Big Data Analytics as a mediator in Lean, Agile, Resilient, and Green (LARG) practices effects on sustainable supply chains

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Abstract
The effect of big data on the lean, agile, resilient, and green (LARG) supply chain has not been explored much in the literature. This study investigates the role of 'Big Data Analytics' (BDA) as a mediator between 'sustainable supply chain business performance' and key factors, namely, lean practices, social practices, environmental practices, organisational practices, supply chain practices, financial practices, and total quality management. A sample of 297 responses from thirty-seven Indian manufacturing firms was collected. The paper is beneficial for managers and practitioners to understand supply chain analytics, and it addresses challenges in the management of LARG practices to contribute to a sustainable supply chain.

Keywords- Big Data Analytics; Manufacturing Firms; Supply Chain and Logistics Management; LARG; Business Performance and Innovation; Sustainability.

1.0 Introduction

Big Data Analytics (BDA), which redefined the field of operations management, has been termed a "game-changer" (Wamba and Akter, 2015). The five major fields of BDA applications are additive manufacturing, predictive analysis, material science, autonomous vehicles, and borderless supply chains (Fawcett and Waller, 2014). BDA in the supply chain (SC) can increase the return on investment (ROI) by 15-20% (Perrey et al., 2013), improve competitiveness (Wamba et al., 2015), mitigate risk (Bi et al., 2016), and boost visibility (McAfee et al., 2012). BDA has the potential to change SC performance radically through process design, supplier integration, and customer integration (Gunasekaran et al., 2016). Through data-driven SC, organisations can gain competitive advantages (Schoenherr and Speier-Pero, 2015) and handle market turbulence effectively (Gunasekaran et al., 2018).

The sustainability aspect of the supply chain has social, economic, and environmental elements (Carter and Liane Easton, 2011). LARG practices assist sustainable SC through lean practices (Chun Wu, 2003; Dora et al., 2016), SC agility (Baramichai et al., 2007), SC resilience (Cabral et al., 2012), and green practices (Srivastava, 2007). LARG SC assists in lowering production lead-time and transportation time, improving integration level, and achieving effective information exchange (Alqudah et al., 2020). Lean SC interconnects the interdependent partners for the elimination of all waste through techniques such as value chain analysis (Taylor and Pettit, 2009; Dey et al., 2019). SC resilience is the reactive capability to shock or disruption (Blackhurst et al., 2011). Manufacturing firms in developing economies, such as Indonesia, Malaysia, and India, have already started the implementation of LARG practices (Rao, 2005; Digalwar et al., 2020). With India becoming an important manufacturing hub, effective implementation of LARG SC has turned out to be an important benchmarking tool (Chavez et al., 2020; Wong et al., 2018).

BDA supports SC sustainability by strengthening capabilities and minimising uncertainties and risks (Wu et al., 2017). BD capabilities help with regular operations and processes, reduction in lead and cycle times, focused factory, and mass customisation (Mišić and Perakis, 2020). BD processing enhances SCs' agility (Giannakis and Louis, 2016) and resilience (Papadopoulos et al., 2017). With BD, an implementation of the green supply chain with better data quality control and integrated data acquisition is possible (Zhao et al., 2016). BD provides plenty of opportunities in SC in terms of supplier performance measurement (Addo-Tenkorang and Helo, 2016), SC analytics (Arunachalam et al., 2018), SC agility (Fosso Wamba et al., 2018), SC sustainability (Hazen et al., 2016; Papadopoulos et al., 2017), and SC innovation (Tan et al., 2015). However, manufacturing firms need to understand BDA in SC from the context of organisational performance (Akter et al., 2016). In addition, the influence of BDA on sustainable business performance and LARG is not entirely clear and needs more investigation (Gunasekaran et al., 2017).

Firms need to use sustainable practices due to public pressure, the concerns of the customer, and government regulations (Lee and Zhang, 2019). Bhanot et al. (2017) argued that sustainable manufacturing is the most significant element of sustainable SC. BDA capabilities can help manufacturing firms to achieve social dimensions (Wadmann and Hoeyer, 2018) and economic benefits (Papadopoulos et al., 2017), while minimizing the environmental impacts (Hazen et al., 2016). BDA can also integrate the data resources in the SC to minimize pollutant emissions and energy consumption (Song et al., 2018). Past studies on BDA for carbon emissions (Doolun et al., 2018; Song and Wang, 2015a), agile SC (Gunasekaran et al., 2018), SC flexibility (Dubey et al., 2018a), and resilient SC (Suifan et al., 2019) show a positive effect of data analytics on LARG. However, these studies discuss the lean, agile, resilient, and green aspects separately. With this motivation, this study aims to understand the mediating role of BDA on sustainable SC by considering LARG practices.

The paper focuses on the linkage between BDA and Sustainable SC Business Performance from a LARG perspective. Firstly, critical factors that affect BDA adoption in the sustainable SC in the context of a developing country were finalized through a literature survey. The literature on 'big data analytics,' 'lean, agile, resilient and green', and 'supply chain management' were studied. Seven factors, namely, total quality management and lean, social, environmental, supply chain, financial, and organisational practices, were identified from the literature and validated following an expert's input. Factor analysis was carried out on the collected data to determine the regression weights and significance of constructs. Identified constructs of BDA adoption for sustainable SC were analysed using the structural equation modelling (SEM) approach. SEM assesses observable and unobservable constructs of BDA implementation through empirical analysis. The focus of the study is to understand whether BDA acts as a mediator to influence the business performance of a sustainable supply chain when considering LARG aspects. Thus, this study explores the impact of BDA on the supply chain performance of Indian manufacturers with the effective implementation of sustainable and LARG practices.

The rest of the paper is organised as follows: Section 2 presents a literature survey on LARG SC, BDA and SC, BDA adoption in SC practices, and BDA for sustainable SC. Then, Section 3 provides the proposed model and hypothesis. Next, Section 4 presents the research methodology, and the empirical results are presented in Section 5. Section 6 summarises the analysis and discussion, and this is followed by the conclusion in Section 7.

2.0 Literature Survey

This section is divided into four sub-sections: i) LARG SC, ii) BDA and SC, iii) BDA for sustainable SC, and iv) research gaps.

2.1 LARG (Lean, Agile, Resilient and Green) Supply Chain

The 'lean' paradigm refers to 'a series of activities or solutions to eliminate waste, reduce non-value-added operations, and improve the value added (Dora et al., 2014; Wu and Wee, 2009 pp. 336). Lean production can be achieved through the 'just in time' (Chun Wu, 2003) and 'zero inventory' (Lyu et al., 2020) strategy. 'Agile' means to respond to rapidly changing demands in variety and volume (Larson and Chang, 2016). According to Baramichai et al. (2007), agility in the SC allows business partners to react to a changing market, with end-to-end information visibility, customised services, and customised products. Unlike the 'lean' paradigm, the 'resilient' paradigm responds to unexpected disturbances to achieve a competitive advantage (Cabral et al., 2012; Dora et al., 2015). Even though the resilient SC may not be the lowest-cost SC, it is equipped for disruptive shocks. The 'green' SC refers to an integrated mindset in SC from the environmental

perspective, with green material selection and sourcing, green design, green manufacturing, green delivery, green consumption, and green end-of-life product management (Srivastava, 2007).
The LARG SC needs to consider all four paradigms. Table 1 shows divergences and synergies of the same (Carvalho et al., 2011).

Table 1: Divergences and Synergies of LARG SC (adopted from Carvalho et al., 2011)

S. N.	SC Attribute		Lean	Agile	Resilent	Green
1	Capacity Surplus	Divergences	↓	↑	↑	↓
2	Replenishment Frequency		↑	↑	↑	↓
3	Inventory Level		↓	↓	↑	↓
4	Lead Time (Production)	Synergies	↓	↓	↓	↓
5	Lead Time (Transportation)		↓	↓	↓	↓
6	Level of Integration		↑	↑	↑	↑
7	Frequency of Information		↑	↑	↑	↔

Notations -

↑ -Increase
↓ -Decrease
↔ -Without Consequence

Table 1 shows the synergies and divergences between elements of the LARG paradigm within SC attributes. The synergies are related to i) reduction of lead time in transportation, ii) reduction of lead time in production, iii) increase in level of integration, and iv) increase in frequency of information. However, frequency of information is without consequence in the green paradigm. Thus, LARG paradigms supplement one another. SC attributes, such as capacity surplus, replenishment frequency, and inventory level, affect the resilient paradigm in a positive way but the green paradigm in a negative way. These three attributes pull in opposite directions in the lean and agile paradigm. Thus, enterprises must establish relationships between different paradigms for SC to be efficient, streamlined, and sustainable.

2.2 BDA and Supply Chain

BDA capabilities can assist with SC functions, such as procurement, warehousing, manufacturing, demand management, transportation/logistics, and general SC (Govindan et al., 2018). The current literature shows other research articles in manufacturing and transportation/logistics (Inamdar et al., 2020). Critical activities in SC manufacturing are production planning and control (PPC), product research and development (product R & D), maintenance and diagnosis, and quality management. BDA adoption in PPC is attracting interest from many researchers, and BDA tools and techniques in this area are relatively mature (Zhong et al., 2015). The BDA approach was used to predict online market sale performance (Li et al., 2016). Wang and Zhang (2016) proposed the BDA framework to forecast the cycle time for a semiconductor manufacturer. In addition, BDA can be used for the maintenance and manufacturing of complex products (Zhang et al., 2017), intelligent manufacturing (Zhong et al., 2017a, 2017b), and RFID-facilitated production data (Zhong et al., 2016). Quality management is another area in manufacturing in which BDA is extensively used (Wang et al., 2016; Zhang et al., 2017). Despite the usage of BDA in maintenance and diagnosis in its initial stage, research in the use of BDA in servitization (Opresnik and Taisch, 2015) and workers' behaviour (Guo et al., 2016) is attracting attention. Kumar et al. (2016a) proposed BD to diagnose faults in cloud manufacturing using the MapReduce framework. In two different studies in the Indian context, Narwane et al. (2020) emphasized the positive impact of cloud computing and the Internet of Things (IoT) on firm performance. BDA is in its nascent stage for product R & D. Tan et al. (2015) proposed a BDA framework based on the deduction graph to enhance the capabilities of SC innovation.

Logistic planning, intelligent transport systems, and in-transit inventory management can all benefit from the adoption of BDA. Some of the studies on BDA-based intelligent transport systems include the prediction of traffic flow (Li et al., 2015), smart transportation (Wang et al., 2016), real-time safety monitoring of expressway traffic (Shi and Abdel-Aty, 2015), and efficient path planning for vehicles (Zhang et al., 2016). BDA research in logistics planning is basically focused on optimisation and simulation. Lee (2017) proposed the BDA optimisation model for anticipatory shipping by using a genetic algorithm. Zhao et al. (2016) proposed an optimisation model using BDA for the green SC. Mehmood et al. (2017) used the Markovian approach to explore the effect of BDA on transportation, whereas Shan and Zhu (2015) used GPS big data for the same.

