Annals of Operations Research (2024) 333:601–626
https://doi.org/10.1007/s10479-020-03887-z

ORIGINAL RESEARCH

Does data-driven culture impact innovation and performance of a firm? An empirical examination

Sheshadri Chatterjee[1] · **Ranjan Chaudhuri**[2] · **Demetris Vrontis**[3]

Accepted: 19 November 2020 / Published online: 3 January 2021

Abstract
Data-driven culture is considered to bring business-oriented cultural transformation to a firm. It is considered to provide substantial dividends to the firms' product and process innovations. Recently, several firms have been using different advanced technology-embedded business analytics (BA) tools to improve their business performance. Again, advancement of information and communication technology has helped firms to explore the option to use BA tools with artificial intelligence. This has brought radical change in the business-oriented cultural landscape of the firms to arrive at accurate decision-making to improve their innovation and performance. In this perspective, the aim of this study is to show how a firm's data-driven culture impacts its product and process innovation, which in turn improves its performance and provides better competitive advantage in the current business environment. With the help of background study, a resource-based view model and different theories, a conceptual model has been developed. The conceptual model has been validated with 456 usable responses from the employees of different firms using different business analytics tools. The study highlights that data-driven culture highly influences both product and process innovation, making the firm more competitive in the industry. In this study, leadership support and data-driven culture have been taken as moderators, whereas firm size, firm age and industry type have been taken as control variables.

Keywords Data-driven culture · Data driven innovation · Competitive advantage · Firm performance · Product innovation · Process innovation

✉ Sheshadri Chatterjee
sheshadri.academic@gmail.com

Ranjan Chaudhuri
ranjan@nitie.ac.in

Demetris Vrontis
vrontis.d@unic.ac.cy

1 Department of Computer Science and Engineering, Indian Institute of Technology Kharagpur, Kharagpur, West Bengal, India

2 Department of Marketing, National Institute of Industrial Engineering (NITIE), Mumbai, India

3 School of Business, Faculty and Research and Professor of Strategic Management, University of Nicosia, Nicosia, Cyprus

1 Introduction

In the business scenario, customer demand is changing rapidly, and technological advancements are keeping pace. In this evolving business scenario, firms need to adapt their innovation strategy to respond to the customers. In this perspective, information and communication technology (ICT) is advancing to combine the effects of customers' data and business analytics (BA) to provide effective inputs to firms (Akter and Wamba 2016). These inputs could help firms to change their activities to include innovating products and processes. The secret of a firm's success lies in how it can scientifically analyze customer data. Huge volume of customer data helps a digitized firm to improve its data driven innovation. Thus, it is necessary for firms to collect data of various nature to analyze towards improving performance. Hence, firms must have appropriate abilities to absorb congenial data from their existing ecosystems and other sources. This needs to improve their data-absorbing capacity, which is in consonance with the concept of absorptive capacity theory (Cohen and Levinthal 1990; Zahra and George 2002). This theory highlights that acquisition of information, its assimilation, synthetization, and exploration would help firms towards improving process and product innovation. The digital firms are those which establish their core business activities with the help of digital networks supported by digital technologies. By enhancing its innovation capabilities, a firm can introduce new products according to customer demand, and it can also improve the quality of the existing products (Ransbotham and Kiron 2017).

In digital firms, data-driven innovation is considered an effective driver of transformational opportunities towards product development (Delen and Demirkan 2013; Davenport and Kudyba 2016). The data-driven culture is associated with the concept of values, beliefs, and assumptions, which guide a firm in the way it should proceed to be successful. Data-driven culture acts as an effective driver to help a firm to best utilize product development opportunities (Duan et al. 2018). The data-driven innovative capabilities have been enhanced by the applications of advanced information and communication technology (ICT), strong analytic capabilities, effective data management and governance mechanisms (Ransbotham and Kiron 2017; Wang et al. 2018). With the help of a data-driven culture, many tech giants have achieved better competitive advantages. The data-driven innovation approach has enhanced the business value of firms, as is evidenced from the benefits derived by Capital One and Amazon, which use the data-driven innovation concept (Hindle and Vidgen 2018; Kunc and O'Brien 2019; Akter et al. 2019). Innovation improves the performance of a firm, provided there is effective leadership support (Morgan 2012). Besides, analysis of customer data by BA solutions helps a firm to respond to the needs of customers. But these data need to be acquired properly, and it is an effective activity of a firm. These data help the firm to define their problems. This acquisition of valuable, inimitable, rare, and nan-substitutable data from internal and external resources is a firm's ability to scan its online ecosystem (Lau et al. 2012). A firm's innovation, productivity, and value can be improved by applying BA (Akter et al. 2019). The firms that analyze data through different means by using advanced ICT are perceived to have accelerated the value, productivity, and innovation. But the extant research in this context is still found to be in a rudimentary stage with minimum progress in this emerging field (Loukis et al. 2019). In such scenario, this article has taken a holistic attempt to analyze how the contribution towards innovation, new product and service development, business model, and performance of firms can be improved by the applications of the data-driven cultural approach. In this background, the aim of this study is to fill the research gap by addressing the following research questions (RQs).

RQ1: Does data-driven culture impact innovation and performance of a firm?

RQ2: What is the moderating role of a firm's leadership support on the linkages of product and process innovation with firm performance?

The other parts of this article are arranged as follows. The next section discusses the literature reviewed for the study. Then, the theoretical background is discussed followed by our formulation of hypotheses and development of a conceptual model. The hypotheses and the model were tested statistically, and the results of the analysis are presented. We then discuss the theoretical contributions and practical implications of this study, and finally, conclude our article and discuss the limitations of our research as well as the directions future researchers could take.

2 Literature review

The concept of BA has been explained in various ways. However, no commonly accepted definition of BA is available. In the context of this study, BA may be interpreted as "the extensive use of data, statistical and quantitative analysis, explanatory and predictive models and fact-based management to drive decisions and actions" (Davenport and Harris 2007, p. 7). Studies have revealed that BA is conceptualized as an evidence-based and data-driven approach (Mortenson et al. 2015). Data-driven culture is considered consistent with the principal of decision-making in the context of patterns of beliefs, behaviors, and practices of a firm (Holsapple et al. 2014). Data-driven culture is referred to as "a pattern of behavior and practices by a group of people who share a belief that having, understanding and using certain kinds of data and information plays a crucial role in the success of their organizations" (Kiron et al. 2013, p. 18). This definition is in conformity with the organizational culture. Data-driven culture has been analyzed by many researchers, who conceptualized this culture as fact-based and data-oriented (Abbasi et al. 2016; Wedel and Kannan 2016). Studies have revealed that, to gain competitive advantage by leveraging BA, a firm needs to improve its data-driven cultural activity. This activity could help the firm to improve performance by taking accurate decisions depending on data-based insights (Kiron et al. 2012; Vidgen et al. 2017).

Studies transpired that a firm must respond to the needs of the external markets with the help of the firm's ecosystem scanning ability. This will help to improve the process and product innovation capabilities of a firm (Keller and Holland 1975). Researchers have agreed that information is considered a vital asset for a firm in developing its processes and innovating its products (Rehm and Goel 2015). Researchers opined that going beyond the technology, a firm's management must manage the available information for gaining competitive advantage (Porter and Millar 1985). This collection of accurate information from appropriate sources through the firm's ability to scan the ecosystem helps the firm improve its capability to innovate. This ultimately improves performance of the firm to gain competitive advantage (Najafi-Tavani et al. 2013). It is a fact that development of innovation ability improves the performance of a firm (Ferreira and Franco 2019; Arfaoui et al. 2019; Chatterjee et al. 2020). But to achieve best results, the firm's support from management plays a vital role in this context (McComb et al. 2008; Morgan 2012). Without top management support, a firm cannot improve its performance, as is evident from other studies (Boonstra 2013). Several studies have highlighted that leadership support is associated with the development of knowledge sharing activities among different firms (Raab et al. 2014; Han et al. 2016). Studies have shown that business analytics impact a firm's innovation, productivity, and value (Akter et al.

2019), but studies covering the contribution of BA in the perspective of data-driven culture for development of innovative ability remain unexplored (Loukis et al. 2019).

Different studies highlight how the ability of firms to accurately analyze data has helped to improve firm performance by devising appropriate business strategy (Abbasi et al. 2016; Davenport and Kudyba 2016). Data is needed to be accurately analyzed, and a study has highlighted how BA tools could analyze the data in the foodbank sector (Hindle and Vidgen 2018). Data-driven culture would smoothen the journey of different marketing organizations by turning managers into successful data-driven decision-makers (Carillo et al. 2019; Johnson et al. 2019). Different studies exist that have dealt with the contributions of business analytics to strategize the business process and also have studied the contributions of data science to business organizations (Kunc and O'Brien 2019; Medeiros et al. 2020).

All these studies emphasized the effectiveness of data-driven culture, but nurtured little about how such data-driven culture could impact innovative abilities including the firms' product and process innovation toward improving performance to make them competitive in the dynamic market. The following table highlights key analytics papers that focus on data-driven culture in different firms (Table 1).

