



Research article

Big data analytics capability and co-innovation: An empirical study

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ARTICLE INFO

Keywords:

Business
Economics
Information science
Big data analytics capabilities
Co-innovation
Big data
Co-creation

ABSTRACT

There are numerous emerging studies addressing big data and its application in different organizational aspects, especially regarding its impact on the business innovation process. This study in particular aims at analyzing the existing relationship between Big Data Analytics Capabilities and Co-innovation. To test the hypothesis model, structural equations by the partial least squares method were used in a sample of 112 Colombian firms. The main findings allow to positively relate Big Data Analytics Capabilities with better and more agile processes of product and service co-creation and with more robust collaboration networks with stakeholders internal and external to the firm.

1. Introduction

The intensive and widespread use of mechanisms for data capture, storage, and analysis became an everyday process for companies a few decades ago. Currently, efforts are focused on the honing of methods for the analysis and treatment of large amounts of data, aiming at strengthening the decision-making process in order to generate greater value for the company (Gobble, 2013; Alharthi et al., 2017; Popović et al., 2018). Companies such as Facebook and Microsoft did not make large investments in the acquisition of social networks, such as WhatsApp and LinkedIn respectively, for nothing. The value of these acquisitions may be thought to lie in the millions of users who make part of these platforms, which is partly true, but it can also be accurately asserted that a large accumulation of data is contained in social networks which, when analyzed and organized through certain tools in a certain way, becomes an invaluable source for value creation in the firm (Chang et al., 2014). IBM apparently understood this when the company decided to change the strategic focus of its business, going from hardware manufacturing to concentrating on the provision of services associated with information technology management (Alharthi et al., 2017).

In the face of this new reality, the analysis of the impact of big data has become a top matter for both executives who wonder how it can be used to improve company performance as well as for academia which seeks to explain the phenomenon, its implications, and even its future direction and scope (Frizzo-Barker et al., 2016; Delen and Zolbanin, 2018; Aydiner et al., 2019). It is safe to say big data is considered a phenomenon on which the competitive advantage of companies will be

leveraged in the future, hence its significance and the need to understand its existing relationship with another competitive-advantage creating factor: innovation (Côte-Real et al., 2019; Shollo and Galliers, 2016; Duan et al., 2018; Côte-Real et al., 2017; Constantiou and Kallinikos, 2015).

In this context, the use of big data suggests the broadening of the boundaries of what so far has been known as mechanisms for business innovation management; it is hence common for companies to report the use of big data in their innovation processes (Ransbotham and Kiron, 2017). For example, Duan et al. (2018) conclude the use of big data has a positive impact on innovation results because it improves the company's ability to scan the environment, providing valuable information to improve the novelty factor and meaning of new products and services. Meanwhile, Lin et al. (2018) showed that in big data intensive environments managers' decisions to build collaborative networks with external organizations have a positive impact on innovative performance. Regarding big data, and based on empirical evidence, Zhang and Xiao (2019) recommend companies to have customers perform two roles: providing and analyzing the data used for product co-innovation.

As noted earlier, it is clear that with the increase in the use of big data and its incorporation into the core of the processes associated with innovation management, and along with the strategy of including different stakeholders in value co-creation initiatives, business innovation has become a more inclusive process and it appears to be an issue that will overlook in the future the limitations that are currently naturally set in the company (Acharya et al., 2018). However, the analysis of how technological aspects, skills relating to human resources, and big data

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management are connected to the processes of ideation and collaboration typical of co-innovation-supporting networks are scarce in the literature, and there is a lack of empirical evidence. At this point, it is particularly important to study in depth the impact of big data usage on business co-innovation (Brunswick et al., 2015; Akhtar et al., 2019; Urbinati et al., 2018).

In this context, the main purpose of this article is to analyze the relationship between the three resources (tangible, human, intangible) which enable to develop the Big Data Analytics Capability (BDAC) in the co-innovation process. Its main contributions are concerned with helping to fill the existing gap in the literature by providing empirical evidence that confirms the relationship and significance of BDACs in improving open innovation processes such as co-innovation. Furthermore, this article allows for a non-engineering and non-technical approach to big data, and guides and calls the attention of managers on the importance of BDACs development, and how their adequate management results in a direct and positive relationship with co-innovation and thus in a competitive advantage for the firm.