The BDA application in SC procurement is primarily seen in three areas, namely, supplier selection, obtaining improvements in risk, and cost optimisation (Huang and Handfield, 2015). The study measures the benefits of ERP to the SC maturity model using the BDA approach. Choi et al. (2016) proposed a fuzzy reasoning map based on BD to prioritise the procurement of IT services. BDA application in SC warehousing is mostly used in three areas, namely, order picking (Li et al., 2016), storage assignment (Tsai and Huang, 2015), and inventory control (Hofmann, 2017). Tsai and Huang (2015) investigated consumer moving behaviour and purchasing using a data mining approach. Hofmann (2017) studied the impact of the three V's of BD, namely, variety, volume, and velocity, on SC decisions using the bullwhip effect. It must be noted that BDA applications in demand management are not discussed much in the literature (Nguyen et al., 2018). BDA capabilities are used in demand shaping with lower prices for customers and an efficient market in terms of energy (Ho and Shih, 2014). Data sensing and data forecasting is another area of demand management that is receiving the attention of researchers (Li et al., 2016).

BDA adoption in SC practices in different countries is as shown in Table 2. Various authors have proposed only the conceptual framework of BDA in SC as follows: BDA capability for SC (Arunachalam et al., 2018), BD with IoT – value-adding (Addo-Tenkorang and Helo, 2016), BDA for collaborative SC (Fawcett and Waller, 2014), BDA for the design and operation of SC (Waller and Fawcett, 2013a), and a maturity model of BDA in SC and logistics (Wang et al., 2016). These studies discussed various significant factors of BDA for SC, as listed in Table 2. Hazen et al. (2016), Waller and Fawcett (2013b), Fosso Wamba et al. (2018), and Zhong et al. (2016) have conducted conceptual studies of the usage of BD in SC. Sustainability aspects were prominently discussed in these articles, which used exploratory analysis tools to understand BDA adoption for SC in various countries. As listed in Table 2, these studies were carried out in developed countries like the USA, China, and France, as well as in developing and underdeveloped countries like India and Nepal. This shows that all types of economies are keen to adopt BDA. However, it must be noted that the challenges faced in these countries differ, as their levels of technological advancement are different. Very few authors, such as Zhong et al. (2015) and Zhao et al. (2016), used the case study approach. Also, a hybrid approach in methodology (Dev et al., 2018), cause-and-effect relationships amongst the critical factors of SC (Wu et al., 2017), and cross-country surveys (Dubey et al., 2019b) were rarely discussed in the literature.

Table 2: BDA Adoption in SC Practices

Sr. No.	Publication	Country	Type of model/ Approach	Type of firm and Sample size	Factors discussed
1.	Arunachalam et al. (2018)	United Kingdom (UK)	Conceptual model	NA	BDA capability framework for SC Intra- and inter-organizational data, visualization and analytics capabilities (descriptive, diagnostic, predictive, and prescriptive), data generation, data integration, data management, and data-driven culture
2.	Addo-Tenkorang and Helo (2016)	Finland	Conceptual model	NA	The framework of BD with IoT – value-adding BD in SC and operations, variety, volume, veracity, velocity, and value-adding
3.	Chavez et al. (2017)	China	Conceptual model, SEM	Manufacturing firms (n=337)	Data-driven SC, delivery, flexibility, cost, quality, customer satisfaction
4.	Chen et al. (2015)	USA	TOE framework, Factor analysis, SEM	Online survey of managers and executives of multiple firms (N=161)	Organisational readiness, technological compatibility, expected benefits, competitive pressure, business growth, asset productivity, environmental dynamism, top management support
5.	Dev et al. (2018)	India	Integration of Fuzzy ANP, simulation, and TOPSIS	SC Operations Reference (SCOR) model with three suppliers, one manufacturer, two distributors, and four retailers	BDA architecture for SC key performance indicators (KPI) Performance of SC, order size, forecasting error, lead time, service level, review period, average demand Average inventory level and time, average cycle time, average fill rate
6.	Dubey et al. (2018a)	India	Conceptual model, exploratory analysis, PLS-SEM	Manufacturer of auto components (n=173), senior manager	BDA framework for SC agility Factors considered: BDA capabilities, competitive advantage, organisational flexibility, industry dynamics, size of the organisation, and organisation age
7.	Dubey et al. (2018b)	India	Conceptual model, exploratory analysis, PLS-SEM	Manufacturer of auto components (n=190)	BD predictive analysis framework Factors considered: Resource complementarity, organisational compatibility, collaborative performance, interdependency, and temporal orientation
8.	Dubey et al. (2019a)	India	Conceptual model, empirical analysis, PLS-SEM	Manufacturing organisations, senior-level SC managers (n= 213)	BDA framework for SC resilience Factors considered: BDA capabilities, organisational flexibility, SC resilience, competitive advantage, competitive intensity, industry dynamics, and size of the organisation
9.	Dubey et al. (2019b)	A survey in 29 different countries	PLS-SEM approach	Different organisations: international NGOs, civil, military, government agencies, and service providers (n=373)	BDA framework based on humanitarian supply chain Factors considered: control orientation, flexible orientation, collaborative performance, swift trust
10.	Fawcett and Waller (2014)	USA	Conceptual model	NA	Correlational decision-making, prediction through profiling, virtual integration, collaborative SC

11.	Gunasekaran et al. (2017)	India	Regression analysis	e-commerce, consulting and manufacturing (n=205)	BDA framework for predictive analysis Factors considered: supply chain performance, organisational performance, BDA assimilation, BDA routinization, BDPA acceptance, connectivity, top management commitment, and information sharing
12.	Hazen et al. (2014)	USA	Correlation analysis	Statistical Process Control (SPC), Quality tools (n=400)	Data quality – timeliness, completeness, accuracy, and consistency SC performance, knowledge resource, strategic decision, SC capabilities, SC processing needs and rescoping
13.	Hazen et al. (2016)	USA	Conceptual model	NA	SC sustainability, TBL, technological infrastructure, aggregate resources, the effect of external environment on organisational processes and structure, the organisation's adaptation to changes, cost economics, relationship with supplier and customer, strategic management, human aspects
14. Je	Jeble et al. (2018)	India	Partial least squares (PLS)-Structural equation modelling (SEM)	Managers of Auto manufacturing firms, (n=215)	Model-based on contingency theory and resource-based view, tangible resources, management skills, technical skills, organisational learning, data-driven approach, BD predictive capability, supply base complexity, social performance, environmental performance, economic performance
15.	Papadopoulos et al. (2017)	Nepal	Content analysis, exploratory factor analysis (EFA), confirmatory factor analysis (CFA)	Unstructured data 36,422 items from tweets, news, etc. and structured data from managers involved in Nepal earthquake disaster relief (n=2015).	The framework of disaster resilience in SC for sustainability Unstructured data within SC networks, swift trust, information sharing, public and private partnership, SC resilience, critical infrastructure resilience, resources resilience, and community resilience
16.	Schoenherr and Speier-Pero (2015)	USA	Conceptual model, Empirical analysis	Online survey of SC professionals, ANOVA (n=212)	The framework of SC predictive analysis Barriers - data related, security and privacy concerns, government policy, organisational, employee-related, integration issues, time constraint Data scientist skill sets - data management, enterprise business process, analytical tools, modelling tools, and decision-making
17.	Tan et al. (2015)	China	Conceptual model, Case study	Deduction graph, Glass manufacturer, two managers and one CEO (N=1, n=3)	Proposed an analytic infrastructure model, SC innovation capability Factors considered - internal skills, present competence sets, required competence sets, competence network, optimal decision
18.	Waller and Fawcett (2013a)	USA	Conceptual model	NA	Proposed a 2 x 2 model of explanation and prediction Design and operation of SC - transportation modes, design of the warehouse, demand forecast, supplier selection, and supplier evaluation

					Firm capability - information sharing, knowledge management, and collaboration
19.	Waller and Fawcett (2013b)	USA	Conceptual model	NA	The expertise of SC data scientists: awareness, understanding, knowledge Types of data (consumer, location, sales, inventory, and time), Types of user (manufacturer, carrier, and retailer), Types of application (inventory management, human resources, forecasting, and transportation management) Multidisciplinary nature of the predictive analysis
20.	Fosso Wamba et al. (2018)	France	Conceptual model	NA	BDA in SC and operations, demand forecast in uncertainties, collaboration with partners in SC network, product quality, SC agility, SC adaptability, SC alignment, SC robustness, SC resilience
21.	Wang et al. (2016)	USA	Conceptual model	NA	Maturity model of BDA in SC and logistics considering five levels of capabilities as process-based, functional, agile, collaborative, and sustainable
22.	Wu et al. (2017)	Taiwan	Fuzzy-DEMATEL, Grey-DEMATEL	LED industry, Sample from CEOs, professors, managers, etc.	SC uncertainties, SC risk, sustainability indicators - organisation related, capacities, controllability, cost, products, reputation, and operation
23.	Zhao et al. (2016)	China	Mathematical model, Case study	Sanitary product supply chain	Green SC network, inherent risk, CO_2 emissions, CH_4 emissions, total cost The constraint of material balance, capacity, decision variables
24.	Zhong et al. (2015)	China	Case Study implementation	Manufacturing shop floors with WSN and RFID (N=4)	BD framework for logistic trajectory, RFID - Cuboids, RFID-supported logistic data, enhancement of information granularity, reduction of dataset volume, evaluation of logistics machine and operator
25.	Zhong et al. (2016)	China	Conceptual study	NA	Methods of data collection, data transmission, data storage, BD processing technologies, decision-making model, BD applications, and BD interpretation
26.	Arya et al. (2017)	India	Conceptual model	Army spare parts	SC-agility, forecasting, visibility, risk, compliance, and collaboration, Visualization, prognostics, diagnostics, optimization (route and warehouse)
27.	Wu et al. (2019)	USA	Empirical Analysis	Publicly traded firms (N=2000), Correlation Analysis	Analysed patent data and survey data, analytics skills, firm characteristics, productivity, firm practices, innovation

N- No. of manufacturing firms; n- Sample size.

2.3 BDA for Sustainable Supply Chain

BDA positively influences all three aspects of sustainability (economic, environmental, and social) (Raut et al., 2019). Past studies in BDA for SC show improvements in competitiveness, productivity, and efficiency (Song et al., 2018; Wamba et al., 2015). Song and Wang (2015a) analysed carbon emissions and found that economic growth and the effect of energy intensity were significant factors influencing the same. Knowledge trade impacts environmental sustainability through progress in technology (Song et al. 2019). In a BDA study carried out for the Malaysian automotive SC, Doolun et al. (2018) found a reduction in CO_2 emissions, effective decision-making, supplier collaboration, and a reduction in the total cost of SC. Meanwhile, a BDA-centred humanitarian SC shows a positive effect on swift trust, flexibility, collaboration, and control (Dubey et al., 2019b). BDA also assists agile SC with operational flexibility and business performance for the determined objectives of an organisation (Gunasekaran et al., 2018). In addition, BDA can assist the government in a sustainable society with effective strategies toward resource management (Song et al., 2015b). However, BDA for sustainable SC faces challenges, particularly in developing and underdeveloped economies such as India and Bangladesh. Moktadir et al. (2019) studied barriers to BDA in the fields of manufacturing and SC. Their study classified barriers into four different categories, namely, i) expertise and investment-related barriers, such as research facilities, IT personnel, funding, and cost; ii) technology-related barriers, such as lack of interest, infrastructure, and availability; iii) data-related barriers, such as privacy, performance, quality, complexity in data integration, and scalability; and iv) organizational-related barriers, such as lack of policy, time constraints, training, and mind-set.

