Journal of Business Research 123 (2021) 1–13

Contents lists available at ScienceDirect

Journal of Business Research

journal homepage: www.elsevier.com/locate/jbusres

Exploring the impact of big data analytics capabilities on business model innovation: The mediating role of entrepreneurial orientation

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ARTICLE INFO

Keywords:
Big Data analytics capabilities
Business model innovation
Entrepreneurial orientation
Dynamic capabilities
fsQCA
PLS-SEM

ABSTRACT

Big Data Analytics Capabilities (BDAC) represent critical tools for business competitiveness in highly dynamic markets. In this connection, by leveraging on the Dynamic Capabilities View (DCV) this study analyses the relationship between BDAC and Business Model Innovation (BMI). It argues that the impact of BDAC (a lower-order dynamic capability) on BMI is mediated by Entrepreneurial Orientation (EO; a higher-order dynamic capability). The proposed model is assessed by PLS-SEM (symmetric) and fuzzy-set Qualitative Comparative Analysis (asymmetric) methods using survey data from 253 UK firms. Our findings demonstrate that BDAC have both direct and indirect positive effects on BMI, with the latter being mediated by EO. These results enrich the innovation management literature on Big Data (BD) by showing that BDAC influence company strategic logics and objectives, rather than depending on them, thus playing a significant role in creating value for companies and their stakeholders.

1. Introduction

The recent development of the Big Data (BD) phenomenon is leading companies to increasingly focus their attention on the management of internal and external data with the aim of seizing new opportunities suitable to sustain their competitive advantage (Shan et al., 2019).

BD has been interpreted as "the next frontier for innovation, competition and productivity" (Manyika et al., 2011, p. 1). By leveraging on customer-generated BD, firms have, for instance, the opportunity to implement user-centred innovation and user-driven innovation (Trabucchi et al., 2018). The former deploys customer analytics to examine the behaviours, evaluations and needs independently manifested by users online with the aim of enhancing the development of new products tailored to their expectations (Hooi et al., 2018). On the other hand, user-driven innovation requires the company to develop new products in collaboration with individual customers in order to trigger and implement value co-creation initiatives (Marzi, Ciampi, Dalli, & Dabic, 2020; Xie, Wu, Xiao, & Hu, 2016). In both cases, BD utilisation assume strategic value in ensuring an iterative engagement process between firms and customers, which represents the foundation of a sustainable value generation cycle for both of them (Kunz et al., 2017).

The possibility to exploit BD to pursue several innovative corporate strategies (Ciampi et al., 2020) is increasingly disrupting business logics in many industries (Santoro et al., 2019; Wang & Hajli, 2017). In this connection, many scholars highlight the importance of examining the impact of digitalisation on Business Model Innovation (BMI; Bouwman et al., 2018). Indeed, companies nowadays are able to effectively deploy internal and external BD (Sheng et al., 2017). For instance, they can leverage BD to make their value creation processes evolve, e.g. by enhancing business relations with customers and other stakeholders (Sorescu, 2017); to develop innovative value propositions where data plays either a supportive or a central role, e.g. through data monetisation (Woerner & Wixom, 2015); and to reconfigure their value capture mechanisms, e.g. by adding new sources of revenue or planning cost-cutting interventions (Lokshina et al., 2018). Furthermore, a growing number of enterprises and industrial networks strive to obtain longer-lasting competitive advantages by utilising the newest digital

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https://doi.org/10.1016/j.jbusres.2020.09.023
Received 25 June 2020; Received in revised form 8 September 2020; Accepted 9 September 2020
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technologies for innovating their business models rather than merely adapting their products, services and/or processes (Spieth et al., 2019).

The possibility to collect, analyse and use large-sized, diverse and fast-generated data to support decision-making processes has prompted many organisations to undertake considerable efforts to develop related infrastructures, technologies, skills and business practices (Ciampi et al., 2018). Though necessary, Big Data Analytics (BDA), i.e. the tools for data analysis and visualisation of results as support to decision-making, are not sufficient to convert a firm into a data-driven organisation capable of transforming data into actionable knowledge (Kwon et al., 2014). Big Data Analytics Capabilities (BDAC) refer to the company's abilities to leverage on technology and talent to exploit BD towards the generation of the insights that are necessary to overperform rivals (Mikalef et al., 2017).

