Annals of Operations Research
https://doi.org/10.1007/s10479-020-03812-4

ORIGINAL RESEARCH

Big data analytics-enabled sensing capability and organizational outcomes: assessing the mediating effects of business analytics culture

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Accepted: 24 September 2020

Abstract
With the emergence of information and communication technologies, organizations worldwide have been putting in meaningful efforts towards developing and gaining business insights by combining technology capability, management capability and personnel capability to explore data potential, which is known as big data analytics (BDA) capability. In this context, variables such as sensing capability—which is related to the organization's ability to explore the market and develop opportunities—and analytics culture—which refers to the organization's practices and behavior patterns of its analytical principles—play a fundamental role in BDA initiatives. However, there is a considerable literature gap concerning the effects of BDA-enabled sensing capability and analytics culture on organizational outcomes (i.e., customer linking capability, financial performance, market performance, and strategic business value) and on how important the organization's analytics culture is as a mediator in the relationship between BDA-enabled sensing capability and organizational outcomes. Therefore, this study aims to investigate these relationships. And to attain this goal, we developed a conceptual model supported by dynamics capabilities, BDA, and analytics culture. We then validated our model by applying partial least squares structural equation modeling. The findings showed not only the positive effect of the BDA-enabled sensing capability and analytics culture on organizational outcomes but also the mediation effect of the analytics culture. Such results bring valuable theoretical implications and contributions to managers and practitioners.

Keywords Data analytics · Dynamic capabilities · Data-driven culture · Organizational outcomes · Sensing capabilities

1 Introduction

The recent emergence and expansion of business analytics (Akter et al. 2020; Krishnamoorthi and Mathew 2018; Mishra et al. 2018; Mikalef et al. 2018; Liu and Yi 2018) and cutting-edge technologies based on data science (Waller and Fawcett 2013) has allowed organizations around the world to experiment new possibilities of transforming their business models (Guha

Extended author information available on the last page of the article

Published online: 07 October 2020

and Kumar 2018; Aboelmaged and Mouakket 2020; Queiroz et al. 2020; Akter et al. 2020; Fosso Wamba et al. 2018; Boone et al. 2018; See-To and Ngai 2018). One of the most popular and influential approaches of business analytics is concerned with big data analytics (BDA) (Dubey et al. 2019b; Akter et al. 2019; Gandomi and Haider 2015; Fosso Wamba et al. 2017b; Mikalef et al. 2018).

While big data is a term used to characterize a considerable volume of structured, semi-structured, and unstructured data while considering its 5 V s (i.e., volume, velocity, variety, veracity, and value) (Fosso Wamba et al. 2017a; Queiroz and Telles 2018), BDA refers to "an integrated data collection and analysis process to provide solid insights for managerial decision-making" (Akter et al. 2017, p. 1013), through sophisticated statistical, computational and visualization tools. As for big data analytics capability, it refers to "a firm's ability to assemble, integrate, and deploy its big data-specific resources" (Gupta and George 2016, p. 1049). Bloomberg (2020) has forecast the current and future boom and frenzy for BDA/business analytics, whose market is expected to reach a value of USD 512.04 billion by 2026.

BDA techniques are to play a leading role in this outstanding progress (Gupta et al. 2019; Prasad et al. 2018, 2020; Aloysius et al. 2018), as they represent a powerful approach for capturing, storing, managing, and analyzing huge volumes of data that traditional approaches can not perform (Manyika et al. 2011; Mikalef et al. 2019). Besides, analyses of and insights into descriptive, prescriptive, and predictive forms of knowledge are expected to be more robust and convincing with such techniques to support better the management's decisions within organizations (Phillips-Wren and Hoskisson 2015; Wang et al. 2016).

In this context, BDA/business analytics is capable of generating singular insights related to various patterns of business, operations, and market monitoring while enabling outstanding predictions for improved firm performance (Mikalef et al. 2019; Fosso Wamba et al. 2020a; Hazen et al. 2018). The relevant extant literature has made significant advances by reporting BDA capabilities in multiple contexts, including e-commerce, disaster management, humanitarian supply chain, firm performance, sustainable consumption, healthcare, and product development (Akter and Fosso Wamba 2016, 2019; Akter et al. 2016; Dubey et al. 2018; Wang et al. 2018; Zhan et al. 2018).

Against this backdrop, organizations will reap the benefits of BDA only if they invest sufficiently in these tools. In this sense, data-driven culture plays an essential role in BDA project success (Upadhyay and Kumar 2020; Duan et al. 2020; Hassna and Lowry 2018), and, consequently, on organizational outcomes. In this work, BDA-enabled sensing capability shall be related to big data analytics capabilities to explore environmental data and information, with a view to gaining supportive insights for decision-making in a wide range of subjects (product/service development, operations and financial performance, competitive advantage, etc.). In this vein, BDA-enabled sensing capability seems to be a contributive factor for improving performance (Fosso Wamba et al. 2020a) and establishing a culture of analytics within organizations.

