledgeable and capable decision-makers	6.42569	0.70278	0.098587	5
C-12	Data-driven organization culture	6.47577	0.60665	0.085656	10
C-13	Process monitoring and control	6.58347	0.46553	0.066042	11
C-14	Integrating customers' requirements with performance framework	6.61085	0.44798	0.05957	12
C-15	Responsive information sharing framework	6.65639	0.42163	0.063464	14

Table 9 Average direct-influence matrix, Z, and the normalized initial direct-influence matrix, N

		C-1	C-2	C-3	C-4	C-5	C-6	C-7	C-8	C-9	C-10	C-11	C-12	C-13	C-14	C-15
C-1	Z	0	2	2	2.5714	1.5714	3	2	2.7143	1.7143	1.8571	2.4286	3	2.5714	2.5714	2.1429
	N	0	0.066	0.066	0.0849	0.0519	0.0991	0.066	0.0896	0.0566	0.0613	0.0802	0.0991	0.0896	0.0849	0.0708
C-2	Z	2.2857	0	2.1429	2	2.2857	2.5714	2.4286	3.1429	2.7143	2.5714	1.7143	2.1429	2.5714	1.7143	2.1429
	N	0.0755	0	0.0708	0.066	0.0755	0.0849	0.0802	0.1038	0.0896	0.0849	0.0566	0.0708	0.0849	0.0566	0.0708
C-3	Z	2	2.4286	0	1.7143	2.1429	2	1.5714	2.7143	1.4286	1.2857	2	1.4286	2	1.4286	2
	N	0.066	0.0802	0	0.0566	0.0708	0.066	0.0519	0.0896	0.0472	0.0425	0.066	0.0472	0.066	0.0472	0.066
C-4	Z	2	1.2857	2.4286	0	2.4286	2.2857	2.1429	2.4286	2.1429	2.5714	2.1429	0.8571	2.4286	1	2.4286
	N	0.066	0.0425	0.0802	0	0.0802	0.0755	0.0708	0.0802	0.0708	0.0849	0.0708	0.0283	0.0802	0.033	0.0802
C-5	Z	1.5714	2.1429	1.8571	1.5714	0	2.8571	1.5714	2	2	2.4286	2	3	2.2857	2.8571	2.5714
	N	0.0519	0.0708	0.0613	0.0519	0	0.0943	0.0519	0.066	0.066	0.0802	0.066	0.0991	0.0755	0.0943	0.0849
C-6	Z	2.1429	2.4286	1.8571	2.5714	2.1429	0	2.1429	2.2857	1.8571	2.2857	2.5714	2.4286	2.7143	1.7143	2
	N	0.0708	0.0802	0.0613	0.0849	0.0708	0	0.0708	0.0755	0.0613	0.0755	0.0849	0.0802	0.0896	0.0566	0.066
C-7	Z	1.8571	1.8571	1.7143	2.4286	2	1.4286	0	2	1.2857	1.5714	1.7143	2.5714	2.1429	1.2857	2
	N	0.0613	0.0613	0.0566	0.0802	0.066	0.0472	0	0.066	0.0425	0.0519	0.0566	0.0849	0.0708	0.0425	0.066
C-8	Z	2.2857	2.1429	2.2857	2.7143	1.8571	2.1429	1.4286	0	2.1429	1.8571	2	1.4286	2.5714	1.8571	2.8571
	N	0.0755	0.0708	0.0755	0.0896	0.0613	0.0708	0.0472	0	0.0708	0.0613	0.066	0.0472	0.0849	0.0613	0.0943
C-9	Z	1.7143	2	2	2	2.2857	1.1429	2	2.7143	0	2.5714	1.5714	1.5714	2.7143	2.1429	1.4286
	N	0.0566	0.066	0.066	0.066	0.0755	0.0377	0.066	0.0896	0	0.0849	0.0519	0.0519	0.0896	0.0708	0.0472
C-10	Z	2.2857	2.7143	2	2.2857	2.2857	2.1429	2.4286	2.7143	2.5714	0	2.5714	2.5714	0.5714	2	3
	N	0.0755	0.0896	0.066	0.0755	0.0755	0.0708	0.0802	0.0896	0.0849	0	0.0849	0.0849	0.0189	0.066	0.0991
C-11	Z	2.2857	2	2.1429	2.2857	2.1429	2.7143	2	2.1429	1.7143	1.8571	0	2.5714	2.1429	1.8571	2.2857
	N	0.0755	0.066	0.0708	0.0755	0.0708	0.0896	0.066	0.0708	0.0566	0.0613	0	0.0849	0.0708	0.0613	0.0755
C-12	Z	2.2857	0.8571	1.2857	1.8571	2.8571	2.2857	2.2857	2	1.5714	2.7143	2.7143	0	2.4286	1.1429	1.4286
	N	0.0755	0.283	0.0425	0.0613	0.0943	0.0755	0.0755	0.066	0.0519	0.0896	0.0896	0	0.080 2	0.0377	0.0472
C-13	Z	2	2.8571	1.1429	2	2.5714	1.7143	2.4286	2.1429	2.4286	0.7143	1.4286	2.4286	0	1.8571	1.8571
	N	0.066	0.0943	0.0377	0.066	0.0849	0.0566	0.0802	0.0708	0.0802	0.0236	0.0472	0.0802	0	0.0613	0.0613
C-14	Z	2	1.8571	1.5714	1.7143	2.8571	1.2857	1.2857	1.7143	2	2.1429	2.1429	1.2857	1.8571	0	2
	N	0.066	0.0613	0.0519	0.0566	0.0943	0.0425	0.0425	0.0566	0.066	0.0708	0.0708	0.0425	0.0613	0	0.066
C-15	Z	2.1429	3	1.57.14	1.4286	2.5714	2	1.8571	2.8571	1.7143	2.1429	1.8571	1.2857	2.7143	2.1429	0
	N	0.0708	0.0991	0.0519	0.0472	0.0849	0.066	0.0613	0.0943	0.0566	0.0708	0.0613	0.0425	0.0896	0.0708	0

Table 10 Total direct-influence matrix (Y)

	C-1	C-2	C-3	C-4	C-5	C-6	C-7	C-8	C-9	C-10	C-11	C-12	C-13	C-14	C-15
C-1	1.8935	2.0044	1.7778	1.9927	2.1296	2.0385	1.8768	2.2602	1.8575	1.9292	1.9633	1.9719	2.167	1.7746	2.0463
C-2	1.9778	1.9592	1.7961	1.9914	2.1652	2.0409	1.9033	2.2908	1.9012	1.9643	1.9564	1.9629	2.1787	1.7648	2.0627
C-3	1.6271	1.6818	1.4196	1.6362	1.7845	1.6735	1.5494	1.8843	1.5372	1.588	1.6224	1.6013	1.7861	1.4493	1.7002
C-4	1.7587	1.7861	1.6138	1.7161	1.9375	1.8166	1.6929	2.0283	1.6835	1.7548	1.7582	1.7166	1.9421	1.5558	1.8515
C-5	1.8599	1.9244	1.6978	1.8786	1.9897	1.9485	1.7848	2.1446	1.7872	1.8648	1.8683	1.8901	2.0622	1.71	1.9718
C-6	1.9049	1.9615	1.725	1.9375	2.0858	1.8927	1.8295	2.1863	1.8105	1.8878	1.9124	1.9028	2.1064	1.7019	1.9861
C-7	1.5977	1.6376	1.4496	1.6309	1.7537	1.6308	1.4766	1.834	1.5085	1.572	1.5897	1.6093	1.7617	1.4211	1.6732
C-8	1.8205	1.8644	1.6577	1.8517	1.9806	1.8673	1.7234	2.0157	1.7348	1.7878	1.8072	1.784	2.0061	1.6278	1.9184
C-9	1.7021	1.7552	1.557	1.7288	1.8814	1.733	1.6422	1.98	1.5725	1.7075	1.6933	1.6884	1.8961	1.5451	1.7717
C-10	1.9674	2.0289	1.7831	1.9879	2.1535	2.0187	1.8923	2.2666	1.8856	1.8779	1.9711	1.9633	2.1099	1.7631	2.0761
C-11	1.8516	1.8903	1.681	1.8711	2.0228	1.9162	1.7697	2.116	1.7508	1.8191	1.7774	1.8496	2.0276	1.6547	1.9338
C-12	1.7237	1.7266	1.5404	1.7306	1.9025	1.7733	1.6561	1.964	1.6252	1.7169	1.733	1.6475	1.8935	1.5209	1.7769
C-13	1.6955	1.7628	1.5185	1.7137	1.8738	1.7351	1.6411	1.9467	1.632	1.6417	1.6744	1.6993	1.8014	1.5235	1.7666
C-14	1.6028	1.6409	1.4473	1.611	1.7798	1.6281	1.5182	1.8278	1.5316	1.5904	1.6032	1.5743	1.7539	1.3842	1.6756
C-15	1.8091	1.8819	1.63	1.8077	1.9927	1.8559	1.7286	2.0931	1.7164	1.7887	1.7954	1.7751	2.0014	1.6307	1.8249

