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Technological Forecasting & Social Change 196 (2023) 122824

Contents lists available at ScienceDirect

Technological Forecasting & Social Change

journal homepage: www.elsevier.com/locate/techfore

Assessing the impact of big data analytics on decision-making processes, forecasting, and performance of a firm

Sheshadri Chatterjee [a], Ranjan Chaudhuri [b], Shivam Gupta [c], Uthayasankar Sivarajah [d,*], Surajit Bag [b]

[a] Department of Computer Science & Engineering, Indian Institute of Technology, Kharagpur, West Bengal, India
[b] Research Center, Léonard de Vinci Pôle Universitaire, 92916 Paris La Défense, France
[c] Department of Information Systems, Supply Chain Management & Decision Support, NEOMA Business School, 59 Rue Pierre Taittinger, 51100 Reims, France
[d] School of Management, University of Bradford, Richmond Road, Bradford BD7 1DP, United Kingdom

A R T I C L E I N F O

Keywords:
Big data analytics
Decision-making
Forecasting
Financial performance
Operational performance
Dynamic capability

A B S T R A C T

There are various kinds of applications of BDA in the firms. Not many studies are there which deal with the impact of BDA towards issues like forecasting, decision-making, as well as performance of the firms simultaneously. So, there exists a gap in the research. In such a background, this study aims at examining the impacts of BDA on the process of decision-making, forecasting, as well as firm performance. Using resource-based view (RBV) as well as dynamic capability view (DCV) and related research studies, a research model was proposed conceptually. This conceptual model was validated taking help of PLS-SEM approach considering 366 respondents from Indian firms. This study has highlighted that smart decision making and accurate forecasting process can be achieved by using BDA. This research has demonstrated that there is a considerable influence of adoption of BDA on decision making process, forecasting process, as well as overall firm performance. However, the present study suffers from the fact that the study results depend on the cross-sectional data which could invite defects of causality and endogeneity bias. The present research work also found that there is no impact of different control variables on the firm's performance.

1. Introduction

Significant emphasis has been given to understand the impact of various applications of big data analytics (BDA) on the performance of the firms and it has invited considerable attention from the researchers (Elhoseny et al., 2020). The data is considered as a critical asset of the firms which could be used to make strategic decisions (Agarwal and Dhar, 2014; Shajalal et al., 2023). The data of the firms can easily be managed as well as integrated with the help of applications of information technology to develop the firm's forecasting as well as decision making processes (Abbasi et al., 2016; Hajek and Abedin, 2020; Petr et al., 2022). Due to the high strategic and operational potential, BDA is believed to be a successful enabler since it could support the firms for achieving superior business performance (Wamba et al., 2017; Khalfaoui et al., 2022; Efat et al., 2022). BDA is considered as a process that helps the decision makers to analyze large volume of data. Such data is processed with the help of machine learning (ML) for extracting several potential useful information. This information could include the performance of the clients, customers' liking and disliking trends in the current market along with contact details of the customers helpful for pushing marketing activities. BDA is helpful for storage of data and effective data analysis approach for better information extraction, proper forecasting process, as well as for making appropriate and accurate decisions (Vrontis et al., 2021; Tseng et al., 2022). It is pertinent to mention here that adoption of BDA in a firm could also invite some challenges concerning the issues of analysis of confidential and personal data which are inimical from the privacy and security perspectives. For smooth deployment of BDA, it is necessary to identify these risks and at the same time should find ways for mitigating those risks (Neirotti et al., 2021). There is a doubt if by storing such huge volume of data, is it possible by the firms to appropriately transform that data into essential knowledge and information helpful for businesses to survive and provide a better competitive advantage? (Voort et al., 2021; Chaudhuri, 2022). But there is also another school of thought which predicts that

* Corresponding author.
E-mail addresses: ranjan.chaudhuri@devinci.fr (R. Chaudhuri), shivam.gupta@neoma-bs.fr (S. Gupta), u.sivarajah@bradford.ac.uk (U. Sivarajah), surajit.bag@devici.fr (S. Bag).

https://doi.org/10.1016/j.techfore.2023.122824
Received 12 March 2023; Received in revised form 4 June 2023; Accepted 1 September 2023
Available online 6 September 2023

with the help of BDA in the regular business activities, firms could derive tremendous beneficial results, particularly for the large organizations like Google, Facebook, Amazon, Walmart, Netflix, and so on (Schildt, 2017). BDA is interpreted as "a holistic process that involves the collection, analysis, use, and integration of data for various functional divisions with a view to gaining actionable insights, creating business value, and establishing competitive advantage" (Gunasekaran et al., 2017, p.308). Accurate decision making and forecasting process require reliable data. In such a context, BDA is a process where such technology usage helps the decision-makers to analyze data obtained from the users with the help of machine learning. Such analysis of data helps leaders and managers of the firms to understand the preferences of the consumers along with current market trends. Different BDA enabled technological applications help to assess the changing consumer preference due to dynamic changes in society as well as in business environment (Voort et al., 2021). BDA helps with better forecasting and for making accurate decisions (Spanaki et al., 2018). Walmart is reported to have collected 2.5 petabytes of the data of the customers in each hour for knowing customers' accurate buying behavior (Bradlow et al., 2017). The impacts of BDA abilities can be considered as DCs (dynamic capabilities) of a firm (Aydiner et al., 2019). Though, several studies have highlighted various contributions of BDA to a firm (Akter et al., 2020; Wang et al., 2022). But there are limited studies which extensively investigated how adoption of BDA in a firm could improve the performance of the firms through the enhancement of some intermediate factors like decision-making and forecasting capabilities along with financial and operational efficiency of the firms (Zytek et al., 2021). Thus, from the above discussion, the following research questions (RQs) are proposed which need to be addressed.

RQ1. *How big data analytics can impact decision making and forecasting process of a firm?*

RQ2. *Whether the applications of big data analytics can influence the firm's overall performance through the improvements of financial and operational performance of the firm?*

The present study has contributed to the fact that adoption of BDA in a firm can impact its decision making and forecasting process which could eventually enhance the overall performance of the firm through the improvement of some intermediate contextual factors like financial and operational performance of the firm.

