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The role of big data for Supply Chain 4.0 in manufacturing organisations of developing countries

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The role of big data for Supply Chain 4.0 in manufacturing organisations of developing countries

Purpose – Big data is relevant to the supply chain as it provides analytics tools for decision-making and business intelligence. Supply Chain 4.0 and big data are necessary for organisations to handle volatile, dynamic, and global value networks. This paper investigates the mediating role of 'big data analytics' between Supply Chain 4.0 business performance and nine performance factors.

Design/methodology/approach –A two-stage hybrid model of statistical analysis and artificial neural network analysis is used for analysing the data. Data gathered from 321 responses from 40 Indian manufacturing organisations are collected for the analysis.

Findings – Statistical analysis results show that performance factors of organisational and top management, sustainable procurement and sourcing, environmental, information and product delivery, operational, technical and knowledge, and collaborative planning have a significant effect on big data adoption. Furthermore, the results were given to the artificial neural network model as input and results show 'information and product delivery' and 'sustainable procurement and sourcing' as the two most vital predictors of big data adoption.

Research limitations/implications – The study confirms the mediating role of big data for Supply Chain 4.0 in manufacturing organisations of developing countries. This study guides to formulate management policies and organisation vision about big data analytics.

Originality/value – For the first time, the impact of big data on Supply Chain 4.0 is discussed in the context of Indian manufacturing organisations. The proposed hybrid model intends to evaluate the mediating role of big data analytics to enhance Supply Chain 4.0 business performance.

Keywords – Big Data Analytics; Digital supply chain; Supply Chain 4.0; Business Performance; Artificial neural network; Structural equation modelling.

Paper type – Research paper

1. Introduction

Big data and predictive analysis were termed as one of the emerging "game changers" for supply chain (SC) design modulation (Fawcett and Waller, 2014). Big data analytics (BDA) aspects in

SC operations is a much discussed topic in the existing literature (Inamdar et al., 2020). The term "SC data science" was used for the application of qualitative and quantitative methods to SC theory to solve SC problems and prediction of outcomes (Waller and Fawcett, 2013). However, with business processes now becoming more data-dependent, BDA provides data-derived insights for operative decision-making (Ramanathan et al., 2017). BDA in SC results in improving the process-level performance (Brinch, 2018), firm-level performance (Dubey et al., 2019a), visibility (Kache and Seuring, 2017), competitiveness (Sanders, 2016), and return management (Roßmann et al., 2018). With BDA capabilities, organisations can handle market turbulence (Gunasekaran et al., 2018) and thus have a competitive edge over competitors (Dubey et al., 2021). Supply Chain 4.0 or Smart SC is an initiative of using Industry-4.0/Smart manufacturing in SC operations (Frazzon et al., 2019). Characteristics of Supply Chain 4.0 includes an interconnectedness between SC and technology, namely via smart objects instrumented with sensors and RFID, intelligent systems, integrated SC activities, automated activities, and innovation (Wu et al., 2016). Supply Chain 4.0 offers virtualisation, interoperability, service orientation, decentralisation, and modularity (Dossou, 2018). Furthermore, the recent outbreak of COVID-19 has impacted many economic activities such as manufacturing, healthcare sports, tourism, supply chain and logistics (Ivanov, 2020a). This disruption could be felt in almost all sectors and significant mismatch has been observed between demand and supply. Under such circumstances, big data is set to play a crucial role and the appropriate application of data analytics can help bring supply chain operations into a new normalcy. With change of consumption pattern in COVID-19 crises, BDA could be used for demand forecasting (Ivanov, 2020b) and supply chain planning (Chang, 2020). BDA has the ability to identify disruption and other supply chain issues and this information could be used for better decision-making and management of various supply chain activities. Thus, the appropriate application of BDA capabilities may help in building a resilient supply chain (Singh and Singh, 2020). Even though BDA is one of the supporting technologies, along with the Internet of Things (IoT) and cloud computing, for Supply Chain 4.0, its role is crucial for business performance (Hazen et al., 2018). However, the negative impacts of BDA include the inadequacy of IT infrastructure, coordination issues between partners, complexity, and cyber-risks (Makris et al., 2019; Kache, 2015). Luthra and Mangla (2018) categorised Supply Chain 4.0 challenges into four categories: technological, strategic, ethical and legal, and organisational. The study conducted by Moktadir et al. (2019), for leather manufacturers in Bangladesh, identified technical infrastructure and reconfiguration complexity as significant challenges of Supply Chain 4.0. BDA capabilities can transform the Supply Chain 4.0 initiative in developing economies provided these challenges are addressed. Many companies require managing multiple SC, partnering with multinationals, customers, and suppliers in various tiers (Min et al., 2019). Consequently, these companies have increased pressure for BDA to manage the SC (Sander, 2016).

Industrialised countries such as China, Denmark, USA, and Germany have started using BDA in SC management (Brinch et al., 2018; Kache and Seuring, 2017, Lai et al., 2018) and the application of Supply Chain 4.0 (Ivanov et al., 2019; Makris et al., 2019). The current literature shows a positive impact of BDA on SC agility (Dubey et al., 2019a), SC resilience (Dubey et al., 2019b), SC sustainability (Cheng et al., 2018), and SC innovation (Queiroz and Telles, 2018). However, BDA for SC and Supply Chain 4.0 are discussed separately, and the contributions of BDA for Supply Chain 4.0 business performance are rarely discussed. This study attempts to bridge this research gaps in the context of developing countries. The research questions (RQs) addressed by the study are as follows:

RQ1: What are the significant factors for BDA in SC and Supply Chain 4.0?

RQ2: How do these factors impact the initiative of Supply Chain 4.0 for developing economies?

RQ3: Does BDA play the role of mediator to improve Supply Chain 4.0 performance?

To address the above RQs, the literature on 'Supply Chain 4.0 ', 'big data analytics,' 'Industry-4.0, and supply chain' was reviewed. Based on the literature survey and experts' opinions, factors, and sub-factors are explored. This study employs a two-step hybrid structural equation modelling (SEM) and artificial neural network (ANN) approach to determine the influence of BDA on business performance. The SEM approach is compensatory and used to verify the linear relationship (Shah and Goldstein, 2006). ANN is non-compensatory and used to verify the linear as well as non-linear relationships. Thus, ANN balances limitations of SEM (Shmueli and Koppius, 2011) and is more progressive compared to multiple linear regression approaches (Chong, 2013).

The research objectives (ROs) of the study are:

RO1: To identify the critical enablers of BDA adoption in Supply Chain 4.0.

RO2: To evaluate observable and unobservable BDA constructs and rank the most significant factors using ANN.

RO3: To determine the effect of these factors to improve SC business performance

The manuscript is structured in sections as follows. Section 2 is the theoretical background of the study. Section 3 elaborates on the proposed hypothesis and framework, followed by research methodology in Section 4. The analysis and discussion of the findings are presented in Section 5. Section 6 consists of the conclusion and future outlook of the study.

2. Theoretical background

In literature, authors have employed various models and theories to understand the adoption of technology advancement. These include "technology acceptance model (TAM), unified theory of acceptance and use of technology (UTAUT), theory of planned behaviour (TPB), technology readiness index (TRI), organisation information processing theory (OIPT), stakeholder theory and contingency theory" etc. In this paper, we utilise OIPT to study the relevant literature of BDA in the supply chain domain. OIPT was developed by Galbraith (1974) which constitutes three basic elements: requirement of processing, capability of processing and the match between these two elements (Tushman & Nadler, 1978; Zhu et al., 2018). OIPT supports the organisation in better decision making while minimising uncertainty by preparing strategies for processing information based on the organisation's technological capabilities (Galbraith, 1974; Tushman & Nadler, 1978). In simple terms, an organisation needs large amounts of data to support various processes in decision-making but have limited processing capability (Zhu et al., 2018). BDA can solve this issue and can be a viable option even within the context of the COVID-19 crises. In this way, uncertainty in supply chain can also be mitigated through proper application of BDA at the organisational level. Therefore, OIPT motivate to use information technology such as BDA to develop insights to fulfil the requirement of data for supply chain 4.0. To clarify, we first explain Industry-4.0 and Supply Chain 4.0, followed by the application of BDA in the SC. Lastly, we illustrate the relationship between BDA and Supply Chain 4.0.