2.4 Research Gaps

Through the literature survey and synthesis, the authors found that developed countries, such as the UK, the USA, and China, have started BDA adoption in SC (Arunachalam et al., 2018; Chavez et al., 2017; Hazen et al., 2014). Developing countries are not far behind, and various studies, such as the works of Dubey et al. (2018a) and Jeble et al. (2018), show that issues of BDA adoption in SC are different in developed and developing countries. Extant studies have mainly focused on LARG SC, BDA for SC (Nguyen et al., 2018; Hazen et al., 2016), and BDA for sustainable SC (Moktadir et al., 2019; Dubey et al., 2019b). However, research papers very rarely discuss BDA adoption for LARG SC. Hence, this study tries to bridge this gap by investigating the effect of lean management, social practices, financial practices, environmental practices, etc. on BDA.

Manufacturing firms that have already implemented LARG practices in SC can further enhance sustainable business performance through BDA. Current research shows the positive effects of BDA on sustainable performance (Raut et al., 2019), SC agility (Dubey et al., 2018a), SC KPI (Dev et al., 2018), and sustainable SC (Papadopoulos et al., 2017). However, the BDA effect on sustainable SC that have implemented LARG practices is rarely investigated. Raut et al. (2019) investigated the mediating role of BDA on sustainable business performance for Indian manufacturing firms. However, the study considered only the lean and green parameters of LARG practices and did not consider the effects of the agile and resilient parameters. The prime concern of Indian manufacturers is to build an agile SC to respond to unexpected and sudden market changes. This study overcomes the shortcoming of Raut et al. (2019) by investigating the effect of LARG practices on BDA. Thus, it investigates the mediating role of BDA on sustainable SC business performance. It must be noted that understanding the effect of BDA adoption will assist manufacturing firms in the effective implementation of sustainable practices in SC.

In this paper, empirical analysis is used to understand the impact of BDA adoption on the sustainable SC performance of Indian manufacturing firms. Structural equation modelling (SEM) assesses unobservable and observable constructs of BDA. The proposed study considers only linear relationships through SEM. However, non-linear relations using tools like artificial neural networks can be considered in future studies. Other limitations of the study are given in section 7.

3.0 Conceptual framework and proposed hypothesis

Based on the above synthesis of the literature survey, Figure 1 shows a proposed conceptual framework. It consists of 9 factors: Organizational Practices (OP), Lean Management Practices (LMP), Supply Chain Management Practices (SCMP), Social Practices in Supply Chain (SPSC), Environmental Practices (ENP), Financial Practices (FP), Total Quality Management (TQM), Big Data Analytics (BDA), and Sustainable supply chain business performance (SSBP). BDA is a mediator amongst SSBP and the other seven factors that is OP, LMP, SCMP, SPSC, ENP, FP, and TQM. To finalize these shortlisted factors, the Delphi method was used (Skulmoski et al., 2007). A preliminary questionnaire with these nine factors was given to thirteen experts and qualitative feedback was collected. The Delphi expert panel approved all the factors. As per the technical specifications of identified factors, logical grouping was performed. A pilot study was carried out in ten manufacturing firms to confirm the grouping. A five-point Likert scale was used to collect 112 responses. After the pilot study, the 67 sub-factors were reduced to 59. Table 1 gives the finalized sub-factors along with factors of BDA for Sustainable SC Business Performance. These factors must be considered together to have a holistic understanding of LARG and BDA on a sustainable SC performance.

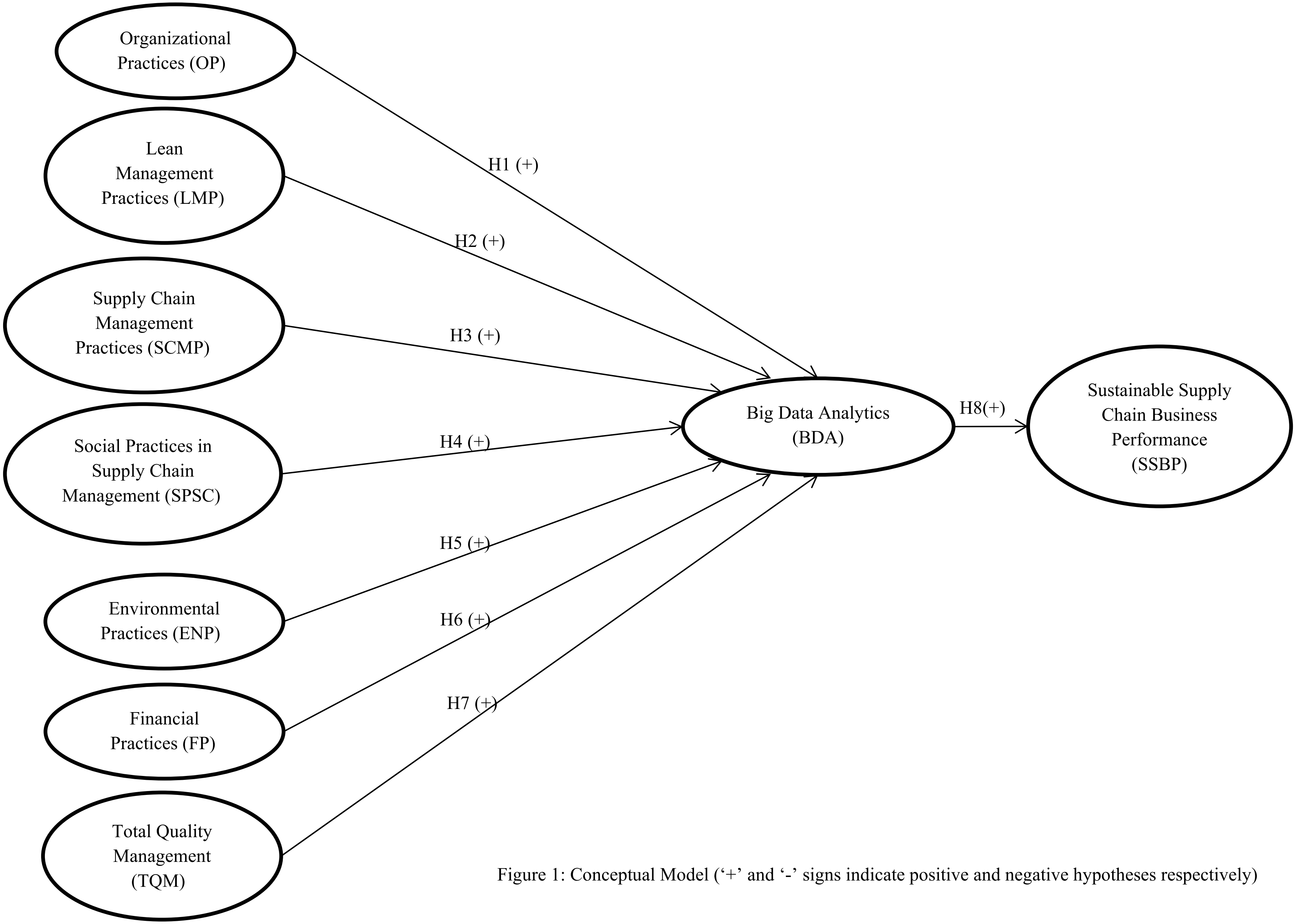

Figure 1: Conceptual Model ('+' and '-' signs indicate positive and negative hypotheses respectively)

Table 3: Constructs and hypotheses

Hypo. No.	Factor	Description	Sub-factors (Items)	Reference
H1	Organisational Practices (OP)	The start of the path to achieving long-term goals is an organisational practice. BDA here becomes a factor while building a strategy that increases the overall performance of the firm. The strategy helps in improving the efficiency of the operations, such as inventory and sales optimisation: analysis of each strategy helps in the decision-making process. The training and education of personnel in any enterprise – i.e., both BDA and manufacturing SC – enhance the value of the use of BDA in manufacturing SC. This could apply to all types of training for all kinds of people in the chain, including the employees, suppliers and customers.	OP 1: Top management support OP 2: Training and education OP 3: Organization vision and strategy OP 4: Communication between workers and management OP 5: Employee empowerment OP 6: Organization culture OP 7: Organization maturity	Dubey et al. (2018a), Gunasekaran et al. (2017), Jabbour et al. (2013)
H2	Lean Management Practices (LMP)	Organisations should focus on lean practices. Minimizing waste can be achieved through lean practices. With techniques such as Just in Time (JIT) and cellular manufacturing, the manufacturing firms can benefit. BDA helps in developing a lean management model of internal processes that can help in making a standardised process and minimise waste. BDA increases the efficiency in processes; it also helps in achieving technical and organisational flexibility and can identify inefficiencies in the organisation.	LMP 1: Understanding of lean LMP 2: Lean waste LMP 3: Value-added SC LMP 4: JIT, Pull system LMP 5: Lead time LMP 6: Cellular manufacturing LMP 7: Mass customisation LMP 8: Standardization in work and operation	Fullerton et al. (2014)
H3	Supply Chain Management Practices (SCMP)	Manufacturing data has to be shared with the suppliers in order to get the required material available in the market, which will lead to a sustainable business strategy. BDA helps in selecting optimal suppliers and vendors and helps in increasing firms' negotiation power. Improved integration with suppliers leads to better decision-making, reduction in waste and a high level of performance. BDA capabilities can enhance the supply chain performance also reduces SC risk. Supplier selection can be achieved more effectively as the involvement of suppliers is most important.	SCMP 1: Supplier relationship SCMP 2: SC competitiveness SCMP 3: SC Resilience SCMP 4: ISO 14000 Certification of Supplier SCMP 5: SC Risk Management SCMP 6: Vendor selection SCMP 7: Supplier collaboration and integration	Dubey et al. (2019b), Tsao (2017), de Sousa Jabbour (2015), Goldbeck et al. (2020), Dahlmann and Roehrich (2019)
H4	Social Practices in Supply Chain (SPSC)	Government policies need to help in promoting advanced manufacturing and SC. The government plays a substantial role in research and the development of new manufacturing technologies, and with proper legal support, these ideas and firms' crucial data can be protected and future misuse prevented. Local bodies and NGOs can play a significant role in	SPSC 1: Stakeholder related SPSC 2: Involvement of NGOs and Local Bodies SPSC 3: Legal Issues SPSC 4: Governmental Regulation	Jeble et al. (2018), Orazalin (2020)