Nevertheless, to the best of our knowledge, there is still no empirical work within the innovation management literature analysing the influence of BDA usage or capabilities on BMI (Ransbotham & Kiron, 2017). Leveraging on the literature that argues the possibility of pursuing a transformational value creation pathway through the deployment of BDA (Elia, Polimeno, Solazzo, & Passiante, 2019), this study intends to fill this gap. More specifically, we resort to the Dynamic Capabilities View (DCV) to investigate whether BDAC, considered as dynamic capabilities (DCs) themselves (Fosso Wamba et al., 2017), can positively impact BMI. Additionally, based on the premise that data-driven BMI usually entails radical business actions to take place (Arnold, Kiel, & Voigt, 2016), we explore the mediation role of a peculiar strategic orientation, Entrepreneurial Orientation (EO), which also fits the DCV framework as it can be assimilated to a higher-order DC gaining strength from BDAC (Rehman et al., 2020).

With this study, we firstly investigate the innovation potential of BD in business contexts by exploring the BDAC-BMI relationship, with the aim of advancing the literature concerning the beneficial effects of DCs on business value (Akter et al., 2016; Fosso Wamba et al., 2017; Mikalef et al., 2019). Secondly, by exploring the mediation role of EO, we aim to validate the BD potential to inform company strategies thanks to the countless market opportunities identifiable through its analysis (Gnizy, 2019; Mazzei & Noble, 2017).

The contribution of this research is twofold. Primarily, it demonstrates the direct impact of BDAC on the identification of new and effective value creation, proposition and acquisition paradigms (BMI). This result enriches both the BD and the DC managerial literature, by empirically confirming that firms' distinctive DCs to effectively deploy BDA may favour a rapid, profitable and innovative evolution of business models, especially in fast-changing environments. Secondly, this study contributes to the strategic management literature by demonstrating that BDAC impact BMI also indirectly by stimulating firms to proactively take innovative and risky decisions (EO), which are facilitated by the development of proactive market information systems, external and internal knowledge sharing and collaboration processes, infrastructure elasticity and decision-making flexibility (Rachinger et al., 2019).

The next section presents our theoretical background and the research hypotheses. Section 3 describes the sample, analyses measurements scales' validity and introduces the methodology used in this study. Section 4 presents the results obtained. Section 5 discusses our findings in terms of theoretical and managerial implications and also highlights the main limitations of our research and some possible future research directions. The concluding section summarises the main contributions of this study.

2. Theoretical background and hypotheses

2.1. Dynamic capabilities view

The DCV emerged as a theoretical extension of the Resource-Based View (RBV) to explain how firms manage to remain competitive in the long run within turbulent environments (Ambrosini & Bowman, 2009). Following the original philosophy of the RBV, an organisation's success depends on the availability and orchestration of valuable, rare, inimitable and non-substitutable assets, which enable the implementation of value-creating strategies capable to generate rents (Barney, 1991). Specifically, a company can obtain a sustainable competitive position by acquiring and controlling the resources perceived as strategic and consequently developing firm-specific capabilities that are highly dependent on the types of resources accumulated (Makadok, 2001). More recently, the literature has highlighted how the static approach adopted by the RBV falls short of explaining how firms utilise their resources and capabilities in dynamic markets, thus paving the way for the diffusion of the DCV (Priem & Butler, 2001). DCs can be defined as "the firm's ability to integrate, build and reconfigure internal and external competencies to address rapidly changing environments" (Teece et al., 1997, p. 516). DCs allow firms to develop distinctive organisational and strategic routines and competencies which are fundamental to remain successful and create new markets (Fornell & Larcker, 1981). According to Prescott (2014), competitive advantage is at risk if companies fail to adapt the tangible and intangible resources available to the newest changes and requirements of the external environment, which otherwise accelerate their transformation into core rigidities. DCs develop over time and can have a strong impact on firm performance (Makkonen et al., 2014).

The DCV represents a suitable framework for investigating whether BDAC could be leveraged to facilitate BMI and exploring the possible mediation of a specific strategic orientation, EO. In managerial literature, scholars have indeed used the DCV as a theoretical perspective to examine all these constructs (Jiang et al., 2018; Khodaei & Ortt, 2019; Mikalef et al., 2017).