3 Theoretical background and development of conceptual model

3.1 Theoretical background

To improve innovative capacity, a firm depends on accurate information being available. It can help to generate new idea, which helps a firm to create new products to satisfy customers' current demands (Rehm and Goel 2015). Information helps a firm to reduce uncertainty and to achieve innovative success (Van Riel et al. 2004). A firm can benefit by using business analytics solutions to assess big data and turn it into knowledge for innovation. The literature has not focused on where data is considered to predict innovation. However, in some studies, knowledge is considered to impact innovation (Pan and Li 2016), although these studies have not explained how knowledge can be developed for innovation. In this context, it is argued that appropriate use of information would improve competitive advantage. Thus, a firm needs to develop its absorptive capacity to extract appropriate data from different sources. This is in conformity with the concept of absorptive capacity theory (Cohen and Levinthal 1990; Zahra and George 2002). This theory posits that the ability to acquire information, assimilate it, and exploit it are the principal criteria to develop product and process innovation. This concept explains how a data-driven firm would impact innovation by acquiring information from different sources by applying BA to scan its environment (Cuellar and Gallivan 2006). Thus, information plays a decisive role, and is considered an important resource of a firm (Chebbi et al. 2017; Christofi et al. 2018; Chatterjee et al. 2019b). This idea is also supported by resource based view (RBV) (Barney 1991), whose core idea is that a firm that has the ability to use appropriate resources to improve its performance will achieve better competitive advantage (Makadok 2001). The appropriate resources are those data which are valuable, inimitable, rare, and non-substitutable (VIRN) (Appelbaum et al. 2017). Extraction of appropriate information brings success for innovation to gain competitive advantage. But merely acquiring data through BA and scanning the environment would not fully serve the purpose, because the firm must exhibit its reaction to the everchanging external marketing needs to achieve peak success. This has been endorsed by dynamic capability view (DCV) (Helfat

Table 1 Source(s) and research highlights

Source(s)	Research highlights
Davenport and Harris (2007)	The study discussed extensive use of data, statistical tools, quantitative analysis, as well as explanatory and predictive models for the fact-based management decision-making process in organizations
Kiron et al. (2013)	The paper discussed data-driven culture. It was referred to as a pattern of behavior and practices by a group of people. They believe that use of certain kinds of data and information plays a crucial role towards the success of the organizations
Holsapple et al. (2014)	It discussed data-driven culture and its consistency with the principle of decision-making process in the context of patterns of beliefs, behaviors, and practices of a firm
Rehm and Goel (2015)	The paper highlighted the importance of information in an organization which is also considered a vital asset for a firm in developing its processes and products
Mortenson et al. (2015)	The study discussed the importance of business analytics (BA) in the firms. It highlighted that BA helps to conceptualize for evidence-based and data-driven approach
Abbasi et al. (2016)	The paper described that data-driven culture in an organization is fact-based and it is data-oriented
Wedel and Kannan (2016)	The study highlighted that data-driven culture in the organization is more practical, fact-based and driven by analytics
Akter et al. (2016)	The research examined how to improve firm performance using big data analytics capability. The study also discussed the alignment between big data and related business strategy
Davenport and Kudyba (2016)	In this study, the authors designed and developed analytics-based data products useful for the organizations
Akter and Wamba (2016)	The study primarily discussed big data analytics in E-commerce. There was a systematic review done by the authors followed by setting up the research agenda for future researchers
Hindle and Vidgen (2018)	Here the authors developed a business analytics methodology with the help of a case study in the foodbank sector
Vidgen et al. (2017)	The study highlighted that data-driven activities could help firms to improve performance by taking accurate decisions depending on data-based insights
Duan et al. (2018)	The authors described the importance and impact of business analytics on innovation in the organizations
Johnson et al. (2019)	The research study described the marketing organization’s journey and highlighted how those organizations can become more data driven
Carillo et al. (2019)	The research highlighted how to turn managers into data-driven decision-makers. The study tried to measure attitudes towards business analytics of the employees of the organizations
Akter et al. (2019)	The study discussed analytics-based decision-making for the service sector. The authors did a qualitative study and proposed the agenda for the future researchers
Kunc and O’Brien (2019)	The study investigated the role of business analytics in supporting strategy processes related to opportunities with some limitations
Medeiros et al. (2020)	The study highlighted the benefits of data science for business. The study also discussed various challenges and opportunities the data science can provide to the organizations

and Peteraf 2009). This idea adds to absorptive capacity theory and RBV to improve a firm's innovative capacity to boost up its performance and achieve better competitive advantage.

3.2 Development of hypotheses and conceptual model

The literature review and theoretical discussion have provided some inputs to formulate hypotheses and develop a conceptual model. BA ultimately improves a firm's performance by developing product and process innovation, which are developed by the help of a firm's scanning ability in the context of data-driven culture. The firm's performance eventually ensures better competitive advantage.

3.2.1 Adoption of business analytics (ABA)

In the digital environment, business analytics (BA) has brought an effective solution for gaining business insights. A firm can gain better intelligent information from multifarious data, helping it to uncover unknown correlations and hidden patterns of different datasets. From this, a firm would gain competitive advantage over rival firms in the contemporary market (Dutta and Bose 2015). BA is conceptualized as set of assorted business and technological activities for collecting data (Sharda et al. 2016), as well as tools that can build a fact-based management system to process necessary information. It will help a firm to develop its innovative activities (Vidgen et al. 2017). BA solutions can accurately analyze different types of data (Battisti et al. 2019; Shams and Solima 2019). Hence, adopting BA is expected to help a firm to develop a data-driven culture (Christofi et al. 2019). With the combined effect of data and analytics, a firm can achieve higher product development abilities (Columbus 2014; Sun et al. 2017; Duan et al. 2018). Accurate analysis of appropriate data helps the firms to generate new ideas that are advantageous for creating a new product that may satisfy the current market demand (Rehm and Goel 2015). Thus, collecting appropriate information is essential (Van Riel et al. 2004) to improve the competitive advantage. The tricks to collecting relevant data beneficial to the firms are associated with the absorptive capacity of the firms, which is in consonance with the concept of absorptive capacity theory (Cohen and Levinthal 1990; Zahra and George 2002). The concept of this theory explains how a firm's data-driven approach impacts on innovation, through the acquisition of appropriate data from various sources for analysis with the help of BA in scanning the business environment (Cuellar and Gallivan 2006). BA can process and analyze the collected data, and through a firm's scanning ability, it is possible to extract the necessary data required for process and product innovation. The adoption of BA is expected to accelerate a firm's scanning ability as well as its data-driven cultural activities. With all these discussions, the following hypotheses are framed.

> **H1** The adoption of business analytics (ABA) by a firm will positively impact its data-driven culture (DDC).
> **H2** The adoption of business analytics (ABA) by a firm will positively impact the firm's ecosystem scanning (FES) ability.

3.2.2 Data-driven culture (DDC)

A huge volume of data is being generated and stored by using modern technologies like blockchain, artificial intelligence (AI), internet of things (IoT), cloud computing, and so on (Wang et al. 2018). Such a huge volume of data helps firms to develop their work methods and their capabilities to generate new ideas (Ransbotham and Kiron 2017). Many firms have been able to extract the best potential from the volume of data to eventually enhance their performance (Vidgen et al. 2017). A firm's culture includes a complex set of beliefs, values, assumptions, and symbols. These factors provide the ways through which a firm conducts its business (Barney 1986). A firm should ensure a specific data-driven culture among its stakeholders. This culture is supposed to help the firm's employees to be open to provide new ideas to management. It may help the firm to place a new product in the market (Watson 2014; Duan et al. 2018). Data-driven culture is perceived to encourage the firm to enhance its data scanning abilities. But merely acquiring data and scanning it will hardly help to extract the best potentials. Firms should appropriately react and respond to the rapid and ever-changing needs of the dynamic market for effectively improving the their ecosystem scanning ability. For this, the data-driven culture would help to influence process and product innovation, which is supplemented by dynamic capability view (DCV) (Helfat and Peteraf 2009). In the context of absorptive capacity theory of innovation, it may be argued that a data-driven culture may affect the scanning ability of the firm. This is conceptualized because this ability is associated with the firms' activities for extracting useful data from different sources. In terms of the above discussions, it is possible to derive the following hypotheses.

H3 Data-driven culture (DDC) of a firm positively impacts the firm's ecosystem scanning (FES) ability.
H4Data-driven culture (DDC) moderates the relationship between the firm's ecosystem scanning (FES) ability and process innovation (PRI) of a firm.
H5 Data-driven culture (DDC) moderates the relationship between firm ecosystem scanning (FES) ability and product innovation (POI) of a firm.

3.2.3 Firm ecosystem scanning (FES)

A firm collects a huge amount of data from its internal and external sources. The BA solution analyses these data, although not all of these data are necessary for developing process or product innovation (Bichler et al. 2017). For developing new products or enhancing the quality of existing products, only some data is needed for idea generation. The firm's ecosystem scanning ability helps it to extract those essential data for product innovation (Dahlander and Gann 2010; Duan et al. 2018). The scanning system of the firm can recognize the needs of the external markets. The system attempts to extract those essential data. These data might meet the needs of the firm to develop process and product innovative activities. The absorptive scanning ability of the firm helps the firm to establish a relation between analytics and innovation (Augusto and Coelho 2009; Hong et al. 2013). This is in consonance with the absorptive capacity theory, which posits that acquisition, assimilation, and exploitation of congenial data are considered as principal data-scanning activities for developing process and product innovation (Cuellar and Gallivan 2006). Firm ecosystem scanning ability is the firm's absorptive capacity for data, and is conceptualized by four dimensions: the acquisition, assimilation, transmission, and eventual exploitation of data (Zahra and George 2002). This scanning ability is perceived to improve the methods of the firm for achieving its target in an easier and cost-effective way. The scanned data would provide the firm with better inputs for generating new ideas. With all these inputs, it is possible to derive the following hypotheses.