2.1 Industry-4.0 and Supply Chain 4.0

Industry-4.0 is defined as the fourth industrial revolution. Industry-4.0 is mostly technology driven and has Cyber-Physical Systems (CPS) as its core constituents. A CPS integrates network and physical processes as control and monitoring mechanisms (Lee et al., 2015). Industry-4.0 transforms technologies into digitalisation, automation, etc. (Lasi et al., 2014) The various techniques of Industry-4.0 are Internet of Things (IoT), Cloud Computing, Augmented Reality, Additive Manufacturing, Robotics, Cybersecurity, BDA, Simulation, and Horizontal and Vertical Integration (Frank et al., 2019). According to Lu (2017), Industry-4.0 is popularly used to make innovative tools and machines, real-time assets tracking, and machine maintenance within the aerospace industry, health care industry, furniture manufacturing industry, and the agriculture industry, to name a few. Industry-4.0 is used in the SC to make its processes more efficient and also helps to increase its productivity (Raut et al., 2020). This supply chain is commonly referred to as Supply Chain 4.0.

Supply Chain 4.0 is beneficial to all stakeholders of the SC, including the supplier, manufacturer, distributor, and customer. This technology advancement offers the following benefits to stakeholders: *i) Supplier* - supplier and capacity flexibility (Oh and Jeong, 2019), supplier selection (Frank et al., 2019), supplier collaboration (Manavalan and Jayakrishna, 2018), controlling lead time (Oh and Jeong, 2019), and market dynamics (Ardito et al., 2019). *ii) Manufacturer* - transparency (Lin et al., 2016), flexibility (Pfohl et al., 2017), innovation (Lin et al., 2016), digitalisation and automation (Ivanov et al., 2019), and lean production (Lin et al., 2016). *iii) Distributor* – reduced delivery time (Pfohl et al., 2017), logistics flexibility (Oh and Jeong, 2019), and lean practices (Lin et al., 2016). *iv) Customer* - Accessibility of product (Frazzon et al., 2019), increase in interaction (Oh and Jeong, 2019), customisation (Oh and Jeong, 2019), and channel flexibility (Oh and Jeong, 2019). Makris et al. (2019) conducted an explorative study on adoption to Supply Chain 4.0 and found that adoption will influence employees, working hours, and flexibility. However, the adoption of Supply Chain 4.0 still faces specific challenges. Moktadir et al. (2019) and Luthra and Mangla (2018) identified challenges in the emerging and developing economies showing that all types of economies are considering the adoption of Supply Chain 4.0. Some industrialised countries such as Germany, France, UK, or the USA have adopted Supply chain 4.0. Moreover, developing economies such as India, Iran, and Brazil, and emerging economies such as Bangladesh are also catching up to this technological advancement.

2.2 BDA and Supply Chain

BDA is one of the forces, which may form future SC (Fawcett and Waller, 2014). Nguyen et al. (2018) argued that BDA capabilities could be useful for demand management, logistics, procurement, and manufacturing functions of SC. In addition, to leverage the fusion of big data in SC analytics, Woldt et al. (2020) found that there exist several job opportunities in this domain. They mapped the course structure incorporating big data and SC analytics based on industry data and a literature review which resulted in 116 types of SC analytics job. Another significant use of big data research is in information systems (Grover et al., 2020). In addition, non-routine cognitive works could be made computerisable with the help of big data (Frey and Osborne, 2017). Jarrahi (2018) suggested that artificial intelligence (AI) coupled with BDA is well suited to handle complex decision making. A general literature on BDA can be found in the work of Larson and Chang (2016). Roberts and Hazen (2016) emphasised the redesign of SC by integrating dimensions of process, people, and technology of big data. In a theory-driven study, Hazen et al. (2018) analysed theories for BDA-based sustainable SC. The eight theories analysed were social capital, economic, network, institutional, resource-based, resource dependence, ecological modernisation, and agency. Fundamental tenets of these theories were analysed along with future research directions for big data in SC with aspects of the triple bottom line. Arunachalam et al. (2018) proposed a framework for SC with BDA capabilities regarding data generation, visualisation, analytics, management, and integration. The four stages that were considered were initiation, adoption stage with poor data and rich analytics, adoption stage with rich data and poor analytics, and the routinisation stage. Rodriguez and Da Cunha (2018), Sanders (2016), and Brinch (2018) proposed conceptual frameworks of BDA for SC. The proposed framework by Rodriguez and Da Cunha (2018) was intended to gather the key categories: absorptive capacity, sustainability performances, and SC innovation, for the firm. The ability that BDA has to support sustainability and organisations can obtain a competitive advantage by responding to customer needs in a dynamic market. Sanders (2016) proposed a four-stage maturity map focusing on data structuring, data availability, fundamental analytics, and advanced analytics. Big data drives leading SC organisations, however, the majority of organisations have yet to implement it because of the lack of understanding by top management. In addition, there exist several roadblocks in ethical, operational, privacy and security aspects for BDA applications in SC (Ogbuke et al., 2020). Brinch (2018) proposed a framework based on value theory and business process theory: SC practitioners must understand the value of BD and need to conceptualise strategies for its implementation. Furthermore, Grover et al. (2018) proposed a research framework for using BDA to create strategic business value. The framework illustrated various constructs and their relationship to value creation of BDA and its implementation. The framework also discussed research components for future BDA research problems.

The factor analysis method is most prevalent in BDA adoption for SC. Whereas other quantitative operation research methods, like neutrosophic set theory, are significantly utilised in the SC domain (Abdel-Baset et al., 2019). Some of the essential recent studies used partial least squares - structural equation modelling (PLS-SEM) (Shafique et al., 2019; Dubey et al., 2019a; Dubey et al., 2021; Lai et al., 2018; Jeble et al. 2018) and SEM (Raman et al., 2018). Wu et al. (2017) used multi-criteria decision-making tools, such as grey DEMATEL and fuzzy-DEMATEL, whereas Lamba and Singh (2018) employed hybrid ISM, Fuzzy-TISM, and the DEMATEL technique. Lamba and Singh (2018) identified the most critical enablers to implement BDA in operations and SC. Roßmann et al. (2018) used fuzzy clustering, whereas Queiroz and Telles (2018) used regression analysis. Roßmann et al. (2018) analysed the social impact of BDA in SC using the Delphi approach. The study showed the positive effect of BDA on the reduction of safety stocks, supplier performance and demand forecasts. Queiroz and Telles (2018) identified a positive relationship between BDA knowledge and SC levels.

2.3 BDA for Supply Chain 4.0

The role of BDA for Supply Chain 4.0 is not explored much in the literature. Enabling technologies for Supply Chain 4.0 are cloud computing, IoT, blockchain, digital twin, cybersecurity, and big data. Calatayud et al. (2019) suggested a concept of self-thinking SC with AI and IoT capabilities. According to de Campos Martins and Simon (2018), more than 80 % of research articles on BDA and Supply Chain 4.0 discuss technical challenges. However, social-cultural challenges such as fear of change, man-technology relation, and a human-resource replacement must also be addressed. Yadav et al. (2020) have pointed out ineffective workers' training, lack of workers employed, and culture change resistance as significant social-cultural challenges.

Zhong et al. (2015) proposed the conversion of typical supply chain resources into smart objects. A framework of BDA for RFID SC data was proposed with transmission mechanism, data warehouse, data clustering and knowledge representation. Ben-Daya et al. (2019) argued that IoT with limited analytical capabilities could have a positive impact on manufacturing SC. Haddud et al. (2017) identified potential challenges for IoT adoption in SC. The top five challenges identified were the integration of heterogeneous data and technologies, global standards in the communication protocol, security issues, top management support, and IoT architecture.