Table 11 Categorization of strategic factors into the cause and effect groups

Strategic factors	Description	R	C	$(S_R + S_C)$	$(S_R - S_C)$	Ranking of strategic factors based on $(S_R - S_C)$	Causes and effects
C-1	Development of contract agreement among all stakeholders	29.68337	26.79219	56.47556	2.891181	Second	Cause
C-2	Commitment and engagement of top management	29.91558	27.50613	57.42171	2.40945	Third	Cause
C-3	Development of capability for handling big data	24.5409	24.29446	48.83536	0.246444	Seventh	Cause
C-4	Robust cyber security system	26.61256	27.08624	53.6988	− 0.47367	Ninth	Effect
C-5	Coordination among big data stake holders	28.38261	29.43312	57.81573	− 1.05052	Twelfth	Effect
C-6	Problems identification and solving capabilities	28.83097	27.56897	56.39995	1.262001	Fourth	Cause
C-7	Process Integration and institutionalization	24.14625	25.68487	49.83112	− 1.53861	Thirteenth	Effect
C-8	Flexible digital infrastructure	27.44729	30.83838	58.28567	− 3.39109	Fourteenth	Effect
C-9	Strategy development for BDA	25.85444	25.53452	51.38896	0.319924	Sixth	Cause
C-10	Availability of quality and reliable big data	29.74539	26.49093	56.23631	3.254461	First	Cause
C-11	Knowledgeable and capable decision-makers	27.93184	26.72567	54.65751	1.206164	Fifth	Cause
C-12	Data driven organization culture	25.93108	26.63639	52.56747	− 0.70532	Eleventh	Effect
C-13	Process monitoring and control	25.62615	29.49395	55.1201	− 3.86779	Fifteenth	Effect
C-14	Integrating customers' requirements with performance framework	24.16918	24.02741	48.19659	0.141777	Eighth	Cause
C-15	Responsive information sharing framework	27.33152	28.03592	55.36745	− 0.7044	Tenth	Effect

effect group. These cause group factors are: development of contract agreement among all stakeholders, commitment and engagement of top management, development of capacity for handling big data, problems identification and solving capabilities, strategy development for BDA, availability of quality and reliable data, knowledgeable and capable
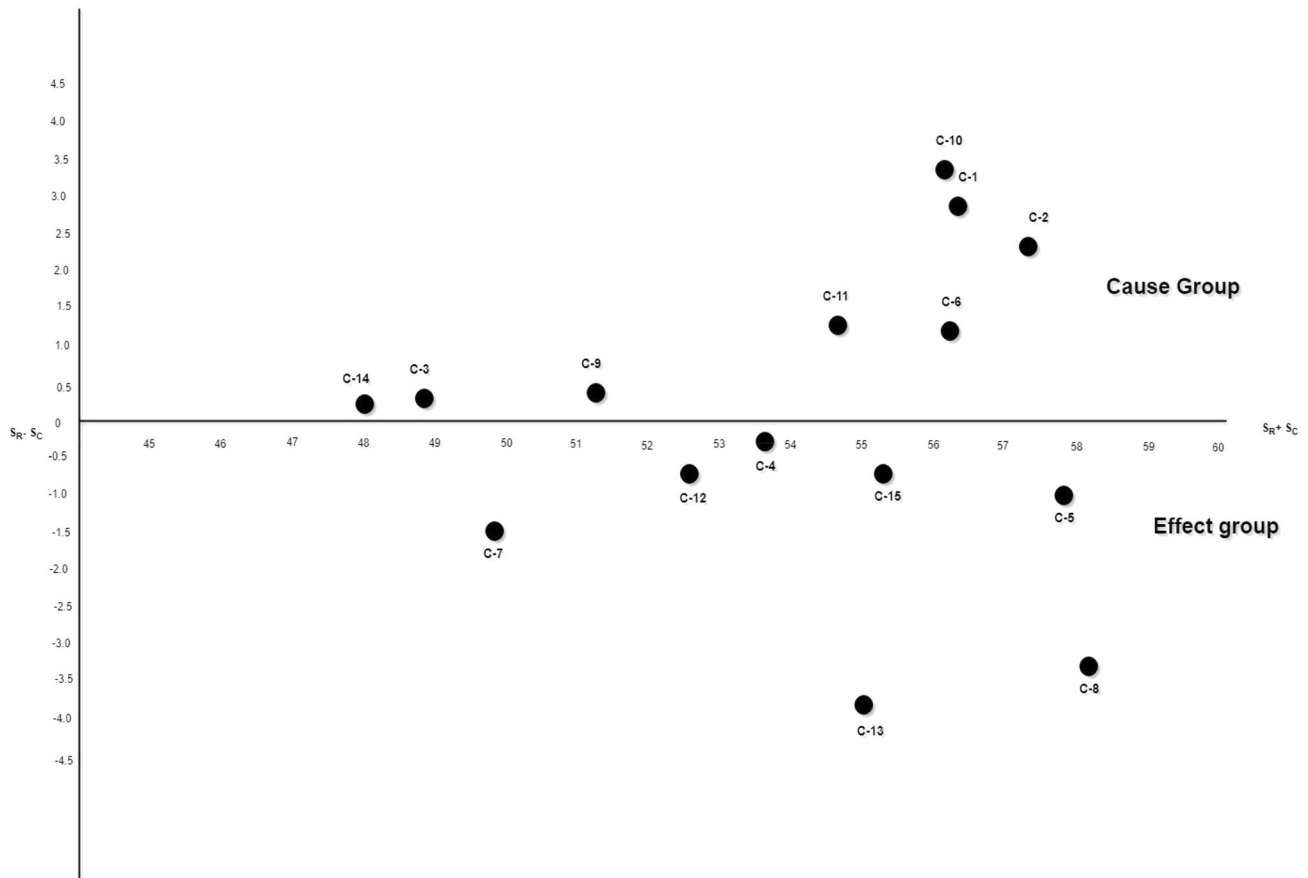
Fig. 3 The Causal diagram for strategic factors

decision-makers and integrating customers' requirements with performance framework. These cause group strategic factors are treated as independent factors and these have direct influence on the organization. These strategic factors require more attention for the successful implementation of BDA in the manufacturing sector.