This article is structured as follows: the literature review and hypothesis development are presented after the introduction section. Then the research methodology and data analysis are described, followed by the results section. Finally, the discussion and implications are reported.

2. Theory

2.1. Big data analytics and big data analytics capability

The treatment and analysis of very large amounts of data in order to support decision-making processes in organizational contexts –and even in public policy– is called big data (Allam and Dhunny, 2019; Gupta et al., 2018; Davenport, 2014). In general terms, the big data phenomenon has resulted into two strong analysis and development aspects: one of them is focused on computational and technological infrastructure aspects, namely technical and data analysis challenges, which has been called Big Data Analytics (BDA) (Dong and Yang, 2018); and a second line of study is associated with the challenges posed by the management and incorporation of big data into organizational processes, known as BDA capability (Gupta and George, 2016).

Theoretical and empirical developments in BDA revolve around the origin, capture, storage, treatment, and analysis of data, aspects which are not unknown to the organizational context, but which take a new and complex dimension given the exorbitant increase in data creation. This is due to the ease with which data is created and the multiple sources of origin such as telemetry, sensors, GPS's and the intensive use of technological devices such as smartphones connected to social networks, among others, which altogether constitute a continuous, very robust source of data. In order to identify the main challenges of BDA, scholars have so far defined seven concepts or characteristics (Mikalef et al., 2018; Sivarajah et al., 2017; Chen et al., 2013; Barnaghi et al., 2013).

The first characteristic of BDA is Volume. This attribute refers to data size, which in the case of big data is of exponential growth, posing challenges concerning data storage, acquisition, and processing, entailing considerable investments in technological equipment (George et al., 2016; Barnaghi et al., 2013). The second attribute of BDA is Variety, linked to data heterogeneity –audio, video, text, images– whose challenge lies in the dissimilar ways data is generated (Constantiou and Kallinikos, 2015; Chen et al., 2013). A third characteristic is the Velocity at which data flow is created, even requiring real-time analysis in some cases, as well as the speed with which data can become obsolete, challenging the development of new tools for data analysis (Sivarajah et al., 2017; George et al., 2016). In the fourth place comes Veracity, related to data quality, that is, the accuracy and reliability of the data and its sources which serve as guarantee for its potential use. A fifth attribute is Visualization, which refers to the ability to present data in ways that render them meaningful (Seddon and Currie, 2017). The sixth attribute is the Value of the data extracted from big data for an end user, and its

contribution to improving performance in the case of companies (Sivarajah et al., 2017; Gandomi and Haider, 2015). Finally, the seventh characteristic of BDA is Variability, referring to the ongoing and rapid variation in data meaning and interpretation (Seddon and Currie, 2017; Sivarajah et al., 2017).

Conversely, the BDA capability refers to a company's management ability, that is, the continuous use and deployment of big data resources with the strategic goal of creating value and developing a competitive advantage for the firm (Wamba et al., 2017; Garmaki et al., 2016; Gupta and George, 2016; Kiron et al., 2014). Three resource categories that account for the BDA capability are identified in the literature.

Tangible resources and infrastructure, as the first resource category, focus their attention on the significance of data as an essential resource taking into account aspects relating to its origin, capture, and nature, as well as elements pertaining to the technological and physical infrastructure requirements that allow for an efficient use of data. Such efficiency is achieved through better database technologies and the guarantee of efficient data management by means of a more robust infrastructure adapted to the gigantic magnitudes of big data. This requires the company's analysis in order to undertake the necessary investments to advance big data initiatives which need an adequate period of time to be implemented and generate the yield that was set (Wamba et al., 2017; Gupta and George, 2016).

The second category refers to human resource, differentiated into two groups: the first group is made up of people who have the technical skills for big data –programming, machine learning, artificial intelligence, statistical analysis, cleaning and extraction of data–including capabilities for learning and understanding new technological trends; the second group of people are those who possess the skills for big data management, and who are in charge of planning, implementation and control of big data-related process and resources, and even more importantly, of understanding how the knowledge extracted from big data can be applied to different areas in the company (Wamba et al., 2017; Gupta and George, 2016).