H6 Firm ecosystem scanning (FES) ability positively impacts a firm's product innovation (POI).
H7 Firm ecosystem scanning (FES) ability positively impacts a firm's process innovation (PRI).

3.2.4 Product innovation (POI)

Idea generation is associated with the concept of innovation (Kiron and Shockley 2011). A firm's creative ability would help it generate ideas for new products that meet current market needs (Ramanathan et al. 2017). These innovative ideas for creating new products is expected to help the firm to improve its performance. It has been opined that "data savvy organizations are using analytics to innovate and increasingly to gain competitive advantage" (Kiron et al. 2012, p. 1). BA applied to big data would help improve innovation and a firm's performance (Stubbs 2014) provided the firms can absorb those data from different sources which are needed to address the ever-changing demands of the market in terms of the concept of DCV (Helfat and Peteraf 2009). However, the firm must realize the market environment to improve its capabilities in product innovation (Kim et al. 2013), which will improve its performance. With these inputs, the following hypothesis is developed.

H8 Product innovation (POI) of a firm positively impacts firm performance (FP).

3.2.5 Process innovation (PRI)

Adopting BA and accurately analyzing data helps a firm to respond to the changing external market situation (Cosic et al. 2015). A firm's BA solution and its scanning ability provides some effective inputs which it can use to restructure its work system in a consistent and convenient way (Larson and Chang 2016). Data-driven culture of a firm helps it to generate new ideas for the development of its strategic approach (Klatt et al. 2011). Studies reveal that there exists a close connection between BA and a firm's process innovation (Troilo et al. 2016). The firm can sail on towards its goal in a systematic, methodical, and cost-effective way by extracting the accurate and useful data. The data must be appropriate for the demand of the rapidly changing market, as envisaged in the DCV (Helfat and Peteraf 2009). Thus, in the context of data-driven culture, it is expected that the firm performance would be improved. Following these discussions, it is hypothesized as follows.

H9 The process innovation (PRI) of a firm positively impacts firm performance (FP).

3.2.6 Firm performance (FP) and competitive advantage (CMA)

In the context of data-driven culture, a digital firm can achieve success if it can use the full potential of its IT capabilities. The success of a firm depends on how the firm can acquire the valuable, inimitable, rare, and non-substitutable data. It is expected to influence firm performance to become competitive in the market. This idea has been supported by resource based view (RBV) theory (Barney 1991). The firm needs to analyze the available customer data using appropriate tools of a BA solution (Kim et al. 2012). The firm can achieve success if it can possess the best data scanning ability (Barton and Court 2012). The firm should ensure it develops new products to meet the current demands of the market (Lin 2007). The firm must optimize how it utilizes its resources (Chen and Hung 2014), which is also an idea that is supported by RBV. If these are achieved, the firm is then exhibiting better performance and it would enjoy competitive advantages over other firms in the contemporary markets. The competitive advantage concept signifies the extent to which a firm's performance is perceived to attain better benefits compared to others in similar conditions (Rogers 1983). These inputs lead us to formulate the following hypothesis.

H10 Firm performance (FP) positively impacts a firm's competitive advantage (CMA).

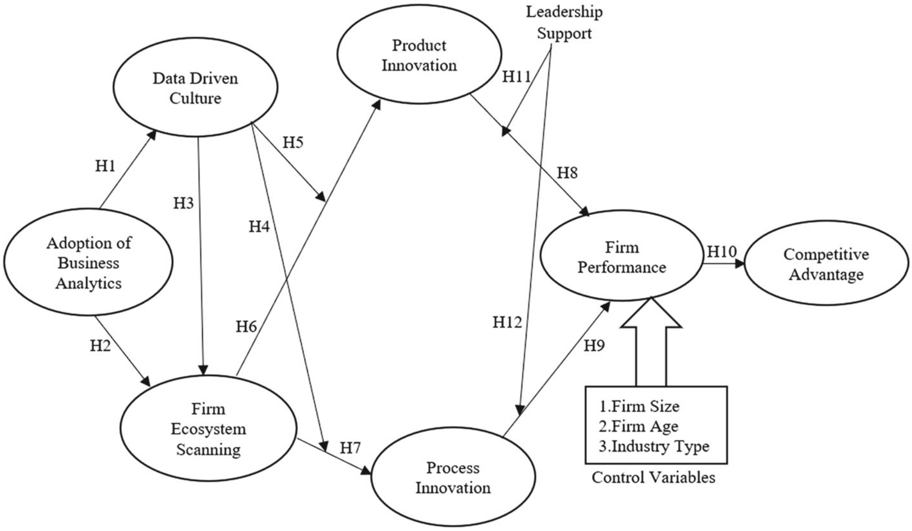


Fig. 1 The conceptual model

3.2.7 Moderating effects of leadership support (LS)

In the context of the role of leadership support in firm's performance and innovation, Dess and Picken (2000) observed that leadership support creates a conducive atmosphere in the firm towards innovation (Christofi et al. 2017; Chatterjee et al. 2019a). Such an atmosphere helps the firm to form innovative teams of people. Leadership support encourages employees' mutual trust, helps to reduce communication costs, and tries to enhance the knowledge exchange activities among the employees. Donate and Guadamillas (2011) observed that leadership support stimulates the employees to transfer those ideas and experiences to others voluntarily, helps in knowledge creation through empowerment, tries to establish an atmosphere of belief and confidence among the employees, and encourages the employees to provide new ideas to develop innovation capability. With all these inputs, the above idea has been generalized and is perceived that leadership support would help to improve a firm's performance. These inputs help to formulate the following hypotheses.

H11 Leadership support (LS) moderates the relationship between product innovation (POI) and firm performance (FP).
H12 Leadership support (LS) moderates the relationship between process innovation (PRI) and firm performance (FP).

Studies suggested that some features of a firm also impact its adoption of BA in the context of its data-driven culture (Porter and Donthu 2006). In this way, some variables of firm performance have been considered to delineate the relation among the antecedents for gaining better competitive advantage. These variables are firm size, firm age, and industry type. These are expected to strengthen the concerned linkage covering H10.

With all these inputs, a conceptual model is developed, which is shown in Fig. 1.

4 Research methodology

We tested the hypotheses and the model using the partial least squares structural equation modelling (PLS-SEM) process from the Smart PLS 2.0 M3 software. In this exploratory study, the PLS-SEM approach has been perceived to be the best fit because, in an exploratory study, the PLS-SEM approach yields better results (Hair et al. 2018; Roy et al. 2019). Besides, a complex model like this can easily be validated by the PLS-SEM technique with a comparatively small sample size (Willaby et al. 2015). In addition, the PLS-SEM technique has better applications in studies concerned with marketing (Hair et al. 2012), operational management and information science (Hair et al. 2017), as well as in international marketing research (Richter et al. 2016; Hair et al. 2018).

4.1 Measurement instrument

From the literature review and the concept of the constructs, the initial list of measurement items was prepared and then a pilot test was conducted. We interviewed six people who were experts on how firms use BA applications in a data-driven cultural context and 35 employees of four firms that use BA. These firms were chosen at random. The input from the experts and the 35 employees helped the researchers to rectify the defects of the items towards their readability and comprehensiveness. In this way, all the constructs were measured using these items. A total of 28 items were prepared. The details of the measurement instruments, including their sources, are shown in Table 2.

4.2 Data collection strategy

This study used the survey method, with a questionnaire for collecting data from screened respondents. To select the respondents, 112 Indian firms were chosen from a list in *Business Standard's* Feature on India's Top 1000 Companies in 2018. Attempts were made to select from large and medium firms, because most small Indian firms are unable to afford BA tools. We communicated with the representatives of some of these firms by phone calls and emails, and in some cases, we contacted them in person. These contacts were done to explain about the aim and motive of this study. We sought the representatives' assistance in collecting responses. In this study, the respondents are employees of medium and large firms, and who are mainly executives, senior managers, and mid-level managers belonging to different departments of the firms. The attempts were made to have get input from respondents of the firms who have knowledge about data-driven culture. The data collection approach was not encouraging. To enhance the response rate, clear guidelines were provided on how to fill in the response sheet. The respondents were assured that their anonymity and confidentiality would be maintained (Chidlow et al. 2015). After sending the questionnaire to the respondents, several reminders were given to them to know if there is any problem to fill in the response sheet. All these attempts were taken to improve the rate of response (Harzing et al. 2012). Most of the firms were reluctant to respond to the questionnaire, however we finally selected 879 respondents from 69 firms. These respondents were requested to respond to the 28 questions within 3 months, from November 2019 to January 2020. Within the scheduled time, 490 responses were obtained, of which 456 responses were found valid. The effective response rate was 51.8%. We used Armstrong and Overton (1977) method to analyze potential non-response bias. The independent sample *t* test and the Chi-square test were also conducted in which we considered the first and last 120 respondents. No significant difference between