Santos et al. (2017) proposed BD architecture for the implementation of Industry-4.0 in a multinational organisation. Case implementation was done for ‘Bosch Braga’ in three-phases:

data collection, data preparation, and visualisation. O'Donovan et al. (2015) emphasised the role of BDA for highly-optimised SC of smart manufacturing. BDA can assist in demand-driven SC from raw material to delivery to end customers, however, it needs a multi-disciplinary team for managing end-to-end SC. In addition, BDA also aids in better forecasting and business planning which further improves the business performance of the organisation (Chang, 2020). Babiceanu and Seker (2016) emphasised the visibility of operations across manufacturing SC and proposed guidelines for the SC collaboration of manufacturing CPS. Arya et al. (2017) conducted an exploratory study for army spare parts, and the impact of Supply Chain 4.0 on planning, maintenance, distribution, and collaboration was discussed. The following conclusions and research gaps are identified:

i) The synthesis of the literature review shows that developed countries such as China, Denmark, USA, and Germany have started using BDA for SC (Brinch et al., 2018; Kache and Seuring, 2017, Lai et al., 2018) and application of Supply Chain 4.0 (Ivanov et al., 2019; Makris et al., 2019). Developing countries are catching up, and research studies show that issues in BDA for Supply Chain 4.0 are different in these economies.

ii) The existing literature mainly focused on BDA for SC and Supply Chain 4.0. Though, these topics were discussed separately and very few articles discussed BDA for Supply Chain 4.0. In a recent study for firms in India, Raut et al. (2019) explored the mediating role of BDA to achieve business performance. However, this study did not investigate the Supply Chain 4.0 aspect.

iii) The current literature shows a positive impact of BDA on SC agility (Dubey et al., 2019a), SC resilience (Dubey et al., 2019b), SC sustainability (Cheng et al., 2018), and SC innovation (Queiroz and Telles, 2018). However, contributions of BDA for Supply Chain 4.0 business performance are rarely discussed.

The abovementioned research gaps suggest to investigate the capabilities of BDA to fulfil the data requirement of Supply Chain 4.0 processes in order to improve business performance. Hence, in this work, we investigate the mediating role of BDA between Supply Chain 4.0 business performance and nine performance factors using qualitative research method based on survey administration. A hybrid SEM-ANN method is developed to determine the influence of BDA on business performance. The SEM approach is compensatory and used to verify the linear relationship. ANN is non-compensatory and used to verify the linear as well as non-linear relationships. Thus, ANN balances SEM (Shmueli and Koppius, 2011) and is more progressive compared to multiple linear regression approaches (Chong, 2013).

3. Proposed Framework and Hypotheses

Figure 1 shows the proposed framework that considers 11 factors: Organisational and Top Management Support Performance (OTMSP), Information and Product Delivery Performance (IPDP), Sustainable Procurement and Sourcing Performance (SPSP), Collaborative Planning Performance (CPP), Sustainable Manufacturing Performance (SMP), Closed-loop Supply-chain performance (CLSCP), Operational Performance (OP), Technical and Knowledge Capability (TKC), Environmental Performance (EP), Big Data Analytics (BDA), and Supply Chain 4.0 Business Performance (SBP). BDA is a mediator amongst SBP and the other nine factors that are OTMSP, IPDP, SPSP, CPP, SMP, CLSCP, OP, TKC, and EP. A Delphi method was used to finalise the shortlisted factors (Skulmoski et al., 2007). All factors were approved by the Delphi expert panel. Furthermore, the mentioned eleven factors were divided into eighty-two items.

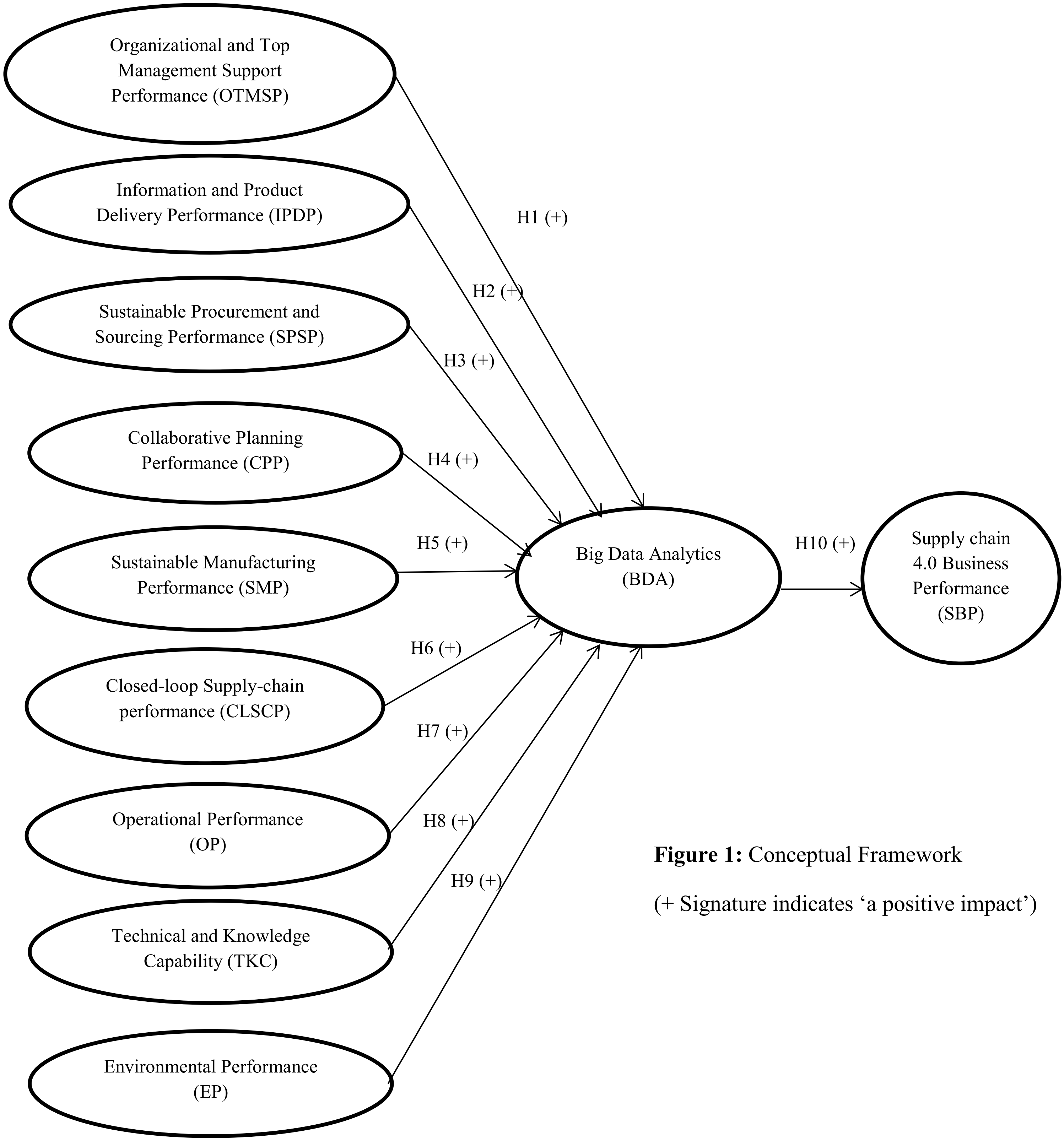

Figure 1: Conceptual Framework

(+ Signature indicates 'a positive impact')

Table 1: Factors and Sub-factors

Hypothesis	Factor	Brief description	Items	References
H1	Organisational and Top Management Support Performance (OTMSP)	BDA needs substantial investment, and support of top management is a must. Being a new technology, an organisation must support employees through training and education. The participation of all employees is a prime necessity and top management needs to eliminate resistance. Dynamic and operational capabilities must be built at all levels of SC.	OTMSP1: Organisation size	Dubey et al. (2019a), Lai et al. (2018), Liboni et al. (2019), Dubey et al. (2021)
			OTMSP2: IT capabilities	
			OTMSP3: Organisation maturity level	
			OTMSP4: Top management support	
			OTMSP5: Training and education	
			OTMSP6: Financial willingness	
			OTMSP7: Dynamics and flexibility	
H2	Information and Product Delivery Performance (IPDP)	Information sharing with SC partners and within an organisation must be complete, timely, and accurate. BDA capabilities ensure the same also sensitive data can be encrypted for data privacy. The availability of quality information plays a significant effect on SC management. BDA ensures proper assessment of product information, which will enhance delivery performance at various stages of the SC.	IPDP1: Inventory management	Parast and Adams (2012), Sanders (2016)
			IPDP2: Data quality	
			IPDP3: Data availability	
			IPDP4: Quality management	
			IPDP5: Consumer feedback	
			IPDP6: Customer satisfaction	
			IPDP7: Timely delivery	
H3	Sustainable Procurement and Sourcing Performance (SPSP)	The focus of sustainable procurement is on environmental sustainability. The cooperation of the supplier is needed for developing environmentally friendly products. BDA encourages sourcing and sustainable procurement using transportation of services and products from supplier to manufacturer to distributor to end customers with the least negative impact on the environment. Certifications like ISO 14001, ISO 9000 can benefit for standardisation of procedures.	SPSP1: Consumer awareness	Zhu and Sarkis, 2004), Cheng et al. (2018), Lai et al. (2018),
			SPSP2: Government policy	
			SPSP3: Investment	
			SPSP4: Regulations	
			SPSP5: Competitor pressure	
			SPSP6: Supplier selection	
			SPSP7: Product eco-labelling	
			SPSP8: Environmental audits	
			SPSP9: Supplier collaboration towards sustainability	
			SPSP10: Customer collaboration	
			SPSP11: Supplier cooperation towards sustainability	
			SPSP12: Supplier performance	
			SPSP13: ISO 14000 certification of supplier	
H4	Collaborative Planning Performance (CPP)	Collaborative performance mainly targets supplier collaboration, logistics integration, and joint development. SC often has inter-dependent and inter-related tasks spread across different organisations. The collaboration on SC actors is needed for problem-solving and decision making. BDA capabilities create diverse and combinative knowledge sets for managing SC operation	CPP1: Cooperation from all stakeholders	Manavalan and Jayakrishna (2018), Narwane et al. (2019)
			CPP2: Cost or delivery variation	
			CPP3: Long term relationship with the supplier	
			CPP4: Strategic visibility	
			CPP5: Minimising non-value costs	
			CPP6: Online system with supplier	
			CPP7: Data-driven decision- making	