The analytics culture has been so far better defined as "the organizational norms, values, behavioral patterns resulting in systematic ways of creating, gathering, consolidating, and analyzing the data and making them available for the right audience" (Krishnamoorthi and Mathew 2018, p. 653). The analytics culture can leverage the organization's data-driven culture, which definitely impacts the routine work of the organization's members, especially when supporting the decision-making process and practices by exploring the insights from data analysis (Gupta and George 2016; Mikalef et al. 2020a).

Most organizations need to put in considerable efforts to acquire, generate, and analyze insights by exploring data from multiple sources. Therefore, the engagement and participation of both top-level decision-makers and staff members are essential to build a genuine analytics culture (Gupta and George 2016). Ultimately, customer linking capability is also critical in this regard. It refers to the organization's ability to create and establish a relationship with the customers (Day 1994; Rapp et al. 2010).

Despite the considerable advances of the BDA literature (Gupta and George 2016; Akter et al. 2019; Mikalef et al. 2019; Fosso Wamba et al. 2020a) and IT-enabled capabilities (Mikalef et al. 2020c), there is a substantial gap concerning the analysis of the influence of BDA-enabled sensing capability and the analytics culture on organizational outcomes. This added to the scarcity of works dealing simultaneously with the dynamics of BDA-enabled sensing capability and the influence of the analytics culture.

To bridge this gap, this study aims to explore the influence of BDA-enabled sensing capability and analytics culture on organizational outcomes (i.e., customer linking capability, financial performance, market performance, and strategic business value). Besides, while the recent literature approached the mediating effect of the organizational culture in the relationship between knowledge and BDAC, as well as the mediating effects of BDAC in the relationship between organizational culture and firm performance (Upadhyay and Kumar 2020), our work will mainly focus on investigating the impact of the organization's analytics culture as a mediator in the relationship between BDA-enabled sensing capability and organization outcomes (i.e., customer linking capability, financial performance, market performance, and strategic business value). Therefore, we look forward to providing useful insights and, if possible, answering the following research questions (R.Q.):

RQ1: Does big data analytics-enabled sensing capability improve organizational outcomes?
RQ2: To which extent does the analytics culture influence the improvement of organizational outcomes?
RQ3: Can the analytics culture be perceived as a significant mediator between the big data analytics-enabled sensing capability and organizational outcomes?

Drawing on the literature concerning dynamic capabilities (Teece 2007; Teece et al. 1997; Helfat and Peteraf 2009), BDA capabilities (Akter et al. 2016; Fosso Wamba et al. 2020a; Upadhyay and Kumar 2020; Mikalef et al. 2020a) and the analytics culture (Arunachalam et al. 2018; Lin and Kunnathur 2019; Krishnamoorthi and Mathew 2018), we developed a conceptual model that was validated by means of SmartPLS (Ringle et al. 2015; Hair et al. 2017). In terms of contributions, this work enriches the relevant literature by proposing and validating an original model for exploring the influence of both the BDA-enabled dynamic capability and the business analytics culture on organizational outcomes, as well as the role of the analytics culture as a mediator.

This paper is organized into sections. Section 2 provides a literature review and a theoretical framework supported by dynamic capabilities, BDA-enabled dynamic capability, and the analytics culture. Section 3 presents the methodology adopted, followed by data analysis, and results in Sect. 4. In Sect. 5, we provide a discussion showing the managerial and theoretical contributions of the study, its limitations, and some directions for future research. Section 6 presents the main conclusions of this work.

2 Literature review and theoretical framework

A conceptual model was developed based on the context of dynamic capabilities (Teece 2007; Teece et al. 1997; Mikalef et al. 2020c), more specifically on sensing capability, BDA capabilities (Akter et al. 2016; Fosso Wamba et al. 2020a; Upadhyay and Kumar 2020; Mikalef et al. 2020a) and the analytics culture (Arunachalam et al. 2018; Lin and Kunnathur 2019; Krishnamoorthi and Mathew 2018), to investigate the organizational outcomes (customer linking capability, financial performance, market performance, and strategic business value) generated by big data-enabled sensing capability and analytics culture.

2.1 Dynamic capabilities

The resource-based theory of competitive strategy posits that firm-specific capabilities and assets and associated isolating mechanisms are the fundamental determinants of firm performance (Rumelt 1984, Wernerfelt 1984). A firm's resources include all physical, human, and organizational capital resources that allow it to conceive and implement strategies to improve efficiency and effectiveness (Barney 1991). Examples include brand names, technical knowledge, skilled personnel, trade contacts, machinery, and efficient procedures and processes. An organization's ability to successfully manage its critical resources determines its capacity to create a competitive advantage and improve firm performance (Grant 1991; Newbert 2007).

In this context, the dynamic capabilities theory has gained visibility for more than two decades (Teece et al. 1997; Teece and Pisano 1994), especially with the speedup of globalization and the emergence of the cutting-edge technologies in the nineties and the years 2000. According to Teece et al. (1997), the dynamic capabilities refer to the ability of organizations in terms of internal and external competencies that can enhance its development, integration, and reconfiguration, in the face of different changes within a specific environment.