Table 2 Measurement instrument

Construct	Sources	Item: statement
Adoption of business analytics (ABA)	Columbus (2014), Duan et al. (2018), Dutta and Bose (2015), Sharda et al. (2016), Sun et al. (2017) and Vidgen et al. (2017)	ABA1: I believe effective BA solution is necessary for faster and accurate decision-making
		ABA2: Our firm has fully adopted a BA solution
		ABA3: Users are satisfied using a BA solution
		ABA4: It is important to get appropriate data for effective BA solution
		ABA5: Keeping a BA solution up to date is expensive
Data-driven culture (DDC)	Barney (1986), Duan et al. (2018), Ransbotham and Kiron (2017), Vidgen et al. (2017), Wang et al. (2018) and Watson (2014)	DDC1: I believe decisions should be based on available information coming from a BA solution
		DDC2: Our firm has a practice of decision-making based on the available data
		DDC3: Data plays an important role in new product development
		DDC4: Data plays an important role in process improvement
Firm ecosystem scanning (FES)	Augusto and Coelho (2009), Bichler et al. (2017), Dahlander and Gann (2010), Duan et al. (2018), Hong et al. (2013) and Zahra and George (2002)	FES1: Our firm has the capability of filtering appropriate data from the available dataset
		FES2: The firms’ ecosystem scanning ability provides more accurate and quicker decision-making
		FES3: I believe the firm should invest more on increasing its ecosystem scanning ability for better output
Product innovation (POI)	Kim et al. (2013), Kiron et al. (2012), Kiron and Shockley (2011), Ramanathan et al. (2017) and Stubbs (2014)	POI1: Analysis of data plays an important role in the development of new products

Table 2 continued

Construct	Sources	Item: statement
		POI2: New product development is important for improving firm overall performance
		POI3: I believe that leadership support of the firm plays a vital role in new product development
		POI4: Data-driven decision-making is important for developing new products
Process innovation (PRI)	Cosic et al. (2015), Klatt et al. (2011), Larson and Chang (2016) and Troilo et al. (2016)	PRI1: Data analytics plays an important role in improving existing process
		PRI2: Process innovation is important for improving overall firm performance
		PRI3: Data-driven decision-making is important for developing new processes
		PRI4: I believe that leadership support of the firm plays an important role in developing new processes
Firm performance (FP)	Kim et al. (2012), Lin (2007) and Rogers (1983)	FP1: Innovation of new products help to improve firm performance
		FP2: Process innovation plays a vital role in improving firm performance
		FP3: Data-driven culture of a firm helps improve firm performance
		FP4: Leadership strategy of the firm helps improve firm performance
Competitive advantage (CMA)	Barton and Court (2012), Chen and Hung (2014) and Kim et al. (2012)	CMA1: Improvement of firm performance helps the firm to gain competitive advantage
		CMA2: New product development helps the firm improve its competitiveness in the marketplace
		CMA3: Data-driven culture of a firm helps to improve its competitiveness in the marketplace
		CMA4: Improving competitiveness in the marketplace increases a firm's profit

Table 3 Demographic statistics (N = 456)

Characteristics	Particulars	Frequency	Percentage (%)
Industry type	Services	144	31.6
	Manufacturing	312	68.4
Firm size	Small (<200 employees)	0	0
	Medium (200–600 employees)	250	54.8
	Large (>600 employees)	206	45.2
Age of the firms	Less than 6 years	110	24.1
	6–14 years	201	44.1
	Above 14 years	145	31.8
Gender	Male	296	64.9
	Female	160	35.1
Working position	Executives	110	24.1
	Senior managers	156	34.2
	Mid-level managers	190	41.7

these two groups was noticed ($p < 0.05$). It signifies that there was no non-response bias. The demographic statistics of 456 respondents are shown in Table 3.

5 Data analysis with results

5.1 Data analysis for reliability, validity, and consistency

The measurement model was assessed by computing the loading factor (LF) of each item and then by estimating the convergent validity of each. Internal consistency, validity, defects of multicollinearity, and consistency of each construct were estimated by measuring composite reliability (CR), average variance extracted (AVE), variance inflation factor (VIF), and Cronbach's alpha (α) respectively. All the parameters were found to be within the allowable range, confirming that items are reliable. The constructs are valid, internally consistent, having no multicollinearity defects (Hair et al. 2018). The results are shown in Table 4.

5.2 Discriminant validity test

We estimated that all the square roots of AVEs of the constructs are greater than the corresponding correlation coefficients. It confirms discriminant validity since it satisfies the Fornell and Larcker criterion (Fornell and Larcker 1981). The results are shown in Table 5.

For supplementing the Fornell and Larcker criterion, heterotrait monotrait (HTMT) correlation ratio test has been done (Henseler et al. 2014). The estimated values show that all the constructs possess values less than the highest threshold value of 0.85 (Voorhees et al. 2016) which reconfirms the discriminant validity of the constructs. The results are shown in Table 6.

Table 4 Measurement properties

Construct/item	LF	CR	AVE	VIF	*t* value	α	No. of item
ABA		0.86	0.83	3.7		0.89	5
ABA1	0.85				19.81		
ABA2	0.87				19.02		
ABA3	0.85				22.68		
ABA4	0.96				29.11		
ABA5	0.92				26.54		
DDC		0.92	0.90	4.8		0.93	4
DDC1	0.95				19.37		
DDC2	0.90				29.12		
DDC3	0.89				27.04		
DDC4	0.87				21.13		
FES		0.88	0.85	3.9		0.90	3
FES1	0.90				26.17		
FES2	0.95				29.19		
FES3	0.92				31.42		
POI		0.90	0.88	3.6		0.92	4
POI1	0.95				27.27		
POI2	0.95				26.62		
POI3	0.90				29.11		
POI4	0.95				24.16		
PRI		0.96	0.93	4.8		0.98	4
PRI1	0.98				29.15		
PRI2	0.90				19.48		
PRI3	0.97				19.72		
PRI4	0.98				31.41		
FP		0.85	0.82	4.1		0.87	4
FP1	0.98				29.71		
FP2	0.84				26.17		
FP3	0.88				28.21		
FP4	0.91				31.35		
CMA		0.90	0.84	3.8		0.93	4
CMA1	0.93				19.41		
CMA2	0.96				29.12		
CMA3	0.89				24.57		
CMA4	0.88				26.11		

5.3 Hypothesis testing

In the context of the PLS-SEM approach, each hypothesis has been tested using bootstrapping to consider 6000 resamples with 456 cases (Henseler et al. 2009). This process of hypothesis testing helps to avoid parametric test (Chin 2010). To obtain cross-validated redundancy, the omission distance has been considered 5 for the exogeneous variables (Lew et al. 2016). The Stone-Geisser result concerning Q^2 (Stone 1974; Geisser 1975) value was 0.68, confirming

Table 5 Discriminant validity test (Fornell and Larcker criterion)

Construct	ABA	DDC	FES	POI	PRI	FP	CMA	AVA
ABA	0.91							0.83
DDC	− 0.21	0.95						0.90
FES	0.23*	0.26***	0.92					0.85
POI	− 0.26	− 0.29	− 0.26	0.94				0.88
PRI	0.19	0.22*	0.32*	− 0.25	0.96			0.93
FP	0.22**	0.19**	0.23	0.29*	0.24	0.90		0.82
CMA	0.32**	− 0.27	− 0.25	0.33	0.34*	0.29*	0.91	0.84

Table 6 Discriminant validity test (HTMT criterion)

Construct	ABA	DDC	FES	POI	PRI	FP	CMA
ABA							
DDC	0.39						
FES	0.43	0.36					
POI	0.47	0.48	0.56				
PRI	0.51	0.37	0.33	0.37			
FP	0.29	0.31	0.44	0.51	0.42		
CMA	0.32	0.34	0.36	0.48	0.37	0.46	

that the model has appropriate predictive relevance. Following this process, the path coefficients of the linkages, p-values, and coefficients of determinants (R^2) could be estimated. The results are shown in Table 7.

5.4 Moderator analysis (MG analysis)

The effects of the moderators, data-driven culture (DDC) and leadership support (LS), were analyzed by multigroup analysis (MGA). The effects of moderator DDC were considered by dividing the moderator into two categories: Strong DDC and Weak DDC. The effects of LS as moderator were also divided into two categories: High LS and Low LS. To estimate the p-value differences, for the two categories of each moderator, the bias-correlated bootstrapping approach was adopted for 6000 resamples. The significance of the moderating effects is accepted if the p-value difference between the two categories for each moderator is either less than 0.05 or greater than 0.95 (i.e. 5% error difference) (Hair et al. 2016). The results show that the moderating effects of both the moderators are significant. The results are shown in Table 8.

5.5 Mediation analysis (for control variables)

To examine the mediating role of the variable FP between the control variables and CMA, the indirect effect verification process was adopted by the using bias-correlated accelerated bootstrapping approach in consideration of 6000 resamples (Nitzl et al. 2016). Results are given in Table 9.

