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Linking big data analytics and operational sustainability practices for sustainable business management

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A B S T R A C T

Big data analytics is becoming very popular concept in academia as well as in industry. It has come up with new decision tools to design data-driven supply chains. The manufacturing industry is under huge pressure to integrate sustainable practices into their overall business for sustainbale operations management. The purpose of this study is to analyse the predictors of sustainable business performance through big data analytics in the context of developing countries. Data was collected from manufacturing firms those have adopted sustainable practices. A hybrid Structural Equation Modelling - Artificial Neural Network model is used to analyse 316 responses of Indian professional experts. Factor analysis results shows that management and leadership style, state and central-government policy, supplier integration, internal business process, and customer integration have a significant influence on big data analytics and sustainability practices. Furthermore, the results obtained from structural equation modelling were feed as input to the artificial neural network model. The study findings shows that management and leadership style, state and central-government policy as the two most important predictors of big data analytics and sustainability practices. The results provide unique insights into manufacturing firms to improve their sustainable business performance from an operations management viewpoint. The study provides theoretical and practical insights into big data implementation issues in accomplishing sustainability practices in business organisations of emerging economies.

1. Introduction

In 2018, the Indian manufacturing sector grew to US$ 198.05 billion with cumulative foreign investment of US$ 76.82 billion since 2000 (IBEF, 2018). Manufacturing firms must follow sustainable practices which demands “top-down” effort by government and “bottom-up” efforts from companies (Tseng and Chiu, 2013). United Nations set sustainable development goals (SDGs) to be achieved till 2030, which includes a drop in gas emission drop by 3–5% per year, the probability of 50% staying inside 2 °C warming (Griggs et al., 2013). Recently, Digital India, Skill India, and Make-in-India campaigns launched by the government aim to improve the competitiveness of industry for sustainable business development (Meity, 2017). However, according to UNEP-WCMC (2018) report manufacturing firms, developing countries need to develop their business capabilities and improve their performance in order to meet SDGs.

Currently, Big-data analytics (BDA) is a very demanding and accepting in Industry as well as in academia. There are five imminent fields in BDA such as predictive analytics, additive manufacturing, autonomous vehicles, borderless supply-chains and material science (Fawcett and Waller, 2014). The big data

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opportunities include business intelligence, value-creation, and business decisions (Kumar et al., 2013). Big-data is evolved more technologically to identify financial welfare of firms. The value of Big-data cannot be analysed only through simple statistics (Sandhu and Sood, 2015). BDA can be useful if industries can develop the capability in practical use of new technologies. BDA capabilities are data-driven, and offer advantages as follows: optimizes of data generation process (Song et al., 2015), suggested data integration from the heterogeneous sources (Zhang et al., 2017), assimilates different types of findings into the business process (Dubey et al., 2018), and data visualisation capability eases the decision-making process (Ren et al., 2019).

It must be noted that BDA can transform the manufacturing industry to apply sustainable practices more efficiently. BDA has a positive impact on supply chain and operations management performance (Gunasekaran et al., 2017), green supply chain (Doolun et al., 2018), sustainable manufacturing (Dubey et al., 2016), sustainable procurement (Kaur and Singh, 2018), and enhanced business values (Ren et al., 2017).

This research aims to link two research streams – BDA and sustainable manufacturing practices from an operations management context. A literature review was carried out to identify constructs for implementation of BDA. The identified constructs were analysed using structural equation modelling - artificial neural network (SEM-ANN). BDA can help organisations to gain sustainable competitive advantage required in the current turbulent market (Gupta and George, 2016). Big-data opportunities include business intelligence, value-creation, and business decisions (Kumar et al., 2013). Economic, social, and environmental sustainability are essential aspects of the business. BDA is transforming manufacturing firms and can help firms in better implementation of sustainable practices (Dubey et al., 2016). However, in case of Indian industries, major concerns for BDA adoptions include infrastructure cost, organisational challenges, privacy, etc. Hence, it is essential to identify factors to BDA adoption for sustainable practices in the context of developing countries like India. The study addresses the following research questions (RQ).

RQ1: What are the critical success factors for BDA adoption?

RQ2: How BDA can assist manufacturing firms in improving their sustainable business performance?

To address the research questions, the literature on 'big data analytics', 'sustainable manufacturing', 'BDA adoption' were reviewed. Then, the factors and sub-factors explored from literature and expert opinion. SEM-ANN two-step hybrid predictive analytics model shows a clear understanding of the organisational influence from the statistical viewpoint (Scott and Walczak, 2009). SEM analysis gives a sequence of the regression weights, which are further ranked using ANN (Priyadarshinee et al., 2017). The objectives of the study are as follows.

RO1: To identify the success factors for implementation of BDA in Indian sustainable manufacturing firms.

RO2: To understand the impact of BDA on manufacturing firms in implementing sustainable practices.

The paper is organised in sections as follows: The next section discusses the literature review on BDA followed by the research gaps. Section 3, focuses on the conceptual framework and hypothesis, whereas Section 4 discusses the research methodology. Section 5 presents the results and discussion with managerial implication. Finally, the paper concludes with limitations and future directions of study.

2. Literature review

This part of the paper is divided into four subsections as i) BDA challenges, ii) BDA and supply chain management iii) Sustainable manufacturing, iv) BDA for sustainable business practices, and v) identification of research gaps.

2.1. Big data analytics challenges

According to Zikopoulos and Eaton (2011), big data is large data sets which traditional DBMS (database management systems) tools are unable to process. Five V's of big data are volume, velocity, variety, veracity, and value (Addo-Tenkorang and Helo, 2016). BDA can be useful for all supply chain functions – procurement, logistics, manufacturing, and demand management (Nguyen et al., 2018). Some of the big-data challenges should be realised for the possible of Big-data challenges. Jin et al. (2015) stated some limitations of the present data processing system. Businesses are continually putting new approaches to decision making, privacy issues, and ethical considerations relevant to data mining (Boyd and Crawford, 2012). One of the most significant challenges in Big-data implementation is the high-cost infrastructures. Sivarajah et al. (2017) stated that humans should analyse to sort the data for constructing the valuable information. Computer technology is required to enhance the storage space and human expertise. As per Akerkar (2013), the main drawbacks of Big-data are data challenges, process challenges, and management challenges. Arunachalam et al. (2018) stated the organisational challenges are time-consuming, insufficient-resources, privacy-security concerns, behavioural issues, issues with return on investment. BDA provides a unique set of opportunities for businesses. Few research articles focused on business and environmental aspects of BDA. The Big-data challenges include data-integration, data privacy issues, insufficient resources, and infrastructure (Kim et al., 2014). In order to deal with the Big-data challenges, advanced BDA requires exceptionally efficient, flexible and scalable skills (Sivarajah et al., 2017).

2.2. BDA and supply chain management

BDA has come up with new decision tools to make data-driven supply chain decisions. Big data in context of supply chain management is a structure, process and performance study. Wang et al. (2016) carried out specific research to review the widespread utility of BDA in supply-chain and logistics management. Big data brings new source of competitive advantages for logistics involvers to carry supply chain management to improve capabilities under demand and capacity variations on a real-time basis in smart price and better product. Fawcett and Waller (2014) argued that BDA can be a basis of future supply chain management. Milan and Gutiérrez (2015) stated BDA provides sufficient opportunities in supply chain management in terms of accuracy. Current research has recognised the significance of studying BDA with supply chain management in multiple-level and interlinked system.

Papadopoulos et al. (2017) examined the integration of BDA and supply chain integration in the context of sustainability, risk management and agility. The study advocated that there are limited studies on data-mining. BDA has an influence on supply chain and integration of these two streams along with human resources improves the sustainable performance of an organisation (Singh and El-Kassar, 2019). Data analytics can also play a crucial role in the sustainable humanitarian supply chain (Li et al., 2019). BDA capabilities can address the problem of carbon emission cost by coordinating low-carbon supply chain (Liu, 2019). Singh et al. (2018) proposed cloud computing based big data framework to select supplier in the beef supply chain for low carbon emission.

