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A study on big data analytics and innovation: From technological and business cycle perspectives

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ABSTRACT

In today's rapidly changing business landscape, organizations increasingly invest in different technologies to enhance their innovation capabilities. Among the technological investment, a notable development is the applications of big data analytics (BDA), which plays a pivotal role in supporting firms' decision-making processes. Big data technologies are important factors that could help both exploratory and exploitative innovation, which could affect the efforts to combat climate change and ease the shift to green energy. However, studies that comprehensively examine BDA's impact on innovation capability and technological cycle remain scarce. This study therefore investigates the impact of BDA on innovation capability, technological cycle, and firm performance. It develops a conceptual model, validated using CB-SEM, through responses from 356 firms. It is found that both innovation capability and firm performance are significantly influenced by big data technology. This study highlights that BDA helps to address the pressing challenges of climate change mitigation and the transition to cleaner and more sustainable energy sources. However, our results are based on managerial perceptions in a single country. To enhance generalizability, future studies could employ a more objective approach and explore different contexts. Multidimensional constructs, moderating factors, and rival models could also be considered in future studies.

1. Introduction

Data-driven technologies serve a fundamental and crucial purpose, which is to proactively identify innovation opportunities and integrate them into strategic plans for next-generation technologies (Kim and Geum, 2021). In this context, the efficacy of an organization's Big Data Analytics (BDA) capabilities emerges as a critical factor, directly impacting the organization's adaptability and capacity for ambidexterity, thus influencing the overall performance (Rialti et al., 2019). This link between BDA and performance is particularly pronounced in highly innovation-oriented firms, which often exhibit a strong commitment to monitoring and responding to market changes, including the adoption of BDA (Dobni et al., 2022). Notably, BDA adoption is widespread across all companies, regardless of their innovation focus as emphasized by Wilson et al. (2023).

Organizations today effectively harness data from digital platforms, using modern BDA to derive novel and innovative insights (Mariani and Nambisan, 2021). However, this process goes beyond technology adoption; it requires a nuanced understanding of organizational ambidexterity. Scholars argue that comprehending and effectively managing organizational ambidexterity is crucial, as it can either propel or hinder firm performance (Yu et al., 2018). This ambidextrous approach involves balancing both explorative innovation (EXI) and exploitative innovation (EPI) activities, which can be facilitated by dynamic capabilities.

Dynamic capabilities, characterized by a higher degree of organizational ambidexterity, positively influence a firm's overall performance (O'Reilly and Tushman, 2008). This adaptability and flexibility enable firms to navigate both EXI and EPI adeptly, achieving ambidexterity (Andriopoulos and Lewis, 2009). Furthermore, the utilization of BDA is positively correlated with achieving an effective balance between EXI and EPI activities, ultimately resulting in enhanced firm performance (FIP) (Božič and Dimovski, 2019; Rialti et al., 2019). This synergy between BDA and innovation underscores the significance of BDA in the

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contemporary business landscape. In summary, data-driven technologies, including BDA, play a pivotal role in identifying innovation opportunities, fostering ambidexterity, and driving firm performance. The commitment to BDA adoption is not limited by innovation orientation, making it a common practice across diverse companies. Effective utilization of BDA in conjunction with dynamic capabilities is instrumental in achieving the delicate balance between EXI and EPI, ultimately contributing to improved firm performance.

The above discussion highlights the connection between BDA, both in terms of EXI and EPI, and firm performance. However, current studies are limited in fully realizing the technological cycle and understanding how performance of firms could affect the extent of use of big data analytics. Further, there is a need to explore how the use of big data analytics technology in firms could impact the explorative and exploitative innovations that ultimately shape firm performance. Hence, the primary objective of this study is to comprehensively explore the technological cycle. This study aims to assess the impact of BDA on innovation capabilities, as measured through organizational ambidexterity, and firm performance, as well as scrutinize how firm performance itself impacts BDA. This study therefore endeavours to address the following questions:

- What is the impact of BDA on both EXI and EPI?
- How does EXI and EPI influence firm performance?
- What is the reciprocal relationship between BDA and firm performance, and how do they mutually influence each other?

To address the above research questions, this study analysed the responses of 356 respondents from India. This study also developed a theoretical model which was subsequently validated by the covariance based structural equation modelling (CB-SEM) approach. To substantiate the empirical findings, the present study revealed how big data analytics could affect firm performance directly and how big data analytics could affect firm performance meditated through explorative and exploitative innovation capabilities of firms. This study adds to the literature by evidencing that applications of big data analytics in firms can improve their exploratory and exploitative innovation capabilities. These capabilities in turn could shape firm performance. Further, this study demonstrates that improvement of firm performance can help to assess the extent to which big data analytics tools need to be used in firms.

The paper is structured as follows: Section 2 provides the literature review; Section 3 establishes the conceptual framework and presents the hypothesis development; Section 4 details the research methodology; Section 5 presents the results and analyses; and Sections 6–8 conclude the paper, covering implications of the findings, limitations of the study, and recommendations for future research.