The third category deals with intangible resources, which reflect the importance of two particular aspects: the first one is a data-driven culture that allows the decisions made by managers at any level in the company to be supported by the evidence that the data suggest rather than following intuition based on past experiences; the second intangible resource is organizational learning which suggests companies that have developed capabilities to explore, accumulate, share and transform knowledge possess a key inventory of valuable knowledge, very useful when validating and contextualizing the results obtained from big data, i.e., high levels of organizational learning enable the combination and validation of knowledge extracted from big data, rendering possible an informed decision-making process in the company (Gupta and George, 2016).

2.2. Big data analytics capability and Co-innovation

Co-innovation is defined as the process that allows the participation of the different stakeholders in the company (clients, suppliers, external collaborators, partner organizations, and the general public), through collaborative work networks, in the creation and development of new products and services, as well as processes or even business models; that is to say, co-innovation achieves value creation for the company through the active participation of external actors (Saragih et al., 2019; Bugshan, 2015; Lee et al., 2012; Romero and Molina, 2011).

Co-innovation is thus linked to two approaches that appear to be different yet are basically complementary: open innovation and collaborative innovation. Open innovation focuses on the importance of innovation supported by developments resulting from knowledge and ideas internally and externally originated (Chesbrough, 2003) whereas collaborative innovation emphasizes the innovation process carried out through the construction of partnership and alliances with other actors, where the participating partners share ideas and knowledge (Bonney et

al., 2007). In summary, co-innovation is based on connecting with multiple actors, since the innovation resulting from collaboration or participation is much more effective than that which is undertaken on a solitary basis.

Lee et al. (2012) consider it is essential for companies to focus on aspects such as convergence, collaboration, and co-creation in order to develop co-innovation. Convergence is the possibility the co-innovation network has of clustering different actors, enabling the synergic development of new products, processes, and business models as a result of the complementarity of resources and capacities (Bitzer and Bijman, 2015). In turn, collaboration requires the development of a culture based on collaborative work within the company; it thus facilitates the building of relationships that foster joint knowledge creation or learning along with other actors in the co-innovation network (van den Broek et al., 2018; Walsh et al., 2016; Tomlinson, 2010). Co-creation focuses on the company's ability to involve its customers in the value-creating process either by creating new products or services or by developing the ones it currently has (Busser et al., 2019; de Oliveira and Cortimiglia, 2017). Therefore, the intensive use of communication and information technologies has achieved the advancement and consolidation of co-innovation processes, facilitating the proximity of different actors who are normally geographically dispersed; that is to say, the actors' involvement –to promote the developing of the various tasks in the co-innovation process– is possible through the use of technologies and social mechanisms (de Oliveira and Cortimiglia, 2017).

In this context, the design and management of the co-innovation platform is particularly relevant to eventually sustain a co-innovation cycle with an actual potential for value creation to the company, which implies paying attention to three dimensions regarding the participation of the actors in a co-innovation network. According to Gloor (2006) and Abhari et al. (2017), these dimensions are: creativity or ideation, collaboration, and communication.

Creativity or ideation refers to actors' participation in the co-creation of new products or services. Collaboration is focused on solving issues or challenges via the participation and interaction of the internal and external actors from the co-innovation network. Finally, communication is conceived as the process that guarantees the fluidity in the exchange or creation of knowledge stemming from the interacting actors.

The significance of the affordances provided by the co-innovation platform becomes clear from the above. In other words, this refers to the ease and functionality with which the actors perceive the different uses and interactions of the various tasks relating to the co-innovation cycle –when interacting through the technological platform designed to manage co-innovation–, including collaborative idea submission, evaluation, and development of co-invention activities (Abhari et al., 2017).

On the other hand, BDA capabilities share an essential and complementary feature with co-innovation: they are managed via technological platforms, both of which are naturally ingrained to the use that the company makes of technology with the aim of improving and generating greater value and building and maintaining competitive advantage over time (Del Vecchio et al., 2018); such complementarity is concerned with the potential of BDA capabilities to improve performance in the co-innovation process.