		the acceptance of LARG and BDA by the masses. Organizations must form regulatory norms to promote the BDA and LARG practices.		
H5	Environmental Practices (ENP)	In this competitive ecosystem, environmental practices lead to gaining a competitive advantage over others. Environmental practices refer to eco-design, waste management, cellular manufacturing, and reduction in energy usage. BDA ensures better environmental practices and enables them to gain economic values. Thus BDA and LARG can transform practices more effectively with eco packaging, reduction in carbon footprints, and recycling	ENP 1: Balancing environmental and social benefits ENP 2: Recycling efficiency ENP 3: Environmental cost ENP 4: Eco-packaging ENP 5: Carbon Emission ENP 6: Standardization	Hazen et al. (2016), Zhao et al. (2016), Fang et al. (2020), Li et al. (2019a), Wang et al. (2020), Chang et al. (2019)
H6	Financial Practices (FP)	Manufacturing firms aim to achieve an economic balance between their assets and liabilities and thus end up investing much money. Long-term financial support helps the firm to protect itself from credit shocks in the chain during a depression. Even though organizations are ready for investment, change over time is a major concern for the top management. BDA helps the manufacturing firm to use financial resources and use the right technology efficiently. However, return on investment (ROI) must be calculated carefully.	FP 1: Initial Capital FP 2: Training Funds FP 3: Financial Advantages/ Benefits FP 4: Cost of Technological Advancement FP 5: Changeover cost/time FP 6: Return of Investment	Hazen et al. (2016)
H7	Total Quality Management (TQM)	Data, if they are to be used effectively in manufacturing firms, need to have the proper quality of information, being both thorough and orderly. Industry practices such as TQM require such high standards of quality to be maintained, and this is what decides the competitive stature of the organisation. HRM plays an essential role in TQM. The integration of BDA in the system would affect information quality and business value to give meaningful insights into SC operations.	TQM 1: Quality Systems TQM 2: Human Resource Management TQM 3: Operational Performance TQM 4: Customer satisfaction TQM 5: Supplier management	Zhang et al. (2020), Lartey et al. (2020)
H8	Sustainable Supply Chain Business Performance (SSBP)	Sustainable business performances are measured in terms of the four ground terms. It then becomes the firms' societal responsibility to ~~do this to help~~ maintain a sustainable system. BDA empowers the organisations to gain control over operational costs and aims to reduce them (better flexibility, improved product quality, lesser lead time); it enables the firms to build a brand image and create a fad in the market. BDA helps with avoiding environmental accidents by monitoring chemical usage and waste disposal. BDA surely enables us to acquire a good share in the competitive market.	SSBP 1: Cost SSBP 2: Quality of Service SSBP 3: Time SSBP 4: Service Level SSBP 5: Responsiveness SSBP 6: Agility SSBP 7: Collaboration SSBP 8: Firm performance	Dev et al. (2018), Cabral et al. (2012), Li et al. (2019b), Centobelli et al. (2020)

Sub-factors for BDA Adoption (8): BDA1: Big Volume, BDA2: Big Velocity, BDA3: Big Variety, BDA4: Big Veracity, BDA5: Big Value, BDA6: Investment and Infrastructure, BDA7: Connectivity and Co-ordination, BDA8: Modularity and Compatibility (Raut et al., 2019; Wamba et al., 2017; Choi et al., 2018).

4.0 Research Methodology

Figure 2 shows the adopted research methodology.

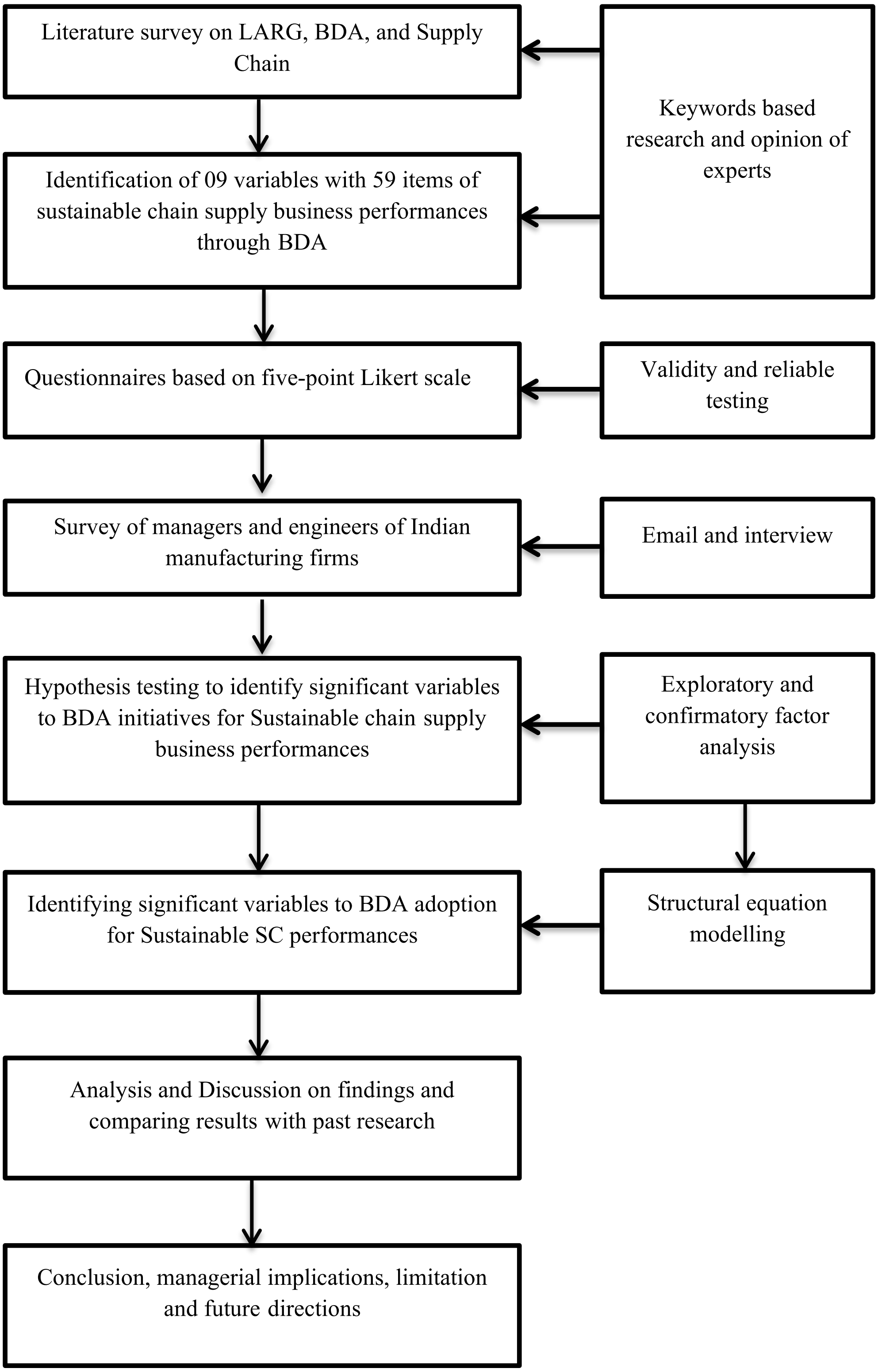

Figure 2: Research Methodology

Initially, a literature survey was conducted on LARG, BDA, and SC. Based on inputs from experts and a pilot study, 9 variables with 59 items for sustainable SC business performance through BDA were finalized. The survey of managers and engineers was carried out followed by factorial analysis.

An exploratory and confirmatory factor analysis approach was used to test the hypothesis. Factorial analysis has a long history in market research. Exploratory factor analysis (EFA) helps when there are no prior assumptions about the factor structure (Marsh et al., 2014). EFA uses a five-step protocol as follows (Steger, 2006; Henson and Roberts, 2006; Williams et al., 2010): suitability of data, factor extraction method, criteria for factor extraction, rotational method selection, and interpretation. Further, according to Bryant and Yarnold (1995), the researcher must have a robust theory underlying the proposed measurement model prior to data analysis. In confirmatory factor analysis (CFA), the hypothesized model is used to estimate a matrix of population covariance, which needs to be compared with the matrix of observed covariance (Hemmelgarn et al., 1995; Schreiber et al., 2006; Strauss and Smith, 2009). Accepted constructs, observed variable patterns, and latent constructs in CFA are further used for SEM analysis (Chan et al., 2007). SEM enhances the analysis and provides added flexibility (Blanthorne et al., 2006). SEM is a statistical technique that was used initially for marketing theory (Bagozzi, 1980). Later, it became popular in studies of social sciences and behavioural studies for theory testing (MacCallum and Austin, 2000). SEM incorporates dependent variables, latent constructs, and independent variables to analyse the multivariate data. In this paper, the following goodness-of-fit indices were considered: normed fit index (NFI), goodness-of-fit index (GFI), root mean square error of approximation (RMSEA), and comparative fit index (CFI). Further, in this study, the analysis of moment structures (AMOS) program was selected, as it can read SPSS files and gives excellent quality path diagrams. Thus, this study uses the EFA-CFA-SEM approach for data analysis. The sample characteristics and details for data collection are provided in the following section.

4.1 Sample Characteristics

The survey was targeted at individuals in SC operations, who were asked to respond to issues related to manufacturing. Indian manufacturers who had already adopted or were in the process of adopting LARG practices were selected for the survey, and managers and engineers from these firms who dealt with SC operations were selected for sample collection. Annexure-I shows the questionnaire used for the survey. Initially, thirty-seven such manufacturing firms were selected. Data was collected during a three-month period through personal interactions and Google sheets. After one month, a gentle reminder was sent to non-responding firms. After two months, a telephonic request was made to the individual participants. Qualitative research often faces practical challenges in data collection. Some of the major challenges faced in this research were gaining access to the manufacturing firms and key participants, incorporating online technologies, data confidentiality, and time constraints. However, with persistence, out of a total of 354 responses received, 297 were found to be valid. Sample characteristics are as shown in Table 4: manufacturers with more than 250 employees formed the largest proportion of responses (116, 39.06%). In terms of organisation turnover, the highest responses were from firms with a turnover of 15-30 million dollars (130, 43.77%). The highest responses in terms of experience were from respondents with 5-10 years' experience (172, 57.91%) and, in terms of education, were from undergraduates (188, 63.30%).