The availability of quality and reliable big data has the highest $(S_R–S_C)$ score, and it is the most important cause that has the highest direct impact on the other strategic factors. Based on $(S_R–S_C)$ score development of contract agreement among all stakeholders and Commitment and engagement of top management are placed at the second and third highest positions in cause group strategic factors. This suggests that the development of contract agreement among all stakeholders and the engagement of top management are necessary for the implementation of BDA in manufacturing organizations.

Problems identified and solving capabilities, with $(S_R–S_C)$ score of 1.262 have fourth position pointing its importance on BDA in the manufacturing sector. Further, the knowledgeable and capable decision-makers with $(S_R–S_C)$ score of 1.2016 are an important factor that will help in taking the right decisions timely for the organization. Next, strategy development for BDA, with $(S_R–S_C)$ score of 0.3199 will aid in development of strategy. Development of capability for handling big data with $(SR–SC)$ score of 0.2464 is another crucial factor that will ensure data handling. Integrating customer requirements with performance framework has the eighth rank with the smallest $(S_R–S_C)$ score of (0.14178).

There is similarity up to a certain extent in drawing inferences from Fuzzy TOPSIS and DEMATEL approaches. The top five strategic factors as ranked by Fuzzy TOPSIS (refer to Table 8) are also falling in cause group as identified by the

DEMATEL approach. Therefore, management should give more attention to these strategic independent factors as they have a crucial role in implementing BDA for manufacturing organizations.

Further, based on the negative (S_R–S_C) values seven strategic factors fall in the effect group. There effect group factors are: robust cybersecurity system, coordination among big data stakeholders, process integration and institutionalization, flexible digital infrastructure, data-driven organization culture, process monitoring and control, and responsive information sharing framework. These strategic factors were most affected by the other strategic factors.

Conclusion, limitations, future scope, and managerial implications

In the present uncertain business environment, organizations are exploring application of emerging technologies for decision making and efficient production planning to ensure sustainable operations. BDA can help organization in managing unstructured huge data generated from digitization of operations. So far, the application of BDA for sustainable operations in the manufacturing sector is not extensively researched specifically in context to developing countries like India. Apart from it, the successful application of BDA in manufacturing processes is another big challenge for most of organizations. Major contribution of present study is that it has explored the application of BDA in manufacturing from sustainability perspective. From the literature, it has been observed that BDA application improves process and energy efficiency, product recovery, resource optimization, waste minimization, sustainable capabilities, etc. In spite of many benefits, several manufacturing organizations are still reluctant to integrate BDA with their processes due to heavy investment and risk of failure. Therefore, firstly based on industry inputs, authors justify BDA applications in manufacturing functions by using AHP. It has been observed from the results that BDA integrated manufacturing processes are more sustainable. This result is in line with the findings of other studies done in different context. Researchers have observed that BDA reduces manufacturing waste (Lee et al. 2013), increases equipment availability for the manufacturing process (Munirathinam and Ramadoss 2014), and improves insights into identification of faulty products and thus prevents returns and rework (Lavalle et al. 2011).

Further, strategic factors for BDA implementation are ranked by fuzzy TOPSIS. It has been found that commitment and engagement of top management, development of

capability for handling big data, strategy development for BDA, knowledgeable and capable decision-makers, availability of quality and reliable data, process integration, and institutionalization are the major strategic factors for successful implementation of BDA in manufacturing. Commitment and engagement of top management is the most important factor as the top management plays an important role in implementation of BDA and other supporting technologies that may ensure the benefits identified in the study.

Finally, the DEMATEL approach is used to categorize strategic factors in terms of cause and effect. Availability of quality and reliable big data, commitment, and engagement of top management, development of contract agreement among all stakeholders are major factors in the cause category. This information of cause factors will help managers to prioritize the actions for the implementation of BDA. Although findings of the study will be highly motivating to industry professionals to invest in BDA applications to achieve the goal of sustainable operations, but results cannot be generalized. For further validation, empirical study along with few case studies can be carried out to validate the findings. The importance of these factors may vary as per sector and country, so in the future studies may be carried out to compare the findings in different contexts. Generally, industries have operational and business data about their inventories, products, human resources, and distributors. Companies may use big data analytics to capitalize on this and many other sources of data to optimize manufacturing operations. Therefore, companies should formulate their policies and channelize the resources as per priority of strategic factor for a smooth implementation of BDA in manufacturing sector.

Compliance with ethical standards

Conflict of interest The authors declare that they have no conflict of interest.

Appendix 1

See Table 12.

Table 12 Thomas Saaty's scale for pairwise comparison of criteria (Saaty 1994)

Importance intensity	Terminology	Explanation
1	Equal importance	Allocate dissimilar value to each element depending on the significance of factor on another factor. If two factors have equal significance, then intensity of significance should be unity and one is allocated to both factors. Therefore, allocate value 3, 5, 7, 9 or the value of two adjoining judgments, i.e., 2, 4, 6, 8 is depending on the significance of each factor
3	Weak importance of one over another	
5	Essential or strong importance	
7	Highly strong importance	
9	Extreme/supreme importance	
2, 4, 6, 8	Intermediate, middle values of two adjoining judgments	
Reciprocals	Allocate any one number from previously mentioned value to activity i when it is compared with j, and allocated the corresponding of its value when the activity j compared to i	

Appendix 2

See Table 13.

Table 13 Average random index value (Saaty 2000)

Size of matrix (n)	1	2	3	4	5	6	7	8	9	10
Random Consistency Index (RCI)	0	0	0.52	0.9	1.1	1.25	1.35	1.4	1.45	1.49

Appendix 3

Let P_1 be the pairwise comparison matrix and P_2 principal vector matrix.

$$P_1 = \begin{bmatrix} 1 & 0.143 & 0.25 & 0.2 & 0.2 & 0.33 & 0.125 \\ 7 & 1 & 5 & 3 & 2 & 6 & 0.33 \\ 4 & 0.2 & 1 & 0.33 & 0.2 & 5 & 0.25 \\ 5 & 0.33 & 3 & 1 & 0.33 & 4 & 0.2 \\ 5 & 0.5 & 5 & 3 & 1 & 7 & 0.5 \\ 3 & 0.167 & 0.2 & 0.25 & 0.143 & 1 & 0.167 \\ 8 & 3 & 4 & 5 & 2 & 6 & 1 \end{bmatrix}$$

$$P_2 = \begin{bmatrix} 0.025 \\ 0.2260 \\ 0.0765 \\ 0.1030 \\ 0.1940 \\ 0.0395 \\ 0.3360 \end{bmatrix} \quad P_3 = P_1 * P_3 = \begin{bmatrix} 0.19087 \\ 1.8283 \\ 0.5750 \\ 0.8213 \\ 1.568 \\ 0.2421 \\ 2.660 \end{bmatrix} \quad \text{and } P_4 = P_3/P_2 = \begin{bmatrix} 0.19087 \\ 1.8283 \\ 0.5750 \\ 0.8213 \\ 1.568 \\ 0.2421 \\ 2.660 \end{bmatrix}$$

λ max, Average of the element of $P_4 = 7.7481$.

Now, consistency Index $(CI) = \frac{\lambda \max - n}{n-1} = (7.7481-7)/(7-1) = 0.12468$.

And, consistency ratio $(CR) = CI/RCI = $ (n Appendix 2).

$CR = 0.12468/1.35$ 0.0923, i.e., $CR < 0.1$. So, result is consistent.

Appendix 4

See Table 14.