The above RQs have been addressed by developing a theoretical model. The model has been duly validated by partial least square structural equation modeling (PLS-SEM) approach by analyzing the responses of 366 respondents. To theoretically substantiate the empirical findings, the present study has integrated resource-based view (RBV) (Barney, 1991), knowledge-based view (KBV) (Maroufkhani et al., 2019), and dynamic capability view (DCV) (Teece et al., 1997), since any single view out of its own could not explain the contribution of BDA on the overall performance of the firms through the improvement of decision-making and forecasting abilities along with the enhancement of financial and operational performance of the firms.

2. Background studies and theories

Studies have demonstrated that for developing smart manufacturing systems and for improving the activities in hospitality and tourism sectors, BDA is considered as an important tool (Wamba et al., 2019; Wang et al., 2022; Brewis et al., 2023; Bag et al., 2023). There are research works which highlighted that firms are aligned to invest massively in deploying BDA tools in their businesses for improving intra and inter firm operations to develop their forecasting and decision-making processes that eventually could ensure better operational efficiency (Chakravarty et al., 2013; Chatterjee, 2019; Akhtar et al., 2018; Choi and Park, 2022a, 2022b). Big data is comprised of transactional data, check-stream data, visual data, and so on which are used for better decision-making as well as forecasting purposes (Tambe, 2014; Wang et al., 2016; Spanaki et al., 2018). There are research works which have highlighted that the BDA capability can impact operational and financial efficiency of the firms which could eventually influence the overall efficiency of the firms (Upadhyay and Kumar, 2020; Basile et al., 2021). Studies have highlighted that BDA along with artificial intelligence (AI) enabled dynamic capability can ensure better operational performance for enhancement of service quality, reduction of cost, manufacturing of new products with lower cost, as well as mitigation of market risks (Dubey et al., 2020). Scholars advocate that BDA driven dynamic capability can ensure better financial effectiveness using big data platforms. The BDA enabled dynamic capabilities can help the firms to address the dynamic uncertain business environments which could enhance the efficiency of the firms (Akter et al., 2020; Nguyen, 2021). In earlier studies, it has been observed that several theories have been employed for examining the effects of BDA on firm performance (Mikalef et al., 2019; Bhattacharjee et al., 2021). The firms need to develop congenial mechanisms for aptly synchronizing as well as integrating their internal valuable, rare, inimitable, and non-substitutable (VRIN) resources with the externally seized opportunities to fully leverage the benefits of BDA applications (Mithas et al., 2013). This concept integrates the ideas of RBV(Barney, 1991) and DCV (Teece et al., 1997).

However, to achieve a better competitive advantage, ownership of VRIN resources is necessary but it is not a sufficient condition (Agha et al., 2012). Since the business environment is changing rapidly, in such volatile market conditions, the firms must also possess dynamic capabilities to address the volatile marketplace (Pisano, 2015). Such arguments are supported by DCV (Teece et al., 1997) to supplement the deficiency of RBV (Barney, 1991). The dynamic capabilities of a firm help to integrate, improve efficiency, and eventually support in reconfiguring the internal as well as the external competencies for addressing the rapidly changing business environments (Teece, 2012; Teece, 2014). DCV is defined as a "high-level routine (or collection of routines) that, together with its implementing input flows, confers upon an organization's management a set of decision options for producing significant outputs of a particular type" (Winter, 2003, p. 991). BDA helps to transform the raw unit of data into substantial and meaningful information helping for reduction of the ambiguity towards making accurate decisions as well as for effective forecasting purposes which could eventually help the firms for reacting and responding quickly in a volatile marketplace (Teece, 2012; Torres et al., 2018). Thus, it is seen that studies have demonstrated that in hospitality and tourism industry, BDA is considered as an important tool (Wang et al., 2022; Wamba et al., 2019). Studies also have highlighted that successful deployment of BDA tool could improve the operational efficiency of a firm (Chakravarty et al., 2013; Akter et al., 2020). Studies have also revealed that forecasting and decision-making processes of a firm can be improved by the adoption of BDA tool (Tambe, 2014; Wang et al., 2016; Spanaki et al., 2018). Studies have also highlighted that BDA could improve the efficiency of a firm (Akter et al., 2020; Nguyen, 2021). Thus, there are several studies which highlighted the various contributions of applications of BDA in a firm. But those studies took place in a fragmented manner. Limited studies are there which extensively investigated how adoption of BDA could improve simultaneously forecasting and decision-making abilities of a firm along with improvement of financial and operational performance of a firm which could eventually enhance the overall performance of the firm. Hence, there is a gap in the extant literature. This study has taken an attempt to fill up such a gap.

BDA covers specific IT skills, domain knowledge, along with analytical competencies needed to impact financial and operational effectiveness of the firms in the complicated data-oriented business environments (Chen et al., 2015). This idea confirms a knowledge-based view that has been derived from the essence of RBV (Maroufkhani et al., 2019). Thus, in the world associated with rapid advancement of technologies, firms must have possessed abilities to promptly configure and develop novel competencies and practices for adapting with new business paradigms. This can be accomplished by the help of BDA enabled dynamic capabilities as well as with the help of VRIN in house abilities, the concept being corroborated by both RBV and DCV.

3. Hypotheses formulation and development of a conceptual model

Taking support of theories and literature, it was possible to establish the nexus between adoption of BDA and overall firm performance by improving some identified endogenous intermediate contextual constructs. Here, the constructs used in this study will be discussed and efforts will be made to develop a few hypotheses to propose a model conceptually.

3.1. Adoption of big data analytics

The applications of BDA are used to explore huge volumes of raw data which could help to ascertain different correlations among various factors, understanding the business style along with other essential insights (Huang et al., 2017). It has been noted by Aydiner et al. (2019) that there exists a nexus between BDA adoption as well as improvement of firm performance through development of process performance. BDA enabled business activities could help the firms develop various business processes through making accurate decision in real time resulting in lowering operating costs, improving product quality, as well as product availability (Wamba et al., 2019; Thrassou et al., 2022). It has been observed through empirical findings that successful adoption of BDA tools could enhance the process efficiency of the firms and eventually can improve the overall firm performance (Gunasekaran et al., 2017; Sheshadri, 2020). BDA has all the characteristics of DCs as opined by Wamba et al. (2019) which supports DCV. BDA has been considered as a basic tool to enable better business performance in different business sectors including hospitality, tourism, and smart manufacturing (Sharma et al., 2021a, 2021b). There are various research works which have highlighted that firms are continuously investing towards adoption of BDA tools to enhance their intra and inter firm operations. Thus, the adoption of different applications of BDA can influence the decision-making as well as forecasting process (Chakravarty et al., 2013; Akhtar et al., 2018; Choi and Park, 2022a, 2022b). Hence, the following hypotheses are prescribed.