The use of huge amounts of data captured and processed thanks to the technological infrastructure of the BDA, and its analysis by data specialist technicians, is a valuable input when identifying the characteristics associated with the perceived product value (e.g., functionality, cost-benefit relation, emotions, ethical responsibility, status) and the elements pertaining to the profiling of niche segments (e.g., beliefs and values, economic level, hobbies, opinions).

This big data-sourced input allows the process of ideation and co-creation to facilitate the collection, refinement and evaluation of ideas with the intent of determining their potential to become formal development projects (Beretta, 2019). It is therefore possible for the efforts to be focused on initiatives that are backed by decisions made based on data that help to improve development time, launch, and the possibilities of

product acceptance in the market, reducing uncertainty-based risks (Zhan et al., 2017).

BDA capabilities also empower actors' collaboration in co-innovation concerning the solution to problems or challenges, facilitating the creation of applied knowledge linked to a specific purpose. In this sense, the company has the possibility to offer valuable information provided by big data as an input to the co-creation of solutions that may have a connection with supply or provision issues with suppliers, or also with the difficulties and challenges stemming from the uncertainty arising from the different scenarios in the value chain (Dubey et al., 2019; Urbinati et al., 2018). Considering the previous discussion, the following hypothesis is proposed:

Hypothesis: Big data analytics capabilities have a direct and positive effect on co-innovation.

3. Methods

3.1. Sample and data collection

The proposed model (see Fig. 1) was contrasted with a sample of low and medium technology manufacturing firms (Eurostat, 2009) and service firms (see Table 1) located in Colombia, and emerging and technology-follower country (Hoskisson et al., 2000; Castellacci, 2011). Field work was conducted between September 2018 and October 2018 through a questionnaire sent by electronic mail and physically applied to the management of a total of 600 firms that work collaboratively in an innovation program sponsored by an institution belonging to the regional innovation system, which articulates companies and universities. 112 valid responses were finally obtained; this sample size guarantees a satisfactory statistical power above 80% (Cohen, 1988).

3.2. Measurement scales

For measuring big data analytics capability, we employed the Gupta and George (2016) scale, which is a construct composed of other constructs: tangibles, human skills and Intangibles. In turn, the tangibles construct is composed of three formative constructs: Data, Technology and Basic Resources; and the intangibles construct is made up of two reflective constructs: Data-driven Culture and Intensity of Organizational Learning. For measuring co-innovation, we used the (Abhari et al., 2017) scale (see Appendix – Scale Items). We also used a Likert scale going from totally disagree (1) to totally agree (5).

3.3. Reliability and validity

The reliability and validity of the measurement model were examined with equations through the consistent partial least squares method (PLSc), which corrects and provides consistent estimations of the reflective constructs and thus represents an improvement with respect to the traditional PLS algorithm (Dijkstra and Henseler, 2015). In the case of the formative constructs, it was verified that the variance inflation factor (VIF) values were below 5 and that the weights of the constructs and of the formative items were significant (Hair et al., 2019). Table 2 shows the validation results of the big data analytics capability.

Regarding the weights of those items that were not significant, it was verified that the loading was significant (Hair et al., 2019) (see Table 3). On the other hand, with respect to the reflective constructs, we verified that all items had a loading equal or greater than 0.7. We also checked that all the constructs presented a Cronbach's alpha (CA), composite reliability indexes (CR) and Dijkstra-Henseler (pA) above 0.7, and a Variance Extracted Index (VEI) greater than 0.5.

3.4. Discriminant validity

To establish discriminant validity, we confirmed that all Heterotrait-Monotrait (HTMT) values were below the threshold of 0.85 (Henseler