			CPP8: Cost performance index CPP9: Logistic visibility CPP10: Product data management	
H5	Sustainable Manufacturin g Performance (SMP)	In order to optimise the processes, manufacturing data needs to be shared with different stakeholders in SC. Many are using lean and agile practices to lead to sustainable performance. BDA capabilities assist in sustainable practices through improved integration with all SC actors. Effective decision making ensures optimal supplier selection, reduction in non-value added processes, and improved performance.	SMP1: Lean practices SMP2: Agile practices SMP3: Total quality management SMP4: Quality of service SMP5: Value-added SC SMP6: Standardisation in operations	Ainul et al. (2017), El Mokadem (2017), Esfahbodi et al. (2017), Ghobakhloo and Azar (2018)
H6	Closed-loop Supply-chain performance (CLSCP)	Organisations should take emphasis on close-loop SC by treating and retrieving the end-of-use product. BDA helps to detect and track the returned product for optimisation of manufacturing, procurement, discarding, or retrieval decisions. Sophisticated business intelligence and analytics capabilities will ensure optimum utilisation of products using recycling.	CLSCP1: Overall cost CLSCP2: Recycling management CLSCP3: Uncertain demand CLSCP4: Waste disposal	Manavalan and Jayakrishna (2018)
H7	Operational Performance (OP)	The operational performance consists of quality, capacity utilisation, and accurately delivers time. The perspective of SC provider, as well as customer, must be considered for better service and quick response to the customer. BDA assists in innovative and radical development in organisations through explorative learning. BDA strategies will help in improving efficiency towards achieving long term goals.	OP1: Delivery OP2: Flexibility OP3: Customer satisfaction OP4: Cost OP5: Innovation	Liu and Lyons et al. (2011), Makris et al. (2019),
H8	Technical and Knowledge Capability (TKC)	Technological capabilities through IoT ensure monitoring of the entire SC network, which will assist in resource management. Real-time information sharing provides better control, emergency management, and coordination. Forecasting and predictive analytics can give risk alter, product failure, and preventive measures. The organisation must focus on skilled personnel with knowledge sets to achieve BDA adoption.	TKC1: Technology complexity TKC2: New market trends TKC3: Perceived benefits TKC4: Knowledge management TKC5: Data quality TKC6: Knowledge scanning TKC7: New market trends	Lai et al. (2018), Frank et al. (2019), Raisch and Krakowski (2020)
H9	Environmenta l Performance (EP)	Environmental performance refers to waste management, eco-design, and energy usage. BDA capabilities can help organisations for better green practices. Three R's, i.e., reduce, reuse, recycle of reconfigurable systems, can be implemented more effectively through BDA. Organisations must ensure energy consumption cost and the penalty for environmental mishaps.	EP1: Carbon emission EP2: Solid wastes EP3: Ecological cost EP4: Regularisation EP5: Green practices EP6: Social benefits EP7: Energy consumption	Cheng et al. (2018), Lai et al. (2018),
H10	Supply Chain 4.0 Business Performance (SBP)	Sustainable business performances are measured in terms of economic performance, societal responsibility, and environmental performance. BDA capabilities enable organisations to achieve environmental performance by monitoring usage and reducing waste. BDA also promotes better public relations and brand image. Through BDA and Supply Chain 4.0, organisations can gain a competitive advantage.	SBP1: Transparency SBP2: Visibility SBP3: Responsiveness SBP4: Efficiency SBP5: Collaboration and integration SBP6: Stakeholder participation	Kache and Seuring (2017), Ghobakhkoo (2018), Lamba and Singh (2018), Frederico et al. (2019)

BDA items considered: BDA1: Velocity BDA2: Variety, BDA3: Veracity, BDA4: Volume, BDA5: Value and market, BDA6: Predictive analytics, BDA7: Service and Infrastructure, BDA8: Modularity and compatibility BDA9: Connectivity and intelligence, BDA10: Planning and control (Raut et al., 2019).

4. Research Methodology

Figure 2 shows the proposed research methodology.

