Research Article

BIR

Business Information Review
2021, Vol. 38(1) 28–39

DOI: 10.1177/0266382120984716
journals.sagepub.com/home/bir
SAGE

Fostering big data analytics capability through process innovation: Is management innovation the missing link?

Edwin Henao-García, José Arias-Pérez and Nelson Lozada
Universidad de Antioquia, Colombia

Abstract

Big data is heralded as the next big thing for organizations to gain competitive advantages. New data-driven firms need to control key resources in order to develop the new data-driven capabilities they need. The present paper analyzes the relationships between process innovation capability, management innovation and big data analytics capability, covering aspects related to a better understanding of how firms can obtain benefit from their investments in big data. PLS-SEM models with data from 195 firms are used. The main results suggest that management innovation and process innovation capabilities have an important role in the development of big data analytics capability. Big data analytics capability is much more than just investing in technology, collecting vast amounts of data, and allowing the technology department to experiment with analytics. The outcomes of this study present evidence on how innovative managers who promote innovations in process as well as innovations in different aspects of the organization favor the development of capabilities in big data analytics.

Keywords

Big data analytics capability, dynamic capabilities view, management innovation, process innovation capability, resource-based theory

Introduction

To date, Big data literature has focused on technical aspects, with limited attention paid to the organizational changes they entail and how they should be leveraged strategically (George et al., 2016; Mikalef et al., 2018). Beyond big data-specific technical skills, organizations face the need to develop or acquire managerial skills for it, as well as organizational learning and a data-driven organizational culture where insights extracted from data are valued and acted upon (Gupta and George, 2016). The present work is based on an emerging body of literature which builds on the notion of big data analytics capability (BDAC) as a key organizational capability oriented toward specific business objectives (Gupta and George, 2016; Mikalef et al., 2019a, 2019b; Wamba et al., 2017).

The new generation of data-driven companies needs to control key resources in order to develop the new data-driven capabilities needed by the organization. Big data technologies create novel decision-making possibilities, which are widely believed to support firms' innovation process (Niebel et al., 2019). Big data is heralded as the next big thing for organizations to gain the competitive edge, but it is important to enlighten big data managers that gaining competitive advantage from big data is not only about making investments, collecting hordes of data, and having access to sophisticated technology (Gupta and George, 2016). Despite the growing number of firms that are launching big data initiatives, there is still limited understanding on how firms translate the potential of such technologies into business value (Mikalef et al., 2019b).

BDAC is defined as the ability of a firm to capture and analyze data for the generation of insights by effectively orchestrating and deploying its data, technology, and talent (Mikalef et al., 2018). Management innovation is related to this capability and deals with the introduction of organizational changes such as new methods for managing external relationships, introducing new practices in the way work is organized or firm procedures to improve the division of responsibilities and decision-making (Damanpour and Magelssen, 2015; Nieves, 2016). In addition, a process innovation is the implementation of a new or significantly improved production or delivery method, which includes

Corresponding author:
Edwin Henao-García.
Email: edwin.henao@udea.edu.co

significant changes in techniques, equipment and/or software (OECD and Eurostat, 2005). Based on the definition provided above, Camisón and Villar-López (2014) used and evaluated the process innovation capability of the firms comparing them with their competitors' average.

Despite the many claims that big data analytics (BDA) can lead to business value (Wamba et al., 2017) and to improve the innovation processes of the firms (Niebel et al., 2019), there is still limited knowledge on the organizational aspects and challenges that are important for good practices in the deployment of BDA. To date, most studies have primarily focused on infrastructure, intelligence and analytics tools, while other related resources such as human skills and knowledge have been largely disregarded (Mikalef et al., 2018). According to the above, the present work tackles the lack of studies on BDAC antecedents and proposes management innovation and process innovation capability for that purpose.

Theoretical and conceptual framework

Resource-based theory and dynamic capabilities view

Since Barney's (1991) paper appeared, Resource-based view already reached maturity as a theory 20 years later in 2011, and today, RBT is widely acknowledged as one of the most prominent and powerful theories for describing, explaining, and predicting organizational relationships (Barney et al., 2011). According to RBT, the accumulation of valuable, rare, inimitable and non-substitutable (VRIN) resources is the basis of business competitiveness (Barney, 1991; Grant, 1991; Wernerfelt, 1984). Later, building on RBT ideas, some authors developed prominent spin-off perspectives (Barney et al., 2011), such as DCV (Teece et al., 1997). A dynamic capability implies the way in which organizational routines transform those resources into the capacities that an organization needs to face a changing environment (Eisenhardt and Martin, 2000; McGrath et al., 1995; Teece, 2009; Teece and Pisano, 1994; Teece et al., 1997).

The transition from RBT to DCV calls the attention to challenges that organizations face when shaping BDA resources, since tangible resources, to some extent, are readily available for all firms of comparable size (Barney et al., 2001); thus, resources related to big data (software, big data specific skills) will be available to many companies; consequently, they need to focus on building firm specific and hard to imitate BDAC (Gupta and George, 2016; McAfee and Brynjolfsson, 2012). As such, firms must acquire and develop a combination of data, technological, human, and organizational resources to create a capability that is difficult to imitate and transfer (Vidgen et al., 2017). Both RBT and DCV have emerged as two of the most important theoretical perspectives in the study of strategic management and technology over the past two decades (Barney et al., 2011; Makadok, 2001; Schilke, 2014).

Big data, big data analytics and big data analytics capability

Big data refers to data that are too large or complex to be handled by conventional data processing tools and techniques (OECD and Eurostat, 2018). Regularly, definitions of big data focus solely on the data and their defining characteristics (Akter et al., 2016). For instance, George et al. (2016) suggest that big data is a large and varied amount of data that can be collected and managed. Some other scholars emphasize the various channels from which data are collected, such as enterprise information systems, customer transactions, machines or sensors, social media, cell phones or other networked devices (Chen et al., 2016); still many other authors highlight the 'three Vs' that characterize big data: volume, velocity, and variety (George et al., 2016; McAfee and Brynjolfsson, 2012).