H1a: Adoption of BDA (ABA) positively influences the decision-making process (DMP) in the firms.

H1b: Adoption of BDA (ABA) positively influences the forecasting process (FCP) in the firms.

3.2. Process impact

In the context of BDA adoption, it has been argued that such adoption has an impact on the business process that principally comprises decision making and forecasting processes. In terms of the observation of Tseng et al. (2022), BDA entails effective analysis approaches which could facilitate smart decision-making helpful to impact performance of the firms by reducing the cost of business operations and thereby impacting firms' financial performance. One of the principal challenges of accurate decision making by using BDA tools lies in the fact that majority of machine learning algorithms are found to have predictability issues and the decisions emerged by using such machine learning algorithms are difficult for understanding as the origin of prediction is indistinct to human users (Zytek et al., 2021; Chaudhuri and Vrontis, 2021). There are three models of decision characteristics which are normative, descriptive, as well as perspective (Sheshadri, 2015; Gati and Kulcsár, 2021; Brewis et al., 2023). The normative model is concerned in examining how the accurate decisions could be arrived at by the individuals. Again, the descriptive model highlights how it is possible to make accurate decisions by individuals. The perspective model helps to understand the career decision-making process that could support the individuals in a better manner. Accurate decision-making process is perceived to have reduced cost of business operations, thereby eventually impacting overall performance of the firms (Chatterjee et al., 2021; Pham and Lo, 2023). Thus, the hypotheses below have been proposed.

H2a: Accurate and quick decision-making process (DMP) positively impacts the financial performance (FIN) of the firms.

H2b: Accurate and quick decision-making process (DMP) positively impacts on the overall firm performance (OFP).

Firms must have the ability to accurately forecast so that they can adopt proper strategy and can make effective business planning (Lee et al., 2009; Chaudhuri et al., 2021). The prediction is principally based on the analysis of available data with the help of BDA (Choi and Park, 2022a, 2022b). Different capabilities like corporate wikis, knowledge management (KM) systems, BI dashboard, and so on are found to have used available information for creation of new insights helpful for better forecasting process (Abbasi et al., 2016; Sheshadri, 2019). Forecasting processes in businesses include the technique for looking at the past and present data along with assessment of trends in marketplace for accurately predicting the future financial performance of the firms (Akter et al., 2020; Yuk and Garrett, 2023). Effective forecasting helps a firm to assess how much revenue can potentially be earned in a specific period for a specific project and could help the firms for articulating proper plan for future (Kang et al., 2021; Sharma et al., 2021a, 2021b; Bag et al., 2023). Thus, accurate forecasting process is perceived to be helpful for designing better business style and eventually can impact the firm's performance. Thus, the following hypotheses are proposed.

H2c: Accurate forecasting processes (FCP) positively impact on the overall firm performance (OFP).

H2d: Accurate forecasting processes (FCP) positively impact on the financial performance (FIN) of the firms.

3.3. Performance impact

It is a fact that financial performance and operational performance could help to improve the firm's overall performance. It has been observed that market power and business style can be considered as two important antecedents of performance of the firms (Dubey et al., 2019). Again, the assessment of performance of a firm now goes beyond estimating only firms' effectiveness and efficiency. Performance of a firm is associated with the concept of assessing the progress, traceability, as well as ability to diagnose and address challenges of a firm (Dubey et al., 2017). In terms of empirical research work, it has been found that successful exploitation of BDA capabilities is construed as a proper assessment of firm performance (Gunasekaran et al., 2017). Another study has demonstrated that data analytics possesses a direct link towards the improvement of firms' operational performance (Srinivasan and Swink, 2018). It has been observed that there exists a close link between BDA adoption as well as enhancement of firm performance through the improvement of process performance (Aydiner et al., 2019). There are studies which have could demonstrate that BDA adoption can have a direct influence on firm's financial as well as operational performance (Gligor et al., 2015; Wamba et al., 2019). The above inputs lead to formulating the following hypotheses.

H3: Improvement of financial performance (FIN) of a firm positively impacts overall firm performance (OFP).

H4: Improvement of operational performance (OPE) of a firm positively impacts overall firm performance (OFP).

In this study, firm age, type, and size have been considered as control variables which could impact the overall performance of the firms (Chen et al., 2015). The above discussion leads to developing a model conceptually shown in Fig. 1.

In Fig. 1, it is observed that adoption of bigdata analytics (ABA) impacts decision-making process (DMP) and forecasting process (FCP) which could influence financial performance (FIN) and operational performance (OPE), and these two factors eventually impact overall firm performance (OFP). Here, firm age, firm size, and firm type have been considered as control variables to impact overall firm performance

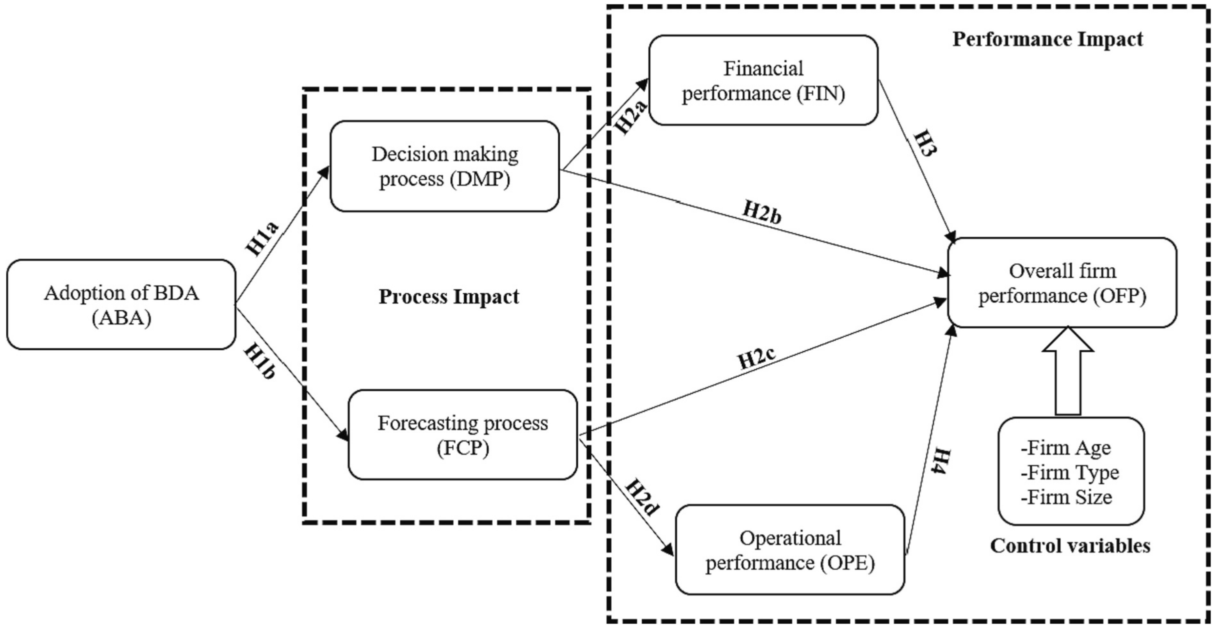

Fig. 1. Theory-based research model.