2.3. Sustainable manufacturing

Manufacturers consider sustainable manufacturing due to resource scarcity, consumer awareness of green products/processes, environmental regulations, and cost savings. Goals of sustainable manufacturing are to create and distribute goods with optimal usage of resources, and removing preventable process outputs including waste, CO_2 emission, toxic materials, etc. (Rachuri et al., 2011; Piyathanavong et al., 2019). Green manufacturing results in a decrease in energy consumption, environmental cost, and business waste (Kazancoglu et al., 2018a). Three pillars of sustainability are improving social and economic impacts through the complete product life-cycle and reducing environmental impact (Mangla et al., 2018). The concept of 'Triple Bottom Line' consisting of social, economic, and environment was coined in 1994 (Elkington, 2018). Based on the pillars of sustainability, Table 1 provides a summary of manufacturing systems (Kaebernick, 2014).

Table 1 provides a clear difference between sustainable manufacturing and green manufacturing. Green manufacturing targets only social and environmental factors, while sustainable manufacturing meets all three factors. Irrespective of drivers for sustainable practices, manufacturing industry, faces challenges such as investment cost, return on investment (ROI), technological and information limitations, standards, decision support system, etc. Manufacturing activities has significant environmental impacts, and with advancements in manufacturing technologies, energy technologies, and nano-particle technologies, environmental indicators must be studied extensively (Esmaeilian et al., 2016). Mani et al. (2018) studied social sustainability aspects in Portuguese manufacturing companies for customer, supply chain, manufacturer, and supplier. Thakur and Mangla (2019) evaluated the change management for sustainability considering operational-human-technological aspects in manufacturing firms in India. Kazancoglu et al. (2018b) proposed a framework for green supply chain based on a circular economy which integrates financial, logistic, marketing, environmental, organisational, and operational performance. Manufacturing firms need a transition to a circular economy for environmental protection and optimal resource consumption.

2.4. BDA for sustainable manufacturing

BDA can be used in sustainable manufacturing, supply chain, and decision making. Dubey et al. (2017) argued that all the types of manufacturing firms could adopt BDA, as flexibility and control orientation of the firm does not play a significant role. BDA with predictive analysis increases not only overall reliability, but also improves firm performance (Gunasekaran et al., 2017). The organisation must be agile due to the current market turbulence situation and their demand, BDA helps firms for adjusting their operational capabilities (Côrte-Real et al., 2017). Gunasekaran et al. (2018) studied the role of BDA in agile manufacturing through a framework, which considers market turbulence. In order to understand the role of BDA on world-class sustainable manufacturing (WSCM), Dubey et al. (2016) proposed a conceptual framework with eight inputs construct and three performance measures for the environment, social and economic gains. Furthermore, to predict condition-based maintenance (CBM), Kumar et al. (2018) proposed a big data driven sustainable manufacturing framework. The author used fuzzy unordered rule induction algorithm for maintenance cost estimation and CBM policy optimisation.

Stock et al. (2018) investigated the impact of Industry 4.0 on the social and environmental aspect of sustainability using three-stage qualitative assessments. For environmental sustainability, value creation factors contribute positively whereas energy consumption and material quantity have a negative impact; for social sustainability, the identified positive contributors were employee involvement, better integration, work enrichment, training, and work-life balance whereas with complete transparency there are chances of performance extortion and exploitation. Miranda et al. (2017) proposed S^3 (smart, sensing, and sustainable) product development framework which considers economic, environmental and social aspects for complete product's life cycle (manufacturing, use, and end-of-life). Objectives of sensing and smart were for monitoring and optimisation of parameters through control respectively; whereas objectives of sustainability were as follows: i) Economic-reduction in manufacturing cost, maintenance cost, and recycling cost, ii) Environmental-reduction in CO_2 footprints, number of components, product packaging, product weight, CO_2 emissions, damage to human health, and electric consumption, easy disassembly intended for recycling, iii) Social-reduction in assembly time and product price, more reuse of parts. Luthra and Mangla (2018) identified various challenges to I4.0 initiatives for sustainable supply chain in the Indian context. Eighteen challenges were categorised into four dimensions: organisational, legal and ethical, strategic, and technological. Ranks of top six challenges were as follows: lack of protocols for data sharing and global standards, lack of government policies and support, financial limitations, lack of internet and infrastructure, lack of top management support and security issues. Connections between Industry4.0 and circular economy have implications for SOM (sustainable operations management). de Sousa Jabbour et al. (2018a) proposed ReSOLVE (Regenerate, Share, Optimise, Loop, Virtualize, Exchange) model for product design, manufacturing, and logistics using key technologies of Industry.0 such as IoT, BD, cyber-physical system (CPS), additive manufacturing, and cloud manufacturing. To understand whether I4.0 can boost environment sustainable manufacturing, de Sousa Jabbour et al. (2018b) proposed an integrative framework through critical success factors (CSF).

2.5. Research gaps

Through a synthesis of the literature review, the author inferred that sustainability practices and BDA are two emerging research agendas and their adoption issues may vary in developing and developed economies. The following research gaps are as follows:

1. Current studies have mostly focused on the basics of BDA that includes value, volume, velocity, and variety. Furthermore, current literature deliberates the sustainable business and BDA

Table 1
Sustainability aspects for different manufacturing systems (summarised from Kaebernick, 2014).

	Green manufacturing	Lean manufacturing	Mass manufacturing	Sustainable manufacturing
Economic		✓	✓	✓
Social	✓		✓	✓
Environmental	✓	✓		✓

separately; few papers discuss the effect of BDA adoption on companies who are practising sustainable practices. Organisations must be aware of the benefits of BDA, which can improve lean, green and sustainable practices. Hence the authors focus on the latest research in the area of BDA, which includes different types of environmental and business-oriented variables.
2. Firms who are already implemented green and lean practices can further improve the system through BDA. Even though many literature articles show a positive association between firm performance and BDA, little is investigated about how BDA can contribute to sustainable business performance. In this study, the hybrid approach of SEM-ANN is employed to understand the effect of BDA adoption variables on sustainable business performance.
3. SEM is capable of verifying linear relationship while ANN can verify linear and non-linear relations. ANN is more advanced than SEM and Multiple Linear Regression (Chong, 2013). ANN analysis which is non-compensatory balances short-comings of SEM, which is compensatory (Shmueli and Koppius, 2011). Proposed methodology did not include any maturity model as this was not the purpose of the research study. Other limitations of the proposed approach are given in detail in section 5. Here the author aims to note the effect of BDA on the firm's sustainable performance.

3. Conceptual framework & hypotheses

Based on a literature review and identified research gap, a conceptual model is developed as shown in Fig. 1. Proposed research model consists of 9 factors namely: Management and Leadership Style (MLS), State and Central Govt. Policy (SCGP), Supplier Integration (SI), Internal Business Process (IBP), Quality Management (QM), Customer Integration (CI), Green Lean Practices (GLP), Big Data Analytics (BDA), and Sustainable Business Performance (SBP). Here BDA as a mediator between SBP and other seven factors namely MLS, SCGP, SI, IBP, QM, CI, and GLP. Understanding the consequence of these seven factors on BDA can help managers and decision makers in effective implementation of sustainable business practices.

Fig. 1. Conceptual framework.

The above-mentioned nine factors are further divided into sixty items. The questionnaire was based on these items and 7- point Likert-scale was used to accept inputs from respondents. The respondents were belongs to Indian manufacturing Industry. Managers of large-scale industries were respondent for this study. Period of the survey was from November 2017 to June 2018, in which e-mails and interviews were used to collect the 350 responses. Out of which, 316 responses found valid. Even though identified industries, adoption necessities varies from full to minimal, 51% of the identified industries have adopted BDA, and 30% are in the progression of BDA adoption. To test the validity of questionnaires and items, the expert opinion of two academic and three industry persons was taken. After incorporation of their valuable comments, a questionnaire was finalized.

The conceptual framework and hypotheses based upon nine factors and 60 items are also developed. The items of the corresponding questionnaire were verified with the nine experts from academia and Industry. Factor analysis and SEM techniques were applied for the data analysis.

Table 2 shows the proposed hypothesis and items.

