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Big Data Analytics Capability and Contribution to Firm Performance: The Mediating Effect of Organizational Learning on Firm Performance

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Purpose
The study examines how firms may transform big data analytics (BDA) into a sustainable competitive advantage and enhance business performance using BDA. Furthermore, this study identifies various resources and sub-capabilities that contribute to BDA capability.

Design/methodology/approach
Using classic grounded theory (GT), resource-based theory and dynamic capability (DC), the authors conducted interviews, which involved an exploratory inductive process. Through a continuous iterative process between the collection, analysis and comparison of data, themes and their relationships appeared. The literature was used as part of the data set in the later phases of data collection and analysis to identify how the study's findings fit with the extant literature and enrich the emerging concepts and their relationships.

Findings – The data analysis led to developing a conceptual model of BDA capability that described how BDA contributes to firm performance through the mediated impact of organizational learning (OL). The findings indicate that BDA capability is incomplete in the absence of BDA capability dimensions and their sub-dimensions, and expected advancement will not be achieved.

Research limitations/implications – The research offers insights on how BDA is converted into an enterprise wide initiative, by extending the BDA capability model and describing the role of per dimension in constructing the capability. In addition, the paper provides managers with insights regarding the ways in which BDA capability continuously contributes to OL, fosters organizational knowledge and organizational abilities to sense, seize and reconfigure data and knowledge to grab digital opportunities in order to sustain competitive advantage.

Originality/value – This article is the first exploratory research using GT to identify how data-driven firms obtain and sustain BDA competitive advantage, beyond prior studies that employed mostly a hypothetico-deductive stance to investigate BDA capability. While the authors discovered various dimensions of BDA capability and identified several factors, some of the prior related studies showed some of the dimensions as formative factors (e.g. Lozada et al., 2019; Mikalef et al., 2019) and some other research depicted the different dimensions of BDA capability as reflective factors (e.g. Wamba and Akter, 2019; Ferraris et al., 2019). Thus, it was found necessary to correctly define different dimensions and their contributions, since formative and reflective models represent various approaches to achieving the capability. In this line, the authors used GT, as an exploratory method, to conceptualize BDA capability and the mechanism that it contributes to firm performance. This research introduces new capability dimensions that were not examined in prior research. The study also discusses how OL mediates the impact of BDA capability on firm performance, which is considered the hidden value of BDA capability.

Keywords: Big data analytics, Big data analytics capability, Digital transformation, Organizational learning, Grounded theory

Paper type: Research article

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1. Introduction

The interest in BDA has been growing as it helps organizations gain a better and more competitive edge in industries. BDA is considered as a strategic resource that transforms businesses strategy to a more forward-looking approach (Liu et al., 2011). BDA is defined as the "next big thing in innovation" (Gobble, 2013, p. 64) and as the ''mother node of disruptive change in a networked business environment" (Baesens et al., 2016, p. 629). Research has shown that successfully leveraging BDA enriches a firm's decision quality (Ghasemaghaei et al., 2018), increases operational efficiency (Chen et al., 2015), enhances innovation (Mikalef et al., 2019), developing customer service, reliability and position in the market (Akter et al., 2016). Furthermore, prior research suggests that BDA enhances supply chain agility and efficiency (Wamba and Akter, 2019). International Data Corporation (IDC) asserts that the worldwide big data and analytics technology and services market reached $90 billion in 2021 and predicts to exceed more than double by 2026 (IDC, 2022). While the classic information value chain embeds in the descriptive analysis and report of structured data for decision-makers (Abbasi et al., 2016), BDA has significantly altered IS value creation through delivering predictive insights (Kiron et al., 2014). Controversially, some researchers argued that despite the hype attention surrounding BDA transformational role, firms' competitive advantage using BDA has been declining (Bag et al., 2021; Inamdar et al., 2020) and firms are unable to design "effective and efficient plans" to utilize BDA (Su et al., 2022, p. 4). In this line, various factors are discussed such as adoption barriers (Ghasemaghaei, 2020) that challenge firms to achieve their "BD dreams" (Mazzei and Noble, 2017) such as organizational culture (Lavalle et al., 2011), the complexity of developing strategies to grab BDA insights (G€unther et al., 2017), data governance, safety and confidentiality (Nisar et al., 2020, p. 1062) and lack of knowledge related to the use of BDA intelligence (McAfee and Brynjolfsson, 2012). For instance, the survey of 1,000 CEOs and industry leaders (NewVantage Partners, 2021) concludes that only 29.2% of BDA investment has transformed business outcomes and created a data-driven organization. Mikalef et al. (2020) argue that investing exclusively in BDA technology does not enhance firm performance, which indicates an insufficient level of transformational maturity in using BDA (Gartner, 2018).

To overcome the BDA challenges and obtain a competitive advantage, a recent research stream introduced the concept of BDA capability (BDAC) through a combination of different data-related resources (Gupta and George, 2016). Subsequently, a significant body of research has focused on BDAC in recent years. However, an examination of the extant literature on BDAC revealed several gaps that motivated this study.

Firstly, there are some variations in the literature concerning the identification of the various facets of the BDAC concept. When examining the effect of BDAC on firms' performance, some studies mostly focused on technological capability (Dubey et al., 2019), while others emphasized both technological and talent capability (Wang et al., 2019) or technological and management capability (Ferraris et al., 2019). To the best of our knowledge, very few studies combined technological, human resource facets and data science department management. Further, an examination of these prior works suggests that some other relevant facets might have been ignored.

Secondly, a closer examination of the literature revealed some major issues relating to the specification of the BDA construct. A vast majority of prior related studies propose the construct as a hierarchical or as a multiple-order construct. For example, while Lozada et al. (2019) and Mikalef et al. (2019) identified BDAC as a formative construct, few scholars (e.g. Wamba and Akter, 2019; Ferraris et al., 2019) assessed BDAC with reflective components. Differently, Gupta and George (2016) used both reflective and formative constructs in their model; however, referring to Lohm€oller's (1989) statistical modelling discussion, the statistical validity of their research is questionable. The misspecification of formative and reflective constructs can influence the statistical power of models and affects the originality of contributions and their importance in the model (Petter et al., 2007).

Lastly, many empirical studies examined the impact of BDAC on firm performance in various study contexts (Jha et al., 2020; Lozada et al., 2019). Most of these studies showed that BDAC has a direct influence on firms' performance in terms of gaining a competitive advantage (Gupta and George, 2016). This finding may be considered simplistic as noted in recent studies (e.g. Mikalef et al., 2019) that suggest that the relation between BDAC and firm performance could be far more complex. Therefore, it is critical to understand how BDA initiatives contribute to firm performance, which highlights the need for additional research into the factors that mediate/moderate the relationship between BDA and firm performance (Bamel and Bamel, 2020). For example, Mikalef et al. (2019), using Gupta and George's (2016) model, found that the impact of BDAC on firm performance is mediated by dynamic capability (DC). Other research found business strategy alignment mediates the relationship between BDAC and firm performance (Akter et al., 2016). Accordingly, we concluded that it is imperative to further explore all possible BDAC dimensions, examine the definition and specification of the BDAC construct and its sub-constructs. Moreover, further research is needed to examine possible mediating factors affecting BDAC's contribution to firm performance.