Table 4: Sample characteristics

Categories		*Frequency*	*Percentage (%)*
Gender	Male	208	70.03
	Female	89	29.97
	Total	**297**	**100 %**
Educational qualification	Undergraduate (B.E./BTech)	188	63.30
	Postgraduate (M.E./MTech)	102	34.34
	PhD.	07	2.36
	Total	**297**	**100 %**
Total years of experience	Less than five years	46	15.49
	Five to ten years	172	57.91
	More than ten years	79	26.60
	Total	**297**	**100 %**
No. of employees in organisation	Less than 150	74	24.92
	150-250	107	36.02
	More than 250	116	39.06
	Total	**297**	**100 %**
Organisation turnover (in million US dollars)	Less than 15	48	16.16
	15-30	130	43.77
	30-40	95	31.99
	More than 40	24	8.08
Total		**297**	**100 %**

5.0 Results

5.1 EFA

In this study, the Sustainable SC Business Performance of manufacturing firms through BDA adoption was measured using a survey-based method. Nine constructs were measured through a quantitative and qualitative approach. A two-phase approach was used to measure items of eleven constructs. In phase 1, the construct and the item dimension were defined, along with the validity and reliability of undefined indicators. In phase 2, a questionnaire based on a five-point Likert scale was developed in order to understand the effect of BDA adoption. In the final survey, the authors received 297 valid responses from managers and engineers who were involved with their firms' SC operations. To test the appropriateness of data, a Bartlett's test and a Kaiser-Meyer-Olkin (KMO) test were carried out. The results show that the KMO value was 0.851, which was satisfactory, as it was greater than 0.6. In the Bartlett's test, significance (p-value) for a 95% confidence level must be less than 0.05; the p-value for the present study was 0.000. In this study, principal component analysis (PCA) was the extraction method, while the rotation method used was varimax (with Kaiser Normalization). The rotated component matrix (converged in six iterations) is shown in Annexure-II. All variables had observed high loadings, i.e., greater than 0.5. The highest loading was observed for 'ENP5' with a value of 0.941; the lowest loading was for 'LMP7', with a value of 0.503. Except for 'LMP7' and 'OP1' (0.567), all variables had loadings greater than 0.6, and no cross-loading was observed. Thus, the results of EFA are satisfactory for further CFA analysis.

5.2 CFA

CFA was performed on seven constructs of BDA adoption and one construct of Sustainable SC Business Performance. All of these eight constructs were allowed to correlate freely with each other. The construct 'Sustainable SC Business Performance' had eight items. Only two constructs, namely 'BDA adoption' and 'Lean management practices', had eight items; all other constructs had fewer than eight items. CFA results show a chi-square test to the degree of freedom ratio 1.922 (<3.0), and CFI 0.916 (>0.90). RMSEA is 0.056, which is not <0.05. However, 0.05-0.10 is the moderate range of RMSEA, while GFI (0.942) is not higher than 0.95; nonetheless, it is within the permissible limit, and thus RMSEA and GFI are acceptable. Thus, it can be concluded that for the collected dataset, the goodness-of-fit statistics have acceptable values.

CFA model estimates are shown in Annexure-III. Loadings between factors and measured variables were greater than 0.5, except for LMP7 (mass customisation), with a value of 0.362, and SPSC2 (Involvement of NGOs and local bodies), with a value of 0.471. Thus, the acceptable level of convergent validity is shown by the loading of indicators in distinct constructs (Barki and Hartwick, 2001). It must be noted that measurement model loadings were mostly greater than 0.6, except for a few loadings, as follows: Understanding of lean (LMP1 with a value of 0.511); Top management support (OP1 with a value of 0.537); Organization vision and strategy (OP3 with a value of 0.567); Communication between workers and management (OP4 with a value of 0.600); Organizational culture (OP6 with a value of 0.574); and Involvement of NGOs and local bodies (SPSC2 with a value of 0.574). This shows acceptable convergent validity. The CFA path diagram is shown in Annexure-IV, which was drawn using AMOS software.

5.3 SEM

SEM was carried out in two phases: i) validating the latent constructs and ii) judging the fitting model based on the structural model (Jenatabadi, 2015). SEM examines non-causal and causal relationships amongst the variables. It indicates relevant precedence where bi-directional arrows in the CFA model must be replaced with single-headed arrows. The developed path diagram is shown in Figure 3. Annexure-V shows estimates for the structural model. The SEM results show a chi-square test in which the degree of freedom ratio is 1.969 (<3.0), and CFI is 0.912 (>0.90). RMSEA is 0.051, which is not <0.05, though 0.05-0.10 is the moderate range of RMSEA, and GFI (0.933) is not higher than 0.95. However, it is within the permissible limit, and thus RMSEA and GFI are acceptable. Thus, the authors can conclude that for the collected dataset, the goodness of fit statistics have acceptable values.

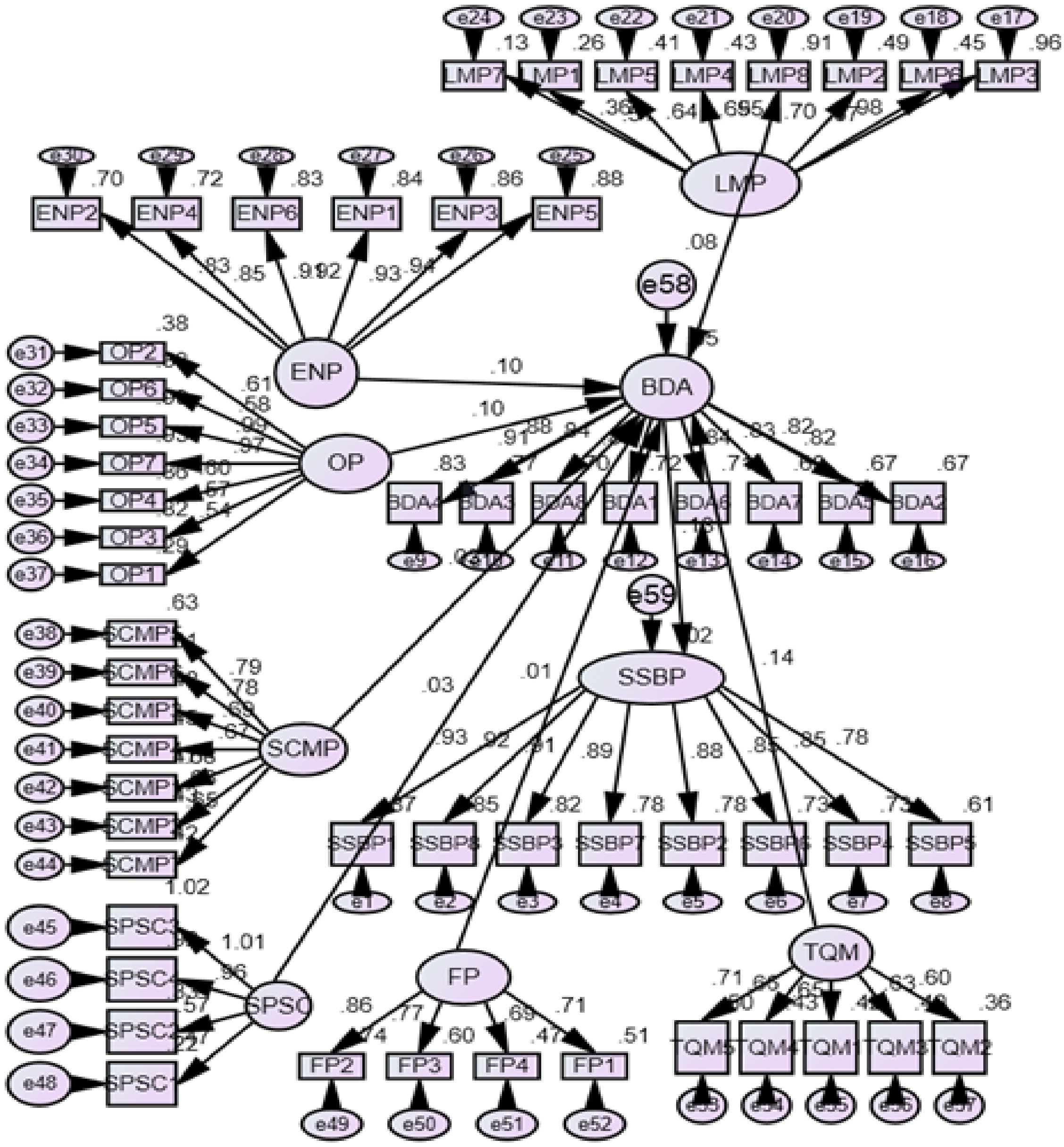

Figure 3: SEM Path Diagram

Based on the SEM analysis, all eight hypotheses based on positive relationships between BDA adoption and Organizational Practices (OP, 0.096), Lean Management Practices (LMP, 0.083), Supply Chain Management Practices (SCMP, 0.031), Social Practices in SC (SPSC, 0.028), Environmental Practices (ENP, 0.097), Financial Practices (FP, 0.006), Total Quality Management (TQM, 0.141), and Sustainable Supply Chain Business Performance (SSBP, 0.129) are supported.

5.4 Robustness Check

In order to check the robustness of the moderating effect of BDA, regression analysis was conducted (Lo et al., 2018). The structural model is built in AMOS. The descriptive analysis of the structural model shows sufficiently high values of Cronbach Alpha (Please refer to

Annexure-VI). The reliability value of six variables SSBP (0.9634), ENP (0.961), BDA (0.9537), LMP (0.9046), OP (0.9046), and SCMP (0.8732) were higher than 0.85 which is considered as "excellent" (Bonett and Wright, 2015). However, the Cronbach Alpha values for SPSC (0.8497) and FP (0.8429) were close to 0.85, whereas for TQM (0.7852) was "acceptable" as it is higher than 0.65 (Bonett and Wright, 2015). Table 5 gives details of correlation analysis, which gives significant correlations at 95 % (2-tailed) and 99 % (2-tailed).

Table 5: Correlation Table

	SSBP	BDA	TQM	LMP	OP	FP	SPSC	SCMP	ENP
SSBP	.7952								
BDA	.127*	.7556							
TQM	.293**	.137*	.7358						
LMP	-.038	.112	.067	.7971					
OP	.032	.079	.140*	.285**	.7473				
FP	.050	.091	.282**	.136*	.425**	.7488			
SPSC	.150**	.085	.152**	.126*	.263**	.257**	.7854		
SCMP	-.002	.014	-.028	.015	-.016	-.032	-.057	.7585	
ENP	-.008	.104	.028	.020	-.001	.062	-.026	-.011	.8337
*. Correlation is significant at the 0.05 level (2-tailed).									
**. Correlation is significant at the 0.01 level (2-tailed).									

Figure 4 shows the structural mediation model, and the results of the mediation effect are tabulated in Table 6. There is one Partial mediation found for TQM and full mediation for ENP. Moreover, there is no mediation effect found on other variables. Annexure-VII gives the details of regression weights, direct and indirect effects.