Furthermore, some authors identify some aspects pertaining to big data as a series of resources to be controlled in order to develop big data analytics capabilities: unstructured nature of data, data storage and data transport, and integration of internal and external data (Gupta and George, 2016; Zhao et al., 2014). Some other authors such as McAfee and Brynjolfsson (2012) emphasize the importance of adopting a data-driven decision-making culture where managers make decisions based on data rather than on their instincts. This work addresses the issue of how to create big data capabilities to reach superior firm performance; as Marr (2015) and Gupta and George (2016) suggest, the major issue faced by today's business leaders does not relate to the characteristics of big data, nor to their connected resources, but to how to make the best use of it and create big data analytics capabilities.

As mentioned before, the present work is part of a new stream of research, which builds on the notion of BDA as a key organizational capability, oriented toward specific business objectives. This emerging concept on big data further asserts that while organizations in all industries are collecting hordes of data, only a small percentage of them have actually benefited from their investments (Gupta and George, 2016; Mikalef et al., 2019b; Ross et al., 2013). The main premise BDA is built on is that by analyzing large volumes of unstructured data from multiple sources, actionable insights can be generated that can help firms transform their business and gain an edge over their competition (Chen et al., 2012). Also some scholars use the term BDA to emphasize the process and tools used in order to extract insights from big data, encompassing not only the entity upon which analysis is performed, but also elements of tools, infrastructure, and means of visualizing and presenting insight (Mikalef et al., 2018).

Following the same vein, Gupta and George (2016) discuss how to create capabilities around big data resources and define BDAC as a firm's ability to assemble, integrate, and deploy its big data-based resources. Not far from the same body of knowledge, Mikalef et al. (2018) define BDAC as the ability of a firm to capture and analyze data toward the generation of insights by effectively orchestrating and deploying its data, technology, and talent. Additionally, Wamba et al. (2017) propose a model of BDAC based on RBT that includes BDA infrastructure flexibility, BDA management capabilities and BDA personnel expertise capability. As it is suggested by the second and third-order constructs proposed by the previous authors, BDAC can be enriched by other capabilities already developed and implemented in the organization. This work proposes process innovation capability and management innovation as precursors of BDAC, seeking to answer the question of how companies create such capacity beyond the accumulation of resources, relying on existing organizational capabilities.

Recently, Mikalef et al. (2020) examined the indirect relationship between firm's BDAC and competitive performance; this effect is fully mediated by dynamic capabilities, which exerts a positive and significant effect on two types of operational capabilities: marketing and technological capabilities. And Albergaria and Chiappetta Jabbour (2020) address the organizational use of BDAC, with the main goal of helping organizations make better business decisions, in terms of information and operations management issues. According to Gupta and George (2016), big data analytics capability is a key organizational capability that effectively leverages big data analytics resources toward specific business objectives; based on which they propose a multidimensional third-order aggregate (or formative construct) of big data-specific tangible, human skills, and intangible resources, which in turn are conceptualized as second-order formative constructs comprising seven first-order constructs. The present work uses the cited approach and will explain in depth the scales used by the authors in the third section.

Process innovation capability and BDAC

As already mentioned, big data literature has paid little attention to the organizational and managerial aspects of big data, emphasizing on the technical aspects (Mikalef et al., 2018); one of this important organizational aspects is related to process innovation; similarly, BDA literature has focused on antecedents of its adoption (Lai et al., 2018; Verma and Chaurasia, 2019). In this regard, process innovation capability is proposed as an important antecedent of BDAC; this capability is conceptualized as a firm's ability to acquire, assimilate, transform, and exploit technically related resources, procedures, and knowledge for process innovation purposes, such as engineering know-how (Frishammar et al., 2012). Another important body of literature is based on OECD's (2005) definition: 'the implementation of a new or significantly improved production or delivery method. This includes significant changes in techniques, equipment and/or software' and is conceptualized as Camisón and Villar-López (2014) proposed.

With reference to innovation process, Wamba et al. (2017) use the process-oriented dynamic capabilities construct as mediator in the relationship between BDAC and firm performance; the authors conclude that both BDAC and process-oriented dynamic capabilities improve business performance, since partial mediation appears to be significant. Meanwhile, Kayser et al. (2018) concentrate on establishing a process for analytics projects to succeed with BDA; the process from data to value must be integrated in the existing organizational structure. In recent works, Trabucchi and Buganza (2019) highlight that previous research often considered big data in innovation as a way to enlarge the current product offer or to make the innovation process more effective or efficient; their results provide a process developed to foster innovation, considering big data as the trigger and enabler of the entire digital innovation process. Therefore, the following hypothesis is put forward:

> ***Hypothesis 1*:** Process innovation capability has a significant positive effect on BDAC.

Management innovation and BDAC

Beyond infrastructure, intelligence, analytics tools, and collecting hordes of data, there are many other related resources; human skills, knowledge, the orchestration of these resources, management commitment and top management support are crucial in the process of how resources should be incorporated into strategy and management activities to foster BDAC. In this regard, management innovation is the implementation of a new organizational method in the firm's business practices, workplace organization or external relations of the firm (OECD and Eurostat, 2005), and stems from a marked diversion from traditional management principles, processes and practices, seeking to significantly alter the way in which management work is carried out (Hamel, 2006). In managers willing to implement new and innovative administrative practices and processes, BDA initiatives will be supported.

Management innovation has to do with new organizational structures, administrative systems, management practices, processes, and techniques that could create value for the company; the foregoing implies the creation and implementation of a managerial practice, process, structure, or technique that is new and is aimed at achieving the goals of the organization (Birkinshaw et al., 2008); it includes new approaches in knowledge, new processes which produce changes in the organization's strategy, as well as new structures, administrative procedures and systems in the performing of management functions (Damanpour and Aravind, 2012). Management innovation has only been recognized as a different type of innovation in the last decade (Camisón and Villar-López, 2014), and its activities are currently attracting considerable academic interest (Nieves, 2016).

Each manager's characteristics make management innovations ambiguous in nature, internal, complex, and often unique to the companies that created them (Damanpour and Gopalakrishnan, 2001). Desirable characteristics of managers toward innovation have been highlighted in the literature, for instance: leadership orientation for risk-taking by top managers (Balabanis and Katsikea, 2003), prior knowledge and experience by top managers in dealing with international business (Herrmann and Datta, 2006), procuring effective and appropriate training for employees, and relevant training by senior management/staff level (Chen and Huang, 2009). Regarding BDAC and management, the literature points out to important topics such as: management commitment (El-Kassar and Singh, 2019), the need of attention from managers at multiple levels (Mikalef et al., 2018), top management support (Gangwar, 2018), data-driven decision-making culture, and managerial skills (analytics acumen) (Gupta and George, 2016; Wamba et al., 2017).