(OFP).

4. Design of research

For testing the hypothesized relationships as well as for validating the proposed conceptual model, help of survey method has been chosen and data has been gathered from the potential targeted respondents. This process is deemed to be befitting for such studies which requires the testing of the hypotheses, elucidating the population, preparing the measures, as well as developing a theoretical model (Lee and Shim, 2007).

4.1. Questionnaire preparation

The set of questions has been developed with the help of existing literature and is provided in Appendix A. The dimensions have been measured on 5-point Likert scale having anchors spanning from SD (Strongly Disagree) [marking as 1] to SA (Strongly Agree) [marking as 5]. The questions prepared have been pre-tested with due consultation from nine experts to simplify the recitals of the questions. Out of these nine experts, five experts belong to the industrial sector with each having professional experience for more than ten years in the related field. The other experts were academicians, each having more than fifteen years of experience in research in the field of this study. Their inputs help to rectify the questions through enhancement of their readability. After completion of the pre-test, pilot test was conducted with analysis of responses of 25 respondents selected through the approach of convenience sampling technique. It is pertinent to mention here that these 25 respondents are mostly leaders and managers of those firms which have adopted BDA or have been contemplating adopting BDA. The inputs of 25 respondents could help to enhance the understandability and the comprehensiveness of the questionnaire. It is pertinent to mention here that all these 25 respondents were not a part of the principal survey. In this way eventually 26 items were prepared.

4.2. Sample collection

There are researchers in this study who belong to India having links with the top officials of some business associations in India like FICCI, NASSOCM, and CII. The connections of the researchers have been used to collect responses from various types of employees of different organizations. An online questionnaire link has been created by using Google docs application. The questionnaire link was shared among the officials of these industry bodies. Taking help of their network capability with various organizations in different industries like IT, healthcare, retail, telecommunication, automobile, pharmaceutical and so on, it was possible to send the questionnaire links to some of the leaders of these firms. Mostly leaders and managers were targeted as most of the critical decisions in the firms are supposed to be taken by the leaders and managers of the firms with different hierarchies. All these prospective respondents (leaders and managers) were given the response sheets. Since the unit of representation of this survey is the firm, an individual from each of the firms was considered representing that firm.

Each response sheet contains 26 questions in the form of statements. A guideline was also provided for the potential respondents highlighting the process of filling up of the response sheet. The respondents were appraised that their identities will be kept secret. All the prospective participants were asked to fill up the response sheet within a specific timeline (October–December 2022). Initially, 917 respondents were targeted. Within the scheduled time, responses of 381 respondents were eventually obtained. The rate of response was found to be 41.5 %. Here, a non-response bias test has been conducted in terms of the recommendations of Armstrong and Overton (1977). For this, chi-square test and independent *t*-test have been conducted by analyzing the responses of first and last 100 responses. No mentionable difference of results was noted in these two cases. As such, non-response bias did not pose a major concern in this study. After the verification process, it was ascertained that 15 responses belonging to the 15 firms were incomplete and they were not considered. Finally, analysis was done with responses from 366 respondents with 26 instruments. The sample characteristics are shown in Table 1.

5. Data analysis along with the results

For testing the hypotheses as well as for validation of the model, PLS-SEM approach is adopted. This approach helps to synthesize complex models and it does not impose any restriction on the number of samples (Willaby et al., 2015). In this technique, the normal distribution of the data is not required which is the essential condition for CB-SEM approach (Kock and Hadaya, 2018). Also, the PLS-SEM approach is

Table 1
Sample characteristics ($N = 366$).

Particular	Characteristics	Frequency	Relative percentage
Industry type	IT	65	17.8
	Healthcare	55	15.0
	Retail	70	19.1
	Telecommunication	75	20.5
	Automobile	50	13.7
	Pharmaceuticals	51	13.9
Firm age	Older firm (>25 years old)	155	42.3
	Younger firm (5–25 years old)	110	30.0
	Startups (<5 years old)	101	27.7
Firm size	Large firm (>25,000 employees)	176	48.1
	Mid-level firms (5000–25,000 employees)	105	28.7
	Small firms (<5000 employees)	85	23.2
Managerial hierarchy	Junior Manager (<5 years' experience)	130	35.5
	Mid-level Manager (5–10 years' experience)	100	27.3
	Senior Manager (>10 years' experience)	80	21.8
	Leaders (Senior executives)	56	15.4

helpful to analyze a study which is exploratory in nature like this study (Peng and Lai, 2012). The inputs of the respondents have duly been quantified by taking help of 5-point Likert scale. Here a 5-point Likert scale has been used because it is simple to apply, and this scale provides an opportunity to the respondents to take a neutral stand by choosing 'neither disagree nor agree' option.

5.1. Measuring parameters and test for discriminant validity

For assessment of convergent validity, LF (loading factor) for each instrument was measured. To verify validity, reliability, and internal consistency, the AVE, CR, and Cronbach's α of all the constructs have duly been estimated. It appears from the results that all the estimated values of LFs are greater than the lowest permissible value of 0.7 (Chin, 2010) and the estimated values of AVEs are all greater than the lowest allowable value of 0.5 (Hair et al., 2017). Table 2 shows the results.

For discriminant validity test, square roots of AVEs are computed. These values are found to be greater than the corresponding correlation coefficients. It satisfies the criteria of Fornell and Larcker (1981). Table 3 reveals the outputs.