Sub-factors considered for BDA are as follows: BDA1: Big Volume, BDA2: Big Velocity, BDA3: Big Variety, BDA4: Big Veracity, BDA5: Big Intelligence, BDA6: Big Analytics, BDA7: Big Infrastructure, BDA8: Big Service, BDA9: Big Value, BDA10: Big Market, BDA11: BDA Control, BDA12: BDA Planning and Co-ordination, BDA13: BDA Compatibility and Modularity, BDA14: BDA Investment, BDA15: BDA Connectivity, BDA16: BDA Technical Knowledge and Technology Management, BDA17: BDA Business and Relational Knowledge (Wamba et al., 2017).

4. Research methodology

Fig. 2 shows the adopted research methodology for the study.

Through literature review, conceptual framework (Fig. 1) and hypothesis (Table 2) were developed. Questionnaires were developed based on sub-factors mentioned in Table 2. Validation of the questionnaire was done from a team of experts from academia and industry. Four experts were professors from IT and Industrial Engineering department; two experts were production managers, and three experts were a data analyst. After pilot testing, data were collected from respondents manufacturing firms. Statistical analysis of data was done using SEM. The output of SEM was given to ANN, followed by a discussion and conclusion of the study.

4.1. Sample characteristics

The demographic profile gives the descriptive statistics of the 316 respondents. As shown in Table 3, the highest number of respondents (69.30%) is from graduates, the highest number of respondents (35.76%) is having five to seven years of experience, and regarding annual turnover of the organisations 62.11% falls in 50–100.

4.2. Statistical analysis

Refinement of data followed the data collection phase. Transcripts were made by referring researcher's extensive notes. The transcripts were again given to the respondents for their feedback and verification. Accordingly, modifications in transcripts gave 316 refined responses. These responses were analysed using Exploratory Factor Analysis (EFA) as well as Confirmatory Factor Analysis (CFA) to examine the reliability, validity, and structure of the factors. The data were tabulated in Microsoft Excel, which then imported to Statistical Package for the Social Sciences (SPSS) software version 20 for analysis. Finally, SEM using AMOS gave path diagram.

4.2.1. EFA analysis

Measurement model refinement is recommended before SEM, EFA is popularly used for empirical investigation (Anderson and Gerbing, 1988). The analysis was conducted for 316 respondents ($N = 316$). EFA is a statistical approach to determining the correlation between the variables in a dataset. This type of analysis provides a factor structure. In general, an EFA prepares the variables to be used for cleaner structural equation modelling. An EFA performs three functions of exploring data patterns, determining relationships and data reduction. The rotated component matrix and KMO measures are given in the Annexure I, which justifies the KMO value 0.867 is more than the threshold limit (0.65) and hence acceptable for the study. Similarly, significance value (Bartlett's test of sphericity) is 0.000 and as it is below 0.05 that is 95% confidence level of significance. All communalities values above 0.5 are acceptable. Annexure I shows six iterations for convergence of rotated component matrix. Loading more than 0.5 of all the variables to the same factors and with no cross-loadings indicates that EFA results are suitable for further analysis.

4.2.2. CFA analysis

Chan et al. (2007) stated that CFA is a vital component of SEM. A latent variable needs to be assessed indirectly by using measured variables. Observed variables are meant to create meaning for latent variables. CFA illustrate the relationship between observed factors and latent variables. Path analysis only inspects the “causal links” between observed variables, whereas CFA examines “casual links” form factors as well as latent variables. Thus, CFA evaluates validity and reliability of measurements by carefully specifying constructs and indicators.

CFA was performed on seven constructs of BDA and one construct of sustainable business performance. These eight constructs were allowed to correlate with one another freely. Seven constructs of BDA are Management and Leadership Style (MLS), State and Central Govt. Policy (SCGP), Supplier Integration (SI), Internal Business Process (IBP), Quality Management (QM), Customer Integration (CI), and Green Lean Practices (GLP). Construct Sustainable Business Performance (SBP) has ten items.

Ideally ratio of chi-square to df must be in between 2.0 and 3.0; however, value up to 5.0 is acceptable. For this study, the ratio of chi-square to df is equal to 3.095 (<5.0) and thus acceptable. RMSEA (Root mean squared error of approximation) less than 0.05 indicate good fit and value between 0.05 and 0.1 indicate average fit. Value of RMSEA (0.082) specifies the average fit. GFI (Goodness-of-fit index) must be higher than 0.90 for best fit, however for this study; GFI value of 0.731 is acceptable. CFI (Comparative fit index) greater than 0.95 indicate good-fit, a value between 0.90 and 0.95 indicate average fit. For this study CFI (0.807) which is more excellent than 0.8 is permissible. NFI (Normed fix index) greater than 0.8 is for best fit, however, value of 0.741 this study is acceptable for an average fit. Thus, this dataset point towards good fitness of measurement model is acceptable.

CFA tests convergent validity of all items of a construct. According to Barki and Hartwick (2001) loading between measured variables and factors should be more than 0.5 and at 1% level, all path estimations were significant. Loadings less than 0.70 in a given measurement model are as follows: BDA Connectivity (BDA15 with value of 0.673), Top management commitment towards sustainable practices (MLS1 with value of 0.538), Discretion of tasks (MLS7 with value of 0.459), Tools and techniques of lean practices (GLP1 with value of 0.637), Cost to quality (QM1 with value of 0.686), Customer feedback for eco-design (CI1 with value of 0.528), Customer cooperation for cleaner production (CI2 with value of 0.614), Involvement of supplier (SI1 with value of 0.645), Sharing of sustainability targets with vendors and suppliers (SI2 with value of

Table 2
Factors and Sub-factors considered for BDA.