Besides, the theory about dynamic capabilities is viewed as an extension of the widespread resource-based view (RBV) theory (Barney 1991). Nowadays, the unprecedented changes imposed by the environment are challenging organizations, thereby pushing them to make use of their internal and external competences to cope with different challenges. For instance, the rapid and exponential growth of cutting-edge technologies like big data analytics (Fosso Wamba et al. 2017a) has led to adaptative measures taken by organizations around the globe. According to Teece (2007, p. 1319), "dynamic capabilities can be disaggregated into the capacity (1) to sense and shape opportunities and threats, (2) to seize opportunities, and (3) to maintain competitiveness through enhancing, combining, protecting, and, when necessary, reconfiguring the business enterprise's intangible and tangible assets."

One of the most critical dynamic capabilities is the market sense, or merely sensing capabilities (Alshanty and Emeagwali 2019; Bayighomog Likoum et al. 2020). According to Day (1994), sensing capability refers to the ability of a firm to learn with its market environment and take the actions supported by this acquired knowledge.

Recent studies have highlighted the prominence of sensing capability (Alinaghian et al. 2020; Fosso Wamba et al. 2020a). They include a study by Hassna and Lowry (2018), who explored the big data capability, customer agility, and organization's performance from the dynamic capability standpoint. Through a case study concerning Alibaba, the authors suggested that customer sensing capability is improved by big data capability. Moreover, recently, the literature established interesting propositions related to the positive influence of sensing capability on firm performance (Bayighomog Likoum et al. 2020) and on knowledge creation (Alshanty and Emeagwali 2019).

2.2 Organizational outcomes enhancement through BDA-enabled sensing capability

BDA is considered as a game-changer and an enabler of competitive advantage, given its ability to enhance business processes at both operational and strategic levels Fosso Wamba et al. 2017a). BDA-enabled sensing capability can use a variety of techniques and tools to sense and predict organizational outcomes. For instance, BDA-enabled sensing capability can enhance organizational performance and agility (Fosso Wamba et al. 2020a). Previous studies have pointed out different levels of organizational outcomes enhancement from the BDA-enabled capability perspective (Akter et al. 2016; Fosso Wamba et al. 2017a; Mikalef et al. 2020a). Thus, BDA techniques are a robust and suitable approach for gaining a deeper understanding of an organization's customers and establishing strategic relationships. This implies that customer sensing capability could be enhanced by big data capability (Hassna and Lowry 2018), and thus positively impact the firm's operations and performance.

It should be noted that the customer linking capability is related to the expertise and capabilities of organizations to develop and maintain a relationship with the customers (Day 1994; Rapp et al. 2010). This means that the customer linking capability is considered a powerful and valuable resource for any organization (Rapp et al. 2010). Concerning the importance of creating and developing customer linking capability to explore and gain insights from the market, scholars have reported the influence on the organization's performance. For instance, Rapp et al. (2010), in a study investigating customer orientation, CRM technology, and the effects of customer linking capability, found that customer linking capability positively affects customer relationship performance. In other words, BDA sensing capability can enable an organization to build and foster relationships (including in-depth ones) with customers, while supporting opportunities for collaborative product/services development. Therefore, we propose the following hypothesis:

H1: BDA-enabled sensing capability has a significant positive influence on customer linking capability.

The BDA capabilities also could bring and leverage considerable gains for a firm's competitive performance (Dubey et al. 2019b; Mikalef et al. 2020a). For instance, BDA capabilities could help firms to consolidate the monitoring of their financial environment (Mikalef et al. 2020a) and, therefore, their market performance (Upadhyay and Kumar 2020). Hence, we hypothesize that:

H2: BDA-enabled sensing capability has a significant positive influence on financial performance.

H3: BDA-enabled sensing capability has a significant positive influence on market performance.

The influence of business analytics capability on business performance has been steadily raised by the literature (Krishnamoorthi and Mathew 2018; Nam et al. 2019). It has been proven, among other things, that BDA capabilities can create strategic business value (Akter et al. 2020) by contributing to the monitoring of the environment and of the various market trends (Mikalef et al. 2020a), all of which is possible when valuable insights are brought to the firm's strategies. Therefore, we hypothesize the following:

H4: BDA-enabled sensing capability has a significant positive influence on strategic business value.

Analytics culture is a broad concept that refers to an organizational behavior associated with value and norms for all data activities (i.e., gathering, storage, techniques to analysis) aimed at informing business decision-making driven by data (Krishnamoorthi and Mathew 2018). Besides, data-driven culture is considered a critical feature of BDA initiatives (Mikalef et al. 2020a; Gupta and George 2016). Hence, we hypothesize the following:

H5: BDA-enabled sensing capability has a significant positive influence on analytics culture.

2.3 Assimilating analytics through business analytics culture

Analytics culture, which is mainly represented by a data-driven culture in an organization, is considered one of the most influential resources that support the other firm's capabilities (Arunachalam et al. 2018). In this regard, organizations should pay attention to the cultural aspects of development values for the purpose of recognizing and addressing customer demands promptly and effectively (Lin and Kunnathur 2019). Thus, we hypothesize that:

H6: Analytics culture has a significant positive influence on customer linking capability.