In the BDA context, top management support refers to the degree to which top management understands the strategic importance of big data adoption (Gangwar, 2018); thus, becoming a data-driven organization is a complex and multifaceted task that demands attention at multiple levels from managers (Mikalef et al., 2018). A firm in which decisions are influenced by the title of some individuals is unlikely to gain any return on its big data investments; consequently, the efforts to collect massive amount of data, acquire technology, and build technical and managerial skills will be in vain (Gupta and George, 2016). Regarding the above, it should be taken into account that the technical challenges of using big data are very real, but managerial challenges are even greater (McAfee and Brynjolfsson, 2012), hence the importance of having managers willing to create and introduce new organizational structures, administrative systems, management practices and processes.

Authors such as McAfee and Brynjolfsson (2012) point that many senior executive teams are genuinely data-driven and willing to override their own intuition when the data do not agree with them, emphasizing the importance of adopting a data-driven decision-making culture where managers make decisions based on data rather than on their instincts. The present work addresses the issue of how to create BDAC to reach superior firm performance; in a similar way as Marr (2015) and Gupta and George (2016) focus on how to manage and make the best use of it and how to create and develop big data analytics capabilities. On this subject, Batistič and der Laken (2019) call to explore the organizational impact of BDA from other functional management perspectives (e.g. marketing, human resource, knowledge management); these standpoints remain largely unanswered to date. Considering the previous literature discussed, the following hypotheses are proposed:

***Hypothesis 2*:** Process innovation capability has a positive effect on management innovation.
***Hypothesis 3*:** Management innovation has a significant positive effect on BDAC.
***Hypothesis 4*:** Process innovation capability has a positive indirect effect on big data analytics capability, which is mediated by a positive effect on management innovation.

Methods and data

Using the positivist approach, this study used survey measures to identify BDAC, process innovation capability and management innovation in order to address the research questions (see details in the 'Measurement scales' section). Initially, BDAC literature was explored in order to identify relationships with innovation in general and, more specifically, relationships with process innovation capability and management innovation. Based on RBV and DCV, the research model was conceptualized (see Figure 1) and surveys and instruments previously validated were used to test the hypothesized relationships, all the above using structural equation modeling (SEM) by partial least squares (PLS), using SmartPLS3 software. Following Gupta and George's (2016) methodology, the BDAC third-order multidimensional construct is first assessed. Using repeated indicators and two-stage approaches, the latent variables scores from stage 1 were used as input for the model specification in stage 2 to validate second and third-order constructs (Hair et al., 2018).

Data collection

The survey questionnaire contains previously published multi-item scales with favorable psychometric properties. Data was collected through a cross-sectional questionnaire sent by electronic mail and physically applied to administrative staff in a total of 600 firms that work collaboratively in an innovation program sponsored by an institution belonging to the regional innovation system. The data collection consisted on a sample of Colombian manufacturing and service companies (see Table 1); Colombia is an emerging economy (IMF, 2015) and technology-follower country (Castellacci, 2011; Hoskisson et al., 2000). A total of 195 usable questionnaires were collected.

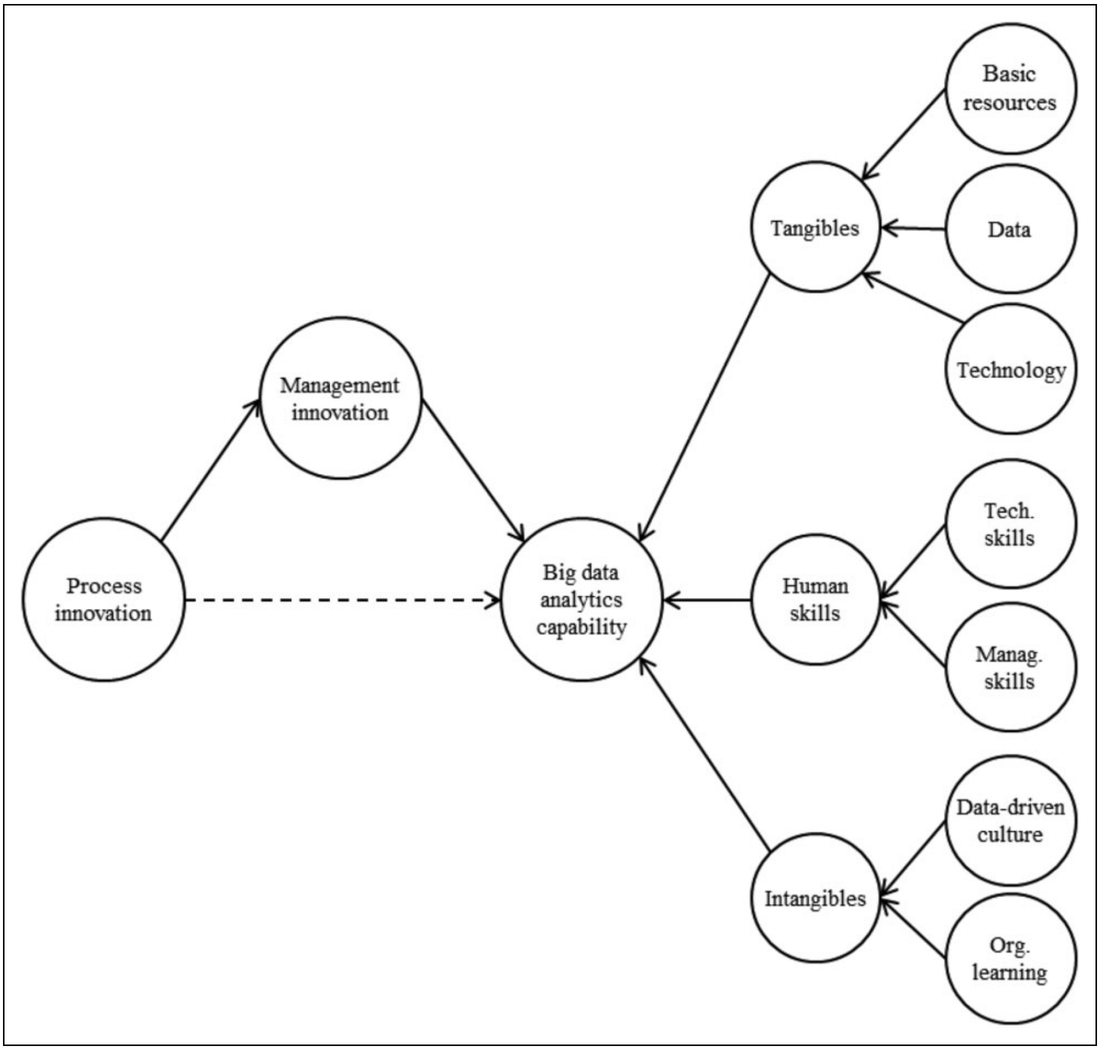

Figure 1. Research model.