2. Literature review

The integration of BDA is recognized for significantly expediting decision-making processes, leading to improvements in both financial and operational performance, ultimately resulting in an enhanced overall firm performance (Chatterjee et al., 2023; Huynh et al., 2023). However, the impact of BDA on organizational performance extends beyond efficiency in decision-making (Calic and Ghasemaghaei, 2021; Xu et al., 2023). These capabilities also act as catalysts for innovation and for the promotion of environmental sustainability within the procurement processes of companies. Subsequently, these capabilities help to elevate the overall environmental performance of firms (Singh and El-Kassar, 2019; Al Nuaimi et al., 2021; Sheshadri, 2021; Siachou et al., 2022). Furthermore, BDA plays a crucial role in driving innovation efforts in energy transition, contributing to the global effort to combat climate change (Mavi and Mavi, 2021). Companies equipped with robust business analytics capabilities demonstrated heightened proficiency in orchestrating resources efficiently, enabling them to excel within the framework of a circular economy and ultimately enhancing their level of organizational performance (Kristoffersen et al., 2021; Thrassou et al., 2022; Vrontis et al., 2022).

Previous research on BDA has also examined how it could affect different aspects of firm performance, such as profitability, return on investment (ROI), and marketing performance, which relates to firms' capacity to attract and retain customers while increasing sales (e.g., Upadhyay and Kumar, 2020; Cadden et al., 2023; Zhou et al., 2023). Although there are signs that BDA and firm performance may be directly related, a better and more complete knowledge of the processes and situational factors that influence this relationship is needed especially from the innovation capability perspective (e.g., Yasmin et al., 2020; Jiang and Liu, 2022; Oesterreich et al., 2022b; Olabode et al., 2022). Moreover, research has predominantly neglected to consider the specific conditions under which BDA acts as enablers of firm performance, leading to limited advancement in knowledge regarding when these capabilities truly drive organizational success (Vitari and Raguseo, 2020; Galati et al., 2021; Chaudhuri et al., 2022a; Olabode et al., 2022; Khorana and Kizgin, 2022).

Furthermore, BDA has been found to contribute to a firm's ability to generate patents and cultivate new knowledge within the realm of intellectual property (Berg et al., 2019; Upadhyay and Kumar, 2020). This underscores the pivotal role of BDA in fostering innovation within organizations, facilitating enhancements to existing products or services, the introduction and development of new offerings, optimization of business processes, and continuous evolution of product or service marketing strategies (Soniewicki et al., 2022; Ranjan et al., 2022). While most prior studies have established the significant impact of both EXI and EPI on firm performance (Božič and Dimovski, 2019; Rialti et al., 2019), Radicic and Petković (2023) have challenged this notion. They found no substantial evidence to suggest that BDA has a positive impact on innovation in small and medium-sized enterprises across various firm size categories.

Given all these complexities and gaps in the existing literature, it is evident that prior research has shed light on the relationship between BDA, EXI, EPI, and firm performance. However, there remains a crucial gap concerning the complete technological cycle, particularly in understanding how a firm's performance contributes to the enhancement of its BDA. Consequently, the primary objective of our current study is to delve into this technological cycle. This study endeavours to assess not only the influence of BDA on innovation capabilities, measured through organizational ambidexterity, and firm performance, but also to investigate how firm performance itself affects the development and improvement of BDA. In essence, this study aims to provide a holistic perspective on the interplay between BDA and innovation capabilities, and firm performance. By doing so, it will shed light on the intricate relationship between these elements and will highlight how they collectively drive organizational success in the era of data-driven decision-making. Thus, in summary, previous studies have highlighted that the application of big data analytics can improve the innovative abilities and environmental sustainability of firms (Al Nuaimi et al., 2021; Mavi and Mavi, 2021). Studies have also demonstrated that integrating big data analytics applications into firms can improve the resource mobilization and strengthen processes associated with energy transition and the circular economy model (Kristoffersen et al., 2021). However, there is a scarcity of studies that examine how big data analytics may impact the exploratory and exploitative innovation capabilities of firms, which ultimately will contribute to the development of ambidextrous firms and influence overall firm performance. This study fills this gap in the extant literature through taking a holistic approach.

3. Conceptual framework and hypothesis development

3.1. Big data analytics (BDA) and explorative (EXI)–exploitative (EPI) innovations

The effective use of data analysis tools plays a pivotal role in fostering customer agility, which in turn, significantly influences the success of new product development endeavours (Tseng et al., 2022). Organizations that excel in new product development often prioritize EXI strategies when integrating BDA into their processes (Sheshadri, 2020a; Cheng and Shiu, 2023). Previous studies consistently show the significant impact of BDA on both EXI and EPI (Božič and Dimovski, 2019; Rialti et al., 2019; Ghasemaghaei and Calic, 2020). Therefore, it is postulated that BDA has a positive and substantial influence on both incremental and radical innovation capabilities (Mikalef et al., 2020; Vrontis et al., 2022). This highlights the multifaceted role of BDA in driving innovation across the spectrum, from incremental improvements to groundbreaking advancements. As such, we hypothesize as follows,

H1. Big data analytics (BDA) has a positive impact on Explorative Innovations (EXI).

H2. Big data analytics (BDA) has a positive impact on Exploitative Innovations (EPI).