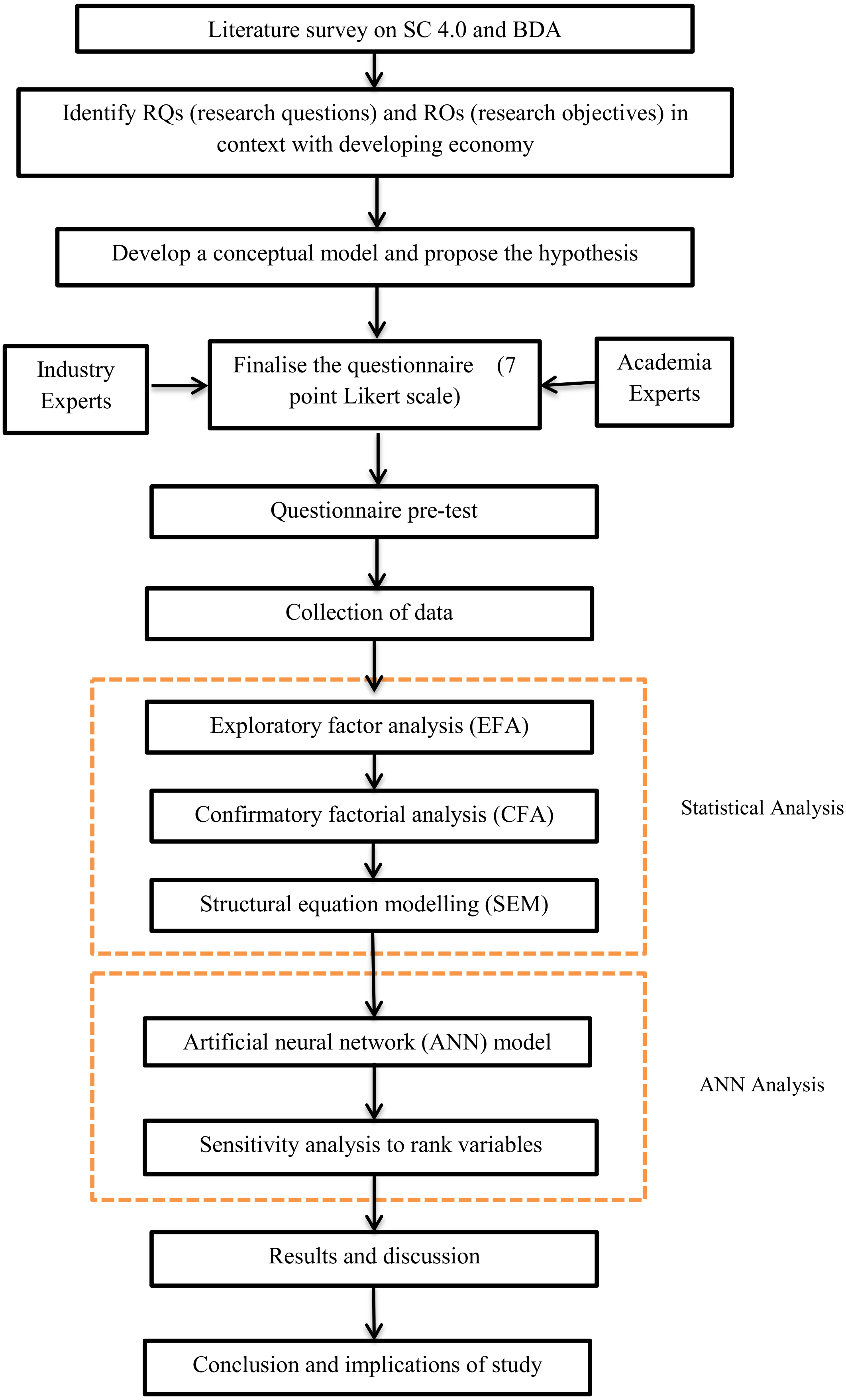

Figure 2: Research Methodology

The study was conducted in three phases. In the first phase, the literature was reviewed using the keywords ‘Supply Chain 4.0’, ‘big data analytics,’ ‘Industry-4.0, and supply chain’. This led to the formation of RQs and ROs in the Indian context. Furthermore, a conceptual framework was developed, and hypotheses were proposed. In the second phase, a questionnaire was developed for the survey based on a 7-point Likert-scale. Thirteen experts were requested to respond to the questionnaire, out of which, ten experts, comprising of four professors and six industry personnel, responded. A pilot study was carried out with 115 responses. Based on experts’ inputs and pilot studies, the final survey was finalised. 40 different types of manufacturing organisations were contacted. The survey was conducted from October 2018 to April 2019 through personal interviews and e-mails. Around 8-10 samples were collected from each Indian manufacturing organisation. The identified samples were collected from managers of different departments such as Supply Chain, HR, Purchasing, R&D, Production, and Accounting. A total of 325 questionnaires were distributed in these organisations. Four questionnaires were not filled in correctly, and thus, 321 responses were used and digitised in a statistical package of social science (SPSS). In the third phase, three stages of EFA-CFA-SEM were used for hypothesis testing and ANN was used to rank the identified factors and verify the SEM results. Thus, this work makes use of statistical analysis (EFA-CFA-SEM) and ANN analysis to analyse the surveyed data. Furthermore, the results obtained from these two analyses were discussed which shows the mediating role of BDA in improving business performance in Supply Chain 4.0.

4.1 Sample Characteristics

Table 2 shows the descriptive statistics of the 321 responses. It shows that the highest number of responses (52.34%) are graduates; and 32.09% have between 11-15 years of experience. The highest number of responses were from the auto component manufacturer (24.61%), and 35.51% fall in the 21-30 million USD annual sales revenue.

4.2 Statistical Analysis

The 321 responses were analysed using EFA-CFA in order to examine validity, reliability, and structure. Microsoft Excel was used to tabulate the data. This data was imported to SPSS 20.0 software for the analysis. Analysis of Moment Structures (AMOS) software was used for SEM analysis.

Table 2: Descriptive statistics of the sample

Particular	Classifications	No. of responses	%
Gender	Male	224	69.78
	Female	97	30.22
	Total	**321**	**100%**
Years of Experience	5-7	46	14.33
	8-10	83	25.86
	11-15	103	32.09
	More than 15	89	27.72
	Total	**321**	**100%**
Educational Qualification	Graduates (B.E./BBA/ B.Tech)	168	52.34
	Post-graduates (M Tech/ MBA)	140	43.61
	PhD (Technology/Management)	13	4.05
	Total	**321**	**100%**
Type of industry	Auto component manufacturer	79	24.61
	CNC Machine Tool	57	17.76
	Turbo sub-assemblies	71	22.12
	Chemical products	54	16.82
	Furniture	60	18.69
	Total	**321**	**100%**
Annual sales revenue (million USD)	10-20	52	16.20
	21-30	114	35.51
	31-40	105	32.71
	More than 40	50	15.58
	Total	**321**	**100%**
Organisation size (No. of employees)	100-150	37	11.53
	151-300	85	26.48
	301-500	122	38.00
	More than 500	77	23.99
	Total	**321**	**100%**

4.2.1 Exploratory factor analysis (EFA)

EFA analysis uses a statistical approach to determine the correlation between the variables (Anderson and Gerbing, 1984). In EFA, firstly, data suitability is checked (Williams et al., 2010). Bartlett's test of sphericity and KMO (Kaiser-Meyer-Olkin) statistics are the two measures used for checking data appropriateness. The significance value < 0.05 and KMO > 0.7 are considered as within the desirable range (Hair et al., 1995). EFA analysis was carried out of 321 responses received. Measures were as follows: KMO = 0.851 >0.7 and $p = 0.000 < 0.05$ i.e. 95% confidence level. The extraction method used was Principal Component Analysis (PCA) and Varimax as a rotation method. The rotation converged in six iterations and loading of greater than 0.6 was observed for all variables without cross-loading. Thus, EFA results were found to be satisfactory for SEM.

4.2.2 Confirmatory factorial analysis (CFA)

CFA illustrates the relationship between latent variables and observed factors (Chan et al., 2007). CFA assesses validity and reliability through goodness-of-fit indices. According to Hu and Bentler (1999), threshold values of goodness-of-fit are as follows:

Ratio of Chi-square test to degree of freedom (DF) = <5 occasionally permissible; <3 good

Goodness-of-fit index (GFI) =>.95

Comparative fit index (CFI) = >.95 Very good; >.90 good; >.80 occasionally permissible

Normed fit index (NFI) =>.80

Adjusted goodness of fit index (AGFI) =>.80

Root mean squared error of approximation (RMSEA) = <.05 very good; .05-.10 moderate; >.10 not permissible

In this study, CFA analysis was done on nine constructs of BDA and one construct of Supply Chain 4.0 Business Performance (SBP). The ten constructs were permitted to correlate with each other freely. The nine constructs of BDA were "Organisational and Top Management Support Performance (OTMSP), Information and Product Delivery Performance (IPDP), Sustainable Procurement and Sourcing Performance (SPSP), Collaborative Planning Performance (CPP), Sustainable Manufacturing Performance (SMP), Closed-loop Supply-chain performance (CLSCP), Operational Performance (OP), Technical and Knowledge Capability (TKC), and Environmental Performance (EP)." For this study, a Chi-square test for the degree of freedom (DF) is 2.342, which is between 2.00 and 3.00, therefore acceptable. GFI= 0.924 > 0.90, CFI = 0.957 > 0.95, and NFI = 0.864 >0.80 indicates best fit. RMSEA <0.05 is considered remarkable. However, the obtained value of RMSEA is 0.065, which is in the permissible range of 0.05 - 0.1 and thus acceptable. It concludes that the dataset point is in the direction of the goodness-of-fit and acceptable for further analysis.

As discussed, CFA was performed for all ten constructs in order to test the convergent validity of all items. Loading between factors and measured variables at a 1% level must be more than 0.5 (Barki and Hartwick, 2001). For the measurement model, standard estimates less than 0.70 are as follows: Knowledge management (TKC4: 0.631), Carbon emission (EP1: 0.526), Ecological cost (EP3: 0.591), Transparency (SBP1 with a value of 0.529), Inventory management (IPDP1: 0.690), Data quality (IPDP2: 0.675), Timely delivery (IPDP7: 0.650), Lean practices (SMP1: 0.471), Agile practices (SMP2: 0.581), and Total quality management (SMP3: 0.575). Out of these ten items, nine items have a value of more than 0.5, except Lean practices (SMP1) with a value of 0.471. This analysis shows sufficient evidence of convergence validity as the rest of the loadings are beneficial to internal consistency. AMOS-20.0 was used for the CFA analysis, estimates and the path diagram are shown in Figure 3.