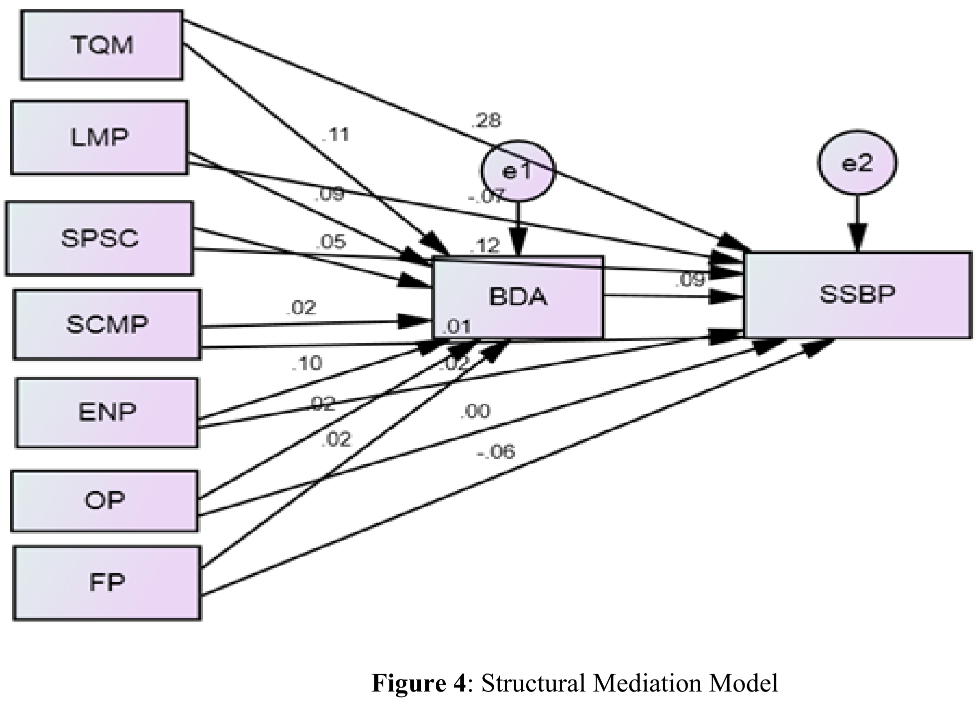

Figure 4: Structural Mediation Model

Table 6: Results of Mediation Effect

Relationship	Direct Effect	Indirect Effect	Result
TQM ⟶ BDA ⟶ SSBP	*.392 (.001)	*.015 (.074)	Partial Mediation
LMP ⟶ BDA ⟶ SSBP	-.093 (.153)	.010 (.113)	-------
SPSC ⟶ BDA ⟶ SSBP	*.129 (.064)	.005 (.258)	---------
SCMP ⟶ BDA ⟶ SSBP	.016 (.830)	.003 (.578)	--------
ENP ⟶ BDA ⟶ SSBP	-.015 (.700)	*.008 (.071)	Full Mediation
OP ⟶ BDA ⟶ SSBP	-.002 (.981)	.002 (.645)	--------
FP ⟶ BDA ⟶ SSBP	-.066 (.408)	.002 (.572)	---------

*Significant at $\alpha < 0.10$ (2-tailed test)
P- Values are shown in parentheses.

The mediation model explains the casual effect of antecedent on the dependent variable (Hair et al., 2011). Three types of mediation effects are i) No Mediation indicating no indirect effect, ii) Partial Mediation indicating both indirect and direct effect, and iii) Full Mediation indicating only indirect effect (Lowry and Gaskin, 2014). From Table 6, out of seven hypotheses, two are supported. In these two hypotheses, one is fully mediated, and the other is partially mediated. The variable Environmental Practices (ENP) fully mediate Sustainable supply chain business performance (SSBP) whereas total Quality Management (TQM) partially mediates the relationship. The remaining five variables do not show any mediation effect. The result indicates that the proposed model only focuses on environmental practices and total quality, whereas organizational practices, lean management, SC management, social practices, and financial practices remain neglected. However, these factors must be considered for BDA adoption in Indian organizations.

6.0 Discussion

In this paper, the BDA role for Sustainable SC Business Performance is analysed through the SEM approach. Table 7 shows the path analysis results, which supports all eight hypotheses. Significant factors in order of standardised estimate values are Total Quality Management (TQM), Sustainable supply chain business performance (SSBP), Environmental Practices (ENP), Organizational Practices (OP), Lean Management Practices (LMP), Supply Chain Management Practices (SCMP), Social Practices in SC (SPSC), and Financial Practices (FP). The obtained results were compared with the past literature and are shown under the 'in contrast with' and 'in agreement with' columns in Table 7.

The study finds that "Total Quality Management (TQM: 0.141)" is the most significant factor; this agrees with Chavez et al. (2017) and Dubey et al. (2016). Chavez et al. (2017) surveyed Chinese manufacturing firms and concluded that producing high performance, reliability, and consistently high-quality products to meet customer needs was most significant in data-driven manufacturing SC. Similarly, the study by Dubey et al. (2016) emphasised TQM techniques, TQM tools, customer satisfaction, supplier quality, quality standards, and quality management for the successful implementation of BDA for manufacturing. Hence, Indian manufacturers must focus on TQM systems with current resources and must train employees to meet customer demands. With the support of top management, BDA can play an essential role in refining the complete system.

The study by Dubey et al. (2019a) of Indian manufacturing organisations concluded that BDA capabilities help organisations to make the SC resilient and gain competitive advantage. Dev et al. (2018) used an integrated fuzzy ANP-TOPSIS approach to understand BDA-based SC performance ability. The study shows that BDA provides a practical approach to a crucial performance index of SC under the dynamic situation. In this study, the hypothesis based on SC business performance (SSBP: 0.129) resulted in the second highest level of significance. Supply chain analytics can help manufacturing firms to achieve long-time goals along with better firm performance. However, achieving operational and technical performance with excellent initial investments is a significant concern in developing and underdeveloped countries.

The study supports the hypothesis on "Environmental Practices (ENP: 0.097)", which is in line with Jeble et al. (2018). Their study was conducted on Indian auto manufacturing firms and emphasised the reduction of air emissions, the use of waste water recycling, and the prevention of solid waste and toxic material. This shows that environmental performance is positively associated with business performance. The hypothesis on "Organizational Practices (OP: 0.096)" is ranked as per the standard estimate value. It agrees with Chen et al. (2015), who proposed a dynamic capability theory to establish the positive effect of organisational factors on BDA. However, the study carried out by Dubey et al. (2018b) in Indian auto component manufacturers does not show a positive correlation between BDA and organisational capabilities. The hypothesis on "Lean Management Practices (LMP: 0.083)" is ranked fifth and agrees with studies carried by Gunasekaran et al. (2017) and Dubey et al. (2016) on Indian manufacturers. The other three hypotheses supported are shown in Table 7.

The findings of this study agree with the current literature; however, some results differ from those reported in earlier studies. This could be because of the difference in i) sector and economy, ii) internal, external, technical, and non-technical factors towards BDA adoption, and iii) type of methodology in past studies. However, the findings will help decision makers to understand significant factors for the implementation of BDA for Sustainable SC Business Performance.

Table 7: Comparison of path analysis results with past literature

Sr. No.	Regression Relation	Standardised Estimate	Significance level	Supported (Y/N)	In agreement with	In contrast with	Remark
1	H1: Organizational Practices (OP) positively influence *BDA adoption*	0.096	4	Yes	Chen et al. (2015), Mikalef et al. (2019)	Dubey et al. (2018b)	
2	H2: Lean Management Practices (LMP) positively influence *BDA adoption*	0.083	5	Yes	Gunasekaran et al. (2017), Dubey et al. (2016)		
3	H3: Supply Chain Management Practices (SCMP) positively influence *BDA adoption*	0.031	6	Yes	Gunasekaran et al. (2018), Yu et al. (2018)		
4	H4: Social Practices in SC (SPSC) positively influence *BDA adoption*	0.028	7	Yes	Jeble et al. (2018)		
5	H5: Environmental Practices (ENP) positively influence *BDA adoption*	0.097	3	Yes	Jeble et al. (2018)		
6	H6: Financial Practices (FP) positively influence *BDA adoption*	0.006	8	Yes	Jeble et al. (2018)	Dubey et al. (2018a), Yu et al. (2018)	While supported, it has the lowest value
7	H7: Total Quality Management (TQM) positively influence *BDA adoption*	0.141	1	Yes	Chavez et al. (2017), Dubey et al. (2016)		Most significant factor, which emphasizes the importance of TQM
8	H8: Big data analytics (BDA) adoption positively influences *Sustainable supply chain business performance (SSBP)*	0.129	2	Yes	Dubey et al. (2019a)		Second most significant factor, which proves the mediation role of BDA

6.1 Theoretical contributions

The theoretical contributions of the study are as follows:

- The previous studies have analysed LARG SC and BDA for sustainable SC separately. This study is one of the first to validate linkages and correlations and to explore the integration between these perceptions holistically.
- This study provides tangible evidence that supports the mediating role of BDA for Sustainable SC Business Performance by considering seven factors, namely, total quality management, supply chain practices, financial practices, lean practices, organizational practices, social practices, and environmental practices.
- Manufacturers of developing countries need a theoretical framework to develop BDA for manufacturing SC in the context of LARG and sustainability. The study adds value to the current research and literature by providing an understanding of BDA for sustainable SC to improve the business performance of manufacturing firms through the proposed framework.

In summary, sustainable SC needs a BDA revolution, and this study provides researchers and academicians with an in-depth understanding of the mediating role of BDA by using a case of Indian manufacturing firms. Further, it paves the way for future research exploring the mediating role of BDA to achieve firm performance.

6.2 Managerial contributions

The significant managerial contributions of the study are as follows:

- Firstly, this study provides insights to the consultants and managers who involved in digitization initiatives in the context of LARG SCs. To implement the new technologies, support from the firm's top management is essential. Top executives and CEOs must aim at long-term benefits. The intervention of policymakers and top management is vital for a BDA adoption. Policymakers can use the findings of the study to formulate strategic policies.
- Secondly, the list of factors and sub-factors can assist supply chain managers as well as production engineers to understand the overall implications of BDA. Decision-makers can scrutinize the significant factors of BDA adoption and the LARG paradigm. The study reveals that total quality management and environmental practices are most crucial for BDA adoption. Thus, organisations must ensure quality management, whereas sustainable practices need to be deliberated through regulation and laws by policymakers.
- Thirdly, the current competitive environment requires manufacturing firms to adopt BDA practices. The proposed framework can help with the successful adoption of BDA for Sustainable SC Business Performance for industrialists of emerging economies like India. Manufacturing firms can improve their profitability with BDA and LARG capabilities. Firm growth can be hindered by not adopting this technology.

A service provider needs to ensure a timely and reliable service to improve SC performance with LARG and sustainable practices. The study assists industrial managers with BDA adoption through practical, sustainable practices, and training. The role of training and education becomes crucial to overcome resistance to change and develop trust (DeJong et al., 2020).

7.0 Conclusion

Past research highlights the importance of BDA for sustainable SC and BDA for firm performance separately; our paper integrates both in order to understand its impact on the overall business performance of the organisation. In manufacturing firms, sustainable practices are extremely important. It is indispensable to have a conceptual model in order to investigate the effect of BDA on Sustainable SC Business Performance, particularly for developing countries. To address this problem, the authors conceptualised BDA adoption for sustainable SC of manufacturing firms from India.

In the proposed framework, the authors identified seven factors affecting intentions to adopt BDA. To validate the conceptual model, a survey was conducted among manufacturing firms in India. Developing economies like India need BDA adoption for the effective implementation of sustainable practices in manufacturing SC. This study will guide manufacturers in identifying the critical factors that affect BDA adoption in sustainable SC. Various stakeholders in SC can understand the particular nature of sub-factors in order to adopt BDA. The study can help governing bodies to develop an effective policy for BDA in manufacturing firms.