3.2. Explorative (EXI)-exploitative (EPI) innovations and firm performance (FIP)

Companies that adeptly harness the full potential of their implemented technologies to foster both radical and service innovations position themselves for a significant competitive advantage (Blichfeldt and Faullant, 2021; Chaudhuri et al., 2022b). This multifaceted approach to innovation enables organizations to differentiate themselves and adapt effectively to changing market dynamics. Building on these observations, Mikalef et al. (2019) argue that in environments characterized by significant environmental diversity, the influence of BDA on dynamic capabilities is magnified. Consequently, this positively affects incremental innovation capabilities. Conversely, in highly dynamic environments, the impact of dynamic capabilities on incremental innovation capabilities becomes even more pronounced. This underscores the adaptability of organizations in varying environmental contexts. Companies' performance can be explained and measured by different indicators, such as growth, profitability, market value, customer satisfaction, return on investment, and others. In brief, organizational performance can be explained as how well firms can use their resources to achieve their goals timely and efficiently (Harmancioglu et al., 2020).

Furthermore, studies by Božič and Dimovski (2019) and Rialti et al. (2019) have established that both explorative innovation (EXI) and exploitative (EPI)[1] significantly influence organizational agility and firm performance, particularly in larger organizations. These findings reinforce the idea that both types of innovation are vital for enhancing firm performance by improving overall efficiency, turnover, and the competency to successfully achieve the objectives of firms (Harmancioglu et al., 2020; Ranjan et al., 2023). Thus, we proposed the following,

H3. Explorative innovations (EXI) have a positive impact on firm performance (FIP).

H4. Exploitative innovations (EPI) have a positive impact on firm performance (FIP).

3.3. Big data analytics (BDA) and firm performance (FIP)

The significance of BDA in enhancing business and firm performance enjoys widespread recognition within the scholarly community (e.g., Akter et al., 2016; Gunasekaran et al., 2017; Božič and Dimovski, 2019; Ferraris et al., 2019; Rialti et al., 2019; Gupta et al., 2020; Kamble and Gunasekaran, 2020; Yasmin et al., 2020; Oesterreich et al., 2022a, 2022b). By harnessing insights extracted from BDA, organizations empower themselves to uncover new opportunities and leverage them to their advantage (Rialti et al., 2019). Furthermore, the capabilities in BDA have the potential to impact not only the operational but also the financial efficiency of firms, resulting in a broader and more profound influence on their overall performance (Wamba et al., 2017; Sheshadri, 2020b; Upadhyay and Kumar, 2020; Siachou et al., 2022). This underscores the transformative potential of BDA across various facets of organizational performance.

In addition, investments made in BDA assets have exhibited a positive correlation with enhanced firm performance, with particularly robust outcomes witnessed in specific industries (Müller et al., 2018; Koohang et al., 2023). This suggests that organizations that strategically allocating resources to bolster their capabilities in BDA are positioned to achieve tangible improvements in their overall performance, which can translate into a competitive advantage. Therefore, we propose the following,

H5. Big data analytics (BDA) capabilities have a positive impact on firm performance (FIP).

H6. Firm performance (FIP) has a positive impact on investment in developing Big Data Analytics (BDA) capabilities.

With all these inputs, a theoretical framework is proposed conceptually which is shown in Fig. 1.

Fig. 1 demonstrates that big data analytics (BDA) impacts firm performance directly (H5) and it impacts the firm performance through exploratory innovation (EXI) (H1, H3) and exploitative innovation (EPI) (H2, H4). The figure also proposes that firm performance could have an impact on the development of big data analytics capabilities (H6).

4. Research methodology

4.1. Data collection and sample size

Data for this study was collected using a cross-sectional offline survey method. The survey targeted industry experts, particularly managers (Leite et al., 2016), in Pune, India, which is a significant hub for both manufacturing and IT services in the country (Patil, 2021). Before conducting the survey, the questionnaire was first presented to and discussed with experts (Raj et al., 2020), and the preliminary version of the questionnaire was tested on a random selection of industry professionals (Trivedi, 2016). The questionnaire was administered in simple Indian English to ensure that participants could easily understand it (Trivedi and Sama, 2020; Kumari et al., 2020).

In the context of Covariance-Based Structural Equation Modelling (CB-SEM), the data must meet the minimal sample size criteria (Lin et al., 2020). Hair et al. (1999) recommended a minimum 5 observations per independent variable examined, with a desired number in the range of 15–20 observations. This research comprises three independent variables, namely, Big Data Analytics (BDA), Exploratory Innovation (EXI), and Exploitative innovation (EPI). The dependent variable is Firm Performance (FIP). Therefore, the required sample size is 80, calculated as 20 observations per variable (3 of them) plus 20 for robustness, as suggested by Trivedi (2016). Out of the 600 questionnaires distributed, 358 were returned. Two respondents were found to have consistently

[1] Explorative innovation seeks to take advantage of existing skills and knowledge so that the organizations could develop new products and services to effectively embrace dynamic market needs. Exploitative innovation is developed on the existing skills and processes of the organizations. It has incremental characteristics and focuses the needs of the existing customers leading to ensure incremental product changes. See He and Wong (2004), Andriopoulos and Lewis (2009) and Hou et al. (2019) for further detailed explanations.