Hypothesis No.	Factor	Description	Sub factor	Reference
H1	Management and Leadership Style (MLS)	BDA needs considerable initial investment. However, ROI can be calculated beforehand for approval of top management. Top management must be committed towards sustainability, and the role of training is most crucial. Employees from all levels must participate in deciding the vision and mission of organisation for BDA adoption as well as sustainable business performance.	MLS1: Top management commitment MLS2: Training and Education for awareness MLS3: Role of middle-level management MLS4: Appreciation of employees MLS5: Employee involvement MLS6: Well- defined sustainability policy MLS7: Discretion of tasks	Dubey et al. (2016)
H2	Green Lean Practices (GLP)	Lean manufacturing must be designed for sustainability. It would reduce the energy consumption, impact on the environment, cost, and risk associated. 3 R's (reuse, reduce, and recycle) of reconfigurable manufacturing are more prominently used by organisations to gain competitive advantage. BDA insures accurate decision making, thereby making implementation of green lean practices more effective.	GLP1: Tools and techniques of lean practices GLP2: Energy efficient technologies GLP3: Green manufacturing GLP4: Reuse, recycle, and re-manufacture GLP5: Reconfigurable Manufacturing Systems	Dubey et al. (2017), Sharma et al. (2017)
H3	Quality Management (QM)	Data quality includes data completeness (degree of necessary data for current and future activities) and data consistency (data uniformity across network, applications, and systems). BDA ensures quality management of data. Total quality management (TQM) and total preventive maintenance are the two most important aspects of an organisation. Sustainable practices along with BDA improve quality of service (QoS) and quality of experience (QoE).	QM1: Cost to quality QM2: Total quality management QM3: Total productive maintenance QM4: Data quality QM5: Quality of Service and Experience	Kwon et al. (2014), Dubey et al. (2016)
H4	Customer Integration (CI)	Customers do appreciate sustainable products. Using BDA, customers can be actively involved in green purchasing practices, cleaner production, eco-labelling, and eco-design feedback. Also, BDA can ensure timely recovery of used products from customers. Customer satisfaction can be improved with BDA capabilities and green practices. The firm must have a BDA based information sharing structure with its customers.	CI1: Customer feedback for eco-design CI2: Customer cooperation for cleaner production CI3: Customer cooperation for green purchasing CI4: Information sharing structure with customer	Dubey et al. (2016), Sharma et al. (2017)
H5	Supplier Integration (SI)	Organisations must have collaboration with their supplier for technological integration, environmental criteria, and environmental audit. BDA capabilities will assist in selection of supplier. BDA tools ensure active involvement of supplier, which improves data sharing. Sustainability targets must be shared with vendors and suppliers. With supplier cooperation, firms can achieve greater sustainability targets.	SI1: Involvement of supplier SI2: Sharing of sustainability targets with vendors and suppliers SI3: Supplier as a green partner or not SI4: Information sharing structure with the supplier SI5: Cooperation of supplier	Dubey et al. (2016), Sharma et al. (2017)
H6	Internal Business Process (IBP)	The firm should ensure information exchanges within and with partners. BDA abilities ensure information sharing which is relevant, timely, accurate, complete, and sensitive. Organisations should infiltrate sustainability policy and objectives to everyone (worker, middle management, and top management) in the firm. BDA can assist organisations for permanent adjustment to incorporate sustainable practices. Certifications like ISO 9000, ISO 14001 can help in standardising business procedures.	IBP1: Written objective and policy for sustainability IBP2: Routinization IBP3: Information sharing (IS)	Gunasekaran et al. (2017), Sharma et al. (2017)
H7	State and Central Govt. Policy (SCGP)	In a country like India, regulatory pressure for sustainable practices is mandatory. Regional regulations must force the organisation to implement sustainable practices. Promoting these practices can be done through incentives, subsidy, and rewards from the government. Boards of directors/CEO are aware that these reward improves the brand image of the organisation. BDA can play a crucial role in assisting the organisation in user documentation and communication. Also, a non-government organisation (N.G.O.) can help the organisation in the implementation of sustainable practices.	SCGP1: Support of state/central government SCGP2: Regulatory pressure to promote sustainable practices SCGP3: Regional environment to implement sustainable practices SCGP4: Policy about security and privacy if data	Dubey et al. (2016), Sharma et al. (2017)
H8	Sustainable Business Performance (SBP)	Sustainable business performance is mainly measured regarding environmental performance, economic performance, and operational performance. Environment performance includes a reduction in air pollution (emission), water, and solid pollutants. BDA encourages the use of preservative as standard and thus help in the reduction of pollution. Reduction in costs of energy consumption, material, waste discharge, and service cost are economic factors. Adoption of BDA practices will ensure better economic performance with increased revenue, better market share, and reduction in compensation/penalty for ecological mishaps. Operational performance includes precise delivery time, better capacity utilisation, and quality. BDA capabilities will not only improve operational performance but also promote brand image and better public relations.	SBP1: Environment technology SBP2: Air pollution control, carbon footprint SBP3: Eco-packaging SBP4: Recycling efficiency SBP5: Environment cost SBP6: Responsiveness cost SBP7: Supply chain cost SBP8: Customer satisfaction SBP9: Reduction in solid and water waste SBP10: Improvement in organisational relevant knowledge	Dubey et al. (2017), Sharma et al. (2017), Gunasekaran et al. (2017)

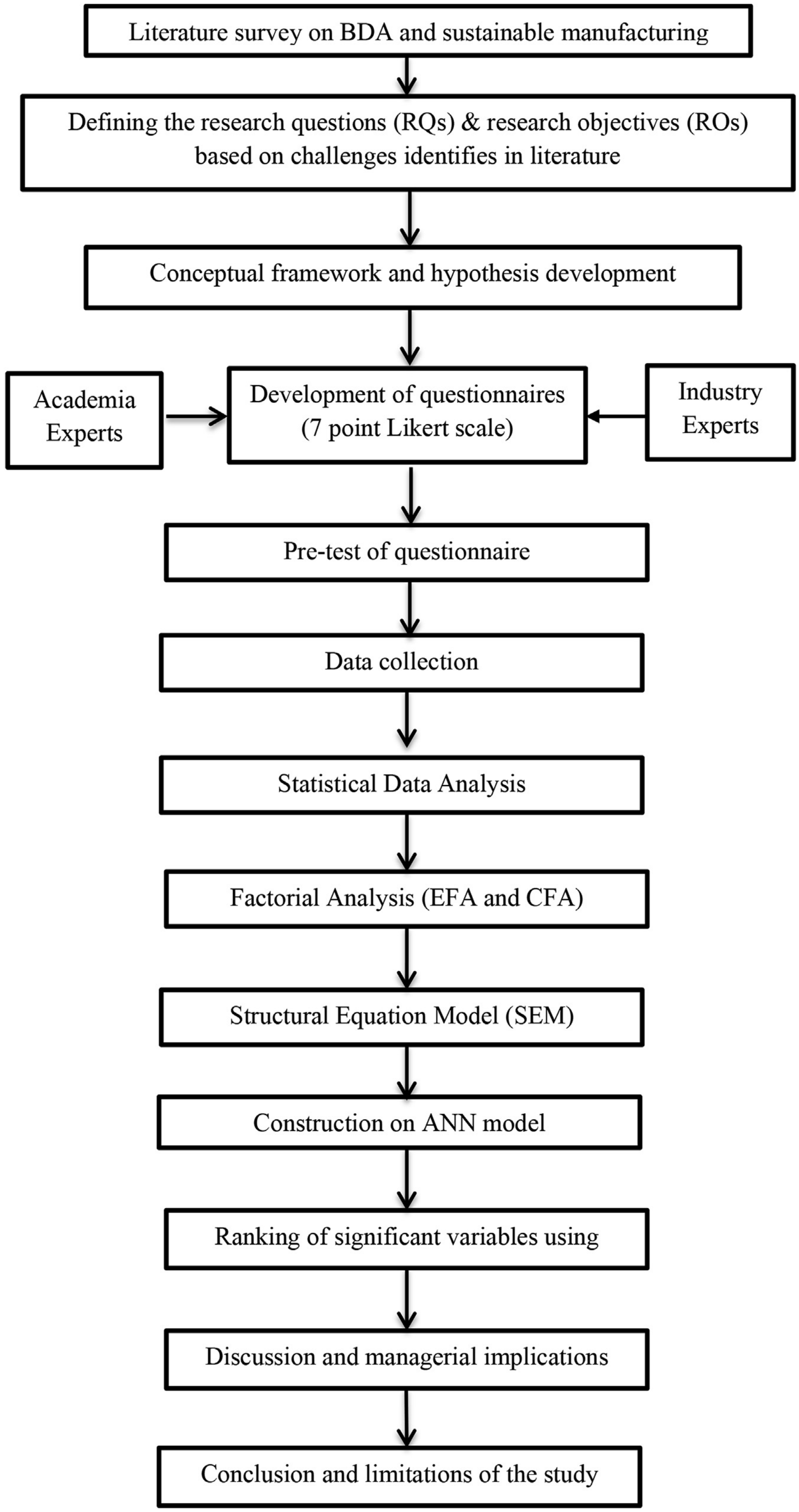

Fig. 2. Research methodology.

Table 3
Demographic profile of the respondents.

Sample Characteristics	Categories	Number of responses	Percentage (%)
Gender	Male	230	72.78
	Female	86	27.22
Total		**316**	**100%**
Education (Highest Qualification)	B.E./B.Tech.	219	69.30
	M.E./M.Tech./MBA	97	30.70
Total		**316**	**100%**
Turn-over (Revenue in Crore)	50–100	196	62.02
	More than 100	120	37.98
Total		**316**	**100%**
Years of Experience	2–5	101	31.96
	5–7	113	35.76
	7–11	102	32.28
Total		**316**	**100%**

0.635), Supplier as green partner or not (SI3 with value of 0.661), Information sharing structure with supplier (SI4 with value of 0.658), and Cooperation of supplier (SI5 with value of 0.689). Out of these 12 items, except two items Top management commitment towards sustainable practices (MLS1 with a value of 0.538) and Discretion of tasks (MLS7 with a value of 0.459), other ten items are marginally less than 0.7. As remaining loadings are not detriment internal consistency, it shows acceptable evidence of convergence validity. AMOS (Analysis of Moment Structures) version 20.0 was used for analysis. Annexure II shows estimates of the CFA model and Fig. 3 shows the path diagram.