Measurement scales

As mentioned above, the survey questionnaire used in the study consists of previously published multi-item scales with favorable psychometric properties (see Appendix 1). All the constructs in the model were measured using five-point Likert scales (strongly disagree to strongly agree). For measuring BDAC, Gupta and George's (2016) scale was employed, which is a multidimensional third-order construct. BDAC is the third-order construct made up of big data-specific tangible resources, human skills, and intangible resources constructs, which in turn are conceptualized as second-order formative constructs comprising seven first-order constructs: data, technology, basic resources, managerial skills, technical skills, data-driven culture and intensity of organizational learning.

For measuring process innovation capability, Liao et al. (2007) use a five-item construct that includes testing of new operation procedures, acquirement of new skills or equipment, developing of more efficient manufacturing process, flexibility providing products and services and arousing competitors' imitation of firm's new manufacturing process. Management innovation was measured with a scale designed to reflect the three components of management innovation established in the Oslo Manual (OECD and Eurostat, 2005): workplace organization, external relations or business practices (Nieves, 2016). Additionally, one item was included to measure the company's emphasis in recruiting staff with innovative and creative capability (Ali and Park, 2016; Liao et al., 2007).

Assessment of third-order BDAC construct

Initially the multidimensional third-order BDAC construct will be validated for the study's data. In the Gupta and George's (2016) scale, BDAC (formative) is the third-order construct made up of big data-specific tangible

Table 1. Sample characteristics.

Economic activity	Freq.	%
Manufacture of food and beverage products	12	6.2
Manufacture of machinery, equipment and vehicle-assembly	5	2.6
Manufacture of basic pharmaceutical and chemical products	4	2.1
Manufacture of rubber and plastic products	2	1
Manufacture of wearing apparel	6	3.1
Mining	2	1
Other manufacturing industries	10	5.1
Wholesale and retail trade	34	17
Management consultancy and business support activities	14	7.2
Financial, retirement funds and insurance activities	25	13
Human health and social work activities	12	6.2
Information service activities	7	3.6
Architectural, construction and engineering activities	8	4.1
Education	7	3.6
Computer programming, consultancy and related activities	5	2.6
Warehousing and support activities for transportation	8	4.1
Other service activities	29	15
Public sector and government	4	2.1
Missing	1	0.5
Size (number of employees)		
Small	48	25
Medium	39	20
Large	108	55
Respondent's position		
CEO	18	9.3
Human Resources	26	13
Marketing	21	11
Systems and Technology	11	5.7
R&D	3	1.5
Production	20	10
Finance	26	13
Other	69	36

resources, human skills, and intangible resources constructs, which in turn are conceptualized as second-order formative constructs comprising seven first-order constructs: data (formative), technology (formative), basic resources (formative), managerial skills (reflective), technical skills (reflective), data-driven culture (reflective) and intensity of organizational learning (reflective).

For reflective constructs all items except one (DD3) had outer loadings above 0.70 and the average variance extracted (AVE) of all the measures exceeded 0.50 (Hair et al., 2017). For the most part, the indicators of formative constructs had significant weights and variance inflation factors (VIF) were below 0.50 (Hair et al., 2017). Only two weights of data (D1) and technology (T3) were not significant. Discriminant validity assessment for reflective constructs requires Heterotrait-monotrait ratios (HTMT) below 0.85; the HTMT ratio for technical skills and managerial skills was 0.944, suggesting a problem of discriminant validity between the two constructs and indicating the necessity to merge those in one construct (Henseler et al., 2015).

Table 2. Construct validation, formative constructs.

Construct	Measure	Weights	VIF	R^2_a
Basic resources	BR1	0.790***	3.953	0.956
	BR2	0.235*	3.953	
Data	D2	0.361**	1.945	0.913
	D3	0.715***	1.945	
Technology	T1	0.349***	3.028	0.893
	T2	0.270*	3.367	
	T4	0.233**	2.545	
	T5	0.265**	3.044	
Tangibles	Basic resources	0.318***	3.907	0.872
	Data	0.212**	1.817	
	Technology	0.557***	4.609	
Intangibles	Data-driven culture	0.556***	1.946	0.921
	Organizational learning	0.529***	1.946	
BDAC	Tangibles	0.333***	2.723	0.877
	Human skills	0.411***	2.620	
	Intangibles	0.385***	1.743	

Note: VIF: Variance inflation factor; R^2_a: Edwards adequacy coefficient.
***$p < 0.01$; **$p < 0.05$; *$p < 0.1$.

In accordance with the above, items with outer loadings or weights below what was necessary or that were not significant were eliminated; also, managerial skills and technical skills constructs were combined in a single reflective construct for human skills. After this the assessment was carried out again. This time all the indicators of formative constructs had significant weights and VIFs were below 0.50 (Hair et al., 2017). Additionally, for formative constructs, Edwards' (2001) adequacy coefficient (R^2_a) was calculated by averaging the squared correlations of each indicator and its construct (Gupta and George, 2016; MacKenzie et al., 2011; Schmiedel et al., 2014); all R^2_a values were above 0.50 (see Table 2), suggesting that most of the variance in the indicators is shared with the construct; therefore, the indicators of the formative construct were valid.

Finally, in the assessment of the BDAC construct, for reflective constructs all the outer loadings (above 0.70) and AVEs (above 0.50) were verified (Hair et al., 2017). Concerning construct's reliability and validity, all constructs presented a Cronbach's alpha and composite reliability indexes (CR) above 0.80 (Hair et al., 2017). And for constructs' discriminant validity, HTMT ratios were below 0.85, see Table 3 (Henseler et al., 2015).