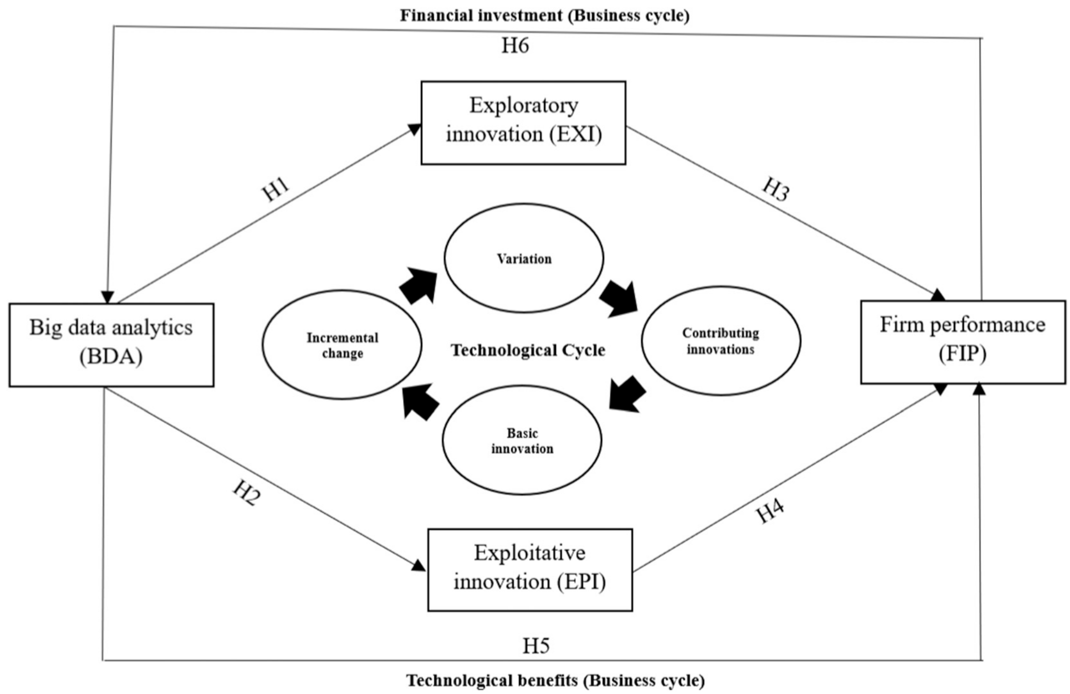

Fig. 1. Conceptual framework.

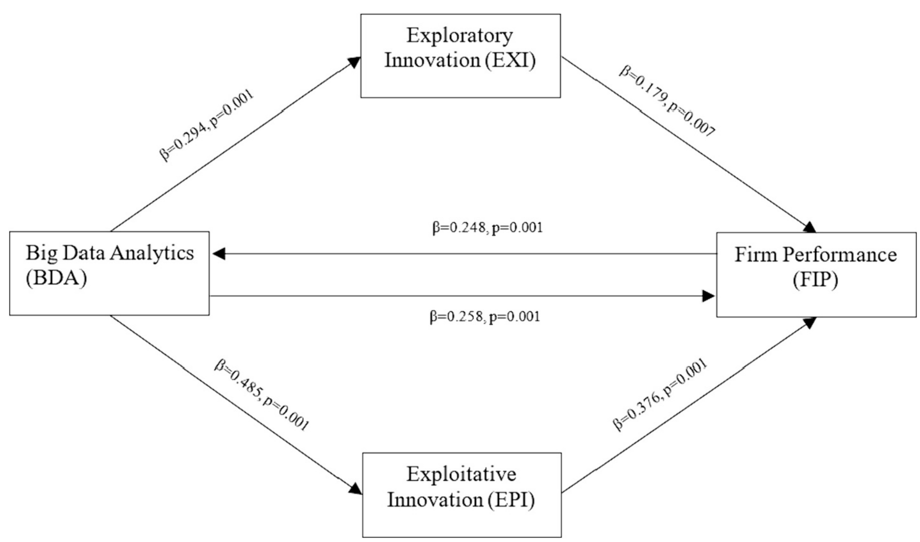

Fig. 2. Structural model.

selected the same response option for all questions, and thus were excluded to avoid introducing noise to the data. After excluding these two questionnaires, 356 responses remained for final analysis, surpassing the recommendation of Hair et al. (1999). We employed purposive sampling method for the distribution of questionnaires to industry professionals in line with previous studies (e.g., Apostolopoulos and Liargovas, 2016; Campbell et al., 2020; Denieffe, 2020).