Many organizations are investing in analytics solutions to enhance their financial and market performance, but also their business value (Raguseo and Vitari 2018). Improved business value outcomes require meaningful analytics culture (Duan et al. 2020; Arunachalam et al. 2018), which accounts for a competitive advantage to be enhanced (Upadhyay and Kumar 2020; Mikalef et al. 2020a). Therefore, we derive the following hypotheses:

H7: Analytics culture has a significant positive influence on financial performance.
H8: Analytics culture has a significant positive influence on market performance.
H9: Analytics culture has a significant positive influence on strategic business value.

2.3.1 Mediating effect of the analytics culture

An analytics culture, which is epitomized by the organization's beliefs, practices, norms, and values, is fundamental for supporting BDA project efforts and enabling the firm to reach the desired level of performance (Hallikainen et al. 2020; Krishnamoorthi and Mathew 2018). Regarding the customer linking capability, it highlights that organizations' operations should take into account the relationship between the firms and their customers, in a coordinated business model, so as to better understand the customer needs (Rapp et al. 2010). Gaining insights from the relationship with the customer implies that the organization concerned has established a culture that reinforces the importance of BDA sensing capabilities.

Recently, Upadhyay and Kumar (2020) found that organizational culture exerts a significant positive effect on the relationship between big data analytics capability and firm performance. Also, these authors reported a mediation effect not only in the relationship between knowledge and BDAC (caused by organizational culture), but also in the relationship between organizational culture and firm performance (this time, by BDAC).

From that perspective, it is suggested that analytics culture can exert influence on both BDA capabilities and financial and market performance (Hallikainen et al. 2020; Duan et al. 2020). Once again, the analytics culture is essential for firms with BDA capabilities to achieve their desired business value (Lin and Kunnathur 2019). Therefore, we hypothesize that:

H10: Analytics culture, as a mediator, has a significant positive influence on the relationship between BDA-enabled sensing capability and customer linking capability.
H11: Analytics culture, as a mediator, has a significant positive influence on the relationship between BDA-enabled sensing capability and financial performance.

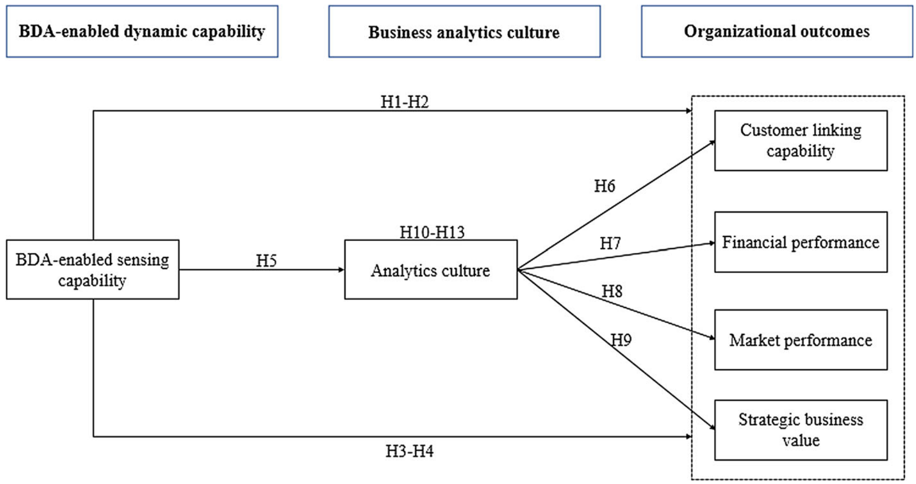

Fig. 1 Research model

H12: Analytics culture, as a mediator, has a significant positive influence on the relationship between BDA-enabled sensing capability and market performance.
H13: Analytics culture, as a mediator, has a significant positive influence on the relationship between BDA-enabled sensing capability and strategic business value.

Figure 1 describes the conceptual model of this work. Here, BDA-enabled dynamic capability and business analytics culture are supposed to contribute to attaining organizational outcomes considerably. Also, as presented previously, the analytics culture (Upadhyay and Kumar 2020; Duan et al. 2020; Arunachalam et al. 2018) is expected to play a fundamental role in the relationship between BDA-enabled sensing capability and organizational outcomes.

3 Research methodology

This study is part of a large research project aiming at assessing the critical determinants of BDA adoption, use, and impacts. A web-based questionnaire method was used as it enabled us not only to capture the causal relationships between the different constructs but also to generalize (and thus replicate) the findings obtained (Pinsonneault and Kraemer 1993).

In this vein, all constructs included in the questionnaires were derived from prior studies and adapted to fit the BDA context. Big data-enabled sensing capability was adapted from Morgan, Slotegraaf et al. (2009), while analytics culture was adapted from Kiron et al. (2014). Rapp et al. (2010) was used to adapt customer linking capability, and the adaptation of financial performance relied on Tippins and Sohi (2003). Market performance was adapted from Wang, Liang et al. (2012), and the strategic business value was adapted from Gregor et al. (2006). Items were measured using a seven-point Likert scale with anchors ranging from strongly disagree (1) to strongly agree (7).