To fill the above gap, we adopted a classic grounded theory (GT) methodology (Glaser and Strauss, 1967; Glaser, 1978, 1992) using an exploratory stance to answer 'how can BDA contribute to firm performance and lead to sustainable competitive advantage? Hence drawing classic GT we (1) identified the many possible facets of BDAC, (2) to further shed light on the proper assessment of these facets of BDAC, also (3) GT enabled us to draw a fruitful conclusion on how BDAC contribute to firm performance, not only directly, but also indirectly through the mediated impact of organizational learning (OL). This is particularly important since deductive prior studies concluded OL as the BDAC dimension, not the mediator factor, which consequently influences the management of BDA resources and capabilities.

2. Literature Review

Following the classic GT approach, we used the literature as an additional source of data during the later phases of our research. However, the BDA and capability literature is presented in the second section in order to facilitate reading and understanding of the present article. Also, as a means of describing our findings' contribution to the literature and providing a summary of BDA capabilities in the literature, we used the systematic literature review (SLR) approach. There is no consensus among researchers on how to define BDA and construct BDAC, hence, it was vital to conduct a SLR guidelines by Kitchenham and Charters (2007) to define BDA and understand how different constructs build BDAC. The process started by searching for several terms. Research articles were screened from the "Google Scholar" database with publication years ranging from 2010 to 2020. Using several keywords such as "big data analytics capability", "analytics capability", and "big data capability" through the Boolean operator (AND; OR) 525 articles were discovered. Following a thorough check, we finally selected 15 articles that fitted our inclusion criteria. The selected papers were used to define the three concepts discussed in the following subsections and they were used as a backbone of the theoretical background of our study.

2.1. Big Data and Big Data Analytics

Big data (BD) is defined regarding some specific data characters that are often described by various "Vs". McAfee and Brynjolfsson (2012) consider "3Vs" for BD as "Volume, Velocity, Variety", while Hasan et al. (2022) assert "7Vs" for BD that include "Volume, Velocity, Variety, Variability, Veracity, Visualization and Value". In this research, BD definition encompasses "5Vs", which were identified through data collection and analysis. These include Volume: a large amount of data, Variety: the different types of structures in the data flow, Velocity: the frequency and the speed of data generation, Veracity: trustworthy, authentic and qualified data produced by the BD resources, Value: the potential benefits within the available data flow (Wamba et al., 2015; Sivarajah et al., 2017). Although some scholars define BD by using the data characteristics, it is argued that BD in a vacuum is worthless and only represents enormous quantities of ever-changing data (Lycett, 2013). Thus, the term BDA is proposed to illuminate the critical role of analytics to unlock the potential value of BD and transform it into practical knowledge (Wamba et al., 2017). Regarding Saggi and Jain (2018) and Sivarajah et al. (2017), BDA refers to a variety of predictive algorithms, semantic analysis, statistical analysis methods and technologies to explore actionable insights from BD. However, some studies assert BDA is more than just technology; rather, BDA should include a range of factors to generate insight, transform the running business and the competition context (Jha et al., 2020; McAfee and Brynjolfsson, 2012). In this line, BDA Capability has been introduced to cover various aspect of technology, technique, human resource, strategy and management, which are jointly employed to manage, analyze and interpret the five characteristics of BD (Wamba et al., 2015).

2.2. BDA Capability

BDAC is built upon the concept of IT value creation, which emphasizes the importance of an integrated bundle of various resources to realize the full potential of IT investments; therefore, only investing in technology does not result in the successful development of a firm (Bharadwaj, 2000, Kim et al., 2012). BDAC demonstrates the organizational ability to successfully integrate various data and non-data resources to generate actionable insights via "firm-wide processes, roles and structures" (Mikalef et al., 2019. p.274). BDAC is characterized by different constructs through hierarchical or non-hierarchical models.

Introducing the non-hierarchical model, BDAC can be conceptualized as a “single construct” (Ashrafi et al., 2019. p.2) that relies on information technology, or BDAC may include analytics alignment with business to meet business goals (Krishnamoorthi and Mathew, 2018), technological and human resource ability to interpret data (Popovič et al., 2018), analytical and predictive capability (Wang et al., 2018), as well as organizational culture and analytical team capability (Rialti, et al., 2019).

BDAC is also conceptualized as a multi-dimensional construct through a reflective or formative hierarchical model. For example, drawing upon the resource-based view (RBV) and/or the Dynamic Capability approach, BDAC is defined as the bundle of valuable, distinctive, and inimitable resources, and capabilities. Gupta and George (2016) introduced BDAC as a third-order formative construct that aggregates three types of resources: tangible resources (i.e., technology, data, investment and time), human resource (i.e., skills), and intangible resources (i.e., data-driven culture and intensity). The formative hierarchical BDAC directly develops firm performance (Gupta and George, 2016), while constantly adapting an organization to environmental volatility (Lozada et al., 2019).

Using RBV and socio-materialism, Akter et al. (2016) and Wamba et al.(2017) operationalized BDAC as the third-order reflective construct that comprises three dimensions through 11 measures that manifest the overall BDAC. The dimensions are defined as 1) BDA technology capability 2) BDA management capability embeded in BDA unit's ability to effectively operate BDA related resources regarding business needs, and benefits, and 3) BDA expertise capability to undertake analytics process and transform insights.

Although there is inconsistency on the BDAC model, the literature acknowledges that BDA insights positively affects firm performance by developing market, financial and operational performance (Dubey et al., 2019; Gupta and George, 2016). To reveal how BDAC contributes to value creation and competitive advantage, different mediated and moderated effects of other organizational constructs are investigated. Mikalef et al. (2019) argue BDAC indirectly contribute to firm performance by advancing co-innovation, incremental and radical innovation. Moreover, the relationship between BDAC and firm performance is mediated by environmental heterogeneity, hostility, and dynamism. Gupta et al. (2019) indicate that while BDA is reinforced by Cloud-based ERP, the impact of BDPA on market performance is moderated by organizational culture (i.e. control-oriented and flexibility-oriented).

Testing the BDAC reflective model in the US market, Akter et al. (2016) conclude that the alignment between analytics capability and business strategy moderates the effect of BDAC on firm performance, while Wamba et al. (2017) establish that dynamic capability is a mediating factor. In their study, Rialti et al. (2019) conclude that the effect of BDAC on firm performance is mediated by “*organizational ambidexterity and agility*” (p.148). Moreover, two moderator factors influence the relationship between BDAC and firm performance: the fit between the organization and information management system, and organizational resistance to the implementation of information management.