The following limitations of the study are acknowledged: i) collection of data was through structured questions; ii) the factor Financial Practices (FP) was identified with a very low regression weight; and iii) as the study was conducted on Indian manufacturing firms, its findings cannot be generalized beyond this context. The future scope of the paper will be as follows: i) quantitative data through questionnaires may be heterogeneous for further studies; and qualitative data collected through structured and semi-structured interviews could be used; ii) the sample size of data could be increased with different geographical locations, and data samples in other developing economies could also be used; and iii) hybrid SEM-ANN could be incorporated to handle the non-linear relationships and improve the predictive accuracy. Further studies could be conducted to understand the mediating role of BDA for project performance and supply chain-4.0. Furthermore, whether digitalisation through Industry 4.0 improves SC performance can be investigated. In addition, the role of artificial intelligence, the circular economy, and BDA could be explored to minimize risk in the supply chain.

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Annexure-I: Questionnaire

Instructions: All the questions are rated on a 1–5 scale. A value of 5 indicates a high degree of agreement (strongly agree), 4 represents agreement with the statement (agree), 3 represents neutrality, 2 represents a degree of disagreement (disagree), and 1 indicates a very high degree of disagreement (strongly disagree).

Note: Please Mark √ on your choice.

Here the indicators are “Strongly Disagree” = 1; “Disagree” = 2; “Neutral” = 3; “Agree” = 4; “Strongly Agree” = 5.								
Sr. No.	**Variable**	**Item**	**Description**	**Scale**				
				1	**2**	**3**	**4**	**5**
1	**Organisational Practices (OP)**	OP1	Our top management is committed towards LARG practices and BDA.					
		OP2	Training and education is must for BDA.					
		OP3	Organization has well-defined vision and strategy policy					
		OP4	Our employees actively participate in policy making.					
		OP5	Company leadership is aware of importance of deciding roles of individual.					

		OP6	Our lower and middle level management to support new ideas.					
		OP7	Organization leadership is aware of importance of deciding roles of individual.					
2	**Lean Management Practices (LMP)**	LMP1	Organization adopts lean practices effectively.					
		LMP2	Organization follows principle to minimise seven wastes					
		LMP3	With lean, organization can develop value-added SC					
		LMP4	Organization has successfully implemented JIT and pull system					
		LMP5	Due to lean practices, there is reduction in lead time					
		LMP6	Cellular manufacturing/ Group Technology minimizes material movement.					
		LMP7	Our organization is compatible for mass customisation.					
		LMP8	Lean practices help in standardization in work and operation.					
3	**Supply Chain Management Practices (SCMP)**	SCMP1	We involve our supplier in decision making about issues of LARG practices and BDA.					
		SCMP2	LARG practices improve SC competitiveness.					
		SCMP3	With BDA and LARG practices builds resilient SC.					
		SCMP4	Our supplier is green partner of organization and has ISO certification.					
		SCMP5	LARG practice mitigates SC risk.					
		SCMP6	Organization has policy for vendor selection.					
		SCMP7	LARG practices and BDA helps in supplier collaboration and integration.					
4	**Social Practices in Supply Chain (SPSC)**	SPSC1	Our stakeholders are aware of LARG practices.					
		SPSC2	Involvement of NGOs and Local Bodies is must for adoption of LARG and BDA.					
		SPSC3	Regulatory norms helped our company to promote LARG practices.					
		SPSC4	Our state and central government support adoption of LARG practices.					
5	**Environmental Practices (ENP)**	ENP1	Organization must balance environmental and social benefits.					
		ENP2	BDA improves recycling efficiency.					
		ENP3	LARG practice minimizes environmental cost.					
		ENP4	Eco packaging is easy with assistance of BDA.					
		ENP5	BDA can assist in reduction of carbon footprints.					
		ENP6	LARG practices helps organization in standardization.					
6	**Financial Practices (FP)**	FP1	Organization is ready to invest initial capital.					
		FP2	Organization is ready to allot funds for training.					
		FP3	With adoption of BDA, organization has competitive edge over competitors.					
		FP4	Cost of technological advancement must be calculated.					
		FP5	Change over cost/time is major concern for top management.					
		FP6	Return onInvestment (ROI) must be calculated carefully.					
7	**Total Quality Management (TQM)**	TQM1	Our organization follows practices of total quality management.					
		TQM2	Human Resource (HR) policies plays critical role in organization.					
		TQM3	TQM practices improves overall operational performance.					
		TQM4	Organization considers customer feedback for eco-design.					

		TQM5	Our supplier management helps in information sharing.					
8	**Big Data Analytics (BDA)**	BDA1	Organization is capable of parallel computing to address voluminous data.					
		BDA2	Real-time assess of data and information has helped organization in better decision making.					
		BDA3	System is capable to handle semi-structured and unstructured data.					
		BDA4	Truthfulness and accuracy of data has helped organization.					
		BDA5	Data driven intelligence has made decision making more effective.					
		BDA6	Organization has good infrastructure and facilities.					
		BDA7	Interchange ability of services (cloud, mobile, and analytics) plays key role.					
		BDA8	Analytics personnel are proficient with programming, data management, new tools etc.					
9	**Sustainable Supply Chain Business Performance (SSBP)**	SSBP1	BDA can reduce environment, supply chain, and responsiveness cost.					
		SSBP2	BDA improves customer satisfaction.					
		SSBP3	BDA can help in saving the time.					
		SSBP4	BDA improves organization service level.					
		SSBP5	With BDA, responsiveness of organization has improved.					
		SSBP6	BDA improves organization agility.					
		SSBP7	BDA help in customer and supplier collaboration.					
		SSBP8	BDA improves overall firm performance.					

Annexure-II: Rotated Component Matrix

	Component								
	1	2	3	4	5	6	7	8	9
SSBP1	.931								
SSBP8	.921								
SSBP3	.912								
SSBP7	.900								
SSBP2	.882								
SSBP6	.867								
SSBP4	.862								
SSBP5	.792								
BDA4		.915							
BDA3		.884							
BDA8		.861							
BDA1		.860							
BDA6		.855							
BDA7		.852							
BDA5		.842							
BDA2		.834							
LMP3			.868						
LMP6			.844						
LMP2			.831						
LMP8			.823						
LMP4			.806						
LMP5			.786						

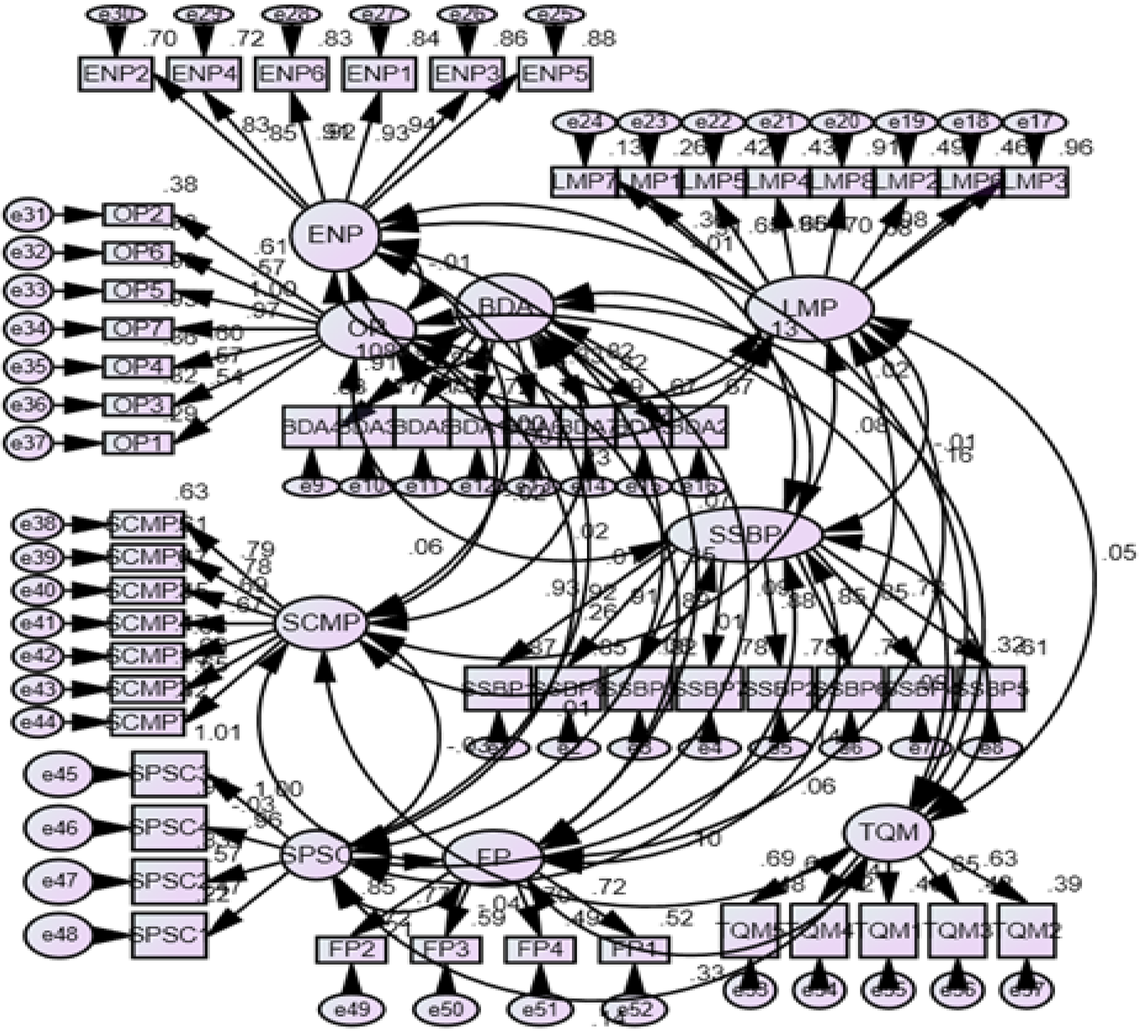
LMP1			.668						
LMP7			.503						
ENP5				.941					
ENP3				.931					
ENP1				.931					
ENP6				.923					
ENP4				.878					
ENP2				.869					
OP2					.839				
OP6					.826				
OP5					.821				
OP7					.803				
OP4					.770				
OP3					.718				
OP1					.567				
SCMP5						.805			
SCMP6						.796			
SCMP3						.756			
SCMP4						.745			
SCMP1						.736			
SCMP2						.731			
SCMP7						.699			
SPSC3							.918		
SPSC4							.900		
SPSC2							.729		
SPSC1							.659		
FP2								.837	
FP3								.813	
FP4								.738	
FP1								.713	
TQM5									.743
TQM4									.731
TQM1									.719
TQM3									.695
TQM2									.639
Extraction Method: Principal Component Analysis. Rotation Method: Varimax with Kaiser Normalization.									
a. Rotation converged in 6 iterations.									