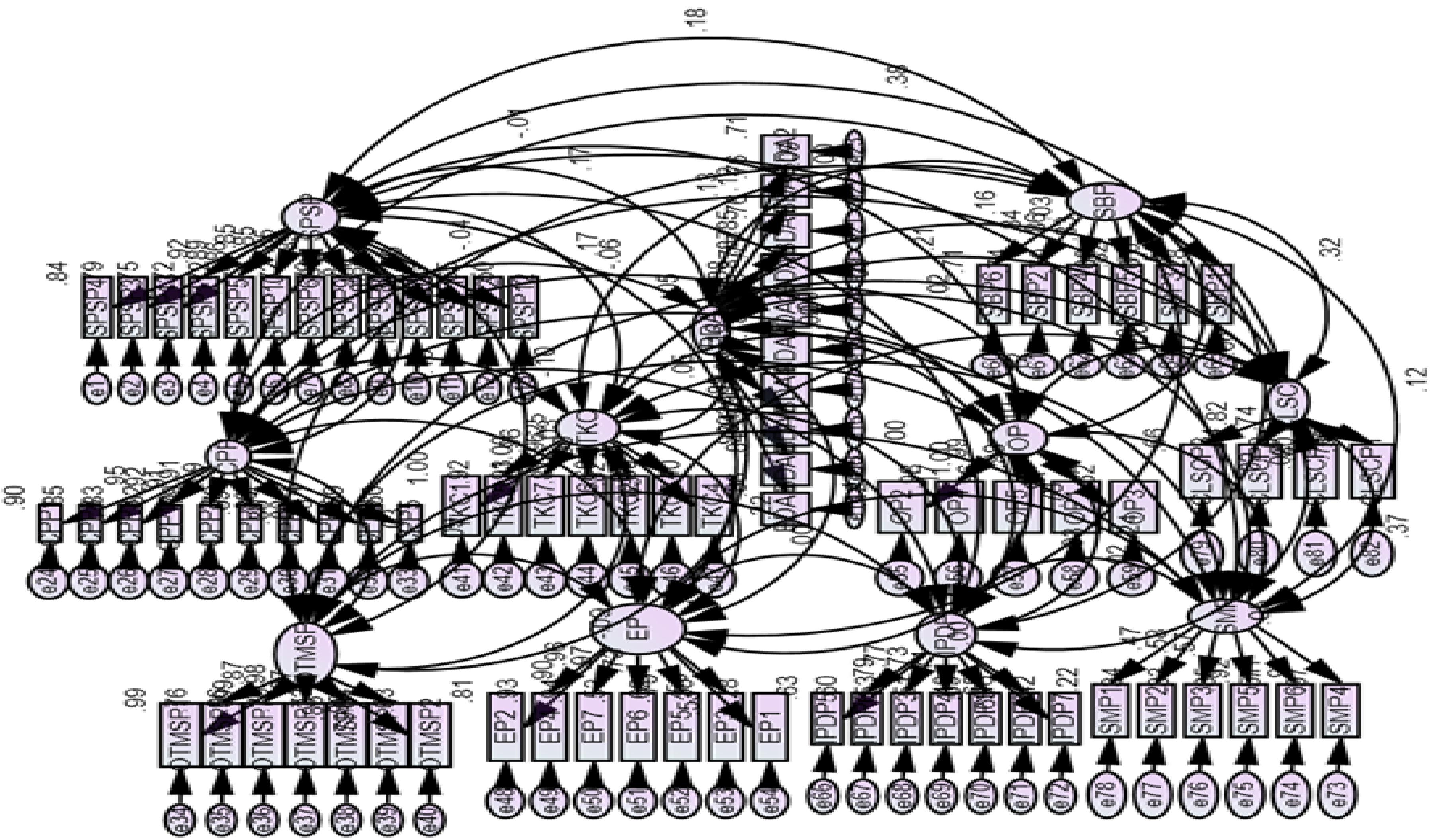

Figure 3: Path Diagram for CFA

4.2.3 Structural equation modelling (SEM)

SEM investigates multivariate data by including independent variables (IVs), latent constructs (LCs), and dependent variables (DVs). IVs and DVs can be measured factors or variables which can be continuous or discrete. Two phases of SEM include the validation of LCs i.e. judging a complete fitting model and distinct structural models hypothesised amongst LCs (Jenatabadi, 2015). Referring to logical precedents, bi-directional arrows of the CFA model were replaced with single-headed arrows. This obtained SEM test results that were initially verified for the model fit. This study uses AMOS-20.0 as it reads SPSS files and offers quality path diagrams. The ratio of Chi-square test to DF is 2.380, which is considered acceptable as it is between 2.00 and 3.00. The GFI= 0.967 > 0.90, and NFI = 0.864 >0.80 which indicate the best fit. Moreover, the RMSEA <0.05 and CFI >0.95 are considered remarkable. However, the obtained value of RMSEA and CFI are 0.065 and 0.942 respectively. RMSEA and CFI are in the permissible range of 0.05-0.10 and 0.90- 0.95 respectively, therefore acceptable. Figure 4 shows SEM path diagram.

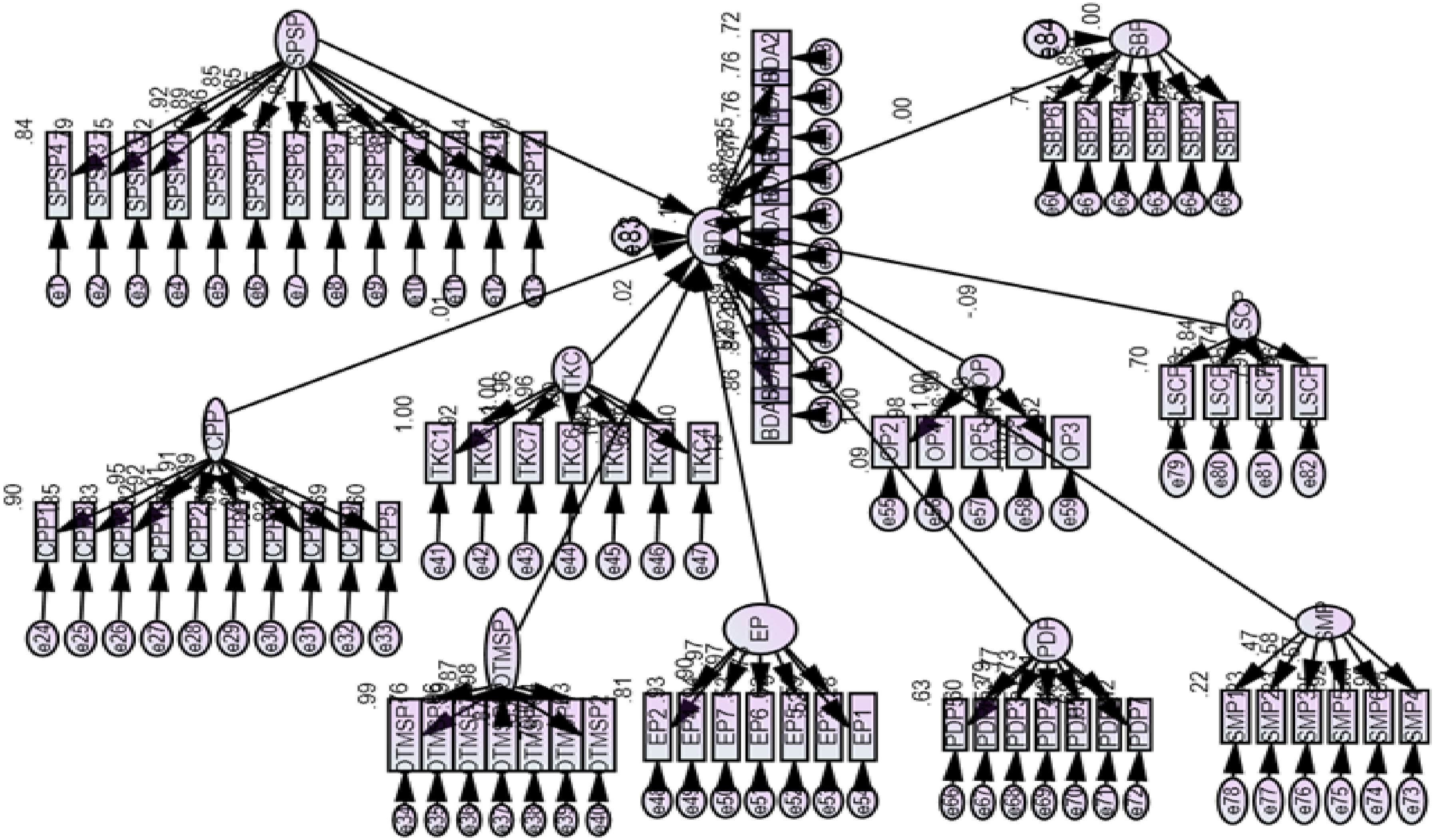

Figure 4: Path Diagram for SEM

4.4 Artificial Neural Network Analysis

ANN is a popular artificial intelligence method used for improving the performance and quality of analysis (Wang et al., 2020). Predictive accuracy of ANN is higher not only for linear relationships but also for nonlinear relationships (Priyadarshnee et al., 2017). ANN processes information through interconnected neurons via weighted links (Leong et al., 2015). The benefits of ANN are that it does not need multivariate assumptions of homoscedasticity, normality, or linearity (Abubakar et al., 2017).