Table 14 Fuzzy decision matrix D

	1	2	3	4	5	6	7
C-1	(0.7,0.9,1.0)	(0.1,0.3,0.5)	(0.7,0.9,1.0)	(0.3,0.5,0.7)	(0.1,0.3,0.5)	(0.1,0.3,0.5)	(0.1,0.3,0.5)
C-2	(0.7,0.9,1.0)	(0.7,0.9,1.0)	(0.7,0.9,1.0)	(0.5,0.7,0.9)	(0.3,0.5,0.7)	(0.5,0.7,0.9)	(0.5,0.7,0.9)
C-3	(0.7,0.9,1.0)	(0.7,0.9,1.0)	(0.3,0.5,0.7)	(0.5,0.7,0.9)	(0.3,0.5,0.7)	(0.5,0.7,0.9)	(0.5,0.7,0.9)
C-4	(0.3,0.5,0.7)	(0.3,0.5,0.7)	(0.1,0.3,0.5)	(0.5,0.7,0.9)	(0.1,0.3,0.5)	(0.3,0.5,0.7)	(0.3,0.5,0.7)
C-5	(0.3,0.5,0.7)	(0.5,0.7,0.9)	(0.7,0.9,1.0)	(0.1,0.3,0.5)	(0.3,0.5,0.7)	(0.3,0.5,0.7)	(0.1,0.3,0.5)
C-6	(0.5,0.7,0.9)	(0.5,0.7,0.9)	(0.7,0.9,1.0)	(0.5,0.7,0.9)	(0.7,0.9,1.0)	(0.5,0.7,0.9)	(0.1,0.3,0.5)
C-7	(0.7,0.9,1.0)	(0.5,0.7,0.9)	(0.7,0.9,1.0)	(0.5,0.7,0.9)	(0.3,0.5,0.7)	(0.5,0.7,0.9)	(0.3,0.5,0.7)
C-8	(0.5,0.7,0.9)	(0.5,0.7,0.9)	(0.5,0.7,0.9)	(0.3,0.5,0.7)	(0.1,0.3,0.5)	(0.7,0.9,1.0)	(0.3,0.5,0.7)
C-9	(0.7,0.9,1.0)	(0.7,0.9,1.0)	(0.5,0.7,0.9)	(0.3,0.5,0.7)	(0.7,0.9,1.0)	(0.5,0.7,0.9)	(0.5,0.7,0.9)
C-10	(0.5,0.7,0.9)	(0.7,0.9,1.0)	(0.3,0.5,0.7)	(0.3,0.5,0.7)	(0.1,0.3,0.5)	(0.5,0.7,0.9)	(0.5,0.7,0.9)
C-11	(0.5,0.7,0.9)	(0.7,0.9,1.0)	(0.1,0.3,0.5)	(0.5,0.7,0.9)	(0.3,0.5,0.7)	(0.5,0.7,0.9)	(0.3,0.5,0.7)
C-12	(0.5,0.7,0.9)	(0.5,0.7,0.9)	(0.5,0.7,0.9)	(0.3,0.5,0.7)	(0.3,0.5,0.7)	(0.3,0.5,0.7)	(0.3,0.5,0.7)
C-13	(0.5,0.7,0.9)	(0.3,0.5,0.7)	(0.5,0.7,0.9)	(0.5,0.7,0.9)	(0.5,0.7,0.9)	(0.3,0.5,0.7)	(0.3,0.5,0.7)
C-14	(0.5,0.7,0.9)	(0.3,0.5,0.7)	(0.3,0.5,0.7)	(0.3,0.5,0.7)	(0.3,0.5,0.7)	(0.3,0.5,0.7)	(0.3,0.5,0.7)
C-15	(0.1,0.3,0.5)	(0.3,0.5,0.7)	(0.1,0.3,0.5)	(0.3,0.5,0.7)	(0.1,0.3,0.5)	(0.1,0.3,0.5)	(0.3,0.5,0.7)

Appendix 5

See Table 15.

Table 15 Un-weighted fuzzy matrix R

	1			2			3			4			5			6			7		
C-1	0.7	0.9	1	0.1	0.3	0.5	0.7	0.9	1	0.3	0.5	0.7	0.1	0.3	0.5	0.1	0.3	0.5	0.1	0.3	0.5
C-2	0.7	0.9	1	0.7	0.9	1	0.7	0.9	1	0.5	0.7	0.9	0.3	0.5	0.7	0.5	0.7	0.9	0.5	0.7	0.9
C-3	0.7	0.9	1	0.7	0.9	1	0.3	0.5	0.7	0.5	0.7	0.9	0.3	0.5	0.7	0.5	0.7	0.9	0.5	0.7	0.9
C-4	0.3	0.5	0.7	0.3	0.5	0.7	0.1	0.3	0.5	0.5	0.7	0.9	0.1	0.3	0.5	0.3	0.5	0.7	0.3	0.5	0.7
C-5	0.3	0.5	0.7	0.5	0.7	0.9	0.7	0.9	1	0.1	0.3	0.5	0.3	0.5	0.7	0.3	0.5	0.7	0.1	0.3	0.5
C-6	0.5	0.7	0.9	0.5	0.7	0.9	0.7	0.9	1	0.5	0.7	0.9	0.7	0.9	1	0.5	0.7	0.9	0.7	0.9	1
C-7	0.7	0.9	1	0.5	0.7	0.9	0.7	0.9	1	0.5	0.7	0.9	0.3	0.5	0.7	0.5	0.7	0.9	0.3	0.5	0.7
C-8	0.5	0.7	0.9	0.5	0.7	0.9	0.5	0.7	0.9	0.3	0.5	0.7	0.1	0.3	0.5	0.7	0.9	1	0.3	0.5	0.7
C-9	0.7	0.9	1	0.7	0.9	1	0.5	0.7	0.9	0.3	0.5	0.7	0.7	0.9	1	0.5	0.7	0.9	0.5	0.7	0.9
C-10	0.5	0.7	0.9	0.7	0.9	1	0.3	0.5	0.7	0.3	0.5	0.7	0.1	0.3	0.5	0.5	0.7	0.9	0.5	0.7	0.9
C-11	0.5	0.7	0.9	0.7	0.9	1	0.1	0.3	0.5	0.5	0.7	0.9	0.3	0.5	0.7	0.5	0.7	0.9	0.3	0.5	0.7
C-12	0.3	0.5	0.7	0.5	0.7	0.9	0.5	0.7	0.9	0.3	0.5	0.7	0.3	0.5	0.7	0.3	0.5	0.7	0.3	0.5	0.7
C-13	0.5	0.7	0.9	0.3	0.5	0.7	0.5	0.7	0.9	0.5	0.7	0.9	0.5	0.7	0.9	0.3	0.5	0.7	0.3	0.5	0.7
C-14	0.5	0.7	0.9	0.3	0.5	0.7	0.3	0.5	0.7	0.3	0.5	0.7	0.3	0.5	0.7	0.3	0.5	0.7	0.3	0.5	0.7
C-15	0.1	0.3	0.5	0.3	0.5	0.7	0.1	0.3	0.5	0.3	0.5	0.7	0.1	0.3	0.5	0.1	0.3	0.5	0.3	0.5	0.7

Appendix 6

See Table 16.