According to the literature, RBV and dynamic capability are the main theoretical foundations for examining the contributions and effect of BDAC on firm performance. While we discovered that BDAC models are operationalized through both reflective and formative models, we found only limited agreement among BD scholars on BDAC conceptualization, and how BDAC may contribute to firm performance. Table I summarizes the findings of our SLR on BDAC dimensions.

Table I. Summary of the literature on BDA Capability

Reference	Constructed Model	BDAC is the	BDAC dimensions	Mediated construct	Moderated construct	BDAC impacts on
Jha, et al., 2020	Non-hierarchical model		-Data management -Human resources -Organizational politics -Global integration -Environmental determinism			Competitive advantage
Mikalef et al., 2019	Hierarchical Formative model	3rd order construct	-Data & technology -Human resource -Data-oriented culture -Organizational learning	Dynamic capability	-Environmental dynamism -Environmental heterogeneity -Environmental hostility	-Incremental innovation -Radical innovation
Ashrafi et al., 2019	Non-hierarchical model		Technology	-Information quality -Innovation capability -Firm agility	-Technological turbulence -Market turbulence	-Return on Investments -Market share -Sales growth -Profit
Rialti, et al., 2019	Non-hierarchical model		-BDA infrastructure flexibility -BDA management -BDA personnel expertise	-Organizational ambidexterity -Agility	- Organization information management system-Fit -Organizational Resistance to information management	Firm performance
Lozada et al, 2019	Hierarchical Formative model	3rd order construct	-Data & technology -Human resource -Organizational culture -Intensity of learning			Co-innovation
Dubey et al., 2019	Non-hierarchical model		Analytics technologies		Organizational flexibility	-Supply chain resilience -Competitive advantage
Ferraris et al., 2019	Hierarchical reflective model	2nd order construct	-BDA technology -BDA management	KM orientation		Firm performance
Wamba and Akter, 2019	Hierarchical model-Reflective first & second-order dimensions -Formative third-order dimensions	3rd order construct	-Supply chain analytics technology capability -Supply chain analytics management capability -Supply chain analytics talent capability	Supply chain agility		-Customer retention -Sales growth -Profitability -Return on investment

Wang et al., 2019	Non-hierarchical model		-Data integration capability -Analytical capability -Predictive capability -Data interpretation capability			-Average excess readmission rates and patient -Customers' satisfaction
Krishnamoorthi and Mathew, 2018	Non-hierarchical model		-Analytics adoption -Analytics alignment with business -Analytics culture -Analytics organizational structure -Analytics people and skills -Evidence-based decision making		-Analytics value enhancers -Organizational level variables	-ROI -Intangible benefits derived by leveraging enterprise-wide business analytics use.
Gupta et al., 2019	Non-hierarchical		-Data -Managerial skills -Technical skills	Cloud ERP	-Flexible orientation -Control orientation	-Market performance -Operational performance
Popovič et al., 2018	Non-hierarchical model		-Data provisioning -Analytical capability -People skills			Decision making and value business performance.
Akter et al., 2016	Hierarchical Reflective	3rd order construct	-BDA management capability -BDA technology capability -BDA talent capability		Analytics capability-business strategy alignment	-Financial performance -Market performance
Wamba et al., 2017	Hierarchical Reflective	3rd order construct	-BDA infrastructure flexibility BDA management capability -BDA personnel capabilities	Process-oriented dynamic capability		-Financial performance -Market performance
Gupta and George, 2016	Hieratical model -First-level: both formative and reflective -Second and third level: formative	3rd order construct	- Data, technology, time and investment -Human resource -Organizational culture -Intensity of learning			-Market performance -Operational performance

3. Methodology

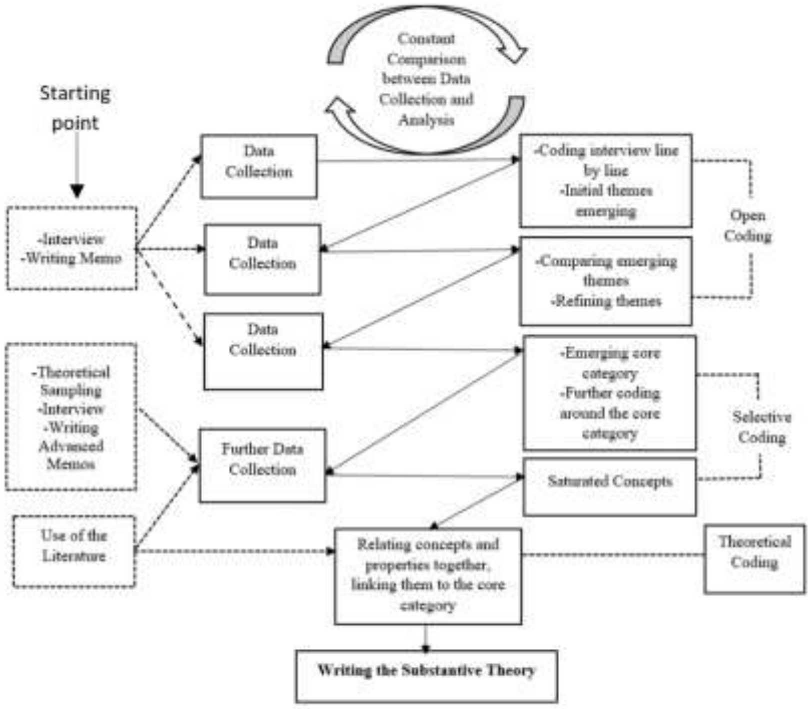

Figure 1. GT protocol used in this research

3.1. A Classic Grounded Theory Approach

Given the lack of coordination on BDAC dimensions in prior research, we found the GT methodology (Glaser and Strauss, 1967) to be the most effective exploratory methodology for our study, in terms of conceptualizing the different dimensions and sub-dimensions of BDAC. Furthermore, GT helps us to explore possible mediating factors that affect the BDAC's contribution to firm performance. We conducted a continuous iterative process between the collection, analysis and comparison of data (Walsh et al., 2015). The literature is used in the later phases of data collection and analysis, as part of our data set to determine how our findings fit with the extant literature, to enrich emerging concepts and their relationships (Glaser, 1978), and to make data analysis more generalizable and durable (Glaser, 2001). Before starting our main data collection, we conducted a pilot test on three interviews, which were reviewed by two senior consultants, as external experts, to validate and/or amend our coding skills and process.