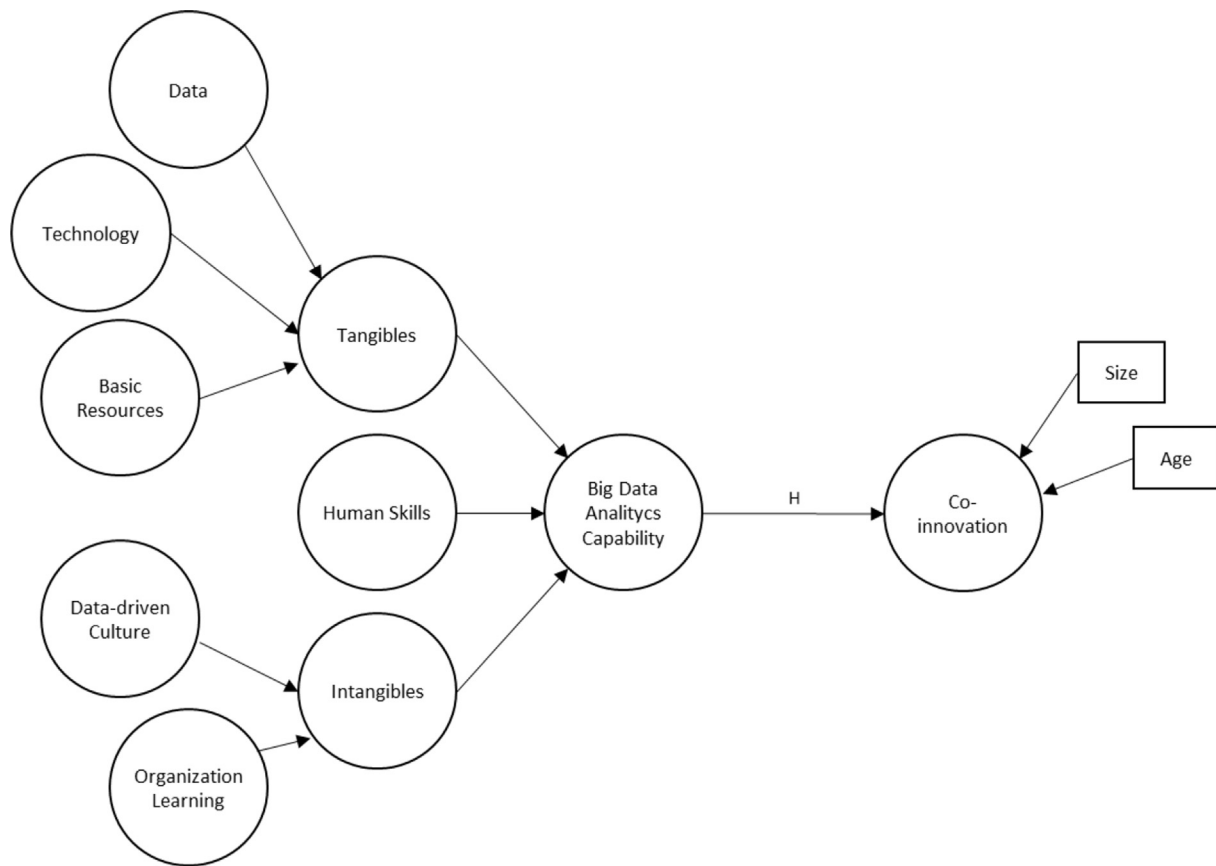


Fig. 1. Research model.

et al., 2015) (see Table 4).

4. Results

This study used structural equations by the consistent partial least squares method (PLSc), in order to obtain the t values of the coefficients of the different trajectories from a resampling of 5000 subsamples (Henseler et al., 2009). Table 5 shows that the trajectory between big data analytics capability and co-innovation ($\beta = 0.23$; t-value = 2.50) is significant and has a positive sign. Thus hypothesis is accepted. As regards the control variables, only size is significant.

4.1. Prediction power of the model

Table 5 also shows that the model explains 63% of the co-innovation variance, which indicates that the prediction power is above the moderate level and close to the substantial one. The table also shows that the Q^2 value is 0.4, which means that the predictive relevance of the model is greater than the medium level and close to the high level (Hair et al., 2019). Additionally, we assessed the out-of-sample predictive power of the model by conducting the PLSpredict procedure (Shmueli et al., 2016); Table 6 shows that the prediction error values of the PLS-SEM, root mean squared error (RMSE) or mean absolute error (MAE) are lower in comparison with the values of a linear regression model (LR), which indicates that the model has a high out-of-sample power.

5. Discussion and conclusions

Despite the growing interest to understand the big data phenomenon and its influence on the different environments of the firm, there are few empirical studies which analyze the potential big data represents for business innovation. Besides, there are not many studies focusing on such

a relevant concept, given the current competitive co-innovation context. Here lies the importance of this study's contribution, which provides empirical evidence confirming the existence of a direct and positive relationship between BDA capability and co-innovation. From this perspective, this study also contributes to broadening understanding of how big data impacts business results.