4.4.1 Artificial Neural Network Model

In ANN, the multi-layered model is commonly used (Fausett, 1994), which has one input layer, one output layer, and one or more hidden layers. This study uses a multi-layered perceptron (MLP), with one hidden layer, and the Feed Forward-Back Propagation (FFBP) algorithm. In this paper, the given network was examined with one to ten nodes for the hidden layer, and ten nodes were selected. The ANN model is as shown in Figure 5. Each of the input layer and the output layer has seven nodes. As shown in Figure 5, seven significant variables (OTMSP, IPDP, SPSP, CPP, TKC, and EP) of structural analysis were used as inputs for the ANN.

Table 3: Comparison of results with past literature

Hypothesis No.	Hypothesis	SEM Analysis		ANN Analysis		In agreement with	In contrast with	Remark
		Supported (Y/N)	Standardised Estimates	Mean Importance	Rank			
1	Organisational and Top Management Support Performance (OTMSP) positively influences BDA.	Yes	0.180	0.1421	3	Chen et al. (2015), Moktadir et al. (2019)	Dubey et al. (2018)	Most significant factor in SEM
2	Information and Product Delivery Performance (IPDP) positively influences BDA.	Yes	0.088	0.1675	1	Ardito et al. (2019)		Fourth most significant factor in SEM; Rank 1 in ANN
3	Sustainable Procurement and Sourcing Performance (SPSP) positively influences BDA.	Yes	0.169	0.1478	2	Doolun et al. (2018)		Second most significant factor in SEM; Rank 2 in ANN
4	Collaborative Planning Performance (CPP) positively influences BDA.	Yes	0.008	0.1352	6	Kache and Seuring (2017)	Eriksson et al. (2017)	
5	Sustainable Manufacturing Performance (SMP) positively influences BDA.	No	-0.027	-	-		Gunasekaran et al. (2018)	Not supported in SEM
6	Closed-loop Supply-chain performance (CLSCP) positively influences BDA.	No	-0.091	-	-		Manavalan and Jayakrishna (2019)	Not supported in SEM
7	Operational Performance (OP) positively influences BDA.	Yes	0.027	0.1302	7	Queirozand and Telles (2018)		
8	Technical and Knowledge Capability (TKC) positively influences BDA.	Yes	0.020	0.1363	5	Lai et al. (2018)		
9	Environmental Performance (EP) positively influences BDA.	Yes	0.132	0.1405	4	Cheng et al. (2018), Jeble et al. (2018)	Song et al. (2018)	Third most significant factor in SEM; Rank 4 in ANN
10	BDA positively influences Supply-chain- 4.0 Business Performance (SBP).	Yes	0.003			Dubey et al. (2019b)		Mean RMSE (BDA-0.9641, SBP-0.9917)

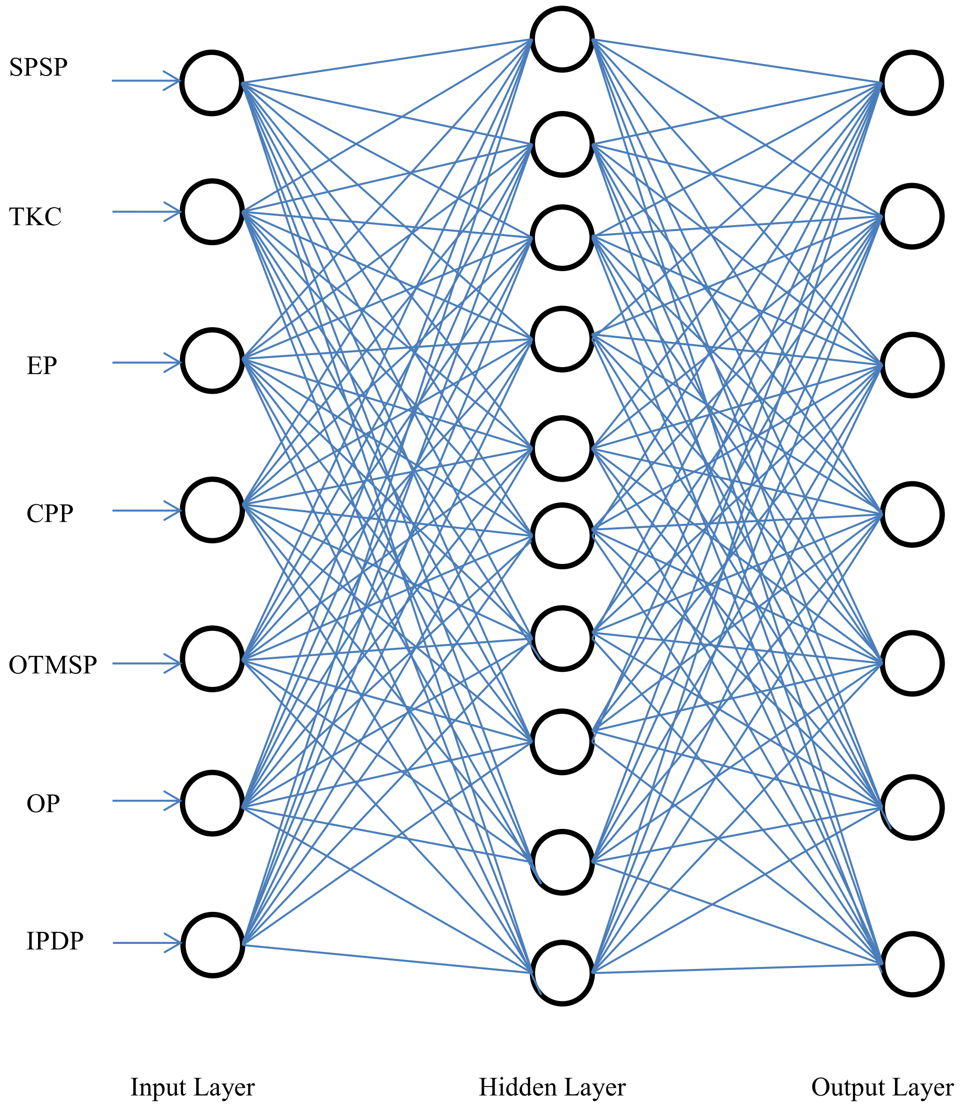

Figure 5: ANN Model

4.4.2 Sensitivity Analysis

In neural networks, cross-validation with 90% data for training and 10% data for testing is recommended (Tan et al., 2014). The bipolar sigmoidal function was used for the hidden and output layers for better accuracy. To confirm the significance of the predictor variables, non-zero synaptic weights were linked to the hidden layer. Table 4 and 5 give details of the analysis.