4.2. Measures

To evaluate the proposed framework, we employed eighteen items related to four constructs. These constructs were adapted from established research with necessary modifications to align them with the Indian context. The measurement items for BDA were adopted from Chatterjee et al. (2023), while those for EXI and EPI were adapted from Ngo et al. (2019), He and Wong (2004) and Jansen et al. (2006). For dependent variable, firm performance, we adopted the items from Chatterjee et al. (2023), Li and Atuahene-Gima (2001), and Ngo et al. (2019). We employed a five-point Likert scale for these measures (as shown in Table 1), where a rating of "1" represented "strongly disagree," and "5" signified "strongly agree." A 5-point Likert scale was used (see e.g., Dawes, 2008; Aybek and Toraman, 2022) given its ease of use and its inclusion of a neutral midpoint allowing the respondents to take a neutral stand by selecting the 'Neither Disagree nor Agree (NDNA)' option. It is also considered to have a good balance between having enough response options to allow meaningful differences in the responses and avoiding excessive granularity that might lead to confusion or response fatigue. The use of this widespread 5-point Likert scale will also allow future research to compare their results and findings with this study.

Table 1
Construct items.

Construct	Item code	Item
Biga Data Analytics (BDA)	BDA1	Adopting new technologies brings value to the firms.
	BDA2	I believe that efficient use of big data applications needs trained manpower.
	BDA3	We have adequate leadership support to adopt new technologies in our firm.
	BDA4	I think that big data analytics capability of an organization is like dynamic capability.
	BDA5	Successful adoption of big data analytics enhances firm efficiency.
Exploratory Innovation (EXI)	EXI1	Introducing new generations of products
	EXI2	Opening up new markets
	EXI3	Entering new technology fields
Exploitative Innovation (EPI)	EPI1	Introducing improved but existing products and services for our local market.
	EPI2	Increasing economies of scales in existing markets.
	EPI3	Expanding services for existing clients.
Firm Performance (FIP)	FIP1	Return on sales
	FIP2	Profit growth
	FIP3	Return on assets
	FIP4	Sales growth
	FIP5	Market share growth
	FIP6	Cash flow from market operations
	FIP7	Customer satisfaction

Note(s): the constructs were taken on five points, where a rating of “1” represents “strongly disagree,” and “5” signifies “strongly agree”.

4.3. The non-response bias tests

Since the data were collected through survey, non-response bias is a potential concern. Following the recommendation of Armstrong and Overton (1977), we compared the first and last 100 responses concerning each item. We assumed that responses of the later 100 respondents were equivalent to non-respondents. Through *t*-test, we found no significant difference in the first and last 100 responses. Hence, non-response bias is considered not to be a major issue in the present study.

5. Results and analysis

In this study, we used structural equation modelling (SEM) to estimate the “maximum likelihood of the proposed model” (Hair et al., 2015; Collier, 2020), using Covariance-Based SEM (Shiau et al., 2019). The statistical software packages, SPSS v25 and AMOS v21, were used for the analysis (Garcia Martinez, 2017; Ramadani et al., 2022).

Our analysis involved conducting confirmatory factor analysis (CFA) along with SEM to test the hypotheses. Further, we explore the reciprocal relationship between two key constructs, i.e. BDA and firm performance, as recommended by Chen and Mau (2009), Khan et al. (2022), and Kock (2022, 2023).

5.1. Demographics

Table 2 provides a breakdown of the demographic characteristics of the 356 responding industry professionals. The majority fell within the age group of 35–45 years (50.28 %), followed by the 44–55 years age group (28.94 %). The remaining 20.78 %. represented various other age categories. In terms of gender distribution, vast majority of the respondents (91.85 %) were male, while 8.15 % were female. In educational background, 61.24 % held postgraduate degrees, and 38.76 % graduates. Work experience among the respondents was predominately within the range of 10–20 years’, comprising (48.59 %) of the sample. Those with >20 years of work experience accounted for 41.57 % of the respondents.

Table 2
Demographics.

Demographics	Categories	Frequency	Percent
Age	<35 years	23	6.46
	35–45 years	179	50.28
	45–55 years	103	28.94
	Above 55 years	51	14.32
Gender	Male	327	91.85
	Female	29	8.15
Work experience	<10 years	35	9.84
	10–20 years	173	48.59
	Above 20 years	148	41.57
Education	Graduate	138	38.76
	Post graduate and above	218	61.24

Note: sample size ($n = 356$).

5.2. Measurement model assessment

Using AMOS v21, confirmatory factor analysis was employed to evaluate the study constructs using the maximum likelihood method (Lavuri et al., 2023). The results of the measurement model are presented in Tables 2, 3, and 4.

The scale reliability was evaluated first. As demonstrated in Table 3, the values of Cronbach’s α and composite reliability were above the minimum cut-off value of 0.70, thus meeting the condition of internal and convergence consistency of the scale (Hair et al., 2015).

Next, we evaluated the validity of scale, considering both convergent and discriminant validity. Convergent validity was assessed using average variance extracted (AVE) of latent factors, meeting the recommended threshold by Hair et al. (2015). Factor loadings within the measurement model ranged between 0.643 and 0.862, surpassing the threshold value suggested by Kline (2015). The acceptable range of AVE and factor loading values confirm the convergent validity of the constructs. Thereafter, the discriminant validity was assessed using the master validity plugin (Gaskin and Lim, 2016). Discriminant validity test is essential to ensure the measures of the constructs are not highly related to each other. By comparing the square root of AVE values with off-diagonal values, as recommended by Fornell and Larcker (1981) and Hair et al. (2015), the results demonstrated the validity of the constructs, which are presented in Table 4.