Table 7 Hypothesis testing with coefficient of determinant, β value, and p value

Paths	Hypotheses	β values/R^2	p values	Remarks
Effects on DDC		0.33		
By ABA	H1	0.21	$p<0.05$*	Supported
Effects on FES		0.36		
By ABA	H2	0.31	$p<0.01$**	Supported
By DDC	H3	0.19	$p<0.05$*	Supported
Effects on FES → PRI				
By DDC	H4	0.44	$p<0.01$**	Supported
Effects on FES → POI				
By DDC	H5	0.47	$p<0.05$*	Supported
Effects on POI		0.43		
By FES	H6	0.41	$p<0.001$***	Supported
Effects on PRI		0.38		
By FES	H7	0.22	$p<0.05$*	Supported
Effects on FP		0.49		
By POI	H8	0.46	$p<0.05$*	Supported
By PRI	H9	0.52	$p<0.001$***	Supported
Effects on CMA		0.74		
By FP	H10	0.59	$p<0.001$***	Supported
Effects on POI → FP				
By LS	H11	0.32	$p<0.01$**	Supported
Effects on PRI → FP				
By LS	H12	0.22	$p<0.05$*	Supported

Table 8 Multigroup analysis to test moderating effects

Paths	Moderators	p value differences	Remarks
FES → DDC → PRI	DDC	0.97	Significant
FES → DDC → POI	DDC	0.99	Significant
POI → LS → FP	LS	0.03	Significant
PRI → LS → FP	LS	0.02	Significant

Table 9 Control variable analysis

Paths	Indirect effect	*p* value	LCL	UCL
Firm size → OP → CMA	0.11	0.00	0.04	0.16
Firm age → OP → CMA	0.13	0.07	0.03	0.17
Industry type → OP → CMA	0.16	0.04	0.02	0.13

NB, LCL means lower confidence level; UCL, upper confidence level

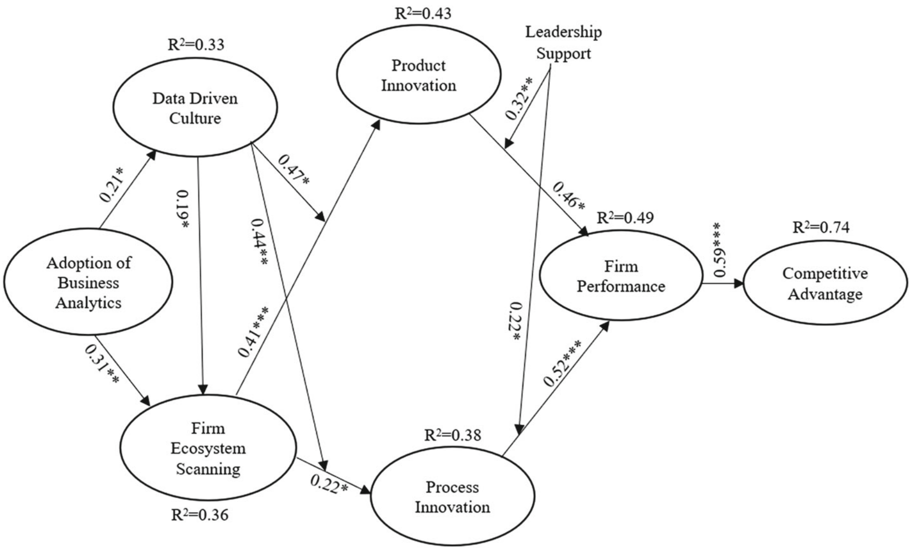


Fig. 2 Validating model

The results highlight that FP assumes an effective complementary role as a mediator. The results also highlight that the confidence interval, in the context of bias-correlated bootstrapping covering OP, is other than zero. It is 0.04–0.16; 0.03–0.17, and 0.02–0.13 for firm size, firm age, and industry type, respectively. This confirms that OP acts as a significant mediating variable between the control variables and Competitive Advantage (CMA).

With all these inputs the model after validation is shown in Fig. 2.

5.6 Common method bias

This study was conducted using self-reported data. Hence, it is necessary to perform a common method bias (CMB) test. While validating the model through PLS-SEM analysis, the survey was conducted. In that survey, the respondents were given assurance that their data would be kept confidential to reduce bias in the responses. To verify CMB, a post hoc Harman's SFT (single factor test) was conducted. It was found that the first factor resulted in only 42.3% variance. It is less than the highest cutoff value of 50% (Podsakoff et al. 2003). To confirm Harman's single factor test (SFT), the marker variable technique (Lindell and Whitney 2001) has been adopted. It shows that the difference concerning CMV and adjusted

CMV was found to be less than 0.06 for all the constructs, which complements Harman's SFT. Hence, the CMB could not distort the results and the data is unbiassed.

5.7 Results

The study formulated 12 hypotheses. After statisical validation, it appears that all the hypotheses have been supported. Results of the effects of ABA on DDC and FES show that ABA affects FES more, as the concerned path coefficient is 0.31 with a level of significance of $p < 0.01$(**). The effects of DDC on FES (on the FES → PRI linkage and on the FES → POI linkage) indicate that the moderating effects of DDC on H6 (FES → POI) is maximum, as the concerned path coefficient is the highest (0.47 with a significance level of *$p < 0.05$). It appears that the effects of FES on POI (H6) is more than the effects of FES on PRI since the corresponding path coefficient is greater (0.41 with a significance level of ***$p < 0.001$). between effects on FP by POI and by PRI, it appears that effects of PRI on FP (H9) is more because the concerned path coefficient is 0.52 with a significance level of ***$p < 0.001$. The effects of FP on CMA (H10) is appreciable, as the concerned path coefficient is 0.59 with a significance level of ***$p < 0.001$. Between moderating effects of LS on POI → FP (H8) and PRI → FP (H9) linkages, the effects of LS on POI → FP (H8) is more, since the concerned path coefficient is 0.32 with a significance level of **$p < 0.01$.

So far as coefficient of determinants are concerned, the results show that ABA can explain 33% of the variation in DDC, ABA and DDC can jointly explain 36% of the variation in FES. FES can explain 45% and 38% of the variations in POI and PRI, respectively, and 49% of FP can be explained by POI and by PRI jointly. Again, FP can explain CMA to the extent of 74%. The explanative power of the model is 74%.

6 Discussions on results

This study has highlighted that BA helps to improve a firm's innovation. To do this, a firm should exhibit better absorptive capacity in scanning appropriate data to generate new ideas. This concept has been supported by studies by Dutta and Bose (2015) and Mohr et al. (2012). Dutta and Bose (2015) studied Indian company Ramco Cement Ltd. and observed that the firm achieved success, its absorptive capacity increased and its performance improved by using big data and BA. Mohr et al. (2012) observed that in the healthcare industry, firms achieved better performance depending on their data-driven cultural aspects. This study has validated, through statistical analysis, two hypotheses: that ABA helps to improve data-driven culture (H1); and ABA impacts positively FES (H2). These ideas are in support of various studies of related issues, as discussed earlier. Duan et al. (2018) highlighted that BA improves a firm's scanning ability, which in turn improves innovation. This study applied this idea to develop hypotheses H6 and H7, which were duly validated. This study showed that FES ability impacts positively on firms' innovation capability, which is also supported by Dahlander and Gann (2010), who observed that sourcing and acquiring, as well as revealing and selling, makes a firm open for accurate data scanning for improving innovation. This study also confirmed that innovation capabilities of a firm impact positively on performance (H8 and H9), as supported in study by Chen and Hung (2014), who, focusing on the context of green innovation, observed that a firm's innovation impacts its performance. Chen and Hung (2014) further emphasized that improvement of a firm's performance helps it to gain competitive advantage. Again, our study validates H11 and H12, and it also confirms the

Fig. 3 Effects of DDC on H6

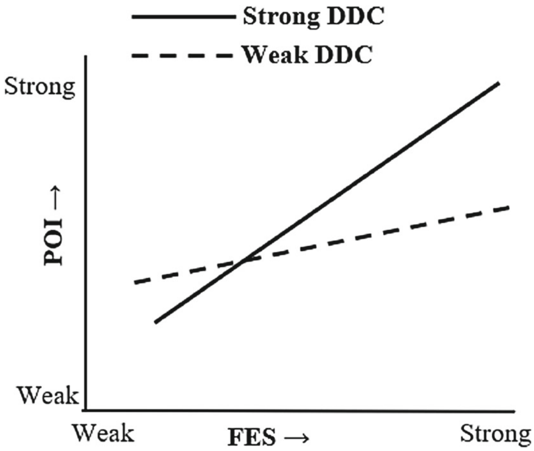
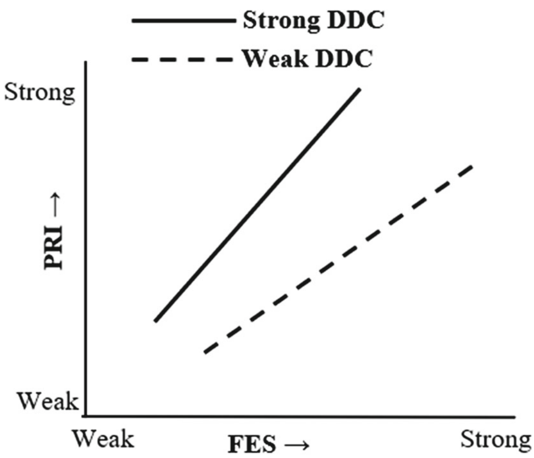


Fig. 4 Effects of DDC on H7



study from Dess and Picken (2000), who demonstrated that leadership support impacted positively in improving knowledge sharing activities of a firm. In our study, the idea derived from Dess and Picken (2000) has been generalized.