This study uses a cross-sectional design to collect data. A leading U.S. market research firm conducted the data collection in July 2016 among mid-level executive analytics professionals with prior experience of business analytics projects. Before this final data collection, a pre-testing of the questionnaire was realized using 20 random samples, thus allowing us to check for the content validity of the survey. For the final data collection, an invitation explaining the objectives of the study was sent to a selected sample of 538 mid-level executive analytics professionals who had agreed to participate in the study. At the end of the data collection period, a careful analysis of all responses was realized, and 202 valid questionnaires were eventually considered to have been appropriately filled out and suitable for further investigation; this corresponded to a response rate of 37.55%.

Regarding the demographic profile, male and female participation was somewhat similar, with 52% and 48%, respectively. The age of the majority of respondents ranged from 50 and more (39.1%), while 23.3% were between 34 and 41 years old. Concerning the educational attainment, the majority of the respondents were holders of a tertiary level degree (82.1%), and most of them had already spent between 2 and 10 years in their employer organization (55.4%). About the industry of participants, the predominant size was 2500+ (employees), accounting for 32.2% of the respondents, while the different types of a sector included accommodation and food service activities; electricity, gas, steam and air conditioning supply; financial and insurance activities; wholesale and retail trade; and real estate activities, among others.

4 Data analysis and results

For data analysis, we used partial least squares structural equation modeling (PLS-SEM) (Akter et al. 2017; Moqbel and Kock 2018; Mikalef et al. 2020c). PLS is a robust approach (Kock 2019) for the simple reason that it does not necessarily require normal distribution and is suitable for small sample sizes (Hair et al. 2014). During the model analysis process, we followed the best practices and recommendations about the partial least squares approach (Peng and Lai 2012; Kock and Hadaya 2018; Hair et al. 2017). For instance, we used SmartPLS 3.0 (Ringle et al. 2015) to estimate the structural model and its path relationships. The evaluation of the measurement model and the structural model are described below.

4.1 Measurement model

This consisted of primarily testing the Cronbach's alpha and Composite reliability in order to measure the internal consistency reliability of the questionnaire (Hair et al. 2017). It should be noted that the Cronbach's alpha and Composite reliability results were greater than 0.70, thus outperforming the literature cutoff (Hair et al. 2017; Nunnally 1978; Fosso Wamba et al. 2020b) and suggesting adequate reliability of the selected constructs.

In addition, the loadings of the items were also greater than the 0.70 cutoffs, thereby supporting the indicator's reliability (Hair et al. 2017). The average variance extracted (AVE) was then used to measure convergent validity. All AVE values appeared greater than the literature's 0.50 cutoff (Fornell and Larcker 1981; Malesios et al. 2018; Hair et al. 2017; Fosso Wamba et al. 2020b), suggesting an adequate convergent validity (Fornell and Larcker 1981).

Table 1 shows the loadings, Cronbach's alpha, Composite reliability, and AVE results. Finally, we measured the discriminant validity (Table 2). We also used the AVE to measure the latent variables intercorrelations, in which the square root of all constructs was greater than the correlations between a primary construct and all other constructs (Fornell and Larcker 1981). Therefore, the discriminant validity of the constructs was assessed by means of diagonal values, all of which needed to be greater than others. In our case, the discriminant validity of the constructs was eventually testified (Fornell and Larcker 1981).

4.2 Structural model assessment

Table 3 points out the predictive power of the model. We performed Stone-Geisser's Q^2 test (Manupati et al. 2019; Hair et al. 2017; Stone 1974) to assess the predictive relevance of the model. The SmartPLS uses the blindfolding technique founded by cross-validated redundancy to estimate the model and its parameters. A Q^2 higher than 0 is sufficient to show the predictive power of the model. In addition, the study by Hair et al. (2019) highlights that Q^2 values that are higher than 0.25 depict a medium predictive power, while those higher than 0.50 indicate a robust predictive power of the PLS model.

On the other hand, the coefficient of determination (R^2) emphasizes the protective accuracy of the model (Hair et al. 2017). It should be noted that the structural model explained the variance in analytics culture by 45.9%, in the customer linking capability by 58.2%, in the financial performance by 48.7%, in the market performance by 45.5%, and in the strategic business value by 45.3%. Therefore, this suggests the good explanatory power of the structural model (Hair et al. 2017).

4.2.1 Assessment of hypotheses

We relied on the SmartPLS 3.0 (Ringle et al. 2015) to assess the hypotheses of the model. In H1-H5, we hypothesize the positive influence of the BDA-enabled sensing capability on customer linking capability, financial performance, market performance, strategic business value, and analytics culture, respectively. The path results obtained ($\beta = 0.347$, $p = 0.002$), ($\beta = 0.462$, $p = 0.000$), ($\beta = 0.412$, $p = 0.000$), ($\beta = 0.214$, $p = 0.016$), ($\beta = 0.677$, $p = 0.000$) supported the positive effect of the BDA-enabled sensing capability on all these variables. In this regard, it should be noted the strong positive effect (H5) that BDA-enabled sensing capability causes on analytics culture.