4.2.3. SEM model

SEM consists of two steps: the first one is to validate the latent factors and the second one this model is used to validate the hypotheses framed based upon the unobservable factors. The path coefficients are examined, and loadings are made to ensure whether it has changed after the CFA model (Pawaskar et al., 2018). SEM standardised estimations are somewhat similar to the CFA model (Raut et al., 2019). Technically it indicates there is no problem in the model that supports the validity of the SEM model. The factors reliabilities are identical, as it shows very little change in the factor loadings. Model validation will be incomplete without estimating the individual factors. The statistical significance of each factor is checked. Model fit values satisfy the threshold limits. The measurement model of CFA is converted to SEM by eliminating the bi-directional arrows with a single-headed arrow. After checking the SEM results for model fits, results obtained are as given below.

The ratio of chi-square to df is equal to 3.239 (<5.0) and thus acceptable (Gardas et al., 2019). RMSEA value obtained is 0.084, which indicate the average fit. GFI (Goodness-of-fit index) must be higher than 0.90 for best fit, however for this study; GFI value of 0.708 is acceptable. For this study, CFI (0.791) which is close to the permissible value of 0.8. Value of NFI (0.724) is acceptable for an average fit. Estimates hypotheses testing were done built on the value of standardised loading. Depending upon the path estimates the conclusions are drawn whether the hypothesis is supported or not. SEM results supported the conceptual model based on the literature. Annexure III shows estimates of the structural model and Fig. 4 shows the path diagram.

4.3. Hypothesis testing

The structural model evaluates the hypotheses of the study. The path coefficients of the final model are shown in Fig. 4. Out of eight hypotheses, six are significant. Table 4 below shows the standardised weight of each hypothesis.

Green Lean Practices (GLP) and Quality Management (QM) are negatively impacting Big Data Analytics (BDA) whereas Management and Leadership Style (MLS), Customer Integration (CI), Supplier Integration (SI), Internal Business Process (IBP), State and Central Government Policy (SCGP) and Big Data Analytics (BDA) are positively influencing sustainable business performance (SBP).

It must be noted that some of the findings of this study are in contrast with the past research articles. The reasons could be because of differences in geographic region, issues towards BDA, and methodology employed by previous studies is different from this study.

4.4. ANN application

ANN is an artificial intelligence (AI) method for predictive analysis. In ANN, information processing is done by neurons, which are connected with other neurons through weighted connection links. ANN has high predictive accuracy for linear as well as nonlinear relationships (Leong et al., 2015). ANN analysis does not require multivariate assumptions such as linearity, homoscedasticity, or normality (Abubakar et al., 2017).

4.4.1. ANN model

Multi-layered model with an input layer, hidden layers, and the output layer is commonly used in ANN (Fausett, 1994). In this study, MLP (Multilayer Perceptron) with an FFBP (Feed Forward-Back Propagation) algorithm is considered. The MLP constitutes of input and output layers and one hidden layer. The input layer is stimuli of the model and the output layer is the outcome of this stimuli. Hidden layer maps relations between the output layer and input layer. There is no heuristic way to determine the number of neurons in the hidden layer (Fausett, 1994). In this study, the network was inspected using 1 to 10 hidden nodes, and ten nodes were selected for the hidden layer. Fig. 5 shows the ANN model.

Fig. 5 shows that the five significant variables of SEM were used as inputs for the neural network.

4.4.2. ANN analysis

Tan et al. (2014) recommended cross-validation with ten folds and parting data such that 10% for training and 90% for testing. The sigmoid function gives better accuracy and hence used for hidden as well as the output layer. Total of non-zero synaptic weights which are linked to the hidden layer was used for confirmation of predictor variables significance. The detailed analysis is shown in Tables 5 and 6.

RMSE (Root Mean Square of Error) values indicate the accuracy of the neural network model whereas each factor is evaluated through the sensitivity analysis of the significant factors. The RMSE changes for the training for ten neurons shown in Fig. 5. Except for

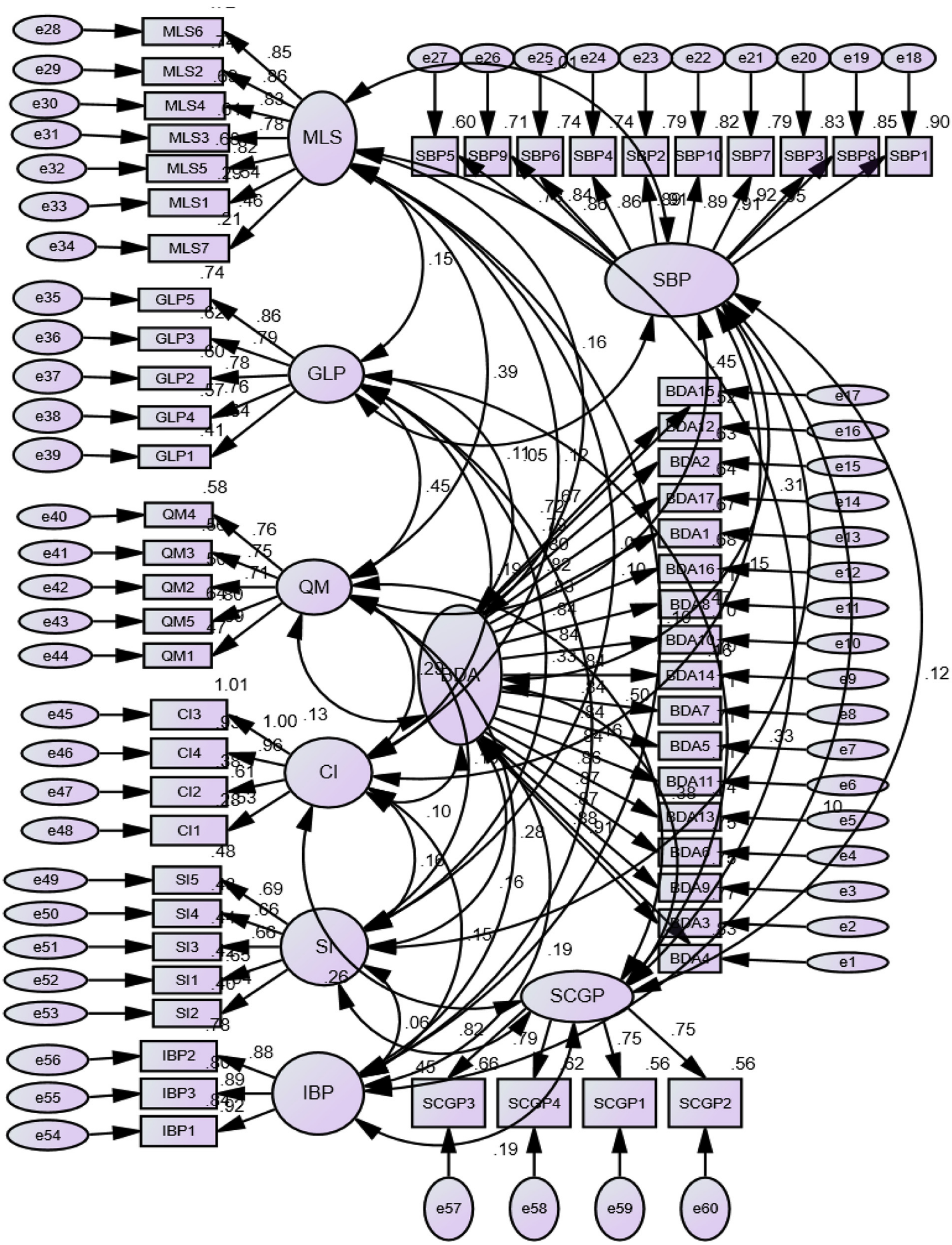

Fig. 3. Path diagram for CFA

few points, error value was around zero, which shows that estimated values by ANN in return for the associated inputs are close to the real value. The analysis shows that MLS has the highest influence on BDA and CI has the lowest influence on BDA.