Reliability and validity for the complete model

After the validation of BDAC with the study's data, and the use of repeated indicators and the two-stage approaches

Table 3. Inter-correlations of the latent variables for first-order constructs.

Construct	CR	α	AVE	1	2	3	4	5	6
1. Data	NA	NA	NA	NA					
2. Basic resources	NA	NA	NA	0.592	NA				
3. Technology	NA	NA	NA	0.658	0.872	NA			
4. Human skills	0.980	0.976	0.815	0.527	0.765	0.763	**0.903**	0.660	0.547
5. Data-driven culture	0.858	0.779	0.602	0.442	0.520	0.576	0.583	**0.776**	0.802
6. Organizational learning	0.944	0.921	0.810	0.480	0.477	0.540	0.517	0.695	**0.900**

Note: CR: Composite Reliability; α: Cronbach's Alpha; AVE: Average Variance Extracted. AVEs' square roots on the diagonal (bold). HTMT ratios on upper right triangle.

Table 4. Reliability and validity.

Construct	Measure	Weights	Loadings	VIF	CR	α	AVE
BDAC (Formative)	Human skills	0.376***		2.620	NA	NA	NA
	Intangible resources	0.471***		1.743			
	Tangible resources	0.290***		2.723			
Management innovation (Reflective)	ManagInn_1		0.849***	2.784	0.930	0.728	0.728
	ManagInn_2		0.874***	3.050			
	ManagInn_3		0.877***	3.110			
	ManagInn_4		0.822***	2.479			
	ManagInn_5		0.841***	2.551			
Process innovation (Reflective)	ProcessInn_1		0.872***	3.165	0.924	0.709	0.709
	ProcessInn_2		0.907***	4.350			
	ProcessInn_3		0.891***	3.665			
	ProcessInn_4		0.770***	2.232			
	ProcessInn_5		0.759***	1.851			

Note: VIF: Variance inflation factor; CR: Composite reliability; α: Cronbach's alpha; AVE: Average variance extracted.

(Hair et al., 2018), BDAC's structure changes for the evaluation of the overall model. The reliability and validity of the complete measurement model were examined with equations through the partial least squares (PLS) method. In the case of the BDAC formative construct, all the weights were significant, and it was also verified that VIF values were below 5 (Hair et al., 2019). According to Hair et al. (2019) VIF values greater than 5 show collinearity issues, and VIF values between 3-5 could have possible collinearity problems; ideally VIF values should be below 3 (see Table 4). On the other hand, with respect to the reflective constructs, it was verified that all items had a loading equal or greater than 0.70, indicating good internal consistency and reliability; regarding convergent validity all AVEs are greater than or equal to 0.50 (Hair et al., 2019); also, all constructs presented a Cronbach's alpha between 0.70-0.90 and composite reliability indexes (CR) greater than 0.80 (Hair et al., 2017) (see Table 4). Finally, to assess discriminant validity, only two reflective constructs were left, so only one HTMT ratio between process innovation and management innovation was calculated (0.655), well below the recommended 0.85 (Henseler et al., 2015).

Structural equation model

The structural model from the PLS analysis is summarized in Table 5, where the effect size of path coefficients is presented. The significance of estimates is obtained by performing a bootstrap analysis with 5000 resamples. A firms' process innovation capability has a positive and significant impact on BDAC (0.366, t-value = 6.522, $p < 0.01$) and on management innovation (0.560, t = 8.643, $p < 0.01$); thus, Hypotheses 1 and 2 are supported. Also, management innovation in organizations has a positive and significant impact on BDAC (0.432, t-value = 7.894, $p < 0.01$), therefore, Hypothesis 3 cannot be rejected. Hypothesis 4 was tasted too, and the results (0.242, t-value = 6.714, $p < 0.01$) suggest that it is also supported. The structural model explains 65 percent of the variance of BDAC ($R^2 = 0.650$, $Q^2 = 0.488$), and 39.8 percent of the variance of management innovation ($R^2 = 0.398$, $Q^2 = 0.277$). These coefficients of determination represent moderate to substantial predictive power; and Q^2 values for BDAC and management innovation indicate a medium (0.277) to large (0.488) predictive accuracy of the PLS path model (Hair et al., 2019).

Table 5. Structural equation model and summary of hypotheses.

Structural path	Effect	t-value	Hypothesis
Management innovation → BDAC	0.432***	7.894	H3 supported
BDAC ($R^2 = 0.650$, $Q^2 = 0.488$)			
Process innovation → BDAC	0.366***	6.522	H1 supported
Process innovation → Management innovation	0.560***	8.643	H2 supported
Management innovation ($R^2 = 0.398$, $Q^2 = 0.277$)			
Indirect effects			
Process innovation → BDAC via Management innovation	0.242***	6.714	H4 supported
Control variables			
age → BDAC	−0.041	0.736	
age → Management innovation	−0.013	0.170	
sector → BDAC	0.076	1.853	
sector → Management innovation	0.080	1.405	
size → BDAC	0.210**	3.240	
size → Management innovation	0.173*	2.212	

***$p < 0.01$; **$p < 0.05$; *$p < 0.1$ (two-tailed test).

Table 6. PLS predict.

	PLS-SEM			LM		
Dependent construct items	RMSE	MAE	$Q^2_{predict}$	RMSE	MAE	$Q^2_{predict}$
Human skills	0.785	0.620	0.392	0.791	0.611	0.383
Intangibles	0.774	0.615	0.409	0.766	0.608	0.421
Tangibles	0.799	0.650	0.370	0.801	0.646	0.366
ManagInn_2	1.036	0.807	0.262	1.026	0.813	0.275
ManagInn_1	1.160	0.927	0.248	1.161	0.922	0.246
ManagInn_4	1.121	0.896	0.254	1.139	0.900	0.230
ManagInn_5	1.157	0.925	0.280	1.166	0.910	0.268
ManagInn_3	1.020	0.799	0.263	1.025	0.805	0.257

Note: PLS-SEM: Partial Least Squares-Structural Equation Modeling; LM: Linear regression modeling; RMSE: Root Mean Squared Error; MAE: Mean Absolute Error; $Q^2_{predict}$: this value in PLS Predict compares |prediction errors of the PLS path model against simple mean predictions.