Table 4: Root Mean Square of Error (RMSE) Values

ANN	For output BDA		For output SBP	
	Training	Testing	Training	Testing
1	0.868	0.925	0.995	0.969
2	0.991	1	0.986	0.968
3	1	1.001	0.995	0.973
4	0.998	1.001	1.007	0.997
5	0.975	0.981	1.002	0.999
6	0.941	0.951	1.008	0.973
7	1.022	0.987	1.007	1.004
8	0.975	0.941	0.981	1.032
9	0.307	0.829	0.983	0.997
10	0.587	1.025	1.014	1.005
Mean RMSE	**0.8664**	**0.9641**	**0.9978**	**0.9917**
Standard Deviation	**0.234533**	**0.056781**	**0.011593**	**0.020651**

Table 5: Sensitivity Analysis

ANN	SPSP	TKC	EP	CPP	OTMSP	OP	IPDP
1	0.16	0.143	0.151	0.141	0.146	0.12	0.138
2	0.154	0.15	0.141	0.162	0.142	0.104	0.147
3	0.194	0.121	0.117	0.116	0.161	0.115	0.175
4	0.151	0.142	0.155	0.138	0.15	0.127	0.137
5	0.197	0.099	0.128	0.139	0.129	0.163	0.144
6	0.157	0.146	0.137	0.12	0.159	0.11	0.172
7	0.127	0.154	0.142	0.134	0.126	0.147	0.17
8	0.133	0.149	0.145	0.138	0.137	0.104	0.193
9	0.109	0.135	0.133	0.138	0.131	0.133	0.221
10	0.096	0.124	0.156	0.126	0.14	0.179	0.178
Mean Importance	**0.1478**	**0.1363**	**0.1405**	**0.1352**	**0.1421**	**0.1302**	**0.1675**
Ranking	**2**	**5**	**4**	**6**	**3**	**7**	**1**
Normalised Importance (%)	**88.23**	**81.37**	**83.88**	**80.71**	**84.83**	**77.73**	**100**

Each factor was calculated through a sensitivity analysis of seven significant factors. The Root Mean Square of Error (RMSE) is an indication of the accuracy of the ANN model. Apart from a few points, the ANN estimated values were close to the actual values. The sensitivity analysis shows that the top three factors that influence BDA are "Information and Product Delivery Performance (IPDP), Sustainable Procurement and Sourcing Performance (SPSP), and Organisational and Top Management Support Performance (OTMSP)"; whereas Operational Performance (OP) has the least impact on BDA.

5. Analysis and Discussion

5.1 Hypothesis testing

Table 3 shows standardised estimates of each hypothesis. Out of ten hypotheses, eight are supported: Organisational and Top Management Support Performance (OTMSP), Information and Product Delivery Performance (IPDP), Sustainable Procurement and Sourcing Performance (SPSP), Collaborative Planning Performance (CPP), Operational Performance (OP), Technical and Knowledge Capability (TKC), and Environmental Performance (EP) positively influence Big Data Analytics (BDA). In addition, BDA positively influences Supply Chain 4.0 Business Performance (SBP). However, two of the hypotheses Sustainable Manufacturing Performance (SMP) and Closed-loop Supply-chain performance (CLSCP) doesn't positively influence BDA.

5.2 Significance of Each Variable

Table 3 shows that the findings of this study are congruent with past literature. ANN ranks "Information and Product Delivery Performance (IPDP)" highest, followed by SPSP, OTMSP, EP, TKC, CPP, and SP. The ANN analysis gives the highest rank to "Information and Product Delivery Performance (IPDP)," which shows that the organisation must ensure timely delivery and information sharing. Critical factors for SC management marketing include operational and market data, inspection and merging of operational and market information, concurrency in planning, secured data flow, and improved decision making at SC level (Ardito et al., 2019). BDA ensures information availability over the end-to-end SC. However, ethical issues such as data security and privacy still need to be addressed (Chang et al., 2021). "Sustainable Procurement and Sourcing Performance (SPSP)", with the second rank in the ANN analysis, has the second-highest standardised estimate. Doolun et al. (2018) emphasised the usage of BDA for decision-making in location-allocation. They found that the adoption of sustainable procurement practices must be guaranteed through Government policies and ISO standards. Surprisingly, "Organisational and Top Management Support Performance (OTMSP)" ranked third in the ANN analysis, whereas it has the highest standardised estimate. The results are aligned with the work of Moktadir et al. (2019), who emphasised the significance of strategies towards SC-4.0 and policy-making for BDA adoption. Indeed, they showed the significant role of top management in the adoption of the latest technologies.

According to Cheng et al. (2018), Jeble et al. (2018), and Moktadir et al. (2019), environmental factors need to be considered for BDA adoption. Our results support these findings by recognising Environmental Performance (EP) as a significant factor with a rank of four. BDA with SC connectivity can work as a moderator technology with perceived benefits, data quality, and IT capabilities (Lai et al., 2018). Moreover, the study emphasises the positive effect of Technical and Knowledge Capability (TKC) of BDA. Kache and Seuring (2017) argued about BDA's role on logistics, SC transparency, and visibility, which is supported by our results of Collaborative Planning Performance (CPP) positively influencing BDA. The BDA-SC triangle consists of i) SC partnership: BDA for the short term, BDA for logistics and SC, Strategies for SC innovation; ii) Human knowledge: BDA knowledge, skill professionals in an organisation, market's professionals, awareness; iii) Innovation culture: IT tool, investments, IT security (Queirozand Telles, 2018). This study also emphasises the positive effect of Operational Performance (OP) on BDA. This study can help managers to understand the characteristics of significant factors in order to establish tactical and strategic policies of BDA adoption.

5.3 Theoretical contribution of the study

The theoretical contribution of this study is twofold. Firstly, we propose an approach based on the integration of SEM and ANN to identify and evaluate significant BDA factors for Supply Chain 4.0 in developing economies. This approach allows overcoming the limitations of the SEM by considering non-linear relations due to the particular features of ANN. In that case, ANN is non-compensatory and used to verify the linear, as well as non-linear, relationships. The results emphasise the mediating role of BDA for Supply Chain 4.0 business performance. Secondly, the study can help researchers and academicians understand, assess and evaluate the impact of BDA factors and sub-factors on Supply chains. The strategic policy will help in effective implementation with due consideration to relevant factors. Decision-makers can prepare roadmaps for BDA for Supply Chain 4.0. Furthermore, to achieve SC business performance, support of top management, the participation of employees, organisational culture, collaboration, and sustainable practices are most important. Decision-makers must construct BDA as one of the organisation vision to overcome the hurdles in adoption. Top management must arrange training in order to enhance the IT skills of the employees. According to Gijzen (2013), big data can help achieve the United Nations Sustainable Development Goals (SDGs). Adoption of BDA and Supply Chain 4.0 needs a systematic approach to achieve SDG 9 'Industry, Innovation and Infrastructure', SDG 11 'Sustainable Cities and Communities', and SDG 12 'Responsible Consumption and Production'.

6. Conclusion

According to SAS (2013), the number of organisations that use BDA is relatively low. This stresses the need to study BDA adoption and its impact on firm performance. In this regard, the present study addresses three research questions (RQ). The first RQ investigates the significant factors for the adoption of BDA in supply chain 4.0 environments. This is addressed by carrying an exhaustive literature search and validating them with experts' opinions. The second RQ investigates the impact of these factors on BDA adoption, while the third RQ investigates whether BDA has a mediation effect on supply chain 4.0 performances. To do so, an integrated SEM-ANN analysis is developed on the data collected from 40 manufacturing firms. The results reveal eight factors that positively influence BDA adoption, while we obtained the confirmation that BDA has a meditation effect on supply chain 4.0 performances.

Further advanced analytics, followed by digital communication to various stakeholders in SC, will assist organisations in focusing on customer needs. Based on technology integration, data management, advanced analytics, and digital interfaces, organisations can develop improved operations, reconfigure the SC model, and develop business strategies (Thienen et al., 2016). Thus, the paper has a notable contribution to BDA adoption for Supply Chain 4.0. Developing countries like India are in the process of implementing Supply Chain 4.0. Latest studies like the adoption of Supply Chain 4.0 in multinationals (Makris et al., 2019), digital SC with Industrial IoT (Manavalan and Jayakrishna, 2019), smart SC (Frank et al., 2019), and dynamics in SC (Roßmann et al., 2018) confirm the benefits of BDA in SC. The study proposes a conceptual model of BDA as a mediator to describe the SC business performance. This study will help researchers to outline experimental research in BDA and Supply Chain 4.0 business performance. The study will also guide BDA practitioners on how to develop potential business performance through different stages.

There are some limitations to the study as it was conducted in Indian manufacturing organisations. Indeed, with minor modifications, similar works can be carried out in other developing economies. Moreover, a structured questionnaire was used for data collection, which may create heterogeneity, and the data sample can be increased. Thus, more data samples can be collected with another method of data collection. As questionnaire-based data collection was done individually, the decision may vary based on organisational culture, industry, and time. Furthermore, additional analysis, where the unit of analysis is the company, may be carried out to determine BDA adoption in specific industries.

Future research work would investigate the mediating role of BDA for Lean, Agile, Resilient, and Green (LARG) effects on SC performance. Another research direction inspired from the current findings would be the identification of the roles of blockchain and Artificial Intelligence in conjunction with BDA in Supply chain 4.0.

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