5. Discussion on findings

In this paper, the SEM-ANN hybrid methodology was used to understand the role of BDA for sustainable business practices. SEM

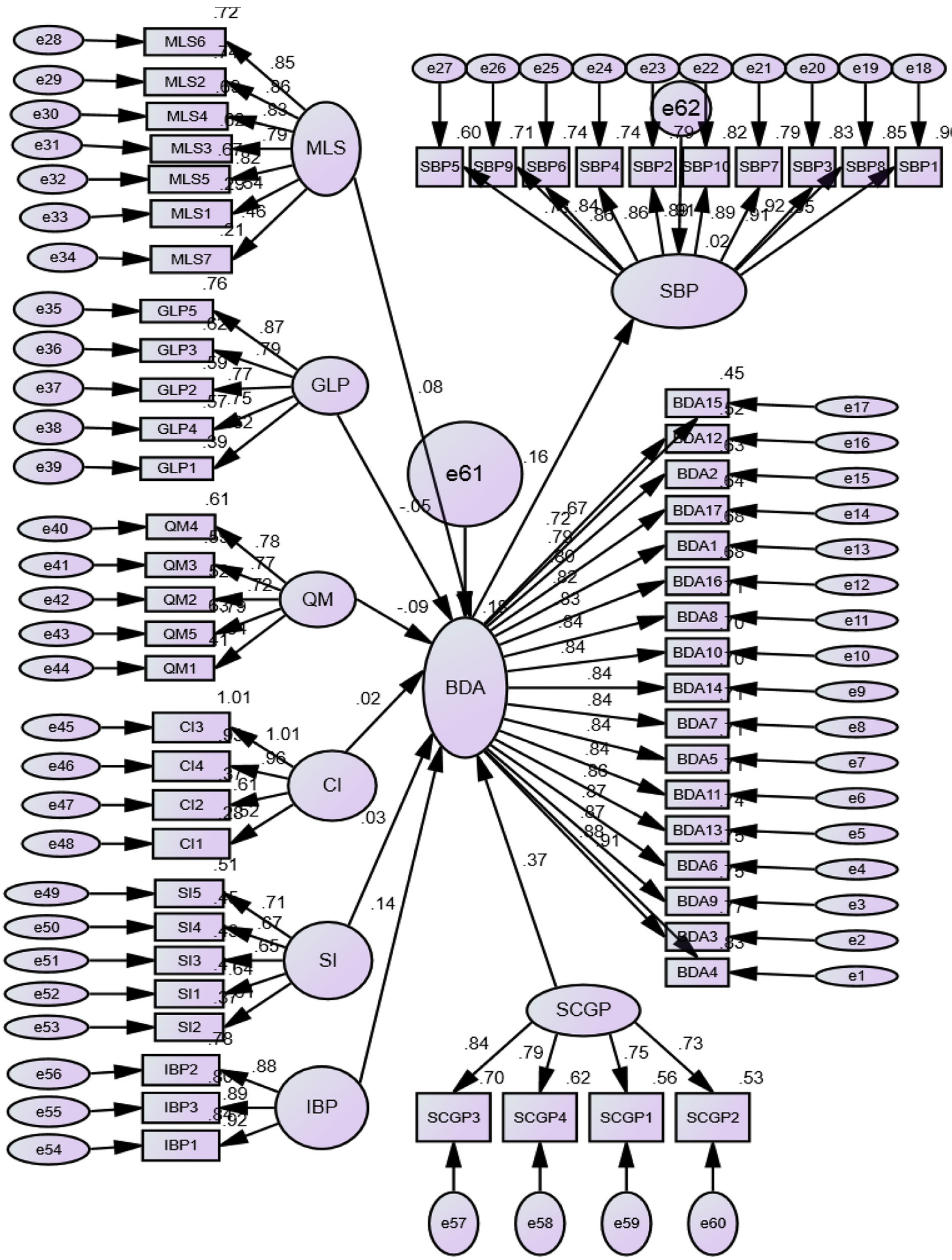

Fig. 4. Path diagram for SEM

analysis supports six hypotheses out of the proposed eight hypotheses. Five significant factors for BDA adoption in order of standardised estimates are “State and Central Government Policy (SCGP),” “Internal Business Process (IBP),” “Management and Leadership Style (MLS),” “Supplier Integration (SI),” and “Customer Integration (CI).” However, sensitivity analysis ranks this five-factor is different. ANN analysis ranks “Management and Leadership Style (MLS)” highest, followed by SCGP, SI, IBP, and CI.

Table 4
Results of hypotheses testing.

Sr. No.	Hypothesis	Standardised Estimates	Supported (Y/N)	In agreement with	In contrast with
1	Management and Leadership Style (MLS) positively influences Big Data Analytics (BDA).	.079	Yes	Gunasekaran et al. (2017)	
2	Green Lean Practices (GLP) positively influences Big Data Analytics (BDA).	-.051	No		Doolun et al. (2018)
3	Quality Management (QM) positively influences Big Data Analytics (BDA).	-.091	No		Ren et al. (2017)
4	Customer Integration (CI) positively influences Big Data Analytics (BDA).	.019	Yes	Salehan and Kim (2016)	
5	Supplier Integration (SI) positively influences Big Data Analytics (BDA).	.032	Yes		Kache and Seuring (2017)
6	Internal Business Process (IBP) positively influences Big Data Analytics (BDA).	.144	Yes	Gupta and George (2016)	Côrte–Real et al. (2017)
7	State and Central Government Policy (SCGP) positively influences Big Data Analytics (BDA).	.372	Yes	Dubey et al. (2016)	
8	Big Data Analytics (BDA) positively influences Sustainable Business Performance (SBP).	.156	Yes	Ren et al. (2019)	

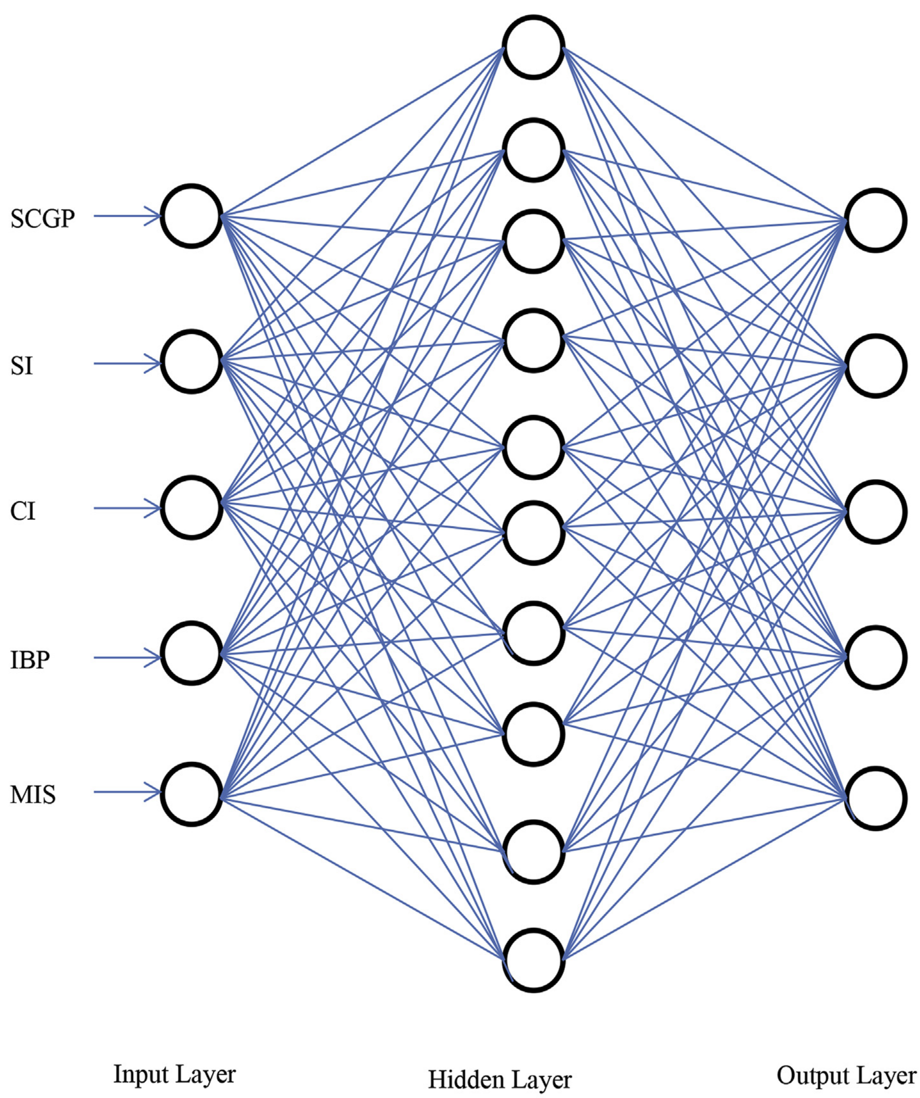

Fig. 5. Ann model.