3.2. Data Collection and Analysis

We conducted interviews with open and flexible questions. The number of participants and questions were not pre planned. We theoretically sampled data-driven firms that had been working with BDA over the past few years, and should have been able to gain and retain customers, advance sales, profitability and return on investment. All interviews began with an open question aimed at eliciting a comprehensive definition of BDA as well as identifying the main concerns of the participants. As the research progressed and the concepts and relationships emerged, we proceeded with theoretical sampling as Glaser and Strauss (1967) explained, and the interview questions became narrower to address the different properties of emerging concepts and their relationships better. We stopped collecting data after reaching a saturation level and new themes/categories were not discovered. We conducted 25 interviews (coded from P1 to P25) with C-suite executives (i.e. CEOs, CIOs and CDOs), from different types of industries. Confidentiality about data-treatment was formally guaranteed. In some cases, interviews were conducted twice; participants were motivated to continue the discussion, and in other cases, the second interview was conducted to refine concepts/categories, or collect more information. In the first interview with each interviewee, the duration ranged from 60 to 90 min and in the second interview, the duration ranged from 30 to 60 min (Appendix).

3.3. Data Coding

We applied Glaser's (1998) coding proposal through the iterative process of data collection and analysis to propose a conceptual model of the findings. This protocol includes substantive coding (open coding and selective coding), and theoretical coding. Open-coding involves analyzing data in all directions pertaining to the research issue, and initial themes emerge (e.g. sharing data, learning) at this stage. The similarity and differences among themes helped us to group and label them, until the participants' main concern (i.e. technological capability, organizational culture), and the core category (i.e. BDAC) that explains the main concern emerged (Glaser, 1978), which refers to selective coding. Finally, theoretical coding was applied to identify the relationships between concepts among our substantive codes to conceptualize them as propositions and integrate them into a theory (Walsh et al., 2015). Through this stage of data analysis, the literature was employed to enrich our findings. The data analysis also included writing case-based memos, which assist us to compare interviews' discussion and determine more concepts and relationships. We used NVIVO when coding and analyzing the data. Figure 1 demonstrates data collection and analysis using the Glaser coding protocol.

4. Findings

In this section, we discuss the concepts that emerged from our data. These concepts emerged through an iterative process of data collection and analysis and are summarized in Table 2. The findings indicate BDAC is a DC that advances firm performance through the combination of various organizational capabilities. Also, BDAC constantly reinforces OL and creates a "questioning-learning" approach, which is beyond solving a specific problem or overcoming a current challenges. Regarding the GT approach, emerged concepts and their relationships are formed around participants' concerns in order to generate the final model. In light of our participants' main concern for creating and sustaining a competitive advantage, we categorized the emerged concepts into two-pronged, (1) The firm's dynamic BDAC: the firm's capability to acquire, process, analyze and generate predictive insights for decision makers. BDAC comprises different dimensions and their properties

Table II. The Emerging Concepts of GT Coding

Category/ Dimension	Description	Properties
BDA Technology Capability (BDA-TEC)	The required information technology and system that empower data workers to employ advanced analytics.	• Scalability • Compatibility • Connectivity • Visualization
Top Management Team Capability (TMTC)	The level of executive' support and commitment to the data-oriented approach and applying BDA through the firm's routines.	• BDA Perception • BDA-Business Strategy Synchronization • BDA Training
BDA Talent Capability (BD-TAC)	The BDA team's knowledge and skills to undertake analytical techniques and translate BDA insights for business.	• Data Science • Business Knowledge • Technology Knowledge

BDA External Partnership Capability (BDA-PAC)	The dynamic sharing resources within a network partner to speed up data circulation, discover environmental challenges and opportunities, enhance the analytical process.	• Agility in sharing resources • Reliability • Relevance
Data-Driven Culture (DDC)	The firm's attitude and culture to the analytical approach and use of BDA for every decision.	• Data-Driven Decision Making • Data Sharing
Organizational Learning (OL)	The progressive learning approach that comprises information acquisition, dissemination the learned ability and knowledge to develop the firm's knowledge memory and accelerate the firm's creativity (adopted from Tippins and Sohi, 2003).	• Organizational Knowledge Memory • Questioning-Learning Approach

4.1. Dynamic Big Data Analytics Capability

We define Dynamic BDAC as the dynamic organizational ability that consists of five sub-capability dimensions and thereby empowers firms by generating insights for effective decision-making. The sub-capabilities construct idiosyncratic development of resources (IT and organizational resources), to unlock hidden patterns of BD flow via predictive analytics, in order to generate practical knowledge that contributes to the firm's decisions. However, defining BDAC as such would be of little practical use towards the achievement of competitive advantage, if we did not investigate its dimensions and their properties, which are discussed below as they emerged from our data.

4.1.1 BDA Technology Capability (BDA-TEC)

BDA technology capability represents technological adaptability to meet BDA characters (5Vs), while implements advanced analytics swiftly: "*We use the right technology at the right time*" (P8[1]). Through the coding process five common technological features were found to explain BDA technological capability:

(i) Compatibility: enables the technology to integrate and analyze various types of data (structured, semi-structured, non-structured) and implement sophisticated analytics to create value. *"BDA refers to flexible systems that can easily adapt to new datasets"* (P19). Compatibility describes the technological ability to transform a firm's data without limitations on data structure and format, in order to enhance innovation (Akter et al., 2016) and accelerate system redeployment: *"Our systems support all types of data formats"* (P15), *"you need a compatible system to bring flexibility to data processing*" (P24).

(ii) Connectivity: demonstrates the ability of technology to transfer data from various sources between units (internal and external), which extends data accessibility and consequently improves the chance of pattern discovery among the data flow; *"data is distributed across different sectors and also with our partners"* (P3). Since sharing and accessing data significantly influence decision-making, an inter and intra-connected system is critical: "*Connecting systems within the organization has enhanced data accessibility and sharing that are imperative for our data scientists*" (P25). Connectivity enriches data storage and analytical process, and fuels data-driven decision-making to exploit business opportunities (Akter and Wamba, 2016).

(iii) Scalability: It represents the technological capacity to store, retrieve, analyze, and reuse massive data flows, now and in the future. While investing in novel commodities and hardware may result in cost overruns and

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[1] . 'P' refers to the participants in our theoretical sample

executives' disagreement, a scalable system addresses the cost concern of BDA investment: "O*ur system is fully scalable to meet our current and future data needs"* (P8). Though BDA is the revolution of Business Intelligence and Analytics (Chen et al., 2012), conventional and classic information systems are less efficient at processing BD. Slowness in responsiveness, lack of scalability and adaptability to diverse datasets, to support analytics are the main challenges of traditional IT. Furthermore, scalability is crucial for data processing and analysis: "*Hadoop Mapreduce has capacity for parallel computing of distributing large data sets across multiple servers* (P24), *"it is scalable, everything is shared and delivered on it, as a service on a massive scale. Also, it is easily developed for parallel processing"* (P20).