Annexure-III: Estimates for CFA Model

Item		Construct	Standardized Estimate	Unstandardized Estimate	Standard Error (S.E.)	Critical Ratio (C.R.)
SSBP1	<---	SSBP	.931	1.000		
SSBP8	<---	SSBP	.919	1.011	.035	28.895
SSBP3	<---	SSBP	.907	1.004	.036	27.643
SSBP7	<---	SSBP	.885	.959	.037	25.650
SSBP2	<---	SSBP	.881	.977	.039	25.319
SSBP6	<---	SSBP	.853	.954	.041	23.200
SSBP4	<---	SSBP	.852	.956	.041	23.138
SSBP5	<---	SSBP	.779	.866	.046	18.833
BDA4	<---	BDA	.912	1.000		
BDA3	<---	BDA	.879	.972	.041	23.607
BDA8	<---	BDA	.839	.925	.044	21.123
BDA1	<---	BDA	.849	.957	.044	21.698
BDA6	<---	BDA	.843	.936	.044	21.344
BDA7	<---	BDA	.833	.922	.044	20.833
BDA5	<---	BDA	.819	.932	.046	20.065
BDA2	<---	BDA	.818	.933	.047	20.014
LMP3	<---	LMP	.978	1.000		
LMP6	<---	LMP	.675	.699	.046	15.137
LMP2	<---	LMP	.702	.739	.045	16.249
LMP8	<---	LMP	.954	.755	.019	40.582
LMP4	<---	LMP	.655	.709	.049	14.379
LMP5	<---	LMP	.646	.701	.050	14.037
LMP1	<---	LMP	.511	.595	.060	9.983
LMP7	<---	LMP	.362	.477	.073	6.563
ENP5	<---	ENP	.938	1.000		
ENP3	<---	ENP	.928	.991	.033	30.501
ENP1	<---	ENP	.917	.979	.033	29.285
ENP6	<---	ENP	.914	.973	.034	28.853
ENP4	<---	ENP	.850	1.079	.046	23.270
ENP2	<---	ENP	.834	.935	.042	22.172
OP2	<---	OP	.614	1.000		
OP6	<---	OP	.574	.960	.107	8.933
OP5	<---	OP	.995	1.672	.126	13.220
OP7	<---	OP	.966	1.386	.106	13.061
OP4	<---	OP	.600	1.037	.112	9.253

Item		Construct	Standardized Estimate	Unstandardized Estimate	Standard Error (S.E.)	Critical Ratio (C.R.)
OP3	<---	OP	.567	.933	.106	8.840
OP1	<---	OP	.537	.796	.094	8.438
SCMP5	<---	SCMP	.792	1.000		
SCMP6	<---	SCMP	.782	1.015	.073	13.907
SCMP3	<---	SCMP	.689	.920	.077	12.018
SCMP4	<---	SCMP	.672	.807	.069	11.683
SCMP1	<---	SCMP	.682	.942	.079	11.882
SCMP2	<---	SCMP	.657	.888	.078	11.377
SCMP7	<---	SCMP	.651	.755	.067	11.259
SPSC3	<---	SPSC	1.003	1.000		
SPSC4	<---	SPSC	.963	1.071	.024	44.458
SPSC2	<---	SPSC	.574	.562	.047	11.863
SPSC1	<---	SPSC	.471	.469	.051	9.101
FP2	<---	FP	.850	1.000		
FP3	<---	FP	.770	.804	.058	13.911
FP4	<---	FP	.698	.804	.065	12.449
FP1	<---	FP	.720	.842	.065	12.897
TQM5	<---	TQM	.691	1.000		
TQM4	<---	TQM	.650	1.149	.125	9.158
TQM1	<---	TQM	.636	1.070	.119	9.003
TQM3	<---	TQM	.649	1.071	.117	9.146
TQM2	<---	TQM	.627	1.060	.119	8.898

Annexure-IV: CFA Path Diagram



Annexure-V: Estimates for the structural model

Item		Construct	Standardized Estimate	Unstandardized Estimate	Standard Error (S.E.)	Critical Ratio (C.R.)	P-Value
BDA	<---	ENP	.097	.080	.049	1.636	.102
BDA	<---	LMP	.083	.080	.057	1.399	.162
BDA	<---	OP	.096	.165	.101	1.636	.102
BDA	<---	SCMP	.031	.044	.089	.493	.622
BDA	<---	SPSC	.028	.023	.048	.480	.631
BDA	<---	FP	.006	.006	.063	.095	.924
BDA	<---	TQM	.141	.218	.102	2.132	.033
SSBP	<---	BDA	.129	.138	.065	2.144	.032
SSBP1	<---	SSBP	.931	1.000			
SSBP8	<---	SSBP	.919	1.011	.035	28.935	***
SSBP3	<---	SSBP	.907	1.004	.036	27.686	***
SSBP7	<---	SSBP	.886	.959	.037	25.713	***
SSBP2	<---	SSBP	.881	.976	.039	25.289	***
SSBP6	<---	SSBP	.853	.954	.041	23.187	***
SSBP4	<---	SSBP	.852	.955	.041	23.119	***
SSBP5	<---	SSBP	.778	.865	.046	18.801	***
BDA4	<---	BDA	.912	1.000			
BDA3	<---	BDA	.878	.972	.041	23.485	***
BDA8	<---	BDA	.837	.925	.044	21.002	***
BDA1	<---	BDA	.847	.957	.044	21.574	***
BDA6	<---	BDA	.841	.936	.044	21.230	***
BDA7	<---	BDA	.832	.922	.044	20.727	***
BDA5	<---	BDA	.818	.932	.047	19.957	***
BDA2	<---	BDA	.817	.934	.047	19.907	***
LMP3	<---	LMP	.979	1.000			
LMP6	<---	LMP	.673	.696	.046	15.063	***
LMP2	<---	LMP	.700	.735	.045	16.175	***
LMP8	<---	LMP	.954	.754	.018	40.921	***
LMP4	<---	LMP	.653	.705	.049	14.304	***
LMP5	<---	LMP	.643	.698	.050	13.974	***
LMP1	<---	LMP	.509	.593	.060	9.947	***
LMP7	<---	LMP	.362	.476	.073	6.562	***
ENP5	<---	ENP	.938	1.000			
ENP3	<---	ENP	.928	.991	.033	30.496	***
ENP1	<---	ENP	.917	.979	.033	29.289	***

Item		Construct	Standardized Estimate	Unstandardized Estimate	Standard Error (S.E.)	Critical Ratio (C.R.)	P-Value
ENP6	<---	ENP	.914	.974	.034	28.865	***
ENP4	<---	ENP	.850	1.079	.046	23.269	***
ENP2	<---	ENP	.834	.935	.042	22.164	***
OP2	<---	OP	.615	1.000			
OP6	<---	OP	.575	.961	.107	8.946	***
OP5	<---	OP	.994	1.669	.126	13.220	***
OP7	<---	OP	.967	1.386	.106	13.077	***
OP4	<---	OP	.601	1.038	.112	9.266	***
OP3	<---	OP	.568	.933	.105	8.844	***
OP1	<---	OP	.536	.794	.094	8.426	***
SCMP5	<---	SCMP	.791	1.000			
SCMP6	<---	SCMP	.782	1.015	.073	13.884	***
SCMP3	<---	SCMP	.690	.921	.077	12.023	***
SCMP4	<---	SCMP	.673	.808	.069	11.688	***
SCMP1	<---	SCMP	.683	.944	.079	11.888	***
SCMP2	<---	SCMP	.657	.889	.078	11.374	***
SCMP7	<---	SCMP	.650	.755	.067	11.235	***
SPSC3	<---	SPSC	1.008	1.000			
SPSC4	<---	SPSC	.959	1.061	.025	42.464	***
SPSC2	<---	SPSC	.572	.557	.047	11.755	***
SPSC1	<---	SPSC	.466	.462	.051	8.996	***
FP2	<---	FP	.862	1.000			
FP3	<---	FP	.772	.795	.057	13.840	***
FP4	<---	FP	.686	.779	.064	12.153	***
FP1	<---	FP	.712	.821	.065	12.691	***
TQM5	<---	TQM	.708	1.000			
TQM4	<---	TQM	.658	1.135	.123	9.246	***
TQM1	<---	TQM	.648	1.063	.116	9.137	***
TQM3	<---	TQM	.635	1.022	.114	8.994	***
TQM2	<---	TQM	.600	.991	.115	8.594	***

*** significant at $p<0.001$

Annexure -VI: Descriptive Analysis

	AVE	Composite Reliability	R Square	Cronbachs Alpha	Communality	Redundancy
BDA	0.7556	0.9611	0.083	0.9537	0.7556	0.0092
ENP	0.8337	0.9678	0	0.961	0.8337	0
FP	0.7488	0.8795	0	0.8429	0.6488	0
LMP	0.7971	0.9192	0	0.9056	0.5971	0
OP	0.7473	0.8914	0	0.9046	0.5473	0
SCMP	0.7585	0.6618	0	0.8732	0.2585	0
SPSC	0.7854	0.8949	0	0.8497	0.6854	0
SSBP	0.7952	0.9688	0.018	0.9634	0.7952	0.0132
TQM	0.7358	0.8521	0	0.7852	0.5358	0

Annexure-VII: Regression weights, direct and indirect effect

Regression Weights: (Group number 1 - Default model)

			Estimate	S.E.	C.R.	P	Label
BDA	<---	TQM	.143	.073	1.979	.048	
BDA	<---	LMP	.103	.066	1.560	.119	
BDA	<---	SPSC	.049	.055	.888	.374	
BDA	<---	SCMP	.030	.082	.372	.710	
BDA	<---	ENP	.079	.045	1.742	.082	
BDA	<---	OP	.021	.074	.281	.779	
BDA	<---	FP	.024	.060	.394	.693	
SSBP	<---	BDA	.101	.061	1.673	.094	
SSBP	<---	TQM	.392	.076	5.140	***	
SSBP	<---	LMP	-.093	.069	-1.354	.176	
SSBP	<---	SPSC	.129	.057	2.258	.024	
SSBP	<---	SCMP	.016	.085	.188	.851	
SSBP	<---	ENP	-.015	.047	-.321	.748	
SSBP	<---	OP	-.002	.077	-.026	.979	
SSBP	<---	FP	-.066	.063	-1.050	.294	

Direct Effects - Two Tailed Significance (BC) (Group number 1 - Default model)

	FP	OP	ENP	SCMP	SPSC	LMP	TQM	BDA
BDA	.759	.821	.064	.757	.431	.150	.106	...
SSBP	.408	.981	.700	.830	.064	.153	.001	.081

Direct Effects (Group number 1 - Default model)

	FP	OP	ENP	SCMP	SPSC	LMP	TQM	BDA
BDA	.024	.021	.079	.030	.049	.103	.143	.000
SSBP	-.066	-.002	-.015	.016	.129	-.093	.392	.101

Indirect Effects - Two Tailed Significance (BC) (Group number 1 - Default model)

	FP	OP	ENP	SCMP	SPSC	LMP	TQM	BDA
BDA	...	...	...	...	...	...	...	...
SSBP	.572	.645	.071	.578	.258	.113	.074	...

Indirect Effects (Group number 1 - Default model)

	FP	OP	ENP	SCMP	SPSC	LMP	TQM	BDA
BDA	.000	.000	.000	.000	.000	.000	.000	.000
SSBP	.002	.002	.008	.003	.005	.010	.015	.000