The highest rank of MLS shows that strategic quality management planning is required from an organisational context. Role of management is vital in BDA adoption. Organisational profit alone as a goal cannot be sustainable in the long run from a societal point of view. BDA tools can assist managers for better visualisation and efficient decision making. However, the interdisciplinary nature of BDA along with initial cost is a significant concerns. Thus, ROI needs to be calculated for BDA adoption.

Table 5
RMSE values.

Artificial Neural Network	For O/P BDA		For O/P SBP	
	Training	Testing	Training	Testing
1	0.929	1.057	1.024	1.044
2	.745	.865	1.003	.965
3	.923	.958	.986	.996
4	.991	.987	.971	.974
5	.811	.896	.969	.988
6	.989	1.001	.983	1.003
7	.945	.951	1	.99
8	.841	.974	1.007	.983
9	.607	.936	.915	.996
10	.979	1.081	.955	1.008
Mean RMSE	**.876**	**.9706**	**.9813**	**.9947**
Standard Deviation	**0.125324**	**0.066093**	**0.031045**	**0.021587**

Table 6
Sensitivity analysis.

Artificial Neural Networks(ANN)	SCGP	SI	CI	IBP	MLS
1	.210	.229	.141	.173	.246
2	.283	.156	.176	.206	.180
3	.180	.224	.196	.170	.230
4	.213	.213	.161	.210	.202
5	.287	.163	.107	.207	.236
6	.171	.198	.224	.159	.248
7	.164	.198	.226	.175	.237
8	.191	.267	.182	.166	.194
9	.231	.156	.188	.160	.265
10	.216	.238	.183	.159	.203
Mean Importance	.2146	.2042	.1784	.1785	.2241
Ranking	2	3	5	4	1
Normalized Importance (%)	95.76	91.12	79.6	79.65	100

"State and Central Government Policy (SCGP)" has the highest value of standardised estimates (0.372) and ranked second in ANN analysis. Specific Governmental policies give clear guidelines for pollution control. The pollution control board monitors pollution control in a particular interval. Policymakers seeking to promote sustainable practices in manufacturing industry, and BDA can assist government agencies in this regard. Thus, regulatory pressure will promote sustainable practices. However, privacy concerns of government organisations need to be addressed for its effective adoption.

In developed countries, industries situated far away have poor social practices with their suppliers (Goldberg and Yagan, 2007). Supplier selection is one of the essential criteria for environmental practices. There should be some environmental collaboration with firms in supplier selection as well as in its technology integration. BDA capabilities ensure a useful framework for information sharing with the supplier. It ensures cooperation and involvement of the supplier in implementation of sustainable practices.

BDA capabilities ensure a robust internal business process with infiltration of sustainability objectives in the organisation. It will help manufacturing firms to achieve long term sustainable development goals. Customer satisfaction is one more important factor in green practices. Efficiency recycling, eco-packaging, and environmental technologies are some of essential environmental aspects (Dubey et al., 2016). BDA ensures customer cooperation with useful information sharing for a reduction in carbon footprints, waste emissions, and pollution control. BDA has a role to play in WSCM to improve economic performance through reduced environmental cost, supply chain cost and return on asset, however managers need to consider social concerns as well. Finally, significant challenges need to be overcomed for broader adoption of BDA for manufacturing are scalability, the complexity of data, data availability, data heterogeneity, and privacy issues (Jin et al., 2015).

5.1. Theoretical contributions & managerial implications

The present study links BDA and sustainability practices for sustainable business management. The real need for Big-data analytics is explored through the literature review. Some papers published in recent past are from different technology usage and rarely does it cover upcoming technologies like BDA. BDA can be useful if industries can develop the capability of effective use of new technologies.

BDA capabilities are data-driven. Prescriptive analytics needs a little amount of social intervention in contrast with other analytics techniques like descriptive and predictive analytics that can increase the decision-making process. Cloud computing efficacy in increasing the Big-data asset is also clarified. Thus, the study has a noteworthy contribution to the theory and implementation. This research paper can help researchers in a thorough understanding of BDA for sustainable business by taking a case of Indian manufacturing firms. This study advances the present literature by examining the factors and sub-factors for BDA adoption for sustainability. Top management and executives can understand the relevance of BDA to improve organisational performance of their manufacturing firms. Involvement of top management is an integral factor for a better performance in business. Top management of the organisation should target long-term economic sustainability. Significant factors identified in this study can be further investigated. SAS (2013) reported that application of BDA among industries is quite less. The less adoption of this technology hinders the organisational growth in large. Hence, the model which we proposed in the study will be most useful for adopting BDA in industries if they are interested in the growth of their business.

This paper contributes to understanding the role of BDA in sustainable manufacturing firms in developing countries. The firms can understand influencing factors of BDA adoption and move towards the future of sustainability. Managers can consider factors of BDA for further augmentation of sustainability.

This work also has implications for policy-making and marketing people. Policymakers of sustainable manufacturers can use the results for decision making. The study reveals that customer integration and supplier integration are significant. Thus, service provider must ensure timely and reliable service with given due consideration to privacy concerns. The service provider can also help organisations to improve their operational efficiency.

6. Conclusions

BDA can influence sustainable business performance practices. The study emphasises the benefits of BDA for sustainable business performance in its value extraction. Developing economies like Indiais in the process of implementation of smart manufacturing. Past studies like sustainable layout using BDA for Industry 4.0, BDA based sustainable manufacturing for complete product life cycle, and sustainability control with predictive policies confirm usefulness for BDA enables smart manufacturing. It would help researchers to shape experiential research in the area of Big-data and sustainable business management. The study evolves from a literature review to the conceptualisation of Big-data capabilities. A conceptual BDA framework is developed to link sustainability practices for higher sustainable business performance management. This study will guide supply chain and operations managers how to develop sustainbale business performance through BDA implementation.

There are certain limitations to the study. Firstly, the data collection is based upon a structured questionnaire. Secondly, we did not explore the role of supply chain management in BDA. Next, the factors Green lean practices (GLP) and Quality management (QM) showed negative results in this study. Next to this, Customer Integration (CI) and Supplier Integration (SI) identified with decidedly fewer regression weights. Hence, in the future for the best value of sustainable business performance the factors which showed an inferior result could be verified with some different sample size in other geographical location. Some more process innovations can be made in Big-data in future to raise the quality of life of people.

Future study can also specify, different categories of technological benefits with the specification of what kind of technologies usually firms prefer to adopt for sustainability. Apart from the factors mentioned in the study, some more factors may influence BDA that can be explored by studying some context-related factors in future. For example, some Risk related factors; Perceived IT security Risk might influence BDA that influences sustainable business performance (Priyadarshinee et al., 2017).

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.jclepro.2019.03.181.

Annexure I. : Rotated Component Matrix

	Component								
	1	2	3	4	5	6	7	8	9
BDA4	.906								
BDA3	.878								
BDA9	.872								
BDA6	.865								
BDA13	.862								
BDA11	.848								
BDA5	.845								
BDA7	.844								
BDA14	.842								
BDA10	.838								
BDA8	.837								
BDA16	.829								
BDA1	.828								
BDA17	.806								
BDA2	.793								
BDA12	.737								
BDA15	.703								
SBP1		.942							
SBP8		.923							
SBP3		.913							
SBP7		.900							
SBP10		.897							
SBP2		.885							
SBP4		.865							
SBP6		.865							
SBP9		.856							
SBP5		.783							
MLS6			.865						
MLS2			.844						
MLS4			.828						
MLS3			.825						
MLS5			.810						
MLS1			.617						
MLS7			.548						
GLP5				.862					
GLP3				.802					
GLP2				.788					
GLP4				.769					
GLP1				.646					
QM4					.794				
QM3					.790				
QM2					.776				
QM5					.742				
QM1					.549				
CI3						.917			
CI4						.901			
CI2						.745			
CI1						.685			
SI5							.751		
SI4							.741		
SI3							.710		
SI1							.674		
SI2							.624		
IBP1								.915	
IBP3								.906	
IBP2								.894	
SCGP3									.776
SCGP4									.719
SCGP1									.714
SCGP2									.654

Extraction Method: Principal Component Analysis.
Rotation Method: Varimax with Kaiser Normalization.
a. Rotation converged in 6 iterations.