(v) Data Visualization: refers to the abstractness of results and displays creative scenarios of revealed insights for decision-makers. We found that data visualization translates analytics findings for non-data scientists, and it is a kind of information map for decision-makers: "*The visualization tools reduce the complexity of data and make it meaningful for us"* (P4), *"it provides information based on different hypotheses, which help us make fact-based and measurable decisions"* (P25). Visualizing BDA insights allows decision-makers to combine distributed information into a flexible and customized picture in order to find patterns, test hypotheses, and consequently enhance managerial judgment (Kanika et al., 2016). An appropriate visualization system should be interactive and provide predictive modeling techniques to estimate trends, evaluate relationships and build classifications among data (Wang et al., 2018): *"Data visualization tells us the stories that were discovered by data scientists. And I can say visualization is a key part of the discovery process."* (P16).

4.1.2. Top Management Team Capability (TMTC)

TMTC demonstrates the significant role of the top management team (TMT) to integrate analytics into the firm's decisions and routines and move to the data-driven firm. The TMT drives changes and adaptation within the firm's routines, and processes toward obtaining the maximum possible value out of IT/IS (Chen et al., 2015). The following properties emerged to explain TMTC.

(i) BDA Perception: The TMT's knowledge and perception of BDA productivity construct BDA strategy and value expectation: *"Analytics efforts rely on executives' understanding of BDA value creation"* (P11). In general, the TMT is used to invest in new resources, which deliver an immediate impact on firm performance. However, BDA efforts may not lead to visible results or greatly influence performance during the early steps of a change. The lack of BDA knowledge may induce unreachable expectations from BDA (Mangla et al., 2020), which will have a negative influence on the TMT's willingness to invest further in BDA resources: *"The common approach focuses on low-risk investments and obtaining small-scale benefits, which is far from what the data-driven approach may bring* (P.18). The TMT's knowledge, commitment, and willingness manifest the TMT's perception to endow BDA as the strategic priority for decision-making (Barton and Court, 2012).

(ii) BDA-Business Strategy Synchronization: This property refers to the coordination and synchronization of the planning process between business strategy and BDA strategy. BDA is the new intangible asset that reshapes the structure of strategy (Liu et al., 2011) through an innovative path (Constantiou and Kallinikos, 2015) and drives firm performance (Mazzei and Noble, 2017): "*BDA strategy is the evolutionary view that impresses business strategy, not only aligns with that, rather analytics drives business strategy"* (P21). Considering our data analysis, BDA fundamentally influences the classic business strategy to develop a pattern-based approach by synchronizing BDA and business strategy to fuel each other: *"...the link between them is not a one-way from business strategy to analytics"* (P15). Furthermore, a firm with a specific BDA strategy owns "*a clear long-term analytics goal and the consistent strategy to link BDA initiatives to the firm performance*" (P.24). An explicit BDA strategy creates a comprehensive plan to invest, execute, and transform BDA initiatives into actionable knowledge for decision-makers.

(iii) BDA Training: employees' training facilitates the integration of BDA initiatives within the firm's routines by reinforcing employees' skills to use data and analytics for daily decisions and consequently advances the movement toward a data-driven approach (Shah et al., 2017). The employees' empowerment comprises various

training programs like basic statistics training, data management, business intelligence, working with dashboards and visual tools to better interpret analytics insights: *"we train our personnel to set up the adequate technical environment to speed up digital transformation"* (P16). Moreover, training reduces the possibility of the breakdown of BDA projects: "*Data mining and data management training develop employees' creativity and encouraged them to employ data to support their daily decisions"* (P.21).

4.1.3. BDA Talent Capability (BDA-TAC)

Our findings reveal that the ability and competency of the BDA team encompass different disciplines and knowledge in problem-solving, advanced ICT, statistics, and sector skills: *"Our analytics team consists of data scientists, software engineers, and business members"* (P13). We categorized the BDAC talent properties into three sub-dimensions.

(i) Data Science: is the core competency of the BDA team: *"everything is about data science knowledge"* (P.20). Data scientists are analytical experts who use different knowledge such as mathematics, data and computer science to make sense of massy, unstructured data that are generated from different sources. They also employ their curiosity *to make discoveries in the world of big data"* (Davenport and Patil, 2012, p.72). By asking the "right question" (Matthias et al., 2017) data scientists offer predictive solutions: *"They are experts in machine learning and algorithm development, and project management"* (P9).

(ii) IT Knowledge: this knowledge supports the BDA team and instrument data scientists by creating, operating, and maintaining systems and technologies: *"our IT engineers have complementary roles in the analytics process"* (P.17). Due to the complexity of the digital era, IT members are responsible for developing technologies based on technological trends. (Akter et al., 2016): *"since the digital domain is continuously evolving and new technologies are being introduced, IT members enable the team to establish and utilize advanced technologies"* (P4).

(iii) Business Knowledge: our data analysis indicated data science is not sufficient to integrate BDA insights into firms' routines and decisions: *"data workers without business knowledge are not able to deliver knowledge to other departments; hence some business members accompany them"* (P.6). Firms require a translator to link the business context to the analytics: *"business members serve as storytellers"* (P.10) within a BDA team. Business knowledge delivers information on the business environment, processes, structure, policies, strategy, and goals to the BDA team, and translates BDA insights into practical knowledge for business members "*they deliver knowledge on business context to data scientists, and transfer analytics findings to the business staff and for our executive board"* (P25).

4.1.4. BDA External Partnership Capability (BDA-PC)

We concluded that solely internal capabilities are not adequate to transform BDA into a competitive advantage and firms do require external collaborations to develop a firm's capability and "win with data" (Brokaw, 2010). The majority of data resources are situated outside of the firms' boundaries, with restricted or no control over them: "*the external resources should be continuously collected to facilitate our interactions with the environment"* (P.14). Considering our participants' discussions, BDA partnership capability refers to a dynamic supply of different resources (data and technology) to accelerate data circulation and strengthen analytics: *"a qualified partnership network opens up opportunities to acquire appropriate data to feed the analytics"*(P16).

The IS literature asserts that the IT/IS partnership network develops firms' intensity and sensitivity reaction to the market by transferring resources and knowledge (Bharadwaj, 2000), and enhances the accuracy and timeliness of data and information sharing (Maiga et al., 2015). The ability to determine "*digital and real-world trends and requirements"* relies on firms' innovative capabilities (Capurro et al., 2021), which can be developed by a BDA partnership network in order to integrate market-driven and technology-driven approaches. The different advantages of the BDA partnership network were discussed in our data analysis e.g. accessing qualified data, low-cost deployment of old systems and fast-moving development of technology, which are categorized into the agility in sharing resources (data, technology, and techniques), reliability, and relevance.

(i) Agility in sharing resources: the agility in accessing resources is the primary concern in the digital era and is understood as a firm's ability to undertake BDA resources for the real-time processing of data, producing insights and employing them for decision-making. The agile partnership network can "*rapidly deliver complementary resources to support data processing"* (P.2). Agility leverages data circulation in a firm, facilitates the rapid deployment of technologies, and adapts a firm to environmental changes, through offering the right resources at the right time: *"While data is easily available, only accessing timely sources improve real-time decision making, which is the main role of our partners"* (P7).