With regard to hypotheses H6-H9, we assessed the likelihood of the positive influence of the analytics culture on customer linking capability, financial performance, market performance, and strategic business value, respectively. Again, the path results ($\beta = 0.484$, $p = 0.000$), ($\beta = 0.297$, $p = 0.001$), ($\beta = 0.324$, $p = 0.000$), and ($\beta = 0.510$, $p = 0.000$) supports all the above-mentioned hypotheses. The focus should be made on the strong positive effect of the organization's analytics culture on strategic business value. These findings reinforce the conclusions of previous studies that highlighted the critical influence of the analytics culture on the achievement of an organization's business strategic value (Lin and Kunnathur 2019; Mikalef et al. 2020a). Table 4 draws attention on the direct effects of the model, while Table 5 shows its indirect effects.

Concerning the indirect relationships of the structural model, the results ($\beta = 0.358$, $p = 0.000$), ($\beta = 0.195$, $p = 0.027$), ($\beta = 0.224$, $p = 0.012$), and ($\beta = 0.402$, $p = 0.000$) showed a significant positive effect of the analytics culture as mediator in the relationship between BDA-enabled sensing capability and customer linking capability (H10), financial performance (H11), market performance (H12), and strategic business value (H13), respectively.

These results confirm that the organizations should pay attention to how important is the data-driven culture (Duan et al. 2020) for enhancing business performance and generating strategic business value. Moreover, the mediating outcome obtained is in line with a previous

Table 1 Measures of the internal consistency reliability and of the convergent validity

Variable	Items	Loadings	Cronbach's alpha	Composite reliability	AVE
Big data-enabled sensing capability	BSEN1	0.902	0.911	0.944	0.849
	BSEN2	0.941			
	BSEN3	0.921			
Analytics culture	ACUL1	0.816	0.944	0.951	0.566
	ACUL2	0.785			
	ACUL3	0.805			
	ACUL4	0.746			
	ACUL5	0.825			
	ACUL6	0.761			
	ACUL7	0.775			
	ACUL8	0.658			
	ACUL9	0.711			
	ACUL10	0.823			
	ACUL11	0.705			
	ACUL12	0.790			
	ACUL13	0.635			
	ACUL14	0.710			
	ACUL15	0.701			
Customer linking capability	CLINK1	0.904	0.941	0.958	0.851
	CLINK2	0.946			
	CLINK3	0.938			
	CLINK4	0.900			
Financial performance	FPERF1	0.850	0.921	0.944	0.809
	FPERF2	0.922			
	FPERF3	0.915			
	FPERF4	0.909			
Market performance	MPERF1	0.866	0.915	0.940	0.797
	MPERF2	0.883			
	MPERF3	0.888			
	MPERF4	0.933			
Strategic business value	SVAL1	0.792	0.898	0.922	0.664
	SVAL2	0.816			
	SVAL3	0.734			
	SVAL4	0.828			
	SVAL5	0.836			
	SVAL6	0.876			

Table 2 Intercorrelations between the latent variables

	ACUL	CLINK	FPERF	MPERF	BSEN	SVAL
ACUL	**0.752**					
CLINK	0.719	**0.922**				
FPERF	0.610	0.621	**0.900**			
MPERF	0.603	0.606	0.712	**0.893**		
BSEN	0.677	0.675	0.663	0.631	**0.921**	
SVAL	0.655	0.572	0.484	0.498	0.559	**0.815**

Bold represent the square roots of AVE on the diagonal

Table 3 Results of R^2 and Q^2 values

Endogenous latent variable	R^2	Q^2
Analytics culture	0.459	0.254
Customer linking capability	0.582	0.486
Financial performance	0.487	0.384
Market performance	0.455	0.356
Strategic business value	0.453	0.292

study by Upadhyay and Kumar (2020), which found a positive effect of the organizational culture on the relationship between big data analytics capability and firm performance. Table 6 highlights the results of the hypotheses, all of which were supported (with direct and indirect effects).

5 Discussion

The objective of this work was to provide a better understanding of how big data analytics-enabled sensing capability influences organizational outcomes and, in particular, demonstrate the mediating role of analytics culture. The findings indicate that our research model is fully supported. In other words, BDA-enabled sensing capabilities do have both a direct and indirect effect on organizational outcomes in relation to customer linking capability, financial performance, market performance, and strategic business value.

In this context, it should be noted that all the hypotheses were supported. That is, BDA-enabled sensing capabilities showed a significant positive influence on customer linking capability, financial performance, market performance, strategic business value, and analytics culture. These findings bring important contributions and implications to the BDA literature, mainly concerning the BDAC approach (Mikalef et al. 2018). Some studies (Akter et al. 2016; Dubey et al. 2019a, c; Fosso Wamba et al. 2017a; Gupta and George 2016; Mikalef et al. 2019, 2020a; Fosso Wamba et al. 2020a) have already skimmed over the impact of BDAC on organizations, but this could not contribute to a deeper understanding of the effects of BDA-enabled sensing capabilities. In this sense, the outcomes of our study about such relationships appear as valuable contributions to the BDA literature.