Model's prediction power

Additionally, the out-of-sample predictive power of the model was assessed by conducting the PLS predict procedure (Shmueli et al., 2016). Table 6 shows the prediction error values of the PLS-SEM, Root mean squared error (RMSE), Mean absolute error (MAE) and $Q^2_{predict}$ values. The PLS predict procedure was conducted with 10 k equally sized subsets of data (k-fold cross-validation) and with 10 repetitions. The $Q^2_{predict}$ values greater than zero indicate that the model outperforms the most naive benchmark; regarding the values of RMSE, PLS-SEM analysis compared to the LM yields higher prediction errors in the minority of measures, indicating medium predictive power; contrary to this the results for the MAE suggest low predictive power (Hair et al., 2019).

Discussion

There is considerable policy interest in the ability of firms to use or develop emerging and enabling technologies, particularly those with applications across multiple industries, for instance, Internet-based applications such as cloud services and big data analytics (OECD and Eurostat, 2018). Administratively speaking, firms face serious challenges in developing this type of BDAC-related capabilities; adopting a data-driven decision-making culture where the senior-level executives make decisions based on data rather than on their instincts is one of them (McAfee and Brynjolfsson, 2012), while lack of managerial support is also a critical factor affecting the success of big data initiatives (LaValle et al., 2011).

Many other challenges are concerned with recruiting fresh talent and training current employees in big data-specific skills, since working with big data requires new kinds of technical and managerial abilities which are not commonly taught in universities (McAfee and Brynjolfsson, 2012). Today, the growing body of knowledge around big data as an organizational capability has mainly focused on analyzing how BDAC generates benefits and competitive advantages as well as on how to foster other organizational resources and capabilities, neglecting the importance of good big data-based resource implementation and deployment. The present study extends existing research by proposing that process innovation capability and management innovation are important to developing BDAC in the new generation of data-driven firms.

Implications for research and practice

The results of the present study show that management innovation and process innovation capabilities play a significant role in BDAC deployment. This, in turn, suggests that by strengthening firms' dynamic capabilities, BDAC is strengthened and positively affected. A new line analyzing which organizational factors may be key for firms to obtain the expected results of their investments in big data-related resources emerges as a research area of interest. Since the nature of existing and potential future sources of information may have big data attributes, namely they are too large or complex to be handled by conventional tools and techniques (OECD and Eurostat, 2018), the present work provides provoking insights for practitioners who are interested in developing BDAC within their companies, emphasizing the importance of adopting a data-driven decision-making culture in senior-level executives, promoting good process-oriented innovation capabilities, and overcoming the lack of managerial support as a critical factor in successful big data initiatives (LaValle et al., 2011).

Conclusions and future lines of research

Although it has been pointed out that few firms really benefit from their investments in BDA (Gupta and George, 2016; Mikalef et al., 2019a, 2019b), works looking into which already-established, organizational capabilities (Wamba et al., 2017) could help in the correct implementation of a BDA strategy are still scarce. This study contributes to shedding light on the unexplored relationship between management innovation, process innovation capabilities and BDAC, mainly motivated by the great interest academics have shown in analyzing the impact of BDAC on the organization, yet neglecting the importance of a good implementation of it. This work has focused on analyzing how innovation-driven managers with good innovation process capabilities can develop BDA capabilities in their organizations. Future sources of information certainly contain intrinsic big data attributes: they are too large and complex to handle so new kinds of technical and managerial abilities are required given that conventional tools and techniques are gradually becoming obsolete.

As Gupta and George (2016), Mikalef et al. (2020) and Wamba et al. (2017) remark, creating a big data analytics capability is much more than just investing in technology, collecting vast amounts of data, and allowing the technology department to experiment with analytics. The outcomes of this study present evidence on how innovative managers who promote innovations in process as well as innovations in different aspects of the organization favor the development of capabilities in big data analytics. These innovative aspects, pertaining to both managers and theirs firms, include many other important organizational resources and capabilities such as supporting and developing managerial understanding of the significance of big data (natural in innovative managers), recruiting people with good big data-related technical skills, and creating and promoting a culture of organizational learning with a strong data-driven decision-making philosophy.

The results of the present study show that management innovation and process innovation capabilities play an important role in BDAC development; however, important future lines of research have emerged and merit further analysis. Emerging technologies, particularly those in areas including Internet-based applications and big data analytics, require other important organizational capabilities to be investigated as drivers of big data analytics capability; that is, BDAC is necessary but not a sufficient condition leading to better performance gains in firms. The subjective nature of the data, in combination with the use of a single informant, could suggest a bias in the analysis. Finally, having prior measures (panel data) of the company's situation in terms of innovation capabilities before the implementation of a big data-oriented strategy would per se help to isolate the effects of the firms' capabilities on the implementation of big data strategy.

Declaration of conflicting interests

The author(s) declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

Funding

The author(s) received no financial support for the research, authorship, and/or publication of this article.

ORCID iD

Nelson Lozada https://orcid.org/0000-0001-7236-6907

References

Akter S, Wamba SF, Gunasekaran A, et al. (2016) How to improve firm performance using big data analytics capability and business strategy alignment? *International Journal of Production Economics* 182: 113–131.

Albergaria M, Chiappetta Jabbour CJ (2020) The role of big data analytics capabilities (BDAC) in understanding the challenges of service information and operations management in the sharing economy: evidence of peer effects in libraries. *International Journal of Information Management* 51: 102023.

Ali M, Park K (2016) The mediating role of an innovative culture in the relationship between absorptive capacity and technical and non-technical innovation. *Journal of Business Research* 69(5): 1669–1675.

Balabanis GI, Katsikea ES (2003) Being an entrepreneurial exporter: does it pay? *International Business Review* 12(2): 233–252.

Barney J (1991) Firm resources and sustained competitive advantage. *Journal of Management* 17(1): 99–120.

Barney J, Ketchen DJ, Wright M (2011) The future of resource-based theory revitalization or decline? *Journal of Management* 37(5): 1299–1315.

Barney J, Wright M, Ketchen DJ (2001) The resource-based view of the firm: ten years after 1991. *Journal of Management* 27(6): 625–641.

Batistič S, der Laken P (2019) History, evolution and future of big data and analytics: a bibliometric analysis of its relationship to performance in organizations. *British Journal of Management* 30(2): 229–251.