Annexure II. : Estimates of CFA Model

Item	Item	Standardised Estimate	Unstandardized Estimate	S.E.	C.R.
BDA4	BDA	.910	1.000		
BDA3	BDA	.878	.973	.039	24.650
BDA9	BDA	.868	.962	.040	23.919
BDA6	BDA	.866	.964	.040	23.819
BDA13	BDA	.858	1.323	.057	23.266
BDA11	BDA	.842	1.520	.068	22.286
BDA5	BDA	.844	.960	.043	22.360
BDA7	BDA	.840	.931	.042	22.161
BDA14	BDA	.837	.869	.040	21.962
BDA10	BDA	.838	.923	.042	22.007
BDA8	BDA	.840	.929	.042	22.146
BDA16	BDA	.827	.911	.043	21.375
BDA1	BDA	.821	.943	.045	21.084
BDA17	BDA	.798	1.008	.051	19.840
BDA2	BDA	.794	.922	.047	19.665
BDA12	BDA	.721	1.091	.066	16.477
BDA15	BDA	.673	.659	.045	14.737
SBP1	SBP	.950	1.000		
SBP8	SBP	.920	1.003	.031	32.435
SBP3	SBP	.910	.984	.032	31.137
SBP7	SBP	.889	.953	.033	28.569
SBP10	SBP	.906	1.234	.040	30.598
SBP2	SBP	.888	.962	.034	28.538
SBP4	SBP	.859	.940	.037	25.719
SBP6	SBP	.862	.940	.036	25.931
SBP9	SBP	.840	.915	.038	24.170
SBP5	SBP	.777	.842	.042	20.057
MLS6	MLS	.847	1.000		
MLS2	MLS	.859	1.035	.054	19.156
MLS4	MLS	.831	1.024	.056	18.155
MLS3	MLS	.782	.913	.055	16.517
MLS5	MLS	.823	1.042	.058	17.865
MLS1	MLS	.538	.708	.071	10.045
MLS7	MLS	.459	.680	.081	8.356
GLP5	GLP	.862	1.000		
GLP3	GLP	.788	1.022	.063	16.230
GLP2	GLP	.775	1.121	.071	15.861

(*continued*)

Item	Item	Standardised Estimate	Unstandardized Estimate	S.E.	C.R.
GLP4	GLP	.755	1.056	.069	15.292
GLP1	GLP	.637	.913	.075	12.148
QM4	QM	.762	1.000		
QM3	QM	.750	.942	.072	13.047
QM2	QM	.706	.862	.070	12.239
QM5	QM	.801	1.072	.077	13.960
QM1	QM	.686	.794	.067	11.873
CI3	CI	1.004	1.000		
CI4	CI	.965	1.064	.021	50.190
CI2	CI	.614	.607	.045	13.592
CI1	CI	.528	.525	.048	10.938
SI5	SI	.689	1.000		
SI4	SI	.658	1.160	.120	9.696
SI3	SI	.661	1.082	.111	9.735
SI1	SI	.645	1.076	.113	9.544
SI2	SI	.635	1.069	.113	9.426
IBP1	IBP	.917	1.000		
IBP3	IBP	.893	.973	.041	23.570
IBP2	IBP	.881	.947	.041	23.009
SCGP3	SCGP	.815	1.000		
SCGP4	SCGP	.790	1.022	.069	14.864
SCGP1	SCGP	.751	1.207	.086	13.988
SCGP2	SCGP	.749	.995	.071	13.947

Annexure III. : Estimates of the Structural Model

Item	Item	Standardised Estimate	Unstandardized Estimate	S.E.	C.R.	P
BDA	MLS	.079	.086	.060	1.449	.147
BDA	GLP	-.051	-.062	.068	-.914	.361
BDA	QM	-.091	-.111	.069	−1.602	.109
BDA	CI	.019	.015	.042	.363	.717
BDA	SI	.032	.049	.091	.546	.585
BDA	IBP	.144	.123	.047	2.620	.009
BDA	SCGP	.372	.512	.081	6.299	***
SBP	BDA	.156	.174	.064	2.729	.006
BDA4	BDA	.911	1.000			
BDA3	BDA	.879	.973	.039	24.718	***
BDA9	BDA	.868	.962	.040	23.981	***
BDA6	BDA	.867	.965	.040	23.883	***
BDA13	BDA	.859	1.323	.057	23.327	***
BDA11	BDA	.843	1.520	.068	22.345	***
BDA5	BDA	.844	.960	.043	22.418	***
BDA7	BDA	.841	.931	.042	22.221	***
BDA14	BDA	.838	.869	.039	22.021	***
BDA10	BDA	.838	.923	.042	22.067	***
BDA8	BDA	.841	.929	.042	22.201	***
BDA16	BDA	.827	.911	.043	21.432	***
BDA1	BDA	.822	.943	.045	21.138	***
BDA17	BDA	.798	1.008	.051	19.891	***
BDA2	BDA	.795	.922	.047	19.717	***
BDA12	BDA	.722	1.091	.066	16.517	***
BDA15	BDA	.674	.659	.045	14.775	***
SBP1	SBP	.951	1.000			
SBP8	SBP	.920	1.002	.031	32.501	***
SBP3	SBP	.910	.984	.032	31.175	***
SBP7	SBP	.889	.953	.033	28.628	***
SBP10	SBP	.907	1.234	.040	30.684	***
SBP2	SBP	.888	.961	.034	28.504	***
SBP4	SBP	.859	.939	.037	25.693	***
SBP6	SBP	.861	.939	.036	25.905	***
SBP9	SBP	.840	.915	.038	24.180	***
SBP5	SBP	.777	.841	.042	20.039	***
MLS6	MLS	.849	1.000			
MLS2	MLS	.859	1.033	.054	19.168	***
MLS4	MLS	.829	1.019	.056	18.109	***
MLS3	MLS	.786	.916	.055	16.660	***
MLS5	MLS	.819	1.035	.058	17.770	***
MLS1	MLS	.539	.709	.070	10.079	***
MLS7	MLS	.460	.680	.081	8.376	***
GLP5	GLP	.873	1.000			
GLP3	GLP	.789	1.009	.062	16.343	***
GLP2	GLP	.769	1.097	.070	15.764	***
GLP4	GLP	.753	1.039	.068	15.315	***
GLP1	GLP	.623	.883	.074	11.869	***
QM4	QM	.781	1.000			
QM3	QM	.766	.940	.070	13.496	***
QM2	QM	.719	.856	.068	12.599	***
QM5	QM	.791	1.032	.074	13.925	***
QM1	QM	.641	.724	.065	11.126	***
CI3	CI	1.007	1.000			
CI4	CI	.962	1.057	.022	48.436	***
CI2	CI	.612	.603	.045	13.508	***
CI1	CI	.525	.520	.048	10.855	***
SI5	SI	.711	1.000			
SI4	SI	.673	1.151	.117	9.837	***
SI3	SI	.653	1.036	.108	9.610	***
SI1	SI	.638	1.032	.109	9.432	***
SI2	SI	.610	.994	.109	9.089	***
IBP1	IBP	.917	1.000			
IBP3	IBP	.893	.973	.041	23.502	***
IBP2	IBP	.881	.947	.041	22.958	***
SCGP3	SCGP	.837	1.000			
SCGP4	SCGP	.786	.991	.067	14.740	***
SCGP1	SCGP	.749	1.173	.084	13.958	***
SCGP2	SCGP	.730	.946	.070	13.547	***

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