Table 16 Distance of the ratings of each factor from A⁺ with respect to each criterion

	1	2	3	4	5	6	7	D+
C-1	0.981	0.979	0.966	0.94	0.931	0.931	0.942	6.67
C-2	0.981	0.941	0.888	0.826	0.86	0.9	0.942	6.338
C-3	0.981	0.941	0.888	0.826	0.87	0.919	0.967	6.391
C-4	0.989	0.971	0.942	0.9	0.919	0.946	0.98	6.647
C-5	0.989	0.958	0.916	0.86	0.879	0.906	0.942	6.45
C-6	0.984	0.955	0.914	0.86	0.879	0.906	0.942	6.441
C-7	0.981	0.953	0.914	0.86	0.879	0.906	0.942	6.434
C-8	0.984	0.955	0.914	0.86	0.884	0.915	0.953	6.467
C-9	0.981	0.941	0.888	0.826	0.865	0.909	0.953	6.363
C-10	0.984	0.943	0.889	0.826	0.87	0.919	0.967	6.398
C-11	0.984	0.943	0.889	0.826	0.875	0.928	0.98	6.426
C-12	0.989	0.958	0.916	0.86	0.884	0.915	0.953	6.476
C-13	0.984	0.968	0.94	0.9	0.91	0.928	0.953	6.583
C-14	0.984	0.968	0.94	0.9	0.914	0.937	0.967	6.611
C-15	0.993	0.974	0.943	0.9	0.919	0.946	0.98	6.656

Appendix 7

See Table 17.

Table 17 Distance of the ratings of each factor from a with respect to each criterion

	1	2	3	4	5	6	7	**D-**
C-1	0.02	0.021	0.039	0.069	0.073	0.073	0.059	**0.352**
C-2	0.02	0.083	0.133	0.176	0.158	0.124	0.059	**0.752**
C-3	0.02	0.083	0.133	0.176	0.156	0.118	0.035	**0.721**
C-4	0.012	0.037	0.068	0.106	0.1	0.082	0.023	**0.427**
C-5	0.012	0.059	0.1	0.144	0.135	0.113	0.059	**0.622**
C-6	0.016	0.06	0.1	0.144	0.135	0.113	0.059	**0.628**
C-7	0.02	0.061	0.101	0.144	0.135	0.113	0.059	**0.632**
C-8	0.016	0.06	0.1	0.144	0.134	0.11	0.048	**0.612**
C-9	0.02	0.083	0.133	0.176	0.157	0.121	0.048	**0.737**
C-10	0.016	0.083	0.133	0.176	0.156	0.118	0.035	**0.717**
C-11	0.016	0.083	0.133	0.176	0.156	0.117	0.023	**0.703**
C-12	0.012	0.059	0.1	0.144	0.134	0.11	0.048	**0.607**
C-13	0.016	0.038	0.069	0.106	0.102	0.088	0.048	**0.466**
C-14	0.016	0.038	0.069	0.106	0.1	0.084	0.035	**0.448**
C-15	0.008	0.036	0.068	0.106	0.1	0.082	0.023	**0.422**

Appendix 8

See Table 18.

Table 18 Influence matrix

	C-1	C-2	C-3	C-4	C-5	C-6	C-7	C-8	C-9	C-10	C-11	C-12	C-13	C-14	C-15
X_1															
C-1	0	2	3	3	2	4	2	3	2	2	3	4	3	4	2
C-2	2	0	3	3	2	4	3	2	3	4	2	3	2	1	1
C-3	2	3	0	2	3	2	1	4	2	1	3	1	2	1	3
C-4	2	3	3	0	3	3	2	3	2	3	3	0	3	0	3
C-5	1	2	2	1	0	3	1	2	2	2	2	4	2	4	2
C-6	2	2	2	3	2	0	3	2	2	3	3	3	3	2	2
C-7	2	1	2	3	2	1	0	2	1	1	2	3	2	1	2
C-8	2	2	2	3	2	2	1	0	2	2	2	1	3	2	3
C-9	1	2	3	2	3	1	2	4	0	3	1	2	3	3	2
C-10	2	2	2	3	2	2	2	2	2	0	3	3	0	2	3
C-11	2	1	2	2	2	3	1	2	2	2	0	2	2	2	2
C-12	2	0	1	2	3	2	2	3	2	3	2	0	2	1	2
C-13	2	3	1	2	3	2	2	2	2	0	1	2	0	2	2
C-14	1	2	2	2	2	1	1	2	2	2	2	1	2	0	2
C-15	2	3	1	1	3	2	2	3	2	2	2	1	3	2	0
X_2															
C-1	0	2	3	3	2	4	2	3	2	2	3	4	3	4	2
C-2	2	0	3	3	2	4	3	2	3	4	2	3	2	1	1
C-3	2	3	0	2	3	2	1	4	2	1	3	1	2	1	3
C-4	2	3	3	0	3	3	2	3	2	3	3	0	3	0	3
C-5	1	2	2	1	0	3	1	2	2	2	2	4	2	4	2
C-6	2	2	2	3	2	0	3	2	2	3	3	3	3	2	2
C-7	2	1	2	3	2	1	0	2	1	1	2	3	2	1	2
C-8	2	2	2	3	2	2	1	0	2	2	2	1	3	2	3
C-9	1	2	3	2	3	1	2	4	0	3	1	2	3	3	2
C-10	2	2	2	3	2	2	2	2	2	0	3	3	0	2	3
C-11	2	1	2	2	2	3	1	2	2	2	0	2	2	2	2
C-12	2	0	1	2	3	2	2	3	2	3	2	0	2	1	2
C-13	2	3	1	2	3	2	2	2	2	0	1	2	0	2	2
C-14	1	2	2	2	2	1	1	2	2	2	2	1	2	0	2
C-15	2	3	1	1	3	2	2	3	2	2	2	1	3	2	0
X_3															
C-1	0	2	1	2	1	2	2	2	1	2	2	2	2	1	2
C-2	3	0	2	0	1	3	3	3	2	2	2	2	3	2	1
C-3	3	3	0	1	2	2	2	2	1	1	2	2	2	2	1
C-4	2	4	2	0	2	1	2	2	2	3	1	1	2	2	3
C-5	2	3	2	2	0	2	2	2	2	3	2	2	2	2	3
C-6	4	3	2	2	3	0	3	2	1	2	3	2	2	1	2
C-7	2	2	1	2	1	1	0	1	2	2	1	2	2	1	2
C-8	3	3	3	3	2	2	2	0	3	2	2	2	2	2	3
C-9	2	2	2	2	2	1	2	2	0	2	2	2	2	2	2
C-10	3	3	2	2	2	2	3	3	3	0	2	2	0	2	3
C-11	3	3	2	2	2	2	3	2	1	1	0	2	3	2	2
C-12	4	0	1	1	4	3	3	1	1	2	4	0	3	1	1
C-13	2	3	1	2	2	1	3	2	3	0	2	3	0	2	2
C-14	4	0	1	1	4	1	2	2	2	2	2	1	2	0	2
C-15	2	3	2	2	2	2	2	3	1	2	2	1	3	2	0
X_4															
C-1	0	2	1	2	1	2	2	2	1	2	2	2	2	1	2
C-2	2	0	2	3	2	3	2	4	2	3	1	3	2	2	3

Table 18 (continued)

	C-1	C-2	C-3	C-4	C-5	C-6	C-7	C-8	C-9	C-10	C-11	C-12	C-13	C-14	C-15
C-3	3	3	0	1	2	2	2	2	1	1	2	2	2	2	1
C-4	2	1	2	0	1	2	3	3	2	2	2	2	1	2	1
C-5	2	3	2	2	0	2	2	2	2	3	2	2	2	2	3
C-6	4	3	2	2	3	0	3	2	1	2	3	2	2	1	2
C-7	2	2	1	2	1	1	0	1	2	2	1	2	2	1	2
C-8	3	3	3	3	2	2	2	0	3	2	2	2	2	2	3
C-9	2	2	2	2	2	1	2	2	0	2	2	2	2	2	2
C-10	3	4	2	2	3	2	3	3	3	0	2	2	1	2	4
C-11	3	3	2	2	2	2	3	2	1	1	0	2	3	2	2
C-12	4	0	1	1	4	3	3	1	1	2	4	0	3	1	1
C-13	2	3	1	2	2	1	3	2	3	0	2	3	0	2	2
C-14	4	0	1	1	4	1	2	2	2	2	2	1	2	0	2
C-15	2	3	2	2	2	2	2	3	1	2	2	1	3	2	0