The moderating effects of DDC (Strong and Weak) on the linkages H6 and H7, as well as moderating effects of LS (High and Low) on the linkages H8 and H9, are shown graphically. The effects of the moderator DDC on the linkages H6 and H7 are shown in Figs. 3 and 4.

In both figures, the effects of strong DDC are shown by solid lines and the effects of weak DDC are shown by dotted lines. In Fig. 3, with an increase of FES, the rate of increase of POI is higher for strong DDC compared to weak DDC, since the solid line has a greater gradient compared to the dotted line. Similarly, in Fig. 4, with an increase of FES, the rate of increase of PRI is greater for strong DDC compared to weak DDC, since the solid line has a greater gradient than the dotted line.

In Figs. 5 and 6, the effects of the moderator LS on the two linkages H8 and H9 are shown graphically.

The solid lines in both graphs represent effects of high LS, whereas the dotted lines show effects of low LS on the two linkages (H8 and H9). In Fig. 5, with an increase of POI, the

Fig. 5 Effects of LS on H8

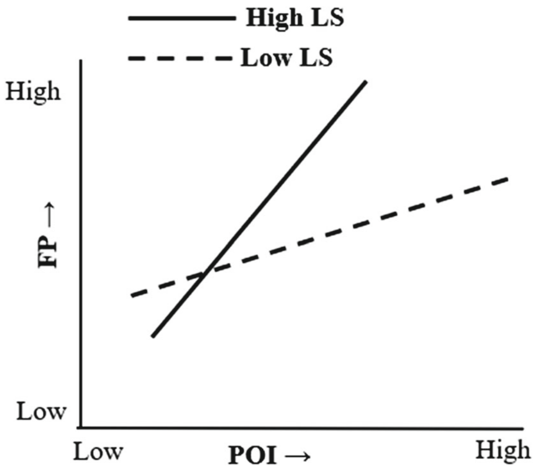
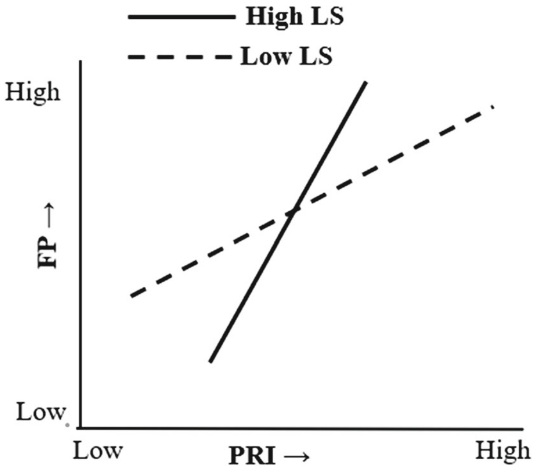


Fig. 6 Effects of LS on H9



rate of increase of FP is more with high LS compared to the effects of low LS, as the solid line bears a greater gradient compared to the dotted line. In Fig. 6, with an increase of PRI, the rate of increase of FP is more with high LS in comparison to the effects of low LS, since the solid line has more inclination than the dotted line, representing effects of low LS.

6.1 Theoretical contribution

The study has provided several theoretical contributions. In structuring the theoretical model, this study applied absorptive capacity theory, resource-based view (RBV), and dynamic capability view (DCV). Through absorptive capacity theory, this study has realized the importance of extracting useful data from different sources and identified constructs including BA and FES. RBV also helped to understand the importance of data acquisition in the context of a firm's data-driven culture. The dynamic capability view revealed the importance of developing new ideas for innovation to create new products to respond to the emerging needs of the market. In the context of organizational theory, dynamic capability view (DCV) theory is construed to be a firm's ability to purposefully adopt the firm's resource base. This ability is associated with integrating, building, and reconfiguring internal and external competences to collect accurate and necessary data for addressing the rapidly changing market environment (Teece et al. 1997). In such context, the DCV theory helps a firm to react and respond to the dynamic needs of the marketing environment by improving the firm ecosystem scanning ability in an appropriate way to extract congenial data. It would impact the process and product innovation capabilities which promote overall performance of the firms. By improving product quality and reducing product cost, a firm can enhance its profitability, which is the traditional idea for achieving a firm's business success. However, in the context of data-driven culture, it is possible to generate and develop innovative ideas to create new products to meet consumer demand, thus improving the competitive advantage of the firm. The idea of applying a firm's data-driven culture has helped to successfully develop the theoretical model through this new concept. This is also another theoretical contribution of this study. Moreover, this study finds that adopting BA improves a firm's innovation and ultimately helps it to gain better competitive advantage. This study might have used a standard adoption model, but instead, by using better suited determinants, the theoretical model was successfully developed and achieved high explanative power (73%), which is also a special theoretical contribution of this study. A final theoretical contribution of this study also showed that leadership support is a moderator in relation to improving firm performance, which was also found in research conducted by Dess and Picken (2000). The use of this concept helped to develop the model that achieved high explanative power, and the researchers claim this is another theoretical contribution of this study. In a study by Larson and Chang (2016), it was observed that a firm can achieve better performance by using its agility, business intelligence, BA and data science. This concept has been lent to this study by extending the idea that data-driven culture can improve product and process innovations, which are helpful towards the betterment of a firm's performance. Consideration of a data-driven cultural aspect with the existing literature is considered a unique theoretical contribution of this study. Finally, the use of some control variables featuring a firm's characteristics could help to analyze firm performance that promotes competitive advantage.

6.2 Practical implication

This study has provided effective inputs to the managers and business analytic practitioners to improve firm performance. The study has shown that leaders of firms need to stress the utility of establishing a data-driven culture to achieve success. This would help enhance the data-driven insights among employees. In the context of a data-driven culture, the stakeholders of the firm should realize the need to acquire quality data. It would help to enhance business analytic impacts in generating new ideas for developing the quality of the firm's innovation. As for cultural aspects, managers should encourage the employees to be more proactive in providing inputs to management regarding different practices undertaken in other firms. Employees should not be hesitant to provide new ideas to management, as it will help in the creation of new products commensurate with current market demands. Data-oriented culture has provided managers effective inputs to develop their reflective ideas. They must realize that BA alone will not make it possible to gain successful advantages over competitors. Managers must be sincerely pay attention to new ideas provided by the employees, which may help them to develop new products. The approach of BA is always data-driven, especially, for the digital firms. However, all data may not generate equal values. Thus, managers should train employees to identify those datasets which are relevant for their particular work. Employees, in the environment of a firm's data-driven culture, should realize that data are valuable, inimitable, rare, and non-substitutable, as opined by Appelbaum et al. (2017). Managers of digital firms need to enhance their firms' ecosystem scanning ability. This requires them to develop their firms' absorptive capacity, as endorsed by absorptive capacity theory.

7 Conclusions, limitations, and directions to the future researchers

This study has enumerated how the concept of data-driven culture can provide substantial dividends towards the process and product innovation of firms. This study has effectively highlighted how advanced ICT has become helpful for a firm to appropriately utilize the option of using BA tools embedded with AI to analyze the collected data with the help of improved absorptive capacity of the firm. The study has effectively utilized the concepts of DCV and RBV theories to analyze how firms should react and respond to their rapidly changing business environments by improving their absorptive capacity towards collecting appropriate data. It supplements the concept of absorptive capacity theory. Thus, it is perceived that this study offers enough theoretical and practical contributions to the extant literature as well as to firms to improve their performance that eventually will help them to sustain competitive advantage.

This study has found that adoption of BA can bring success in innovation, in the context of a data-driven culture, by enhancing absorptive capacity of a firm. The model has been developed with this concept. The study has considered that factors like culture and business analytics can help a firm to develop its innovative capacity, but there are other important factors that influence innovation. Those factors are business strategy, management practices, management of human resources, relationship development in the inter-firm activities and so on. These factors have not been taken into consideration in this study. Future researchers can explore this issue. This study has developed the model and validated it with analysis of respondent feedback from Indian firms. Thus, the results do not project a global picture. Future researchers might address this point to improve the generalizability of the model. The study considered three features of a firm which are size, age, and industry type. Considering these three control variables, this study synthesized their effects on OP to improve CMA. In this study, other features of a firm, such as product diversity, R&D issues, co-creation issues, revenue issues, and so on have not been considered. Future researchers might nurture these points. Results came from an analysis of feedback from employees of large- and medium-sized firms. Small firms were not been considered. Thus, the result in this context, does not project a general picture. Future researchers may take up this issue to improve the model.

References

Abbasi, A., Sarker, S., & Chiang, R. H. L. (2016). Big data research in information systems: Toward an inclusive research agenda. *Journal of the Association for Information Systems, 17*(2), 1–32.

Akter, S., Bandara, R., Hani, U., Fosso Wamba, S. F., Foropon, C., & Papadopoulos, T. (2019). Analytics-based decision-making for service systems: A qualitative study and agenda for future research. *International Journal of Information Management, 48,* 85–95.

Akter, S., & Wamba, S. F. (2016). Big data analytics in E-commerce: A systematic review and agenda for future research. *Electronic Markets, 26*(2), 173–194.