(ii) Reliability: While the massive quantity of data is easily accessible, the executives seek an adequate level of confidence in resources, which subsequently influences the quality of decision: "*Our partners have an imperative role to provide qualified data"* (P9). The usability of data significantly relies on data quality, which has a direct impact on business decisions (Warth et al., 2011). Therefore, the quality of the partnership network is *"a first step"* (Boughzala and Vreede's, 2015, p.129) toward a solution.

(iii) Relevance: collaboration in a partnership network relies on the partners' knowledge of the business and the industry, as well as their proficiency to supply qualified data and implement relevant technology. Whereas external sources are critical, the relevance of resources for the firm's processes is difficult to prove (Kwon et al., 2014). In this line, the qualified network partner demonstrates the firm's priorities based on its business ecosystem. *"Rather than the quantity of data, we focus on the quality of data source and on obtaining better data, which is the main role of our partners to use reliable data sources and deliver qualified data"* (P 22).

The combination of multiple internal and external data sources accelerates the firm's creativity to build advanced analytics models and design data-driven strategy (Barton and Court, 2012). Moreover, grabbing external opportunities relies on a dynamic partnership network, which delivers real-time transactions (Chang et al., 2015) and demonstrates a panoramic and granular view of the business environment (Kwon et al., 2014).

4.1.5. Data-Driven Culture (DDC)

BDAC demonstrates the firm's cultural adaptability and acceptance to transform the decision-making approach from intuition and experience to the use of data analytics. Moving to a data-driven culture embeds in a "fit" between the use of IT and the organizational culture (Bradley et al., 2006), as well as, individuals' commitment to using data rather than the HiPPO (the highest-paid person's opinion) (McAfee and Brynjolfsson, 2012). A data-driven culture is defined *"as the extent to which organizational members make decisions based on the insights extracted from data"* (Gupta and George, 2016, p.5). The lack of data sharing and the use of data for daily decision-making are two reasons why BDA projects fail (Ross et al., 2013), hence shifting the organizational culture from "What do we think?" into the question "What do we know?" (McAfee and Brynjolfsson, 2012. p.68) is vital. The main argument in this dimension refers to the firm's ability to use and share data, as well as, being ready and interested in changing that is reflected by two properties:

(i) Data-Driven Decision Making: BD and predictive analytics are not limited to enhancing executives' decisions, rather, BDA is an integral of the firm's routine and daily activities. However, it requires top-down reinforcement: "*changing the firm's culture aligns with technologies and data science that improve the quality of decisions."* (P16). Data should be a primary factor in all decision-making within the organization, not just the BDA team: "Using data for decision-making has become institutionalized in our organization and we have all committed to using it" (P. 8).

(ii) Sharing Data: one of the barriers in data circulation was argued as the lack of data-sharing: "*data circulation was incomplete because of the weak data sharing that impacted on the findings"* (P12). Wang et al. (2018) contend that sharing data and routinizing this approach are the key enablers in exploring and using new knowledge that directly influence the quality of decision-making. During the interviews, defining a distinct sharing mechanism to highlight the sharing path, participants and accessibility, was discussed as a solution to develop transparency and facilitate data sharing: "*We have precisely mapped the data-sharing mechanism that determines the level of accessibility to data and participants of this process"* (P9).

4.2. The Impact of BDAC on Organizational Learning (OL)

The impact of BDAC on OL was emerged as the second emerged category to address the participants' core concern. Data analysis revealed BDAC fosters organizational knowledge, as well as generates a new learning approach, through influencing the way of thinking, asking a question, solving a problem, acting and globally learning within the firm. We coded the effect of BDAC on OL as the "hidden value" of BDA efforts, which consequently fuels the firm's innovation capability: *"Our data-driven approach engages all parts of the firm and affects all employees' performance by delivering a new way of problem-solving"* (P16).

The speed of technological development and intense competition highlight the importance of OL in facing environmental changes (Okwechime et al., 2018). OL refers to *"the process by which new knowledge or insights are developed by a firm (Slater and Narver, 1995.* Cited in Tippins and Sohi, 2003, p.749). Considering our findings, BDAC reinforces organizational knowledge memory by generating information that is more accessible, transparent, and more segmented than in the past: *"BDA fundamentally changed our organizational learning approach by developing organizational knowledge memory"* (P19).

OL is a dynamic process (Dodgson, 1993) and changes organizational performance, through transforming knowing/learning and doing/practice (Nicolini et al., 2003): *"it has changed how knowledge is accessed, exchanged and embedded into this company"* (P23). BDAC develops the process of knowledge acquisition and usage *"Working with data and analytics involves us in constant learning and developing our interpretation"* (P13). BDAC directly enhances organizational knowledge and creativity regarding comparison and interpretation to confront future challenges and opportunities. Furthermore, BDAC creates an interconnected, intelligent and equipped workplace, where learning occurs in everyday practice and changes hypothesis-testing to a forward-looking approach, while it reduces the cost of risk-taking and encourages personnel to accept risks.

We define this new learning approach as the 'questioning-learning approach': *"Using data analysis techniques and accessing shared data allows our employees to make different experiments and quickly see the results… It is a process based on asking, working and learning that overall enhances performance, innovation, and adoption"* (P21). OL integrates BDAC into business processes, functions and decisions, and subsequently, it was found to improve the firm's performance: *"investing in BDA has allowed us to change our learning and develop our manufacturing"* (P.9).