X_5

	C-1	C-2	C-3	C-4	C-5	C-6	C-7	C-8	C-9	C-10	C-11	C-12	C-13	C-14	C-15
C-1	0	1	1	2	1	2	2	2	1	2	2	2	2	1	2
C-2	3	0	3	1	3	2	2	3	4	3	2	3	4	1	3
C-3	2	3	0	1	2	1	2	3	1	2	2	2	1	1	2
C-4	2	0	2	0	2	3	1	1	2	2	1	2	3	2	1
C-5	2	2	2	2	0	3	2	3	2	2	2	2	3	2	2
C-6	1	2	1	2	1	0	2	2	2	2	1	1	2	1	1
C-7	2	4	1	2	3	2	0	3	1	2	3	3	2	2	1
C-8	2	1	2	1	2	3	2	0	1	2	2	2	2	1	2
C-9	2	2	2	2	3	2	2	2	0	2	2	2	3	2	1
C-10	3	3	2	2	2	3	2	3	3	0	2	3	1	2	2
C-11	2	3	2	2	2	2	2	3	1	3	0	3	1	2	2
C-12	1	2	1	2	2	1	2	2	1	3	3	0	2	1	2
C-13	2	2	2	2	2	2	3	3	3	1	2	3	0	1	1
C-14	2	4	1	1	4	2	1	1	2	2	2	2	2	0	1
C-15	3	2	2	2	2	1	1	3	1	3	2	2	2	2	0

X_6

	C-1	C-2	C-3	C-4	C-5	C-6	C-7	C-8	C-9	C-10	C-11	C-12	C-13	C-14	C-15
C-1	0	3	2	3	2	3	2	4	3	1	2	3	4	3	3
C-2	2	0	3	3	4	2	3	4	4	2	1	2	3	4	3
C-3	2	1	0	3	2	3	2	2	1	2	1	1	3	2	3
C-4	2	1	2	0	3	1	3	2	3	2	2	1	2	1	3
C-5	2	1	1	2	0	4	2	1	2	3	2	3	3	2	4
C-6	0	3	2	3	2	0	2	4	3	1	2	3	4	3	3
C-7	1	2	3	2	3	3	0	3	1	2	1	2	3	2	3
C-8	2	2	2	3	1	2	1	0	2	1	2	1	3	2	3
C-9	3	2	3	2	2	1	2	3	0	3	2	1	3	2	1
C-10	1	3	2	1	3	2	3	4	3	0	3	2	2	2	3
C-11	2	2	3	4	3	4	3	2	3	2	0	1	2	1	4
C-12	1	2	1	3	3	3	2	3	2	3	2	0	3	2	2
C-13	2	3	1	2	3	2	2	2	2	2	1	2	0	2	2
C-14	1	3	2	3	2	2	1	1	2	3	3	2	1	0	3
C-15	2	4	2	1	3	3	2	2	3	2	1	2	2	3	0

X_7

	C-1	C-2	C-3	C-4	C-5	C-6	C-7	C-8	C-9	C-10	C-11	C-12	C-13	C-14	C-15
C-1	0	2	1	2	1	2	2	2	1	2	2	2	2	1	2
C-2	3	0	2	0	1	3	3	3	2	2	2	2	3	2	1
C-3	3	3	0	1	2	2	2	2	1	1	2	2	2	2	1
C-4	2	4	2	0	2	1	2	2	2	3	1	1	2	2	3
C-5	2	3	2	2	0	2	2	2	2	3	2	2	2	2	3

Table 18 (continued)

	C-1	C-2	C-3	C-4	C-5	C-6	C-7	C-8	C-9	C-10	C-11	C-12	C-13	C-14	C-15
C-6	4	3	2	2	3	0	3	2	1	2	3	2	2	1	2
C-7	2	2	1	2	1	1	0	1	2	2	1	2	2	1	2
C-8	3	3	3	3	2	2	2	0	3	2	2	2	2	2	3
C-9	2	2	2	2	2	1	2	2	0	2	2	2	2	2	2
C-10	3	3	2	2	2	2	3	3	3	0	2	2	0	2	3
C-11	3	3	2	2	2	2	3	2	1	1	0	2	3	2	2
C-12	4	0	1	1	4	3	3	1	1	2	4	0	3	1	1
C-13	2	3	1	2	2	1	3	2	3	0	2	3	0	2	2
C-14	4	0	1	1	4	1	2	2	2	2	2	1	2	0	2
C-15	2	3	2	2	2	2	2	3	1	2	2	1	3	2	0

Appendix 9

Variable used in the article.

AHP Methodology

P1 = Pairwise comparison matrix

P2 = Principal matrix

λ_{max} = Average of the elements of P_4.

CI = Consistency index.

CR = Consistency Ratio.

RCI = random consistency Index.

n = Number of elements.

PV = priority Vector.

Fuzzy TOPSIS Methodology

A^+ = Fuzzy ideal solution.

A^- = Fuzzy negative ideal solution.

$Y_{ij} = (d_{ij}, e_{ij}, $ and $f_{ij})$ = Triangular fuzzy number for the linguistic term.

c_{j*}^* and d_j^- = Benefit criteria and cost criteria respectively.

W = Weight of criteria.

V^* and V^- = Values considered for the ideal and negative ideal solution.

g, h, and i = aThe real numbers.

D^+ = Distance between to fuzzy numbers.

D^- = Distance of rating.

C = Closeness the ideal solution.

DEMATEL Methodology

Z = Average matrix.

x_{ij} = Elements of average matrix.

N = Normalized initial direct-relation matrix.

n_{ij} = Elements of normalized initial direct-relation matrix.

Y = Total relation matrix.

I = Identity matrix.

References

Agrawal S, Singh RK, Murtaza Q (2016) Prioritizing critical success factors for reverse logistics implementation using fuzzy-TOPSIS methodology. J Ind Eng Int 12:15–27. https://doi.org/10.1007/s40092-015-0124-8

Altuntas S, Dereli T (2015) A novel approach based on DEMATEL method and patent citation analysis for prioritizing a portfolio of investment projects. Expert Syst Appl 42:1003–1012. https://doi.org/10.1016/j.eswa.2014.09.018

Amui LBL, Jabbour CJC, de Sousa Jabbour ABL, Kannan D (2017) Sustainability as a dynamic organizational capability: a systematic review and a future agenda toward a sustainable transition. J Clean Prod 142:308–322. https://doi.org/10.1016/j.jclepro.2016.07.103

Bag S, Wood LC, Xu L et al (2020) Big data analytics as an operational excellence approach to enhance sustainable supply chain performance. Resour Conserv Recycl 153:104559. https://doi.org/10.1016/j.resconrec.2019.104559

Barlow M (2013) Real-time big data analytics: emerging architecture. O'Reilly Media, Sebastopol, USA

Belhadi A, Zkik K, Cherrafi A et al (2019) Understanding Big Data Analytics for manufacturing processes: insights from literature review and multiple case studies. Comput Ind Eng 137:106099. https://doi.org/10.1016/j.cie.2019.106099

Bi Z, Cochran D (2014) Big data analytics with applications. J Manag Anal 1:249–265. https://doi.org/10.1080/23270012.2014.992985

Braganza A, Brooks L, Nepelski D et al (2017) Resource management in big data initiatives: Processes and dynamic capabilities. J Bus Res 70:328–337. https://doi.org/10.1016/j.jbusres.2016.08.006