Birkinshaw J, Hamel G, Mol MJ (2008) Management innovation. *Academy of Management Review* 33(4): 825–845.

Camisón C, Villar-López A (2014) Organizational innovation as an enabler of technological innovation capabilities and firm performance. *Journal of Business Research* 67(1): 2891–2902.

Castellacci F (2011) Closing the technology gap? *Review of Development Economics* 15(1): 180–197.

Chen C-J, Huang J-W (2009) Strategic human resource practices and innovation performance – the mediating role of knowledge management capacity. *Journal of Business Research* 62(1): 104–114.

Chen H, Chiang RHL, Storey VC (2012) Business intelligence and analytics: from big data to big impact. *MIS Quarterly* 36(4): 1165–1188.

Chen Y, Chen H, Gorkhali A, et al. (2016) Big data analytics and big data science: a survey. *Journal of Management Analytics* 3(1): 1–42.

Damanpour F, Aravind D (2012) Managerial innovation: conceptions, processes, and antecedents. *Management and Organization Review* 8(2): 423–454.

Damanpour F, Gopalakrishnan S (2001) The dynamics of the adoption of product and process innovations in organizations. *Journal of Management Studies* 38(1): 45–65.

Damanpour F, Magelssen C (2015) *The Cycle of Adoption of Organizational Innovation: A Longitudinal Study of Adoption, De-Adoption, and Re-Adoption*. Seminar working paper Universidad Pablo de Olavide.

Edwards JR (2001) Multidimensional constructs in organizational behavior research: an integrative analytical framework. *Organizational Research Methods* 4(2): 144–192.

Eisenhardt KM, Martin AJ (2000) Dynamic capabilities: what are they? *Strategic Management Journal* 21(10–11): 1105–1121.

El-Kassar A-N, Singh SK (2019) Green innovation and organizational performance: the influence of big data and the moderating role of management commitment and HR practices. *Technological Forecasting and Social Change* 144: 483–498.

Frishammar J, Kurkkio M, Abrahamsson L, et al. (2012) Antecedents and consequences of firms' process innovation capability: a literature review and a conceptual framework. *IEEE Transactions on Engineering Management* 59(4): 519–529.

Gangwar H (2018) Understanding the determinants of big data adoption in India. *Information Resources Management Journal* 31(4): 1–22.

George G, Osinga EC, Lavie D, et al. (2016) Big data and data science methods for management research. *Academy of Management Journal* 59(5): 1493–1507.

Grant RM (1991) The resource-based theory of competitive advantage: implications for strategy formulation. *California Management Review* 33(3): 114–135.

Gupta M, George JF (2016) Toward the development of a big data analytics capability. *Information & Management* 53(8): 1049–1064.

Hair JF, Hult GTM, Ringle CM, et al. (2017) *A Primer on Partial Least Squares Structural Equation Modeling (PLS-SEM)*, 2nd ed. Los Angeles, CA: SAGE Publications.

Hair JF, Risher JJ, Sarstedt M, et al. (2019) When to use and how to report the results of PLS-SEM. *European Business Review* 31(1): 2–24.

Hair JF, Sarstedt M, Ringle CM, et al. (2018) *Advanced Issues in Partial Least Squares Structural Equation Modeling*. Los Angeles, CA: SAGE.

Hamel G (2006) The why, what, and how of management innovation. *Harvard Business Review* 84(2): 72.

Henseler J, Ringle CM, Sarstedt M (2015) A new criterion for assessing discriminant validity in variance-based structural equation modeling. *Journal of the Academy of Marketing Science* 43(1): 115–135.

Herrmann P, Datta DK (2006) CEO experiences: effects on the choice of FDI entry mode. *Journal of Management Studies* 43(4): 755–778.

Hoskisson RE, Eden L, Lau CM, et al. (2000) Strategy in emerging economies. *Academy of Management Journal* 43(3): 249–267.

International Monetary Fund (IMF) (2015) *World Economic Outlook: Adjusting to Lower Commodity Prices*. Washington, DC: IMF.

Kayser V, Nehrke B, Zubovic D (2018) Data science as an innovation challenge: from big data to value proposition. *Technology Innovation Management Review* 8(3): 16–25.

Lai Y, Sun H, Ren J (2018) Understanding the determinants of big data analytics (BDA) adoption in logistics and supply chain management. *The International Journal of Logistics Management* 29(2): 676–703.

LaValle S, Lesser E, Shockley R, et al. (2011) Big data, analytics and the path from insights to value. *MIT Sloan Management Review* 52(2): 21–32.

Liao S, Fei W-C, Chen C-C (2007) Knowledge sharing, absorptive capacity, and innovation capability: an empirical study of Taiwan's knowledge-intensive industries. *Journal of Information Science* 33(3): 340–359.

McAfee A, Brynjolfsson E (2012) Big data: the management revolution. *Harvard Business Review* 90(10): 60–68.

McGrath RG, MacMillan IC, Venkataraman S (1995) Defining and developing competence: a strategic process paradigm. *Strategic Management Journal* 16(4): 251–275.

MacKenzie SB, Podsakoff PM, Podsakoff NP (2011) Construct measurement and validation procedures in MIS and behavioral research: integrating new and existing techniques. *MIS Quarterly* 35(2): 293–334.

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

Marr B (2015) *Big Data: Using SMART Big Data, Analytics and Metrics to Make Better Decisions and Improve Performance*. West Sussex: Wiley.

Mikalef P, Boura M, Lekakos G, et al. (2019a) Big data analytics and firm performance: findings from a mixed-method approach. *Journal of Business Research* 98: 261–276.

Mikalef P, Boura M, Lekakos G, et al. (2019b) Big data analytics capabilities and innovation: the mediating role of dynamic capabilities and moderating effect of the environment. *British Journal of Management* 30(2): 272–298.

Mikalef P, Krogstie J, Pappas IO, et al. (2020) Exploring the relationship between big data analytics capability and competitive performance: the mediating roles of dynamic and operational capabilities. *Information & Management* 57(2): 103169.

Mikalef P, Pappas IO, Krogstie J, et al. (2018) Big data analytics capabilities: a systematic literature review and research agenda. *Information Systems and e-Business Management* 16(3): 547–578.