To supplement the Fornell and Larcker criteria (Fornell and Larcker, 1981), Heterotrait Monotrait test (HTMT) has duly been conducted. The HTMT values are found to be all <0.85 (Teo et al., 2008; Henseler et al., 2015). The results are provided in Table 4.

5.2. Common method bias (CMB)

The results of this study are found to have relied on such data which have been obtained from survey. Hence, the question of having CMB cannot be avoided. To mitigate the risks of CMB, this study has taken some effective procedural measures at the outset. During the survey, all the items have duly been edited through the process of pre-test and pilot test. Additionally, all the prospective respondents were assured to keep their identities confidential. All these steps were taken with the expectation of having unbiased responses. Even after that, Harman's single factor test (SFT) has been performed as a statistical test. The results of the SFT clearly indicated that the first factor was 20.62 % of the variance. It is within 50 % as envisaged by Podsakoff et al. (2003). Since Harman's SFT is not considered as a robust and conclusive test for CMB (Ketokivi and Schroeder, 2004), another statistical test has been conducted. To reconfirm the SFT, marker correlation ratio test has duly been conducted (Lindell and Whitney, 2001). This test also indicated that there is no evidence of CMB. These results help to construe that CMB could not pose a major threat to distort the data.

Table 2
Assessment of parameters.

Constructs and Items	LF	AVE	t-statistics	CR	α
ABA		0.75		0.81	0.83
ABA1	0.91		22.17		
ABA2	0.90		24.11		
ABA3	0.78		26.02		
ABA4	0.87		31.17		
ABA5	0.85		29.38		
DMP		0.85		0.87	0.89
DMP1	0.95		24.27		
DMP2	0.85		31.39		
DMP3	0.94		27.31		
DMP4	0.90		29.93		
DMP5	0.96		36.11		
FCP		0.81		0.83	0.86
FCP1	0.85		26.01		
FCP2	0.89		37.92		
FCP3	0.91		24.07		
FCP4	0.95		26.00		
FCP5	0.87		29.78		
FIN		0.80		0.84	0.87
FIN1	0.93		31.22		
FIN2	0.96		37.17		
FIN3	0.89		30.06		
FIN4	0.85		23.88		
OPE		0.82		0.85	0.89
OPE1	0.90		24.72		
OPE2	0.96		36.32		
OPE3	0.92		24.07		
OPE4	0.94		35.31		
OFP		0.79		0.83	0.87
OFP1	0.80		29.17		
OFP2	0.92		30.66		
OFP3	0.95		26.02		

Table 3
Test for discriminant validity.

Constructs	ABA	DMP	FCP	FIN	OPE	OFP	AVE
ABA	0.87						0.75
DMP	0.26	0.92					0.85
FCP	0.29	0.33	0.90				0.81
FIN	0.17	0.28	0.32	0.89			0.80
OPE	0.22	0.39	0.24	0.18	0.91		0.82
OFP	0.31	0.37	0.19	0.27	0.32	0.89	0.79

Note: Diagonal = $\sqrt{\text{AVE}}$.

Table 4
Discriminant validity test (HTMT).

Constructs	ABA	DMP	FCP	FIN	OPE	OFP
ABA						
DMP	0.43					
FCP	0.37	0.32				
FIN	0.26	0.30	0.26			
OPE	0.19	0.23	0.17	0.43		
OFP	0.41	0.19	0.48	0.19	0.37	

5.3. Effect size f^2 test

For verifying the contributions of independent variables on the corresponding dependent variables, the effect size f^2 test has duly been performed. It is said that the values of f^2 are large if they are >0.350, they are said to be medium if their values lie between 0.150 and 0.350, and they are said to be weak if the values are between 0.020 and 0.150 (Cohen, 1988). The results have been highlighted in Table 5.

Table 5
Effect size f^2 test.

Constructs	DMP	FCP	FIN	OFP	OPE
ABA	0.296 (M)	0.167 (M)			
DMP			0.114 (W)	0.378 (L)	
FIN				0.161 (M)	
FCP				0.291 (M)	0.141 (W)
OPE				0.371 (L)	

5.4. Hypotheses testing

For examining the validity of the hypotheses, bootstrapping procedure with consideration of 5000 resamples has been considered. With consideration of separation distance 7, cross validated redundancy has been assessed by computing Q^2 value that has been found to be 0.066 (positive). This shows that the model has predictive relevance (Mishra et al., 2018). For showcasing the model fit, SRMR has been considered as the standard index. Its values emerge as 0.061 for PLS and 0.033 for PLSc. Both these values are less than the cutoff value of 0.08 (Hu and Bentler, 1999). Thus, the model is in order. By the help of structural equation modeling technique, path coefficients, *p*-values, and R^2 values could be ascertained. Table 6 reflects the results.

The validated model (SEM) is provided in Fig. 2.

6. Discussion

The present study has hypothesized eight relationships. All the relationships have been duly supported. The results highlight that ABA is impacting DMP and FCP separately in a positive and significant manner as the concerned β-values (path coefficients) are 0.21 and 0.19 respectively with respective levels of significance as $p < 0.001$(***) and $p < 0.01$(**). The study also reflects that DMP significantly and positively impacts FIN and OFP because the concerned β-values are 0.24 and 0.31 respectively with respective levels of significance as $p < 0.01$(**) and $p < 0.001$(***). The study also highlights that FCP significantly and positively impacts OFP and OPE separately since the concerned β-values are 0.26 and 0.17 respectively with respective levels of significance as $p < 0.001$(***) and $p < 0.05$(*). This study demonstrates that FIN and OPE separately impact OFP significantly and positively since the concerned β-values are 0.41 and 0.33 respectively with respective levels of significance as $p < 0.001$(***) and $p < 0.001$(***). The study results show that all the control variables have an insignificant impact on OFP since firm age, firm type, and firm size insignificantly impact on OFP as the concerned β-values are 0.04, 0.01, and 0.02 respectively each having level of insignificance as $p > 0.05$(ns). So far as coefficients of determination are concerned (R^2), DMP and FCP can be predicted by ABA to the tune of 38 % and 44 % respectively. DMP and FCP predict FIN and OPE separately to the tune of 51 % and 56 % respectively. The study results also highlight that OFP can be predicted by FIN, DMP, FCP and OPE to the tune of 79 % which is the explanatory power of the proposed model. It is mentioned here that coefficient of determination (R^2) is a number lying between 0 and 1 which could assess how well a statistical framework could predict an outcome.

Table 6
Estimation of the model.