Another relevant contribution lies in the fact that this study moves away from the current of analysis prevailing in the literature which focuses on big data from a technical or engineering perspective. This work focuses on delving into the explanation of big data implications as an organizational capability. BDA capability is understood as the orchestration of tangible, intangible and human resources with the aim of strengthening, for the case of this study, the co-creation, collaboration and communication processes, which are typical of the networks supporting co-innovation. In this sense the results suggest that the ideation process for co-creation of new products and services is more effective and agile if the actors involved possess inputs derived from big data analysis. This process is more effective since it allows to make decisions related to the characteristics and attributes of the new and/or enhanced product and/or service supported on data and not only on the opinion or experience of the actors participating in the co-innovation network (Zhang and Xiao, 2019); this considerably reduces the risk associated with the lack of acceptance of the products by the end customer (Zhan et al., 2017). Likewise, the firm develops agility in the processes of launching and introducing products and services to the market on account of the reduction of the time used in the ideation and co-creation phase. Thus, the agile and effective co-creation of new or improved products or services allows the firm to rapidly adapt to the changing conditions of the market, keeping abreast of competitors (Côrte-Real et al., 2017).

Furthermore, the results suggest that the adequate design and governance of the technological platforms supporting the co-innovation process must allow access to data exchange and to the

Table 1
Sample characteristic.

Sector	Economic activity	Frequency	%	
Manufacturing	Manufacture of food products	5	4	
	Manufacture of machinery and equipment	5	4	
	Manufacture of basic pharmaceutical products	3	3	
	Manufacture of rubber and plastic products	2	2	
	Manufacture of wearing apparel	3	3	
	Other manufacturing industries	7	6	
Services	Wholesale and retail trade	19	17	
	Office administrative and support activities and other business support activities	12	11	
	Financial and insurance activities	11	10	
	Human health and social work activities	8	7	
	Information service activities	7	6	
	Architectural and engineering activities	6	5	
	Education	6	5	
	Computer programming, consultancy and related activities	3	3	
	technical testing and analysis	3	3	
	Management consultancy	2	2	
	Services to buildings and landscape activities	2	2	
	Warehousing and support activities for transportation	2	2	
	Other service activities	6	5	
	Size (number of employees)			
	SMEs		57	51
Large		55	49	
Respondent's position				
CEO		18	16	
Human Resources		21	19	
Marketing		18	16	
Systems and Technology		17	15	
Research and Development		10	9	
Production			7	
Finance		5	4	
Other		15	13	

Table 2
Validation of the construct of big data analytics capability.

Construct	Measures	Weight	t value	VIF
Tangibles	Data	0.317	15.303	2.32
	Technology	0.401	15.190	4.94
	Basic Resources	0.373	15.551	3.67
Intangibles	Data-driven Culture	0.624	5.943	2.92
	Intensity of organizational Learning	0.462	4.027	2.92
BDA	Tangibles	0.369	30.385	3.60
	Human skills	0.401	32.324	3.18
	Intangibles	0.347	53.046	1.84

Note: VIF = Variance Inflation Factor.

results of big data analysis with the aim of incentivizing the collaborative nature typical of the actors' interaction. In this sense the results agree with [Urbinati et al. \(2018\)](#) when they conclude that the exchange of data and big data analysis results are essential for co-innovation with suppliers and customers. This ease of data access and use, added to the governance of the technological platform, has a direct relationship with the outcomes of the co-innovation process since it can facilitate or hinder collaborative work and strengthen or crack the relations and commitments of the actors because they belong to a network in which it is essential to achieve value co-creation ([Rehm et al., 2016](#)). Finally, the study results corroborate how important it is for the firm to start and maintain over time the financial effort entailed by investments in technological infrastructure and the development of specific skills required from the human resource involved in BDA capabilities. In this sense the results are coherent with the study by [Müller et al. \(2018\)](#), which provides empirical evidence that positively correlates the investment made in BDA and firm performance.

Table 3
Reliability and validity.