Brinch M, Stentoft J, Jensen JK (2017) Big data and its applications in supply chain management: findings from a delphi study. Hawaii Int Conf Syst Sci. https://doi.org/10.24251/HICSS.2017.161

Chen M, Mao S, Liu Y (2014) Big data: a survey. Mob Networks Appl 19:171–209. https://doi.org/10.1007/s11036-013-0489-0

Cui Y, Kara S, Chan KC (2020) Manufacturing big data ecosystem: a systematic literature review. Robot Comput Integr Manuf 62:101861. https://doi.org/10.1016/j.rcim.2019.101861

Das R, Shaw K, Irfan M (2020) Supply chain network design considering carbon footprint, water footprint, supplier's social risk, solid waste, and service level under the uncertain condition. Clean Technol Environ Policy 22:337–370. https://doi.org/10.1007/s10098-019-01785-y

de Camargo FP, Roman Pais Seles BM, Chiappetta Jabbour CJ et al (2018) Management theory and big data literature: from a review to a research agenda. Int J Inf Manage 43:112–129. https://doi.org/10.1016/j.ijinfomgt.2018.07.005

Del Fabbro E, Santarossa D (2016) Ergonomic Analysis in Manufacturing Process A real time approach. Procedia CIRP 41:957–962. https://doi.org/10.1016/j.procir.2015.12.056

Demirkan H, Delen D (2013) Leveraging the capabilities of service-oriented decision support systems: Putting analytics and big data in cloud. Decis Support Syst 55:412–421. https://doi.org/10.1016/j.dss.2012.05.048

Doolun IS, Ponnambalam SG, Subramanian N, G K, (2018) Data driven hybrid evolutionary analytical approach for multi objective location allocation decisions: automotive green supply chain empirical evidence. Comput Oper Res 98:265–283. https://doi.org/10.1016/j.cor.2018.01.008

Duan Y, Edwards JS, Dwivedi YK (2019) Artificial intelligence for decision making in the era of big data–evolution, challenges and research agenda. Int J Inf Manage 48:63–71. https://doi.org/10.1016/j.ijinfomgt.2019.01.021

Dubey R, Gunasekaran A, Childe SJ et al (2016) The impact of big data on world-class sustainable manufacturing. Int J Adv Manuf Technol 84:631–645. https://doi.org/10.1007/s00170-015-7674-1

Dubey R, Gunasekaran A, Childe SJ et al (2019a) Big data analytics and organizational culture as complements to swift trust and collaborative performance in the humanitarian supply chain. Int J Prod Econ 210:120–136. https://doi.org/10.1016/j.ijpe.2019.01.023

Dubey R, Gunasekaran A, Childe SJ et al (2019b) Empirical investigation of data analytics capability and organizational flexibility as complements to supply chain resilience. Int J Prod Res. https://doi.org/10.1080/00207543.2019.1582820

Elgendy N, Elragal A (2014) Big data analytics: a literature review paper. pp 214–227

ElMaraghy HA, Youssef AMA, Marzouk AM, ElMaraghy WH (2017) Energy use analysis and local benchmarking of manufacturing lines. J Clean Prod 163:36–48. https://doi.org/10.1016/j.jclepro.2015.12.026

Fercoq A, Lamouri S, Carbone V (2016) Lean/green integration focused on waste reduction techniques. J Clean Prod 137:567–578. https://doi.org/10.1016/j.jclepro.2016.07.107

Gandhi S, Mangla SK, Kumar P, Kumar D (2015) Evaluating factors in implementation of successful green supply chain management using DEMATEL: a case study. Int Strateg Manag Rev 3:96–109. https://doi.org/10.1016/j.ism.2015.05.001

Gandomi A, Haider M (2015) Beyond the hype: big data concepts, methods, and analytics. Int J Inf Manage 35:137–144. https://doi.org/10.1016/j.ijinfomgt.2014.10.007

Gawankar SA, Gunasekaran A, Kamble S (2020) A study on investments in the big data-driven supply chain, performance measures and organisational performance in Indian retail 4.0 context. Int J Prod Res 58:1574–1593. https://doi.org/10.1080/00207543.2019.1668070

Gong M, Simpson A, Koh L, Tan KH (2018) Inside out: The inter-relationships of sustainable performance metrics and its effect on business decision making: Theory and practice. Resour Conserv Recycl 128:155–166. https://doi.org/10.1016/j.resconrec.2016.11.001

Gunasekaran A, Papadopoulos T, Dubey R et al (2017) Big data and predictive analytics for supply chain and organizational performance. J Bus Res 70:308–317. https://doi.org/10.1016/j.jbusres.2016.08.004

Gupta A, Singh RK, Suri PK (2018) Prioritizing critical success factors for sustainable service quality management by logistics service providers. Vis J Bus Perspect 22:295–305. https://doi.org/10.1177/0972262918786102

Gupta S, Modgil S, Gunasekaran A (2020) Big data in lean six sigma: a review and further research directions. Int J Prod Res 58:947–969. https://doi.org/10.1080/00207543.2019.1598599

Hazen BT, Skipper JB, Ezell JD, Boone CA (2016) Big data and predictive analytics for supply chain sustainability: a theory-driven research agenda. Comput Ind Eng 101:592–598. https://doi.org/10.1016/j.cie.2016.06.030

Hidayanto AN, Abednego N, Aminah S, Sucahyo YG (2015) Analysis of cloud adoption determinants by using BOCR analysis and DEMATEL. Int J Bus Inf Syst 18:221. https://doi.org/10.1504/IJBIS.2015.067265

Ivanov D, Dolgui A, Sokolov B (2019) The impact of digital technology and Industry 4.0 on the ripple effect and supply chain risk analytics. Int J Prod Res 57:829–846. https://doi.org/10.1080/00207543.2018.1488086

Janssen M, van der Voort H, Wahyudi A (2017) Factors influencing big data decision-making quality. J Bus Res 70:338–345. https://doi.org/10.1016/j.jbusres.2016.08.007

Ji-fan Ren S, Fosso Wamba S, Akter S et al (2017) Modelling quality dynamics, business value and firm performance in a big data analytics environment. Int J Prod Res 55:5011–5026. https://doi.org/10.1080/00207543.2016.1154209

Kalema BM, Mokgadi M (2017) Developing countries organizations readiness for big data analytics. Probl Perspect Manag 15:260–270. https://doi.org/10.21511/ppm.15(1-1).2017.13

Kim G, Park CS, Yoon KP (1997) Identifying investment opportunities for advanced manufacturing systems with comparative-integrated performance measurement. Int J Prod Econ 50:23–33. https://doi.org/10.1016/S0925-5273(97)00014-5

Kumar P, Singh RK (2012) A fuzzy AHP and TOPSIS methodology to evaluate 3PL in a supply chain. J Model Manag 7:287–303. https://doi.org/10.1108/17465661211283287

Lavalle S, Lesser E, Shockley R, Hopkins MS, Kruschwitz N (2011) Big data, analytics and the path from insights to value. MIT Sloan Manag Review 52:21–32

Lee I (2017) Big data: dimensions, evolution, impacts, and challenges. Bus Horiz 60:293–303. https://doi.org/10.1016/j.bushor.2017.01.004

Lee J, Lapira E, Bagheri B, Kao H (2013) Recent advances and trends in predictive manufacturing systems in big data environment. Manuf Lett 1:38–41. https://doi.org/10.1016/j.mfglet.2013.09.005

Lee J, Ardakani HD, Yang S, Bagheri B (2015) Industrial big data analytics and cyber-physical systems for future maintenance and service innovation. Procedia CIRP 38:3–7. https://doi.org/10.1016/j.procir.2015.08.026