Hypotheses	Linkages	Path coefficients	p-values	Remarks
H1a	ABA→DMP	0.21	$p < 0.001$ (***)	Supported
H1b	ABA→FCP	0.19	$p < 0.01$(**)	Supported
H2a	DMP → FIN	0.24	$p < 0.01$(**)	Supported
H2b	DMP → OFP	0.31	$p < 0.001$ (***)	Supported
H2c	FCP → OFP	0.26	$p < 0.001$ (***)	Supported
H2d	FCP → OPE	0.17	$p < 0.05$(*)	Supported
H3	FIN→OFP	0.41	$p < 0.001$ (***)	Supported
H4	OPE → OFP	0.33	$p < 0.001$ (***)	Supported
Control variables				
	Firm age	0.04	$p > 0.05$(ns)	Not supported
	Firm type	0.01	$p > 0.05$(ns)	Not supported
	Firm size	0.02	$p > 0.05$(ns)	Not supported

The study results highlight that big data analytics tools help business communities in fast and accurate decision-making process to improve their businesses. But for accurate decision making as well as for effective forecasting process, firms are to depend on curated and reliable data sets. In this context, this study has highlighted that adoption of BDA tools is valuable to the firms. Such adoption of modern tools helps the decision makers in the firms to extract meaningful and effective information from the collected data. This study highlighted that by using BDA tools, the firms can have the information regarding the preference of the clients, the customers' liking and disliking, and so on. Such information helps the firms for ensuring accurate and effective real-time decision-making processes as well as predicting more accurate forecasting numbers which is also supported by the study of Tseng et al. (2022). This study has demonstrated that the choice of customers is changing rapidly due to quick advancement of technologies and rapid infrastructural changes. For addressing such situation, this study has demonstrated that firms need to adopt big data analytics tools for transforming large volume of data into knowledge in such a dynamic market scenario which will be helpful for making proper prediction and effective decision-making process for articulating proper strategy. Such concept is also supported by Voort et al. (2021).

6.1. Theoretical contributions

This study has demonstrated that adoption of big data analytics tools in a firm can eventually enhance the overall performance of the firms provided some intermediate contextual factors could be improved. These intermediate contextual factors are forecasting and decision-making process as well as the firms' operational and financial performance. No other studies have extensively investigated the nexus between adoption of big data analytics tools in a firm and its relationship with overall firms' performance with consideration of the effects of these intermediate contextual factors. This is claimed as a unique theoretical contribution to this study. This present study has taken a novel attempt to synergize the effects of the literature derived from the three distinct fields of study which are information system management, strategic management, as well as operational management. It is a fact that earlier studies of Chen et al. (2015) and Dubey et al. (2019) took holistic attempts to fill up the literature gap by integrating information system management and operational management using an approach by theorizing the integration of DCV and information processing theory (Wamba et al., 2019). This study has extended the concept of these earlier studies by integrating the three areas of research such as information system management, strategic management, and operational management and developed a holistic theoretical model. This study has taken help of DCV (Teece et al., 1997) and RBV (Barney, 1991) and highlighted the idea of RBV by arguing that having in-house VRIN resources of a firm can bring in success in gaining competitiveness as such in-house resources could bring better efficiency. But it is not sufficient for a firm to achieve success in the dynamic volatile marketplace. In such high velocity market, a firm must have possessed the dynamic capabilities to sense and seize the external resources and can reconfigure itself to avail the external opportunities with the help of existing in-house resources of the firms to gain competitive advantages. This idea is supported by RBV and DCV (Barney, 1991; Teece, 2012). The present study has also theorized that dynamic capabilities can help the firms for

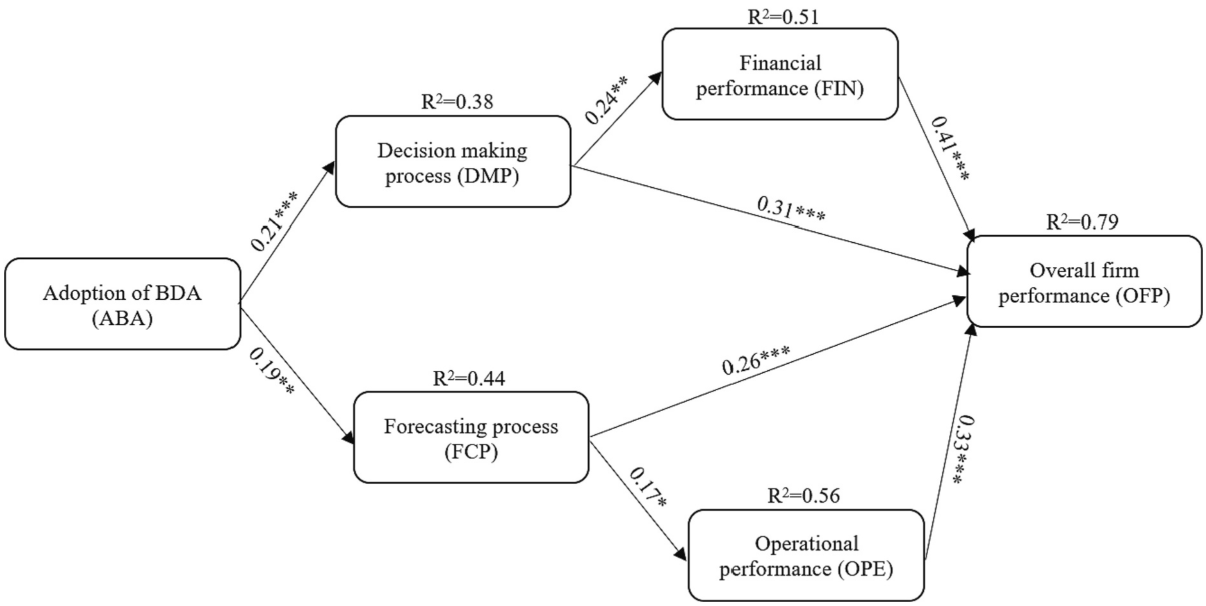

Fig. 2. Validated model.