4.3. Conceptualization of the Impact of BDAC on Firm Performance through the Mediated Effect of OL

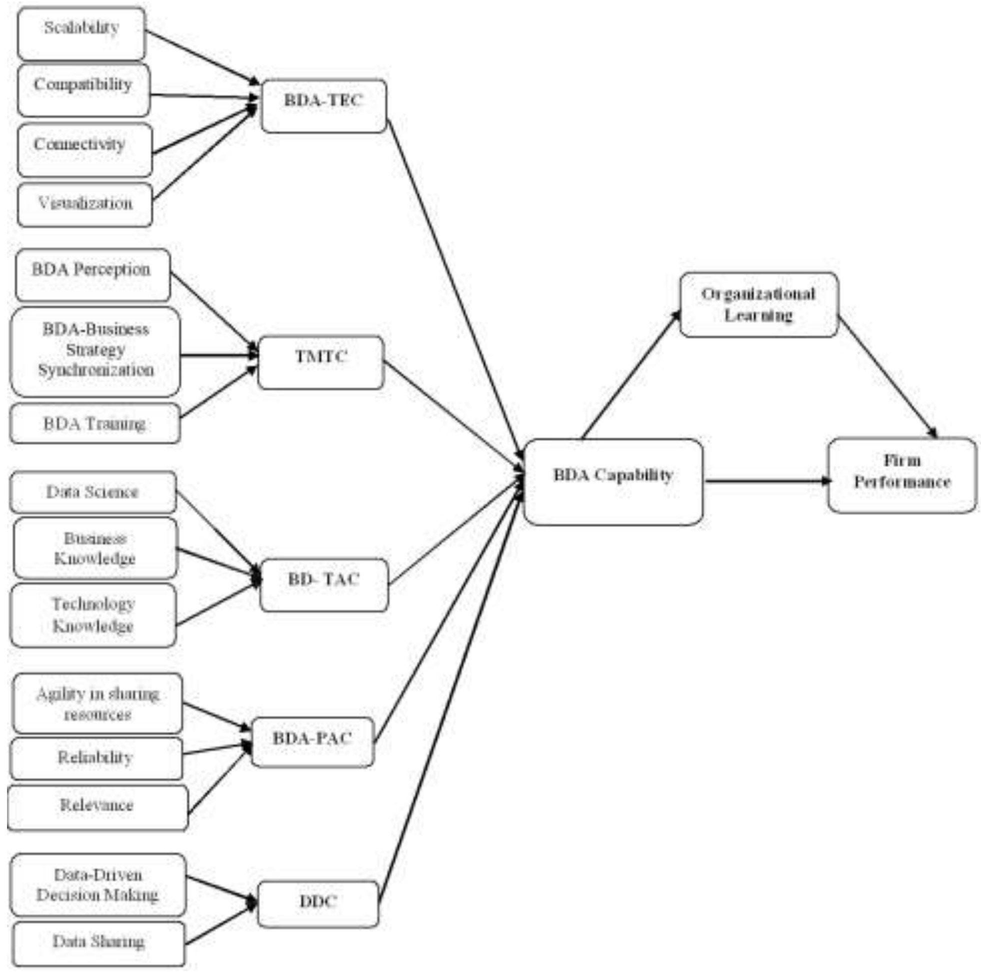

Figure 2. BDAC Conceptual Model.

Drawing on the resource-based view (RBV) and dynamic capability (DC) approach, we propose a conceptual model (Figure 2) to address our research question; 'how can BDA contribute to firm performance and lead to sustainable competitive advantage?' Our findings 1) indicate BDA capability is constructed through the combination of several resources and sub-capabilities, 2) describe BDA capability institutionalizes the use of BDA within firms, 3) imply BDA capability directly contributes to firm performance through generating actionable insights, and 4) also, BDA capability contributes to sustaining competitive advantage by dynamically reinforcing OL and innovation in adapting to environmental changes and enhancing firm performance.

We argue that the dynamic combination of various resources, and not the resources themselves, creates the mechanism that enhances the firm's core competency, which is addressed by BDAC. Barney (1991) asserts that a bundle of valuable, rare, inimitable, and non-substitutable resources contributes to competitive advantage. The heterogeneous distribution of strategic resources restricts the possible transferability of these resources to competitors (Peteraf, 1993) and thus, forms competitive advantage to develop firm performance. However, sustaining the competitive advantage in the digital environment strongly relies on the strategic protection of these resources against imitating and substitution, which is afforded by the firm's capability (Wade and Hulland, 2004).

Drawing dynamic capability, we conclude that BDA capability is a dynamic capability, which embeds in the firm's ability to reconfigure and re-deploy internal and external resources and capabilities. BDAC is critical to adjusting the firm's adaptation to digital changes and fostering the firm's competency (Teece et al., 1997).

Our findings lead us to argue that BDAC is the bundle of tangible resources (BDA technology and partnership as the technology provider), personnel-based resources (TMT and BDA talent) and intangible resources (data-provider partners, data-oriented culture). BDAC is a dynamic capability that constantly senses the environment to capture resources, seizes hidden patterns and insights within a data flow, and redeploys BDA sub-capabilities toward building a new form of competitive advantage for the firm. Furthermore, BDAC develops the learning approach by engaging the firm in the exploration and synthesis of vast amounts of knowledge. BDAC routinizes working with BDA, and learning from data, which shapes the 'questioning-learning approach'. BDA contributes to OL through reforming knowledge to reach appropriate responses, which develops the organizational ability to adapt to environmental changes quickly (Okwechime et al., 2018). The constant development of organizational knowledge memory helps a firm to structure an organizational knowledge foundation for learning and use of BDA (Côrte-Real et al., 2017). While OL is the critical lever to foster innovation in response to digital changes, we argue that the impact of BDAC on OL shows how a firm sustains the competitive advantage from BDA initiatives. The extant literature contends that OL improves firms' ability to grab digital opportunities and develop firm performance (Onağ et al., 2014). Therefore, we argue that BDAC improves performance directly, as well as indirectly, through the mediated effect of OL.

5. Conclusion

This study found BDAC as powerful tool helping firms gaining better competitive advantage. A thorough review of the extant literature on BDAC revealed several gaps as discussed in the introduction section. Despite BDA's potential to transform a company's current business model into a more competitive position, few companies have implemented it successfully. In this study, we proposed a BDAC conceptual model, which extends the previous understanding of BDA's contribution to firm performance. To fill the identified gaps, we applied a classic GT (Glaser and Strauss, 1967; Glaser, 1978) using an exploratory stance to explore how can BDA contribute to firm performance and lead to sustainable competitive advantage. The findings provide several significant contributions to the body of knowledge and practice as discussed in the following sections.

5.1. Theoretical Contributions

This research contributes to the body of knowledge on IT value creation and provides a foundation for further research on BDA capability.

Firstly, our findings indicate BDAC relies on a combination of various capabilities and resources. Our model extends previous BDAC models by adding two new dimensions such as i) TMT capability and ii) BDA partnership capability. To the best of knowledge these two new dimensions have not been applied in prior research. Particularly, we discovered that BDA management capability involves all top managers, however, the vast majority of prior research (e.g. Wamba et al., 2017), operationalized BDA management capability as the managerial skills of "Big Data Managers" only (Gupta and George, 2016, p. 5). Therefore, our research emphasizes the critical role of TMT in integrating BDA into a firm's routines and developing a data-driven approach. Furthermore, to complete the internal capability dimensions, the BDA partnership emerged as an external capability in our data analysis and that yet to be addressed by the extant literature. Whilst competition in the digital environment is dependent on timely, accurate and readily available resources (McAffe and Brynjolfsson, 2012), BDA partners advance resource (data, technology) quality and consequently BDAC. Moreover, we extend the definition of data-driven culture proposed by Gupta and George (2016) by adding data sharing to data-driven decision-making (Gupta and George, 2016) in order to increase management's ability to take full advantage of BDA.

Secondly, we conceptualized BDAC as the aggregative concept that embeds in the combination of all the emerged BDAC dimensions and sub-dimensions. Therefore, we propose a formative BDAC model in which all concepts are formative, which partly aligns with the model proposed by Gupta and George (2016), but with different sub-dimensions and contributions. The complementary dimensions/properties added to our model are particularly critical for providing actionable knowledge to managers and omitting any one of these concepts would result in an incomplete model and jeopardize the accomplishment of the goal.