Niebel T, Rasel F, Viete S (2019) BIG data – BIG gains? Understanding the link between big data analytics and innovation. *Economics of Innovation and New Technology* 28(3): 296–316.

Nieves J (2016) Outcomes of management innovation: an empirical analysis in the services industry. *European Management Review* 13(2): 125–136.

OECD, Eurostat (2005) *Oslo Manual: Guidelines for Collecting and Interpreting Innovation Data*, 3rd ed. Luxembourg: OECD Publishing Paris/Eurostat.

OECD, Eurostat (2018) *Oslo Manual 2018: Guidelines for Collecting, Reporting and Using Data on Innovation*, 4th ed. *The Measurement of Scientific, Technological and Innovation Activities*. Luxembourg: OECD Publishing Paris/Eurostat.

Ross JW, Beath CM, Quaadgras A (2013) You may not need big data after all. *Harvard Business Review* 91(12).

Schilke O (2014) On the contingent value of dynamic capabilities for competitive advantage: the nonlinear moderating effect of environmental dynamism. *Strategic Management Journal* 35(2): 179–203.

Schmiedel T, vom Brocke J, Recker J (2014) Development and validation of an instrument to measure organizational cultures' support of business process management. *Information & Management* 51(1): 43–56.

Shmueli G, Ray S, Velasquez Estrada JM, et al. (2016) The elephant in the room: predictive performance of PLS models. *Journal of Business Research* 69(10): 4552–4564.

Teece DJ (2009) *Dynamic Capabilities and Strategic Management: Organizing for Innovation and Growth*. Oxford: Oxford University Press.

Teece DJ, Pisano G (1994) The dynamic capabilities of firms: an introduction. *Industrial and Corporate Change* 3(3): 537–556.

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

Trabucchi Z, Buganza T (2019) Data-driven innovation: switching the perspective on big data. *European Journal* 22(1): 23–40.

Verma S, Chaurasia S (2019) Understanding the determinants of big data analytics adoption. *Information Resources Management Journal* 32(3): 1–26.

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

Wamba SF, Gunasekaran A, Akter S, et al. (2017) Big data analytics and firm performance: effects of dynamic capabilities. *Journal of Business Research* 70: 356–365.

Wernerfelt B (1984) A resource-based view of the firm. *Strategic Management Journal* 5(2): 171–180.

Zhao JL, Fan S, Hu D (2014) Business challenges and research directions of management analytics in the big data era. *Journal of Management Analytics* 1(3): 169–174.

Author biographies

Edwin Henao-García is a full Professor in technology management, programming methodology and information systems at the Economic Sciences Faculty of the Universidad de Antioquia. He received his college degree in Business administration, his M.Sc. degree in Technology management and innovation, and his Ph.D. degree in Administration. His research interests and publications comprise the areas of management innovation, innovation capabilities, corporate entrepreneurship and strategies for emerging markets; his work has been published in journals such as Journal of Knowledge Management, Business Information Review and International Journal of Business Innovation and Research, among others.

José Arias-Pérez is a full Professor of knowledge management of the Department of Administrative Science at the Universidad de Antioquia, Colombia. His research has been published in journals such as Journal of Knowledge Management, IEEE Transactions on Engineering Management, and Multinational Business Review.

Nelson Lozada is a Professor and Researcher in the fields of organizational theory and innovation management. He works at the Universidad de Antioquia, Department of Administrative Sciences.

Appendix 1

Table A1. Scale items.

Big data analytics capability (Gupta and George, 2016)	
Data	We have access to very large, unstructured, or fast-moving data for analysis
	We integrate data from multiple internal sources into a data warehouse or mart for easy access
	We integrate external data with internal to facilitate high-value analysis of our business environment
Technology	We have explored or adopted parallel computing approaches to big data processing
	We have explored or adopted different data visualization tools
	We have explored or adopted cloud-based services for processing data and performing analytics
	We have explored or adopted open-source software for big data analytics
	We have explored or adopted new forms of data bases for storing data
Basic resources	Our big data analytics projects are adequately funded
	Our big data analytics projects are given enough time to achieve their objectives
Technical skills	We provide big data analytics training to our own employees
	We hire new employees that already have the big data analytics skills
	Our big data analytics staff has the right skills to accomplish their jobs successfully
	Our big data analytics staff has suitable education to fulfill their jobs
	Our big data analytics staff holds suitable work experience to accomplish their Jobs successfully
	Our big data analytics staff is well trained
Managerial skills	Our big data analytics managers understand and appreciate the business needs of other functional managers, suppliers, and customers
	Our big data analytics managers are able to work with functional managers, suppliers, and customers to determine opportunities that big data might bring to our business
	Our big data analytics managers are able to coordinate big data-related activities in ways that support other functional managers, suppliers, and customers
	Our big data analytics managers are able to anticipate the future business needs of functional managers, suppliers, and customers
	Our big data analytics managers have a good sense of where to apply big data
Data-driven culture	We base our decisions on data rather than on instinct
	We continuously assess and improve the business rules in response to insights extracted from data
	We continuously coach our employees to make decisions based on data
Intensity of organizational learning	We are able to search for new and relevant knowledge
	We are able to acquire new and relevant knowledge
	We are able to apply relevant knowledge
	We have made concerted efforts for the exploitation of existing competencies and exploration of new knowledge
Management innovation, items 1 to 4 (Nieves, 2016) item 5 (Ali and Park, 2016; Liao et al., 2007)	
We frequently introduce organizational changes to improve the division of responsibilities and decision-making (e.g., decentralization, department restructuring, etc.).	
We frequently introduce new methods for managing external relationships with other firms or public institutions (e.g., new alliances, new forms of cooperation, etc.).	
We often introduce new practices in work organization or firm procedures (e.g., new quality management practices, new information and knowledge management systems, etc.).	
The new organizational methods that we have incorporated have been pioneering in the sector.	
Our company emphasizes innovative and creative capability when recruiting staff.	
Process innovation capability (Liao et al., 2007)	
Our company often tries different operation procedures to hasten the realization of the company's goals.	
Our company always acquires new skills or equipment to improve the manufacturing operation or service process.	
Our company can develop more efficient manufacturing process or operation procedure.	
Our company can flexibly provide products and services according to the demands of the customers.	
The new manufacturing process or operation procedure employed by our company always arouses imitation from competitors.	