Akter, S., Wamba, S. F., Gunasekaran, A., Dubey, R., & Childe, S. J. (2016). How to improve firm performance using big data analytics capability and business strategy alignment? *International Journal of Production Economics, 182,* 113–131.

Appelbaum, D., Kogan, A., Vasarhelyi, M., & Yan, Z. (2017). Impact of business analytics and enterprise systems on managerial accounting. *International Journal of Accounting Information Systems, 25,* 29–44.
Arfaoui, N., Hofaidhllaoui, M., & Chawla, G. (2019). Social performance of the company: An explanation centralized on the social and technological factors. *EuroMed Journal of Business, 15*(1), 102–126.
Armstrong, J. S., & Overton, T. S. (1977). Estimating nonresponse bias in mail surveys. *Journal of Marketing Research, 14*(3), 396–402.
Augusto, M., & Coelho, F. (2009). Market orientation and new-to-the-world products: Exploring the moderating effects of innovativeness, competitive strength, and environmental forces. *Industrial Marketing Management, 38*(1), 94–108.
Barney, J. B. (1986). Organizational culture: Can it be a source of sustained competitive advantage? *Academy of Management Review, 11*(3), 656–665.
Barney, J. (1991). Firm resources and sustained competitive advantage. *Journal of Management, 17,* 99–120.
Barton, D., & Court, D. (2012). Making advanced analytics work for you. *Harvard Business Review, 90*(10), 78–83.
Battisti, E., Shams, S. M. R., Sakka, G., & Miglietta, N. (2019). Big data and risk management in business processes: Implication for corporate real estate. *Business Process Management Journal*. https://doi.org/10.1108/BPMJ-03-2019-0125.
Bichler, M., Heinzl, A., & Van der Aalst, W. M. P. (2017). Business analytics and data science: Once again? *Business & Information Systems Engineering, 59*(2), 77–79.
Boonstra, A. (2013). How do top managers support strategic information system projects and why do they sometimes withhold this support. *International Journal of Production Management, 31*(4), 498–512.
Carillo, K. D. A., Galy, N., Guthrie, C., & Vanhems, A. (2019). How to turn managers into data-driven decision makers: Measuring attitudes towards business analytics. *Business Process Management Journal, 25*(3), 553–578.
Chatterjee, S., Chaudhuri, R., Vrontis, D., Thrassou, A., Ghosh, S. K., & Chaudhuri, S. (2020). Social customer relationship management factors and business benefits. *International Journal of Organizational Analysis*. https://doi.org/10.1108/IJOA-11-2019-1933.
Chatterjee, S., Ghosh, S. K., & Chaudhuri, R. (2019a). Knowledge management improving business process: An interpretative framework for successful implementation of AI-CRM-KM system in organizations. *Business Process Management Journal*. https://doi.org/10.1007/s40171-017-0173-5.
Chatterjee, S., Ghosh, S., Chaudhuri, R., & Nguyen, B. (2019b). Are CRM systems ready for AI integration? *The Bottom Line, 32*(2), 144–157.
Chebbi, H., Yahiaoui, D., Vrontis, D., & Thrassou, A. (2017). The impact of ambidextrous leadership on the internationalization of emerging market firms (EMF): The case of India. *Thunderbird International Business Review, 59*(3), 421–436.
Chen, P.-C., & Hung, S.-W. (2014). Collaborative green innovation in emerging countries: A social capital perspective. *International Journal of Operations & Production Management, 34*(3), 347–363.
Chidlow, A., Ghauri, P., Yeniyurt, S., & Cavusgil, S. T. (2015). Establishing rigor in mail survey procedures in international business research. *Journal of World Business, 50*(1), 26–36.
Chin, W. W. (2010). How to write up and report PLS analyses. In V. E. Vinzi, W. W. Chin, J. Henseler, & H. Wang (Eds.), *Handbook of partial least squares* (pp. 655–690). Berlin: Springer.
Christofi, M., Leonidou, E., & Vrontis, D. (2017). Marketing research on mergers and acquisitions: A systematic review and future directions. *International Marketing Review, 34*(5), 629–651.
Christofi, M., Vrontis, D., Leonidou, E., & Thrassou, A. (2018). Customer engagement through choice in cause-related marketing: A potential for global competitiveness. *International Marketing Review*. https://doi.org/10.1108/IMR-04-2018-0133.
Christofi, M., Vrontis, D., Thrassou, A., & Shams, S. M. R. (2019). Triggering technological innovation through cross-border mergers and acquisitions: A micro-foundational perspective. *Technological Forecasting and Social Change, 146,* 148–166.
Cohen, W. M., & Levinthal, D. A. (1990). Absorptive capacity: A new perspective on learning and innovation. *Administrative Science Quarterly, 15*(1), 128–152.
Columbus, L. (2014). 84% of enterprises see big data analytics changing their industries' competitive landscapes in the next year. *Forbes*. Retrieved June 15, 2020 from https://www.forbes.com/sites/louiscolumbus/2014/10/19/84-of-enterprises-see-big-data-analytics-changing-their-industries-competitive-landscapes-in-the-next-year/#73e9c76f17de.
Cosic, R., Shanks, G., & Maynard, S. (2015). A business analytics capability framework. *Australasian Journal of Information Systems, 19,* 5–19.
Cuellar, M. J., & Gallivan, M. J. (2006). A framework for ex ante project risk assessment based on absorptive capacity. *European Journal of Operational Research, 173*(3), 1123–1138.
Dahlander, L., & Gann, D. M. (2010). How open is innovation? *Research Policy, 39*(6), 699–709.

Davenport, T. H., & Harris, J. G. (2007). *Competing on analytics: The new science of winning*. Boston: Harvard Business School Review Press.

Davenport, T. H., & Kudyba, S. (2016). Designing and developing analytics-based data products. *MIT Sloan Management Review, 58*(1), 83–88.

Delen, D., & Demirkan, H. (2013). Data, information and analytics as services. *Decision Support Systems, 55*(1), 359–363.

Dess, G. G., & Picken, J. C. (2000). Changing roles: Leadership in the 21st century. *Organizational Dynamics, 28*(3), 18–34.

Donate, M. J., & Guadamillas, F. (2011). Organizational factors to support knowledge management and innovation. *Journal of Knowledge Management, 15*(6), 890–914.

Duan, Y., Cao, G., & Edwards, J. S. (2018). Understanding the impact of business analytics on innovation. *European Journal of Operational Research, 281*(3), 673–686.

Dutta, D., & Bose, I. (2015). Managing a big data project: The case of Ramco Cements Limited. *International Journal of Production Economics, 165*(3), 293–306.

Ferreira, A., & Franco, M. (2019). The influence of strategic alliances on human capital development: A study applied to technology-based SMEs. *EuroMed Journal of Business, 15*(1), 65–85.

Fornell, C., & Larcker, D. F. (1981). Evaluating structural equation models with unobservable variables and measurement error. *Journal of Marketing Research, 18*(1), 39–50.

Geisser, S. (1975). The predictive sample reuse method with applications. *Journal of the American Statistical Association, 70*(350), 320–328.

Hair, J. F., Hollingsworth, C. L., Randolph, A. B., & Chong, A. Y. L. (2017). An updated and expanded assessment of PLS-SEM in information systems research. *Industrial Management & Data Systems, 117*(3), 442–458.

Hair, J. F., Jr., Hult, G. T. M., Ringle, C., & Sarstedt, M. (2016). *A primer on partial least squares structural equation modeling (PLS-SEM)*. London: Sage Publications.

Hair, J. F., Ringle, C. M., Gudergan, S. P., Fischer, A., Nitzl, C., & Menictas, C. (2018). Partial least squares structural equation modeling-based discrete choice modeling: An illustration in modeling retailer choice. *Business Research, 12,* 115–142.

Hair, J. F., Sarstedt, M., Ringle, C. M., & Mena, J. A. (2012). An assessment of the use of partial least squares structural equation modeling in marketing research. *Journal of the Academy of Marketing Science, 40,* 414–433.

Han, S. H., Seo, G., Yoon, S. W., & Yoon, D. Y. (2016). Transformational leadership and knowledge sharing: mediating roles of employee's empowerment, commitment, and citizenship behaviors. *Journal of Workplace Learning, 28*(3), 130–149.

Harzing, A. W., Brown, M., Köster, K., & Zhao, S. (2012). Response style differences in cross-national research: Dispositional and situational determinants. *Management International Review, 52*(3), 341–363.

Helfat, C. E., & Peteraf, M. A. (2009). Understanding dynamic capabilities: Progress along a developmental path. *Strategic Organization, 7,* 91–102.

Henseler, J., Ringle, C. M., & Sarstedt, M. (2014). A new criterion for assessing discriminant validity in variance-based structural equation modeling. *Journal of the Academy of Marketing Science, 43*(1), 115–135.

Henseler, J., Ringle, C. M., & Sinkovics, R. R. (2009). The use of partial least squares path modeling in international marketing. *Advances in International Marketing, 20*(1), 277–319.

Hindle, G. A., & Vidgen, R. (2018). Developing a business analytics methodology: A case study in the foodbank sector. *European Journal of Operational Research, 268*(3), 836–851.

Holsapple, C., Lee-Post, A., & Pakath, R. (2014). A unified foundation for business analytics. *Decision Support Systems, 64,* 130–141.