Constructs	Weight	Loading	CA	CR	VEI	pA
Big data analytics capability (Third-order)						
Tangibles (Second-order)						
Data (First-order)			N/A	N/A	N/A	N/A
BDA1	0.07	0.66***				
BDA2	0.39*					
BDA3	0.64***					
Technology (First-order)			N/A	N/A	N/A	N/A
BDA4	0.33***					
BDA5	0.22*					
BDA6	0.10	0.86***				
BDA7	0.14	0.83***				
BDA8	0.33**					
Basic Resources			N/A	N/A	N/A	N/A
BDA9	0.82***					
BDA10	0.21	0.92***				
Human Skills (Second-order)			0.98	0.98	0.80	0.98
BDA11	0.77***					
BDA12	0.85***					
BDA13	0.92***					
BDA14	0.89***					
BDA15	0.89***					
BDA16	0.89***					
BDA17	0.94***					
BDA18	0.90***					
BDA19	0.90***					
BDA20	0.89***					
BDA21	0.96***					
Intangibles (Second-order)						
Data-driven Culture (First-order)			0.82	0.83	0.63	0.85
BDA22	0.70***					
BDA23	0.86***					
BDA24	0.85***					
Intensity of Organizational Learning (First-order)			0.92	0.92	0.75	0.92
BDA25	0.91***					
BDA26	0.89***					
BDA27	0.84***					
BDA28	0.81***					
Co-innovation			0.97	0.97	0.73	0.97
CO1	0.91***					
CO2	0.90***					
CO3	0.85***					
CO4	0.93***					
CO5	0.88***					
CO6	0.83***					
CO7	0.85***					
CO8	0.83***					
CO9	0.84***					
CO10	0.76***					
CO11	0.75***					

Note: CA = Cronbach's Alpha; CR = Composite Reliability; VEI = Variance Extracted Index; pA = Dijkstra-Henseler; * $p < 0.05$; ** $p < 0.01$; and *** $p < 0.001$.

5.1. Managerial implications

One of the main challenges for the management, and for BDA managers and their innovation partners in particular, is to develop a data-driven culture both within the firm as well as in the co-innovation

Table 4
Discriminant validity.

Construct	HTMT			
	1	2	3	4
1. Human				
2. Data-driven culture	0.59			
3. Intensity of Organizational Learning	0.61	0.81		
4. Co-innovation	0.57	0.62	0.65	

Note: HTMT = Heterotrait-Monotrait.

Table 5
Results of structural equations.

Trajectories	Coefficient	t value
Direct effect BDA -> CO (R ² : 0.63; Q ² : 0.4) Control Variables	0.77	16.834
Age -> CO	-0.12	2.189
Size -> CO	0.05	0.884

Table 6
PLSPredict.

Dependent construct items	PLS-SEM			LR		
	RMSE	MAE	Q ²	RMSE	MAE	Q ²
Coin1	1.135	0.932	0.391	1.324	1.077	0.171
Coin2	1.144	0.919	0.385	1.428	1.102	0.041
Coin3	1.195	0.946	0.309	1.418	1.117	0.027
Coin4	1.071	0.825	0.375	1.362	1.011	-0.011
Coin5	1.150	0.904	0.334	1.294	0.972	0.158
Coin6	1.244	0.982	0.287	1.396	1.071	0.102
Coin7	1.113	0.877	0.351	1.310	1.016	0.101
Coin8	1.112	0.917	0.359	1.275	1.027	0.158
Coin9	1.129	0.916	0.359	1.301	1.031	0.149
Coin10	1.197	0.949	0.269	1.338	1.091	0.088
Coin11	1.255	1.008	0.284	1.543	1.174	-0.081

Note: PLS-SEM = Partial Least Squares-Structural Equation Modeling; LR = Linear Regression; RMSE = Root Mean Squared Error; MAE = Mean Absolute Error; Q² = Cross Validated Redundancy.

network. This implies demonstrating the practical use that the results of big data analysis offer and the practical benefit it provides; in this way, the co-creation and collaboration process can support the data decision-making process so that it will not only be supported on the actors' experience or intuition. Moreover, the current competitive context demands that organizational learning be associated with developing and being able to manage the transversal inclusion of the digital and technological tools and advances in each aspect of the firm's business model. That is to say, big data and co-innovation, as two powerful tools that facilitate and materialize organizational learning, have as common feature the fact both are based on the intensive use of data, digital mechanisms and technological platforms.