shaping and reorienting the available resources in a dynamic market, so that it could create values for the firms (Katkalo et al., 2010). The present study has conceptualized that BDA capability of a firm possesses three sub capabilities like sensing, seizing, and reconfiguring abilities and in this light, this study could reflect that it is possible by the effective use of robust BDA tools to enhance dynamic capabilities of a firm which will ensure agile financial performance and adaptable operational performance to achieve overall superior performance of the firms. This approach is claimed to be a novel approach to theorize DCV in the context of this study. A study of Hamdam et al. (2022) discussed and investigated how big data analytics tool adoption in a firm could help the firm for effective and proper decision-making process. The concept of this study has been extended in the present study to investigate how adoption of BDA tools helps a firm for effective decision making and in addition adopting such modern tools can improve the forecasting process which will eventually enhance the overall firm performance. This unique idea is claimed to have enriched the body of extant literature. Besides, as the research study shows that the proposed model has a high explanatory power and can be generalized, the proposed theoretical model can be applied during and after of any disaster situation like COVID-19 pandemic, natural calamities, and in any conflict situations. The proposed theoretical model is an extension of dynamic capability view (Teece et al., 1997) and highlights that there is no impact of firm size, type, and age on the overall performance of the firms in the certain conditions as described in the study. Thus, the theoretical model can be applied universally by different types of firms in any region in different circumstances which is another contribution of this research study.

6.2. Practical implications

The findings of this study provide several implications for the practitioners. The present study provides a useful guideline to the leaders and managers of the firms intending to adopt big data analytics tools in their firms. Before investing towards adoption of big data analytics tools, the leaders of the concerned firms need to evaluate carefully their decision making and forecasting competencies as to whether these abilities can accurately sense the rapid dynamic changes in the internal and external business environment. This might help the firms to avail the opportunities appropriately and at the same time can reduce the business risks. The leaders of the firms need to weigh properly whether the firms have gained appropriate efficiency to seize the sensed opportunities in a dynamic market environment. The leaders of the firms are scheduled to estimate the capability of the firms in the context of reconfiguring their both tangible and intangible assets for ensuring improvements of financial and operational performance of their firms. After being confident that the firms possess all the above-mentioned qualities, the leaders of the firms should be ready to adopt big data analytics tools for their firms and in this way the firms can achieve superior performance eventually. The leaders and managers must have appropriate foresight for deciding how as well as when the firms could explore as well as exploit such sensing, seizing, and reconfiguring abilities to achieve superior performance. This study has found that the rapid change of external business environment could erode the values of the available resources of the firms or even make them irrelevant strategically (Schilke, 2014). Hence, the leaders and the managers must ensure that the adoption of BDA tools can help the firms to remain ambidextrous as well as adaptable to address any rapid environmental changes by fast and accurate decision-making as well as forecasting to enhance their financial and operational performance. This study has shown that adoption of BDA tools in firms impacts decision making process and forecasting process which helps the firms to ensure superior firm performance. However, to improve better decision-making and forecasting process, employees of the firms must be conversant how to properly use big data analytics applications. For this, leaders and managers should arrange proper training programs for the employees which could help for extracting the best potential from the big data analytics applications.

6.3. Limitations and direction for future studies

This study has several limitations. First, the results of this study rely on the data which are found to be cross sectional. This brings the issue of causality between the relationships of the constructs which eventually creates endogeneity defect. Future researchers need to undertake longitudinal studies to avoid these defects. Second, the results of this study depend on the analysis of the data available from the respondents who are from India. For this, there is an external validity issue. To eliminate this shortcoming, future researchers need to collect data from the respondents spread across the world. The results so arrived at would have more generalizability. Third, in the present study, there has not been any discussion of rival or alternate model. This could be construed as a limitation of this study. By analyzing the rival or alternate model, it would have been possible to examine if the theoretical model is superior to the rival model or not. This could be ascertained through comparison of both the models. Future researchers should investigate this issue. Fourth, the study results depend on DCV. But it suffers from the menace of context insensitivity (Ling-Yee, 2007). DCV fails to identify the required conditions in which the big data analytics capability of the firms could have been most effective (Schilke, 2014). Hence, future researchers need to identify the optimal conditions in which the BDA enabled DCs could yield the best performance of the firms. Fifth, the explanatory power of the model is 79 %. Future researchers need to consider other antecedents and other moderators for verifying if by such inclusion, the explanatory power of the proposed model could be enhanced. Future researchers should attempt to investigate this issue. Sixth, the present study did not analyze a rival model. This could help to compare the rival model with the proposed theoretical model to examine if the proposed theoretical model is superior or not in comparison to the rival model. This deficiency of the present study is considered as a limitation of this study. This is left for future researchers to nurture.

7. Conclusion and policy implication

The present study has extensively explained the BDA enabled dynamic capabilities of the firms. This study has also highlighted how adoption of BDA could help to explore and exploit the decision-making as well as forecasting capabilities of the firms for achieving superior firm performance through the improvements of financial and operational performance of the firms. This suggests that the policymakers in the firms should emphasis to improve the dynamic capabilities of the firms along with improvements in the accuracy of forecasting and decision-making processes. This study has demonstrated that the size of firms, firm type, and firm age could not impact the overall firm performance. This implies that the proposed framework can be universally used by the leaders and policymakers of any type of firms regardless of the size and age of the firms. Thus, it can also be inferred that the proposed theoretical model can be generalized, and it has ubiquitous applicability. Policymakers can use this generic model to formulate different kinds of policies for the betterment of their firm performance. This study has been able to analyze how it is possible to identify market correlation among various market stimulus by different applications of BDA. Thus, policymakers and leaders of the firms can decide regarding the usage of different stimulus to spur the consumption of different products of the firms by the potential consumers. This study has shown how different applications of BDA help to analyze different types of consumers' data which in turn support accurate forecasting for the buying preferences of the consumers. Thus, policymakers can formulate different strategies based on consumer buying preferences and trends of the dynamic market. This study has been able to provide impactful insights as to how BDA could make augmented machine learning predictions for evaluating the extent of high stakes decisions which can support the policymakers and the leadership team of the firms in different decision-making processes.

CRediT authorship contribution statement

Sheshadri Chatterjee: Conceptualization, Methodology, Writing – original draft. **Ranjan Chaudhuri:** Project administration, Formal analysis, Writing – original draft. **Shivam Gupta:** Data curation, Investigation, Visualization. **Uthayasankar Sivarajah:** Supervision, Resources, Writing – review & editing. **Surajit Bag:** Data curation, Validation.

Data availability

Data will be made available on request.