Hong, J., Song, T. H., & Yoo, S. (2013). Paths to success: How do market orientation and entrepreneurship orientation produce new product success? *Journal of Product Innovation Management, 30*(1), 44–55.

Johnson, D. S., Muzellec, L., Sihi, D., & Zahay, D. (2019). The marketing organization's journey to become data driven. *Journal of Research in Interactive Marketing, 13*(2), 162–178.

Keller, R. T., & Holland, W. E. (1975). Boundary-spanning roles in a research and development organization: An empirical investigation. *Academy of Management Journal, 18*(2), 388–393.

Kim, N., Im, S., & Slater, S. F. (2013). Impact of knowledge type and strategic orientation on new product creativity and advantage in high-technology firms impact of knowledge type and strategic orientation on new product creativity and advantage in high-technology firms. *Journal of Product Innovation Management, 30*(1), 136–153.

Kim, G., Shin, B., & Kwon, O. (2012). Investigating the value of socio materialism in conceptualizing IT capability of a firm. *Journal of Management Information System, 29,* 327–362.

Kiron, D., Ferguson, R. B., & Prentice, P. K. (2013). From value to vision: Reimagining the possible with data analytics. *MIT Sloan Management Review, 54*(3), 1–19.

Kiron, D., Prentice, P. K., & Ferguson, R. B. (2012). Innovating with analytics. *MIT Sloan Management Review, 54*(1), 47–52.

Kiron, D., & Shockley, R. (2011). Creating business value with analytics. *MIT Sloan Management Review, 53*(1), 57–63.

Klatt, T., Schlaefke, M., & Moeller, K. (2011). Integrating business analytics into strategic planning for better performance. *Journal of Business Strategy, 32*(6), 30–39.

Kunc, M., & O'Brien, F. A. (2019). The role of business analytics in supporting strategy processes: Opportunities and limitations. *Journal of the Operational Research Society, 70*(6), 974–985.

Larson, D., & Chang, V. (2016). A review and future direction of agile, business intelligence, analytics and data science. *International Journal of Information Management, 36*(5), 700–710.

Lau, R. Y., Liao, S. S., Wong, K.-F., & Chiu, D. K. (2012). Web 2.0 environmental scanning and adaptive decision support for business mergers and acquisitions. *MIS Quarterly, 36*(4), 1239–1268.

Lew, Y. K., Sinkovics, R. R., Yamin, M., & Khan, Z. (2016). Trans-specialization understanding in international technology alliances: The influence of cultural distance. *Journal of International Business Studies, 47,* 577–594.

Lin, B.-W. (2007). Information technology capability and value creation: Evidence from the US banking industry. *Technology in Society, 29,* 93–106.

Lindell, M. K., & Whitney, D. J. (2001). Accounting for common method variance in cross-sectional research designs. *Journal of Applied Psychology, 86*(1), 114–121.

Loukis, E., Janssen, M., & Mintchevc, I. (2019). Determinants of software-as-a-service benefits and impact on firm performance. *Decision Support System, 117,* 38–47.

Makadok, R. (2001). Toward a synthesis of the resource-based and dynamic-capability views of rent creation. *Strategic Management Journal, 22*(5), 387–401.

McComb, S. A., Kennedy, D. M., Green, S. G., Compton, W. D., & McComb, S. A. (2008). Project team effectiveness: The case for sufficient setup and top management involvement. *Production Planning & Control, 19*(4), 301–311.

Medeiros, M. M. D., Hoppen, N., & Maçada, A. C. G. (2020). Data science for business: Benefits, challenges and opportunities. *The Bottom Line, 33*(2), 149–163.

Mohr, D. C., Young, G. J., & Burgess, J. J. F. (2012). Employee turnover and operational performance: The moderating effect of group-oriented organizational culture. *Human Resource Management Journal, 22*(2), 216–233.

Morgan, T. L. (2012). *An examination of project managers' leadership contributions to project success using critical success factors*. Ph.D. Thesis, Capella University, UMI 3498739.

Mortenson, M. J., Doherty, N. F., & Robinson, S. (2015). Operational research from Taylorism to Terabytes: A research agenda for the analytics age. *European Journal of Operational Research, 241*(3), 583–595.

Najafi-Tavani, S., Sharifi, H., & Ismail, H. S. (2013). A study of contingency relationships between supplier involvement, absorptive capacity and agile product innovation. *International Journal of Operations & Production Management, 34*(1), 65–92.

Nitzl, C., Roldan, J. L., & Cepeda, G. (2016). Mediation analysis in partial least squares path modeling: Helping researchers discuss more sophisticated models. *Industrial Management and Data Systems, 116*(9), 1849–1864.

Pan, X., & Li, S. (2016). Dynamic optimal control of process–product innovation with learning by doing. *European Journal of Operational Research, 248*(1), 136–145.

Podsakoff, P. M., McKenzie, S. B., Lee, J. Y., & Podsakoff, N. P. (2003). Common method biases in behavioral research: A critical review of the literature and recommended remedies. *Journal of Applied Psychology, 88*(5), 879–903.

Porter, C. E., & Donthu, N. (2006). Using the technology acceptance model to explain how attitudes determine internet usage: The role of perceived access barriers and demographics. *Journal of Business Research, 59*(9), 999–1007.

Porter, M. E., & Millar, V. E. (1985). How information gives you competitive advantage. *Harvard Business Review, 63*(4), 149–160.

Raab, K. J., Ambos, B., & Tallman, S. (2014). Strong or invisible hands? Managerial involvement in the knowledge sharing process of globally dispersed knowledge groups. *Journal of World Business, 49*(1), 32–41.

Ramanathan, R., Philpott, E., Duan, Y., & Cao, G. (2017). Adoption of business analytics and impact on performance: A qualitative study in retail. *Production Planning and Control, 28*(11/12), 985–998.

Ransbotham, S., & Kiron, D. (2017). Analytics as a source of business innovation. *MIT Sloan Management Review, 58,* 76.

Rehm, S.-V., & Goel, L. (2015). The emergence of boundary clusters in inter-organizational innovation. *Information and Organization, 25*(1), 27–51.

Richter, N. F., Sinkovics, R. R., Ringle, C. M., & Schlagel, C. (2016). A critical look at the use of SEM in international business research. *International Marketing Review, 33*(3), 376–404.

Rogers, E. M. (1983). *Diffusion of innovation*. New York, NY: The Free Press.

Roy, S. K., Balaji, M. S., Doutar, B. G., & Jiang, Y. (2019). The antecedents and consequences of value co-creation behaviors in a hotel setting: A two-country study. *Cornell Hospitality Quarterly, 61*(3), 353–368.

Shams, S. M. R., & Solima, L. (2019). Big data management: Implications of dynamic capabilities and data incubator. *Management Decision, 57*(8), 2113–2123.

Sharda, R., Delen, D., & Turban, E. (2016). *Business intelligence, analytics, and data science: A managerial perspective* (4th ed.). Saddle River, NJ: Pearson-Prentice Hall.

Stone, M. (1974). Cross validatory choice and assessment of statistical predictions. *Journal of the Royal Statistical Society, 36*(2), 111–147.

Stubbs, E. (2014). *Big data, big innovation: Enabling competitive differentiation through business analytics*. Hoboken, NJ: Wiley.

Sun, Z., Strang, K., & Firmin, S. (2017). Business analytics-based enterprise information systems. *The Journal of Computer Information Systems, 57*(2), 169–178.

Teece, D., Pisano, G., & Shuen, A. (1997). Dynamic capabilities and strategic management. *Strategic Management Journal, 18*(7), 509–533.

Troilo, M., Bouchet, A., Urban, T. L., & Sutton, W. A. (2016). Perception, reality, and the adoption of business analytics: Evidence from North American professional sport organizations. *Omega, 59,* 72–83.

Van Riel, A. C., Lemmink, J., & Ouwersloot, H. (2004). High-technology service innovation success: A decision-making perspective. *Journal of Product Innovation Management, 21*(5), 348–359.

Vidgen, R., Shaw, S., & Grant, D. B. (2017). Management challenges in creating value from business analytics. *European Journal of Operational Research, 261*(2), 626–639.

Voorhees, C. M., Brady, M. K., Calantone, R., & Ramirez, E. (2016). Discriminant validity testing in marketing: An analysis, causes for concern, and proposed remedies. *Journal of the Academy of Marketing Science, 44,* 119–134.

Wang, Y., Kung, L., & Byrd, T. A. (2018). Big data analytics: Understanding its capabilities and potential benefits for healthcare organizations. *Technological Forecasting and Social Change, 126,* 3–13.

Watson, H. J. (2014). Tutorial: Big data analytics: concepts, technologies, and applications. *Communications of the Association for Information Systems, 34*(1), 1247–1268.

Wedel, M., & Kannan, P. K. (2016). Marketing analytics for data-rich environments. *Journal of Marketing, 80*(6), 97–121.

Willaby, H. W., Daniel, S. J., Costa, B. D., Burns, C., McCann, C., & Richard, D. R. (2015). Testing complex models with small sample sizes: A historical overview and empirical demonstration of what partial least squares (PLS) can offer differential psychology. *Personality and Individual Differences, 84,* 73–78.

Zahra, S. A., & George, G. (2002). Absorptive capacity: A review, reconceptualization, and extension. *Academy of Management Review, 27*(2), 185–203.