The study results yield empirical evidence allowing to conclude that BDA capabilities positively influence co-innovation process outcomes, and that there is abundant literature positively relating co-innovation with organizational performance, whether financial or non-financial. This implies that the management must understand that efforts related to integrating big data and co-innovation must be considered under the framework of a learning curve, in which the adjustment of organizational processes, mechanisms, application, procedures, and even routines, will demand time. A short-termist approach to the development of this capability destroys the potential it has for value creation and sustainable competitive advantage.

5.2. Academic implications

Firms are transformed by the digital and technological impact, and so are managers. The study results allow to infer that the training of managers should not be alien to the skills required by firms to manage the use of current and future use of the digital and technological aspects. The approach of business schools to the teaching of these skills should allow students to understand the technical implications typical of digitalization and of the use of technology as a source for competitive advantage. Business schools' training must stress the development of skills enabling the future manager to translate the possibilities offered by digital and technological tools into value for the company. In other words, training must empower the manager to generate the links among big data,

artificial intelligence, collaborative work platforms, among many others; considering the practical use that people in the different areas of the organization can make of them to facilitate essential issues such as decision-making, and organizational learning and development.

Business schools must understand that equipping their students with these skills does not mean reaching the training level of technical data scientists or experts in the technological architectural design of collaborative platforms. The above calls for the construction of convergent multidisciplinary curricula (mathematics, statistics, programming, communication) which determine the level of competencies and skills the students must be trained to attain. Failure to bring the future managers closer to the digital and technological environment, its language, its challenges and its logic, means to alienate them or make it difficult for them to understand how the nature of the organization adapts itself to the new realities and challenges entailed by a future in which the social and economic aspects are redefined by the digital and technological ones.

5.3. Limitations and future research

The main limitation of the study is related to the generalization of the results since the hypothesis model was tested in a sample of firms located in a country with an emerging economy which is also a technology follower (WEF, 2016; Hoskisson et al., 2000; Castellacci, 2011). Likewise, it was difficult to contrast the results obtained with those of similar studies since, according to the literature exploration conducted, research specifically analyzing the impact of BDA capability on co-innovation is only an emerging field today.

Due to that contrast, the gap identified in this study calls for future research that enables to delve into the understanding of this phenomenon. Mediating variables such as knowledge leakage, absorptive capability, organizational machiavellianism and narcissism, besides syndromes such as Not Invented Here (NIH) and Not Shared Here (NSH) (de Araujo Burcharth et al., 2014), are important to explain the use people make of data and of the knowledge in collaborative work networks with firm's internal and external actors. Likewise, other mediating aspects such as information technology capabilities, the practices associated with knowledge management, and strategic orientation, can be included in the analysis. On the methodological aspect, research using qualitative methodologies such as case studies, interviews and focal groups are useful to propose other analysis categories enabling understanding of fundamental issues related to the know-how of co-creation teams and their interaction and collaboration dynamics, among others. Comparative studies are also required which analyze the results with statistical samples of firms from different countries so that it is possible to build a baseline allowing the analysis of gaps and thus be able to suggest the mechanisms and strategies to fill those gaps, besides contrasting the direct effects between BDA capabilities and co-innovation.

Declarations

Author contribution statement

Nelson Lozada: Conceived and designed the experiments; Performed the experiments; Analyzed and interpreted the data; Contributed reagents, materials, analysis tools or data; Wrote the paper.

Jose Arias-Pérez: Conceived and designed the experiments; Analyzed and interpreted the data; Contributed reagents, materials, analysis tools or data; Wrote the paper.

Geovanny Perdomo-Charry: Conceived and designed the experiments; Performed the experiments; Contributed reagents, materials, analysis tools or data; Wrote the paper.

Funding statement

This work was supported by Universidad de Antioquia, Colombia; under project number 21530004-FAPP01 and Universidad CEIPA,

Colombia.

Competing interest statement

The authors declare no conflict of interest.

Additional information

Supplementary content related to this article has been published online at <https://doi.org/10.1016/j.heliyon.2019.e02541>.

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