Appendix A. Operationalization of constructs

Items	Source	Statements	Response [SD][D][N][A][SA]
ABA1	Chakravarty et al., 2013; Aydiner et al., 2019	Adoption of new technologies brings value to the firms.	[1][2][3][4][5]
ABA2	Akhtar et al., 2018; Wamba et al., 2019	I believe that efficient use of big data applications needs trained manpower.	[1][2][3][4][5]
ABA3	Huang et al., 2017	We have adequate leadership support to adopt new technology in our firm.	[1][2][3][4][5]
ABA4	Teece et al., 1997	I think that big data analytics capability of an organization is like dynamic capability.	[1][2][3][4][5]
ABA5	Gunasekaran et al., 2017	Successful adoption of big data analytics can enhance the efficiency of a firm.	[1][2][3][4][5]
DMP1	Aydiner et al., 2019	I believe that applications of big data analytics can help in accurate decision-making process.	[1][2][3][4][5]
DMP2	Chakravarty et al., 2013	Application of big data analytics can provide business insights in real time.	[1][2][3][4][5]
DMP3	Wamba et al., 2019	I believe that a quick and accurate decision can help a firm to improve its bottom-line.	[1][2][3][4][5]
DMP4	Akhtar et al., 2018; Wamba et al., 2019	We use big data analytics applications on a regular basis in the decision-making process in our firm.	[1][2][3][4][5]
DMP5	Gunasekaran et al., 2017	The use of big data applications for decision-making purposes does not need much technical expertise.	[1][2][3][4][5]
FCP1	Barney, 1991	I believe that the forecasting process is the key for any firm to allocate appropriate resources.	[1][2][3][4][5]
FCP2	Wamba et al., 2019	Most of the employees in our organizations use big data analytics tools for forecasting purposes.	[1][2][3][4][5]
FCP3	Gunasekaran et al., 2017	Application of big data analytics can provide accurate forecast numbers.	[1][2][3][4][5]
FCP4	Huang et al., 2017	I believe that accurate forecast numbers can help with better decision-making processes.	[1][2][3][4][5]
FCP5	Gunasekaran et al., 2017; Aydiner et al., 2019	Accurate forecasting can provide competitive advantages.	[1][2][3][4][5]
FIN1	Srinivasan and Swink, 2018	I think that successful applications of big data analytics can generate more revenue for the firms.	[1][2][3][4][5]
FIN2	Gligor et al., 2015	The applications for big data analytics are not very expensive.	[1][2][3][4][5]
FIN3	Gunasekaran et al., 2017	I believe that improvement of financial performance of a firm can help to achieve the business goals of the firm.	[1][2][3][4][5]
FIN4	Dubey et al., 2017	Adopting big data analytics tools can help to reduce manual efforts thereby reducing human errors.	[1][2][3][4][5]
OPE1	Srinivasan and Swink, 2018	I think that improvement of operational efficiency of a firm can enhance its overall performance.	[1][2][3][4][5]
OPE2	Gligor et al., 2015	I believe that applications of big data analytics can improve the supply chain efficiency of the firms.	[1][2][3][4][5]
OPE3	Dubey et al., 2017	I believe that real time accurate decision-making processes can reduce the waste in the system.	[1][2][3][4][5]
OPE4	Srinivasan and Swink, 2018	Successful adoption of big data analytics tools can help to improve the sustainability performance of the firms.	[1][2][3][4][5]
OFP1	Dubey et al., 2017	I believe that successful adoption of big data analytics tools increases revenue collection.	[1][2][3][4][5]

(continued on next page)

(*continued*)

Items	Source	Statements	Response [SD][D][N][A][SA]
OFP2	Gunasekaran et al., 2017	I believe that firms should have an adequate budget to deploy big data analytics tools across different departments of the firms.	[1][2][3][4][5]
OFP3	Dubey et al., 2019	I think that adoption of big data analytics tools can enhance the competitiveness of a firm.	[1][2][3][4][5]

Note: SD = Strongly Disagree; D = Disagree; N = Neither disagree nor agree; A = Agree; SA = Strongly Agree.

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Sheshadri Chatterjee is a Post-Doctoral research scholar at Indian Institute of Technology Kharagpur, India. He has completed PhD from Indian Institute of Technology Delhi, India. He is having work experience in different multinational organizations such as Microsoft Corporation, Hewlett Packard Company, IBM and so on. Sheshadri has published research articles in several reputed journals such as Government Information Quarterly, Information Technology & People, Journal of Digital Policy, Regulation and Governance and so on. Sheshadri is also a certified project management professional, PMP from Project Management Institute (PMI), USA and completed PRINCE2, OGC, UK and ITIL v3 UK.

Ranjan Chaudhuri is a Professor in marketing at Léonard de Vinci Pôle Universitaire, France. He has previously worked at Indian Institute of Management Ranchi (IIM Ranchi), India; Indian Institute of Management Mumbai (IIM Mumbai), India; Vinod Gupta School of Management, Indian Institute of Technology, Kharagpur, India; and at the Department of Management Studies, Indian Institute of Technology Delhi, India. He was a Fulbright Fellow to USA in 2012. He has over twenty two years of industrial, teaching and research experience. His teaching and research interests are in the areas of Business-to-Business Marketing, Global Marketing and Retail Management.

Shivam Gupta is a Professor at NEOMA Business School, France with a demonstrated history of working in the higher educ0ation industry. Skilled in Statistics, Cloud Computing, Big Data Analytics, Artificial Intelligence and Sustainability. Strong education professional with a Doctor of Philosophy (PhD) focused in Cloud Computing and Operations Management from Indian Institute of Technology (IIT) Kanpur. Followed by PhD, postdoctoral research was pursued at Freie Universität Berlin and SUSTech, China. He has completed HDR from University of Montpellier, France.

Uthayasankar Sivarajah is a Professor of Technology Management and Circular Economy and the Dean of the School of Management at the University of Bradford, UK. He enjoys interdisciplinarity research and teaching focusing on the use of emerging digital technology by businesses and organizations for the betterment of society. He is the Deputy Editor of the Journal of Enterprise Information Management and has published over 70 scientific articles in leading peer-reviewed journals and conferences.

Surajit Bag is an Associate Professor at the Léonard de Vinci Pôle Universitaire, France. He holds two Ph.D.'s in Logistics and Supply Chain Management from the University of Johannesburg, South Africa, and the University of Petroleum & Energy Studies, India. He has more than eleven years of industry experience. His areas of research interest are industrial supply chain automation, industry 4.0, buyer-supplier relationship, supply chain process optimization, and business excellence.