Further, the model was tested for goodness of fit using CFA, as shown in Table 3. The overall fit indices show that chi-square/degrees of freedom is 1.62, which is <2.0. The goodness of fit (GFI), adjusted goodness of fit (AGFI) and normed fit index (NFI) all exceeded 0.9, with values of 0.93, 0.91 and 0.94, respectively. The values of both the root mean square residual (RMR) and the root mean square error of approximation (RMSEA) were 0.04, which is less than the recommended threshold of 0.05 for representing model fit (Chen and Mau, 2009; Dash and Paul, 2021; Osei-Frimpong and McLean, 2018).

5.3. Common method biasness

The results of this study are based on survey data. Hence, there is a possibility for common method bias (CMB) emerging from multifarious sources. These are due to consistency motif as well as implicit social desirability concerned with respondents responding to questions in a specific manner that causes the indicators for sharing some definite amount of common variation (Podsakoff et al., 2003, 2012). In our study, we adopted a procedural remedy to help avoid the impacts of CMB (Jajja et al., 2018; Kock et al., 2021), where the respondents were assured that their identities will not be disclosed so that they can respond in an unbiased manner (Chang et al., 2010).

We also performed statistical tests to estimate the severity of CMB. We first conducted Harman’s single factor test (SFT) using SPSS v25. We found that CMB was not a major concern since the first factor accounted for 39.18 % of the variance, which is below the 50 % threshold (Kumar

Table 3
Reliability and validity of the constructs.

Construct	Item code	Factor loadings	Cronbach's alpha (α)	Composite reliability (CR)	Average variance extracted (AVE)
Biga Data Analytics (BDA)	BDA1	0.643	0.854	0.855	0.543
	BDA2	0.725			
	BDA3	0.780			
	BDA4	0.787			
	BDA5	0.740			
Exploratory innovation (EXI)	EXI1	0.769	0.861	0.862	0.675
	EXI2	0.842			
	EXI3	0.852			
Exploitative Innovation (EPI)	EPI1	0.693	0.822	0.832	0.625
	EPI2	0.862			
	EPI3	0.807			
Firm Performance (FIP)	FIP1	0.804	0.928	0.928	0.650
	FIP2	0.842			
	FIP3	0.821			
	FIP4	0.781			
	FIP5	0.823			
	FIP6	0.843			
	FIP7	0.722			

Note(s): model fit summary-(Chi square/df 1.62, GFI 0.93, AGFI 0.91, NFI 0.94, RMR 0.04, and RMSEA 0.04).

Table 4
Discriminant validity of the constructs.

Constructs	BDA	EXO	FIP	EPI
BDA	**0.737**			
EXO	0.299***	**0.822**		
FIP	0.436***	0.340***	**0.806**	
EPI	0.471***	0.393***	0.507***	**0.791**

Note(s): diagonal values in bold are square root of AVE and off-diagonal values are shared variance between constructs. *** represents *p*-value <0.001.

et al., 2023), and we did not find any general factor in the unrotated factor structure (Wamba et al., 2019). As argued by Ketokivi and Schroeder (2004), the Harman's SFT may not be a robust and conclusive test for CMB. We then performed the marker correlation ratio test following Lindell and Whitney (2001). We compared our research model with a revised model that introduced a marker variable. The marker variable has no theoretical relationship with the other constructs of our proposed model. It was found that the significance of the correlations did not change, suggesting that the marker variable does not have a substantial impact on the relationships between the constructs in our proposed model. These test results suggest that the impact of CMB is not significant in our study. Further, in line with the recommendation by Kraus et al. (2020), the values of VIF were calculated and were found to be all below 5, suggesting multicollinearity is not a concern (Chien et al., 2022).

5.4. Hypotheses testing

After validating the measurement model, structural equation model was tested for hypotheses using goodness-of-fit and path coefficients. The values of Chi square/df (1.77), GFI (0.93), AGFI (0.90), NFI (0.93), RMR (0.05), and RMSEA (0.04) were found to be statistically significant as recommended by Hair et al. (2015). We employed the bootstrap resampling of 2000 times at 95 % confidence interval, as described by Ahmed et al. (2022), and the results are presented in Table 5.

All six hypotheses H1-H6 are supported. The path coefficient results show that hypothesis H2 (path BDA → EPI) is highly significant ($\beta = 0.485$, $p < 0.001$), followed by hypothesis H4 (path EPI → FIP) ($\beta = 0.376$, $p < 0.001$). Hypotheses H1 (path BDA → EXI, $\beta = 0.294$, $p < 0.001$) and H3 (path EXI → FIP, $\beta = 0.179$, $p < 0.01$) were also found to be highly significant. Moreover, the results of reciprocal relationships in hypotheses H5 (path BDA → FIP, $\beta = 0.258$, $p < 0.01$) and H6 (path FIP → BDA, $\beta = 0.248$, $p < 0.01$) were also found to be highly significant, suggesting a positive reciprocal relationship between BDA and FIP.