Furthermore, in line with previous studies that highlighted the prominence of the analytics culture and data-driven culture in BDA project success stories (Upadhyay and Kumar 2020; Duan et al. 2020; Hassna and Lowry 2018; Krishnamoorthi and Mathew 2018; Gupta and George 2016; Mikalef et al. 2018), and helped in supporting the organizational outcomes, our

Table 4 Results of the structural model—direct effects

Hypothesis	Paths	Path coefficients	Standard deviation	t statistic	*p* value
H1	BDA-enabled sensing capability → Customer linking capability	0.347	0.109	3.178	0.002
H2	BDA-enabled sensing capability → Financial performance	0.462	0.086	5.347	0.000
H3	BDA-enabled sensing capability → Market performance	0.412	0.093	4.439	0.000
H4	BDA-enabled sensing capability → Strategic business value	0.214	0.088	2.428	0.016
H5	BDA-enabled sensing capability → Analytics culture	0.677	0.047	14.525	0.000
H6	Analytics culture → Customer linking capability	0.484	0.096	5.063	0.000
H7	Analytics culture → Financial performance	0.297	0.091	3.246	0.001
H8	Analytics culture → Market performance	0.324	0.088	3.690	0.000
H9	Analytics culture → Strategic business value	0.510	0.082	6.189	0.000

work succeeded in firmly supporting the positive influence of analytics culture on customer-linking capability, financial performance, market performance, and strategic business value.

Furthermore, the previous literature reported the effect of data-driven culture as an intangible resource on BDAC, considering high-order models (Mikalef et al. 2020a; Gupta and George 2016). This research work went further by revealing an interesting positive effect of analytics culture (a similar construct) as a mediator in the relationship between BDA-enabled sensing capability and customer linking capability/financial performance/market performance/ strategic business value.

5.1 Theoretical contributions

Our work makes several and essential theoretical contributions to the big data analytics and dynamic capabilities literature. We developed and validated an original conceptual model that explored the BDA-enabled sensing capability, analytics culture, and their influence on organizational outcomes. Our proposed model showed substantial explanatory power (Hair

Table 5 Results of the structural model—indirect effects

Hypothesis	Paths	Path coefficients	Standard deviation	t statistic	p-value
H10	BDA-enabled sensing capability → Analytics culture → Customer linking capability	0.358	0.097	3.694	0.000
H11	BDA-enabled sensing capability → Analytics culture → Financial performance	0.195	0.088	2.217	0.027
H12	BDA-enabled sensing capability → Analytics culture → Market performance	0.224	0.089	2.514	0.012
H13	BDA-enabled sensing capability → Analytics culture → Strategic business value	0.402	0.083	4.849	0.000

Table 6 Results of the hypotheses test

Hypothesis	Results
H1: BDA-enabled sensing capability has a significant positive influence on customer linking capability	Supported
H2: BDA-enabled sensing capability has a significant positive influence on financial performance	Supported
H3: BDA-enabled sensing capability has a significant positive influence on market performance	Supported
H4: BDA-enabled sensing capability has a significant positive influence on strategic business value	Supported
H5: BDA-enabled sensing capability has a significant positive influence on analytics culture	Supported
H6: Analytics culture has a significant positive influence on customer linking capability	Supported
H7: Analytics culture has a significant positive influence on financial performance	Supported
H8: Analytics culture has a significant positive influence on market performance	Supported
H9: Analytics culture has a significant positive influence on strategic business value	Supported
H10: Analytics culture, as a mediator, has a significant positive influence on the relationship between BDA-enabled sensing capability and customer linking capability	Supported
H11: Analytics culture, as a mediator, has a significant positive influence on the relationship between BDA-enabled sensing capability and financial performance	Supported
H12: Analytics culture, as a mediator, has a significant positive influence on the relationship between BDA-enabled sensing capability and market performance	Supported
H13: Analytics culture, as a mediator, has a significant positive influence on the relationship between BDA-enabled sensing capability and strategic business value	Supported

et al. 2017), accounting for 45.9%, 58.2%, 48.7%, 45.5%, and 45.3% of the variance on analytics culture, customer linking capability, financial performance, market performance, and strategic business value, respectively.

Moreover, we found a significant positive influence of BDA-enabled sensing capability on organizational outcomes, especially in the relationships with financial performance ($\beta = 0.462$) and market performance ($\beta = 0.412$). Furthermore, it should be highlighted the strong effect of the BDA-enabled sensing capability on analytics culture. In this vein, it is suggested that BDA-enabled sensing capability could reinforce an organization's analytics culture.

On the other hand, our work found a strong relationship between analytics culture and strategic business value ($\beta = 0.510$). In this regard, while the literature has been devoted to the relationship between analytics culture and firm performance (Bayighomog Likoum et al. 2020; Upadhyay and Kumar 2020), the results of this study demonstrated the paramount importance of the data-driven culture for the attainment of financial performance and market performance and the development of long-term strategies by different organizations.

Moreover, it is clear that the moderation effect of developmental culture on customer, entrepreneurial, and technology orientation has already been investigated as shown by the literature, but here we have been able to report the significant positive effect of analytics culture as a mediator on the relationship between BDA-enabled sensing capabilities and customer linking capability, financial performance, market performance, and strategic business value.