Li J, Tao F, Cheng Y, Zhao L (2015) Big data in product lifecycle management. Int J Adv Manuf Technol 81:667–684. https://doi.org/10.1007/s00170-015-7151-x

Lima Junior FR, Osiro L, Carpinetti LCR (2014) A comparison between fuzzy AHP and fuzzy TOPSIS methods to supplier selection. Appl Soft Comput 21:194–209. https://doi.org/10.1016/j.asoc.2014.03.014

Lin R-J (2013) Using fuzzy DEMATEL to evaluate the green supply chain management practices. J Clean Prod 40:32–39. https://doi.org/10.1016/j.jclepro.2011.06.010

Lin K-P, Tseng M-L, Pai P-F (2018) Sustainable supply chain management using approximate fuzzy DEMATEL method. Resour Conserv Recycl 128:134–142. https://doi.org/10.1016/j.resconrec.2016.11.017

Luthra S, Govindan K, Kharb RK, Mangla SK (2016) Evaluating the enablers in solar power developments in the current scenario using fuzzy DEMATEL: an Indian perspective. Renew Sustain Energy Rev 63:379–397. https://doi.org/10.1016/j.rser.2016.04.041

Manavalan E, Jayakrishna K (2019) A review of Internet of Things (IoT) embedded sustainable supply chain for industry 4.0 requirements. Comput Ind Eng 127:925–953. https://doi.org/10.1016/j.cie.2018.11.030

Mangla SK, Luthra S, Rich N et al (2018) Enablers to implement sustainable initiatives in agri-food supply chains. Int J Prod Econ 203:379–393. https://doi.org/10.1016/j.ijpe.2018.07.012

Munirathinam S, Ramadoss B (2014) Big data predictive analytics for proactive semiconductor equipment maintenance. In: 2014 IEEE international conference on big data (big data). IEEE, pp 893–902

Mustapha MA, Manan ZA, Wan Alwi SR (2017) Sustainable Green Management System (SGMS)–an integrated approach towards organisational sustainability. J Clean Prod 146:158–172. https://doi.org/10.1016/j.jclepro.2016.06.033

Piyathanavong V, Garza-Reyes JA, Kumar V et al (2019) The adoption of operational environmental sustainability approaches in the Thai manufacturing sector. J Clean Prod 220:507–528. https://doi.org/10.1016/j.jclepro.2019.02.093

Popovič A, Hackney R, Tassabehji R, Castelli M (2018) The impact of big data analytics on firms' high value business performance. Inf Syst Front 20:209–222. https://doi.org/10.1007/s10796-016-9720-4

Raut RD, Mangla SK, Narwane VS et al (2019) Linking big data analytics and operational sustainability practices for sustainable business management. J Clean Prod 224:10–24. https://doi.org/10.1016/j.jclepro.2019.03.181

Saaty TL (1980) The analytic hierarchy process. McGraw-Hill, New York, p 324

Saaty TL (2000) Fundamentals of decision making and priority theory with the analytic hierarchy process. Vol. 6 RWS publications

Samaie F, Javadi S, Meyar-Naimi H, Feshki-Farahani H (2020) Environmental sustainability policy on plug-in hybrid electric vehicle penetration utilizing fuzzy TOPSIS and game theory. Clean Technol Environ Policy. https://doi.org/10.1007/s10098-020-01821-2

Sanders NR (2016) How to use big data to drive your supply chain. Calif Manage Rev 58:26–48. https://doi.org/10.1525/cmr.2016.58.3.26

Singh RK (2012) Justification of coordinated supply chain in small and medium enterprises using analytic hierarchy process. Int J Serv Sci 4:277. https://doi.org/10.1504/IJSSCI.2012.051062

Singh RK (2013) Prioritizing the factors for coordinated supply chain using analytic hierarchy process (AHP). Meas Bus Excell 17:80–97. https://doi.org/10.1108/13683041311311383

Singh RK, Agrawal S (2018) Analyzing disposition strategies in reverse supply chains: fuzzy TOPSIS approach. Manag Environ Qual An Int J 29:427–443. https://doi.org/10.1108/MEQ-12-2017-0177

Singh SK, El-Kassar A-N (2019) Role of big data analytics in developing sustainable capabilities. J Clean Prod 213:1264–1273. https://doi.org/10.1016/j.jclepro.2018.12.199

Singh RK, Luthra S, Mangla SK, Uniyal S (2019) Applications of information and communication technology for sustainable growth of SMEs in India food industry. Resour Conserv Recycl 147:10–18. https://doi.org/10.1016/j.resconrec.2019.04.014

Song M, Fisher R, Kwoh Y (2019) Technological challenges of green innovation and sustainable resource management with large scale data. Technol Forecast Soc Change 144:361–368. https://doi.org/10.1016/j.techfore.2018.07.055

Tan J, Tan RR, Aviso KB et al (2017) Study of microalgae cultivation systems based on integrated analytic hierarchy process–life cycle optimization. Clean Technol Environ Policy 19:2075–2088. https://doi.org/10.1007/s10098-017-1390-5

Tao F, Cheng J, Qi Q et al (2018) Digital twin-driven product design, manufacturing and service with big data. Int J Adv Manuf Technol 94:3563–3576. https://doi.org/10.1007/s00170-017-0233-1

Telukdarie A, Buhulaiga E, Bag S et al (2018) Industry 4.0 implementation for multinationals. Process Saf Environ Prot 118:316–329. https://doi.org/10.1016/j.psep.2018.06.030

Tseng M-L, Lim MK, Wu K-J (2019) Improving the benefits and costs on sustainable supply chain finance under uncertainty. Int J Prod Econ 218:308–321. https://doi.org/10.1016/j.ijpe.2019.06.017

Wamba SF, Dubey R, Gunasekaran A, Akter S (2020) The performance effects of big data analytics and supply chain ambidexterity: the moderating effect of environmental dynamism. Int J Prod Econ 222:107498. https://doi.org/10.1016/j.ijpe.2019.09.019

Wang Z, Xue M, Wang Y et al (2019) Big data: new tend to sustainable consumption research. J Clean Prod 236:117499. https://doi.org/10.1016/j.jclepro.2019.06.330

Weerakkody V, Kapoor K, Balta ME et al (2017) Factors influencing user acceptance of public sector big open data. Prod Plan Control 28:891–905. https://doi.org/10.1080/09537287.2017.1336802

Wilcox T, Jin N, Flach P, Thumim J (2019) A big data platform for smart meter data analytics. Comput Ind 105:250–259. https://doi.org/10.1016/j.compind.2018.12.010

Wood LC, Wang C, Abdul-Rahman H, Jamal Abdul-Nasir NS (2016) Green hospital design: integrating quality function deployment and end-user demands. J Clean Prod 112:903–913. https://doi.org/10.1016/j.jclepro.2015.08.101

Yaqoob I, Hashem IAT, Gani A et al (2016) Big data: from beginning to future. Int J Inf Manage 36:1231–1247. https://doi.org/10.1016/j.ijinfomgt.2016.07.009

Zhong RY, Huang GQ, Lan S et al (2015) A big data approach for logistics trajectory discovery from RFID-enabled production data. Int J Prod Econ 165:260–272. https://doi.org/10.1016/j.ijpe.2015.02.014

Zhong RY, Newman ST, Huang GQ, Lan S (2016) Big Data for supply chain management in the service and manufacturing sectors: Challenges, opportunities, and future perspectives. Comput Ind Eng 101:572–591. https://doi.org/10.1016/j.cie.2016.07.013

Zimmermann H-J (1985) Applications of fuzzy set theory to mathematical programming. Inf Sci (Ny) 36:29–58. https://doi.org/10.1016/0020-0255(85)90025-8