Table 5
Hypotheses results for structural model.

Research hypothesis	Path	Standardised coefficients	t-Value	p-Value	Hypothesis supported
H1	BDA → EXI	0.294	5.099	0.001	Yes
H2	BDA → EPI	0.485	7.457	0.001	Yes
H3	EXI → FIP	0.179	2.701	0.007	Yes
H4	EPI → FIP	0.376	5.356	0.001	Yes
H5	BDA → FIP	0.258	3.551	0.001	Yes
H6	FIP → BDA	0.248	3.860	0.001	Yes

With these inputs, the following Fig. 2 is developed (SEQ).

Notably, BDA exerts a stronger influence on FIP compared to the influence of FIP on BDA.

6. Discussion and conclusion

This study explores the intricate dynamics between big data analytics (BDA), explorative innovations (EXI), exploitative innovations (EPI), and firm performance (FIP). A comprehensive model is constructed that delves into different layers of interrelationships, encompassing both sequential and reciprocal associations. The sequential links, including BDA's influence on EXI and EPI, EXI's influence on FIP, and EPI's influence on FIP, allowed us to dissect the nuanced pathways through which these elements impact FIP. Furthermore, the reciprocal relationship found between BDA and FIP revealed a dynamic feedback loop wherein it is not only BDA that influences FIP but is itself influenced by FIP. This insight sheds light on the intricate interplay between technology, innovation, and performance within organizations.

As the model in this study successfully validated, it solidifies the significance of external factors in shaping the internal endogenous variable of FIP. Notably, the revelation of the reciprocal connection between BDA and FIP is a groundbreaking contribution to the existing body of knowledge in this field. This innovative perspective underscores the evolving nature of the relationship between technology, innovation, and FIP, offering valuable insights.

This study highlights the pivotal role of BDA in driving innovation and, consequently, enhancing FIP, reaffirming a strong connection between BDA and innovation, encompassing both EXI and EPI. These findings are in line with prior research, including the work of Ghasemaghaei and Calic (2020), Ciampi et al. (2021) and Zheng et al. (2022), that emphasize BDA's role as a catalyst for innovation within organizations. Moreover, we extend this understanding by emphasizing the cascading effect of BDA on FIP. As revealed in the study, harnessing large volumes of raw data, as exemplified by Chatterjee et al. (2023), can lead to substantial improvements in overall FIP. This notion is reinforced by the research of e.g., Chatterjee (2020) and Sharma et al. (2021), who highlight the positive relationship between BDA and performance enhancement.

In contemporary organizational settings, BDA emerges as a necessity, as articulated by Chatterjee (2019). Its adoption becomes imperative for optimizing operations, refining forecasting, enhancing decision-making processes and addressing climate change and energy transition challenges. BDA empowers firms to continually seek performance improvement and navigate the complexities of a data-driven world. Thus, this study not only reaffirms the significance of BDA but also highlights its transformative potential in fostering innovation and driving firm performance to new heights. Furthermore, our study delves deeper into the dynamics of firm performance (FIP) by establishing EXI and EPI as critical antecedents of FIP. These findings resonate with prior research conducted by Li et al. (2008), Popadić and Černe (2016), Hou et al. (2019), and Ferreira et al. (2021), which collectively highlight the essential role that both explorative (EXI) and exploitative (EPI) innovations play in shaping firms' overall performance (FIP) and creating competitive advantage.

In addition to these significant findings, this study also explores the reciprocal relationship between FIP and BDA, shedding light on how FIP can significantly affect the adoption and utilization of BDA. This aligns with previous research by Barton and Court (2012) and Akter et al. (2016), who argue that superior firm performance in a big data-driven environment hinges on a unique and inimitable blend of resources. These resources encompass not only the effective management of BDA within an organization but also the establishment of robust Information Technology (IT) infrastructure and the cultivation of expertise in analytics. Hence, the present study provides a comprehensive view of the interconnectedness of BDA, innovation capabilities (both EXI and EPI), and firm performance, underscoring their interdependencies and the potential for creating sustainable competitive advantages in the rapidly evolving landscape of modern businesses.

7. Implications

7.1. Theoretical implications

This study evaluates the impact of BDA on innovation capabilities, as measured by organizational ambidexterity, and firm performance, while exploring how firm performance itself influences the enhancement of BDA. It demonstrates that BDA can directly improve firm performance, and partly through the two contextual intermediate factors of explorative and exploitative innovations. This study also demonstrates that improved firm performance enables increased investment in BDA capabilities, which, as far as we know, has not been simultaneously addressed in previous studies. According to Yasmin et al. (2020) and Olabode et al. (2022), a more thorough comprehension of the mechanisms and contextual factors that underpin the potential direct association between BDA and firm performance is required. Furthermore, Vitari and Raguseo (2020) and Olabode et al. (2022) pointed out that previous research has predominantly overlooked the specific circumstances in which BDA functions as facilitators of firm performance. Thus, this study adds value to the existing literature and fills these critical voids that remained in comprehending the full technological cycle, specifically in elucidating how a firm's performance contributes to the augmentation of its BDA.