Thirdly, while the primary role of BDA is to provide insights leading to better decisions, our empirical research shows that BDAC has also an indirect impact on a firm performance through reinforcing OL, which we call this the 'hidden value' of BDAC, that found to accelerate the firm's adaptability to analytics transformation. Whilst, Gupta and George (2016) determine the intensity of OL as a BDAC dimension, we argue OL as an organizational variable is influenced by BDAC and mediates the impact of BDAC on firm performance. Our study findings show that BDAC constantly fosters OL through changing the way of thinking, solving problems, acting, and learning. Furthermore, the use of BDAC leads to fundamental changes in a business process and approach, which is the key argument of OL contributions to firms. OL scholars emphasize that to transfer learning into actions and develop a firm's innovation, the learning approach should be aligned with a change (Lähteenmäki et al., 2001). It is, therefore, necessary to define a new learning approach, which we call 'questioning-learning'.

Lastly, to the best of knowledge, our research is one of the first exploratory studies used GT to identify how data-driven firms use BDA to constantly adapt themselves to digital advancement and sustain BDA competitive advantage, beyond the extant studies that employed mostly a hypothetico-deductive stance to investigate BDAC.

5.2. Practical Contributions

The present study yields some significant contributions to practice, precisely for the digital transformation. Specifically, the proposed model helps managers diagnose the firm's strengths and weaknesses regarding BDAC. It was found that digital transformation requires a long-term perspective in order to convert small digital experiments into enterprise-wide initiatives (Kane et al., 2017). In line with , our research showed that BDAC builds a digital platform, which allows firms to successfully digitalize through the TMT's enduring commitment to using data, as well as gathering, processing and analyzing data with technologies and advanced analytics while adjusting their practices to adapt to the digital era. We conclude that the learning ability generated by BDAC continuously fosters organizational knowledge and employees' skills to sense insight, seize knowledge and grab digital opportunities. Moreover, data-driven cultures serve as the necessary catalyst to accelerate digital transformation by creating a routine for using BDA initiatives for making decisions.

Moreover, our study discovered that BDA transforms the firm's strategic stance from a reactive to a predictive and proactive position. Therefore, business strategy must be flexible to adjust internal capability to market dynamics (Akter et al., 2016). Explicitly our findings depict that BDA strategy is a forward-looking approach that is not always subordinate to business strategy, despite the classic IT strategy. Rather, there is a synchronization between business and BDA strategy, which could be described as a two-way alignment, in order to effectively use BDA competitive advantage and improve firm performance.

5.3. Limitations

This research is not without limitations, which suggest avenues for future research. In the present research, we used solely qualitative data to propose our model. Further quantitative work could operationalize the proposed measurement model of BDAC as a first and second-order formative model and verify our propositions. For data collection, we contacted participants via LinkedIn for over twenty months, and from 227 emails requesting an interview, only 25 C-suit executives accepted to participate and be interviewed.

5.4. Future Directions

The following will be the future work of this study: 1) considering the number of participants, a larger sample could be useful to ensure that the model is fully saturated and no new concepts or relationships emerge, 2) it could be interesting to use a qualitative method to compare the model resulting from our research with the one proposed by Gupta and George (2016) or Akter et al. (2016) that are based on a deductive approach, but along different paths, to investigate which of the two models best explain BDAC dimensions, 3) possible interrelationships between the different BDA dimensions could be investigated, which remains for future studies. Also, our data indicate that OL is fulfilled by BDAC, while Gupta and George (2016) found that OL is one of BDAC resources. Therefore, future research could investigate the possibly recursive effect between OL and BDAC.

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Appendix A: Interviewees' details

Codes	1st Interview	2nd Interview	Position	Industry	Education	Firm Size	Country
P1	20/11/2017 Uberconference	28/11/2017 - Skype	CEO	Telecommunication	PhD of Business	50-249	USA
P2	05/12/2017 Meeting	15/12/2017 Skype	CDO	Consulting	Master of Computer Science	50-249	Sweden
P3	10/12/2017 Meeting	19/12/2017 Meeting	CDO	Insurance	Master of Informatics	10-49	France
P4	20/12/2017-Meeting		CIO	Automotive Manufacturing	PhD Mathematics	+250	Germany
P5	23/12/2017 Uberconference	25/12/2017 Uberconference	CEO	Consulting	PhD of Marketing	50-249	USA
P6	10/02/2018 Skype	Added some notes to the transcript	CDO	Financial Consulting	Master of Data Science	10-49	UK
P7	12/02/2018 Meeting		CDO	Computer technology	PhD of Computer Science	+250	France
P8	17/05/2018 Uberconference		CMO	Telecommunication	PhD of Business	50-249	India
P9	06/05/2018 Meeting	Added some notes to the transcript	CMO	Telecommunication	MBA	50-249	UK
P10	15/09/2018 Uberconference	06/09/2018 Skype	CIO	HR Consulting	Master of Computer Engineering	10-49	UK
P11	16/10/2018 Uberconference	30/11/2018 Uberconference	CIO	Telecommunication	Master of Computer Engineering	+250	Brazil
P12	24/11/2018 Skype		Vice President	Health care	PhD of Applied Economy	+250	USA
P13	25/11/2018 Meeting	05/12/2018 Phone	Senior Data Chief	Computer technology	Master of Informatics	50-249	France
P14	01/05/2019 Skype	Added some notes to the transcript	CDO	Automotive	Master of Informatics	+250	Japan
P15	02/06/2019 Skype		CEO	Telecommunication	Master of Project Management	+250	Singapore
P16	16/06/2019 Uberconference	20/07/2019 Skype	COO	Healthcare sector	Master of Engineering	+250	Finland

P17	10/08/2019 Meeting		CMO	Education sector	MBA-Marketing	50-249	France
P18	13/09/2019 Skype	Adding some notes to the transcript	CEO	Financial sector	Master of Management	50-249	USA
P19	22/09/2019 Skype		Vice President	Insurance sector	MBA (eCommerce)	+250	UK
P20	03/10/2019 Skype		CDO	Computer Sector	Master of Informatics	50-249	India
P21	13/10/2019 Uberconference	22/11/2019 Uberconference	CEO	Education sector	PhD of Business and Economy	50-249	Sweden
P22	06/12/2019 Uberconference		CIO	Marketing and sales consulting	PhD of Computer Science	50-249	Finland
P23	10/11/2019 Meeting	20/11/2019	CEO	Insurance	Master of Informatics	10-49	France
P24	10/11/2019	Adding some notes to the transcript	CEO	Insurance	PhD of global marketing	10-49	France
P25	10/12/2019 Meeting		CEO	Healthcare	MBA healthcare management	50-249	France