Therefore, our findings bring important implications to the literature, since the majority of research works carried out in this field failed to discuss the effects of BDA-enabled sensing capabilities as a predictor of different organizational outcomes (Akter et al. 2016; Dubey et al. 2019a, c; Fosso Wamba et al. 2017a; Gupta and George 2016; Mikalef et al. 2019, 2020a; Fosso Wamba et al. 2019). Concerning the perception of data-driven culture as a predictor of BDAC, this has been investigated by a number of authors (Mikalef et al. 2020a; Gupta and George 2016), but we went further by unveiling an interesting behavior of analytics culture as a predictor of essential organizational outcomes. In addition, the previous literature (Upadhyay and Kumar 2020) reported the partial mediation effects of organizational culture on BDAC, while in our study, we rather found that analytics culture mediates the relationships between BDA-enabled sensing capabilities and all investigated organizational outcomes (customer linking capability, financial performance, market performance, and strategic business value).

5.2 Managerial implications

Regarding the managerial implications of this research work, it brings interesting insights to managers and practitioners involved in the operations field. Firstly, our findings revealed the importance of BDA-enabled sensing capability for achieving organizational outcomes. Specifically, our model showed that managers should consider the strong positive influence of the BDA-enabled sensing capability on customer linking capability, financial performance, market performance, and strategic business value.

In this vein, by integrating BDA with other robust tools to support the analytics models, like artificial intelligence (Dubey et al. 2019b), simulation (Vieira et al. 2019), and dashboards software to visualization (Jha et al. 2020), managers could improve their organization's sensing capability. Consequently, significant improvements can be expected in terms of conducting operations and identifying business opportunities in the market (Fosso Wamba et al. 2020a), as well as in firm's performance (Arunachalam et al. 2018; Mikalef et al. 2020b).

Secondly, managers and practitioners should pay attention to the organization's analytics culture, by improving internal knowledge (Upadhyay and Kumar 2020), enhancing internal and external collaboration, promoting technology innovation investments, and ensuring diffusion of knowledge between strategic partners. It will also be necessary to monitor cutting-edge technologies and their adoption adequately. Thirdly, it is in the interest of managers to take adequate measures to capture the contribution of the BDA-enabled sensing capability to the attainment of organizational outcomes. Finally, managers and practitioners should be able to discern those organizational outcomes that failed to help reach the expected performance, in case of poor integration of BDA-enabled sensing capability and analytics culture into the organization.

5.3 Limitations and opportunities for future research

Our study harbors some limitations that also acts as future research avenues. The first one is related to our collecting data by using a web-based survey questionnaire, which ended up reflecting a specific behavior at some point in time. In such circumstances, longitudinal studies could be combined with the survey to better capture the dynamics of the effects of BDA-enabled sensing capability and analytics culture on organizational outcomes.

Another limitation resides in that a single geographic area (the USA) was selected for data collection. This may render it difficult to generalize our findings and fully consider them in other parts of the world. Future studies could mitigate this effect by using our model to compare different countries' results concerning the dynamics of BDA-enabled sensing capability and analytics culture for the achievement of organizational outcomes. Finally, we did not analyze whether there are differences according to the respondent's industry type. Future studies could investigate if there is a significant difference in the effects of BDA-enabled sensing capability and analytics culture on organizational outcomes according to the type of industry segment. Moreover, the respondent's field could integrate other representative industry segments such as transportation, manufacturing, fashion industry, education, among others.

6 Conclusion

The main objective of this work was to investigate the influence of big data analytics-enabled sensing capability and the analytics culture on organizational outcomes. Besides, we explored the effects of the analytics culture as a mediator in the relationship between big data analytics-enabled sensing capability and organizational outcomes. Assessing these relationships required an original conceptual model. We applied a web-based survey questionnaire to collect data from U.S. mid-level executive analytics professionals with prior experience in business analytics projects.

Our findings served as meaningful contributions to the literature on dynamic capabilities, data-driven innovations, and operations. The first contribution resides in the fact that we demonstrated the influence of BDA-enabled sensing capabilities on crucial organizational outcomes (i.e., customer linking capability, financial performance, market performance, and strategic business value). As the second contribution, we departed from previous studies where data-driven is modeled as a predictor of BDAC to clearly set out that BDA-enabled sensing capabilities exert important positive influence as a predictor of analytics culture. The third contribution is epitomized by our demonstration of the critical influence of analytics culture on customer linking capability, financial performance, market performance, and strategic business value. Finally, we uncovered the effect of analytics culture as a mediator on the relationship between BDA-enabled sensing capabilities and the aforementioned organizational outcomes.

From the managerial perspective, the work's findings call on managers to pay strong attention to and put in more effort for the organization's analytics culture. They are also suggested to mobilize more funding to enhance organizational outcomes enabled by BDA-based sensing capability and analytics culture while making sure other driving factors such as skills, relationships, collaboration, cooperation, norms, and knowledge sharing are available at the intra-organizational and inter-organizational levels.

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