Building on Ciampi et al. (2021) this study extends their concept by highlighting how BDA capability could both directly and mediating through explorative and exploitative innovations, affect firm performance. The present study also demonstrates how improvement of firm performance enhances successes of BDA utilization, contributing to the innovation literature.

7.2. Practical implications

The results of this study carry significant implications for industry practitioners. Leaders and managers should consider adopting BDA tools not only for improving firm performance but also for climate change mitigation and energy transition facilitation. BDA can generate substantial value for organizations, provided organizations invest in a skilled workforce. The successful integration of BDA and elevation of a company's BDA capabilities can enhance overall firm performance across multiple dimensions, leading to e.g., expanded services, increased profitability, substantial sales growth, a larger market share, augmented cash flow from market operations, and heightened levels of customer satisfaction. Organizations should invest in BDA with the expectation of such investments will result in improved performance.

Enhancing BDA capabilities has the potential to profoundly impact organizational ambidexterity across various strategic dimensions. This enhancement can take the shape of introducing novel product generations, expanding into untapped markets, venturing into emerging technology domains, refining and optimizing existing local product and service offerings, achieving greater economies of scale within current markets, and addressing climate change and energy transition challenges. In essence, improved BDA empower organizations to pursue a diverse set of strategies, fostering ambidexterity and enabling them to thrive in the ever-evolving business landscape. Having said the above, before investing in developing BDAs in organizations, leaders of organizations should consider multiple factors, including examining if the budget permits for such investment, whether the employees have adequate skills and expertise to appropriately use BDA tools so that they can extract best potentials from the new technology. This study also recommends that the employees should receive training to use BDA tools efficiently, ensuring effective and full utilization of BDA capabilities.

7.3. Policy implications

The present study encourages policymakers to consider introducing new policies and frameworks within organizations, recognizing the role of technology cycle in the business cycle and innovation capabilities of organizations. Policymakers should embrace and leverage BDA not only to foster innovations but also for the enhancement of overall organizational performance.

For example, the findings of this study may encourage companies to integrate BDA tools into their organizational processes and procedures through policy interventions. This could thereby promote a culture of data-driven decision-making across the company, leveraging insights from BDA to drive innovations in both process and product development. This scenario may unfold if policymakers are inclined to create policies supporting Research and Development (R&D) by allocating funds and resources to explore the use of BDA in innovation from both technological and business cycle perspectives.

Additionally, policymakers may need to incentivize the adoption of BDA, fostering a conducive environment for innovations. Long-term investment in BDA could be encouraged by establishing short-term and long-term assessment frameworks to evaluate the impact of BDA on improving innovation capability and enhancing firm performance.

The present study recommends that the policymakers develop trust in the use of BDA, while emphasizing the importance of individual privacy and the security of sensitive data. Consequently, comprehensive regulatory frameworks are needed to ensure that the utilization of BDA for innovation complies with ethical and legal standards.

Furthermore, policymakers would also need to work towards reducing barriers to BDA adoption, such as legacy systems and resistance to change. Introducing policies for skill development could equip the workforce with the necessary skills to effectively utilize the latest BDA tools and techniques, fostering a culture of lifelong learning.

8. Limitations and future research agenda

In this study, it is important to acknowledge that the assessment of managerial perceptions regarding BDA, EXI, EPI, and FIP could introduce biases into the findings. In future studies, a more objective approach might involve replacing these subjective variables with actual financial outcomes as a means of evaluating firm performance. It is also crucial to recognize that BDA, EXI, EPI, and FIP are multifaceted concepts. For instance, BDA encompass aspects such as big data management, technology proficiency, and talent utilization. EXI and EPI can be measured across various dimensions, including product development, process improvement, and market exploration. Likewise, firm performance can be evaluated through different lenses, such as operational efficiency, market competitiveness, and financial metrics. Future research should consider these multidimensional constructs to gain a more comprehensive understanding of the relationships at play. Additionally, the framework proposed in this study does not consider the impact of any moderator such as leadership support and technological turbulence. Consideration of such moderators might have impacted the predictive power of the proposed theoretical model. Future research could take the impact of moderating factors into consideration.

Furthermore, this study was conducted in the Indian context, and future studies should explore different contexts and countries to enhance the generalizability of the findings. Comparing various industry types and economies could provide valuable insights into the relationships between BDA, EXI, EPI, and FIP. Another limitation of this study is we did not analyse an alternative or a rival model. Consideration of such alternative or rival model could have provided a scope for comparing with the proposed theoretical model and examine if the proposed theoretical model is superior in quality. Future research could take this aspect into consideration. Lastly, considering the growing importance of sustainability and environmental concerns, future research could examine the impact of BDA and innovation capabilities on environmental performance. This would make valuable contribution to the field of research in climate change and sustainability.

CRediT authorship contribution statement

Uthayasankar Sivarajah: Writing – original draft, Conceptualization. **Sachin Kumar:** Software, Methodology. **Vinod Kumar:** Writing – original draft, Data curation. **Sheshadri Chatterjee:** Supervision, Investigation. **Jing Li:** Writing – review & editing, Visualization, Validation.

Data availability

The authors do not have permission to share data.

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