2.2. Big data analytics capabilities

The DCV is an appropriate lens to examine business analytics utilisation (Chen et al., 2015). According to Ferraris et al. (2018), the use of the DCV allows to overcome the limited vision on BDAC offered by both the RBV, which regards data as a valuable information resource but does not focus on the processes needed to unleash its potential, and the Knowledge-Based View (KBV), which, despite exploring data analysis and knowledge management routines does not deepen the range of problem-solving options enabled by BD. In particular, the DCV not only considers BD as value-creating resource and analyses its multiuse potential, but also allows to investigate how BD assets and processes need to be constantly reconfigured in order to allow the knowledge extracted to be disseminated within the organisation and effectively employed for the various operational and strategic necessities. The need for BD systems to continuously re-apply and learn routines in order to make companies able to examine new multi-faceted data and stay competitive over time is satisfied through the development of organisation-wide BDAC, which can be defined as the firm's distinctive and inimitable abilities to effectively exploit BD to obtain strategic insights (Mikalef et al., 2017). Drawing upon past IT capability literature, Gupta and George (2016) categorise three types of resources that allow companies to create and develop their BDAC: tangible resources, intangible resources and human skills. The former include methods to integrate, store, process, analyse and visualise internal and external data, as well as basic resources (i.e. financial support and time) destinated to BD-based projects (Gupta & George, 2016). Intangible resources are represented by a diffused and strong data-driven organisational culture (Ross et al., 2013) and a high company orientation to collect, share, stock and apply BD-based knowledge (Bhatt & Grover, 2005). Finally, human skills consist of the BDA technical, managerial and relational competences possessed by specialised employees (e.g. data analysts; Fosso Wamba et al., 2017). Scholars have treated BDAC as both a facilitator of organisational DCs such as agility (Mikalef et al., 2019) and a DC itself (Braganza et al., 2017; Fosso Wamba et al., 2017), which needs to be continuously renovated in order to seize market opportunities and maintain a competitive advantage in dynamic environments (Garmaki et al., 2016). Combining these theoretical views and in line with past studies (Mikalef et al., 2019; Xiao et al., 2020), we consider BDAC as lower-order DCs (Grant, 1996), which can create value for a company both directly and through the development of higher-order DCs (e.g. agility; Akter et al., 2016).

2.3. Business model innovation

A Business Model (BM) summarises the configuration and logic of a business (Baden-Fuller & Morgan, 2010). Three essential BM dimensions have been identified in the literature: value creation, value proposition and value capture (Clauss, 2017). The first dimension concerns the resources and capabilities employed in infra- and inter-organisational processes that generate value for the customer (Achtenhagen et al., 2013). The value proposition dimension defines the range, nature and features of the offered products and services and the conditions at which these are provided (Johnson et al., 2008). The value capture dimension explains how the business value proposition is converted into profits in a sustainable way (Teece, 2010). BMI can be interpreted as the deliberate process of reconfiguring one or more components underlying the business value logic for the company, its customers and the other stakeholders (Bucherer et al., 2012); a process that requires a significant modification of at least one core value dimension, thus entailing new ways of creating, proposing and/or capturing value (Amit & Zott, 2012). This definition of BMI fits well with our framework as it allows to effectively investigate the possibility of using BD to disrupt a company's business logic (Bouwman et al., 2018; Schüritz & Satzger, 2016). Indeed, by successfully collecting and employing valuable knowledge regarding customers, competitors and markets, firms are able to design and implement new value creation processes, which translate into brand new data-driven offerings for their customers and ultimately lead to improvements in profitability. BM literature has usually examined the concept of business logic innovation by referring to two contrasting perspectives (Schneider & Spieth, 2013): an evolutive view that considers changes in BMs as gradual fine-tuning adjustments aimed at reaching a dynamic equilibrium between firm resources and capabilities, and a disruptive view, according to which changes in one or more value dimensions of a BM architecture imply some major entrepreneurial actions to be conducted by the organisation (Paiola & Gebauer, 2020). By assuming a dynamic viewpoint, BM can be described as an "evolving bundle of activities" (Khodaei & Ortt, 2019, p. 1), and "a complex set of interdependent routines that is discovered, adjusted, and fine-tuned by "doing" (Winter & Szulanski, 2001, p. 731). Following this approach, BMIs represent natural outputs of DCs, which help firms maintain profitability over the long run by allowing to constantly sense new opportunities and seize them (Heider, Gerken, van Dinther, & Hülsbeck, 2020) through the transformation of corporate strategy, organisational routines and managerial skills (Teece, 2018). Eden and Ackermann (2000) consider BM as the DC that harmonises a company's distinctive competences to organisational aspirations and outcomes. Therefore, the DCV represents a theoretical perspective through which BMI can be appropriately examined.

2.4. Entrepreneurial orientation

EO is a business strategic orientation concerning the practices, processes and activities on which innovation and market entry decision-making is based (Lumpkin & Dess, 1996). It can be defined as a company's attitude towards innovativeness, proactivity and risk-taking in the formulation and implementation of strategies (Covin & Lumpkin, 2011). Innovativeness indicates the firm's inclination to search for new ideas and participate in creative processes aimed at new product and service development (Lumpkin & Dess, 1996). Proactivity reveals the firm's propensity to detect and capitalise on promising market opportunities ahead of competitors. A risk-taking attitude represents the extent and the degree of willingness to which managers employ business resources aimed at the implementation of projects whose outcome is uncertain and failure costs are high (Wiklund & Shepherd, 2005). Entrepreneurially-oriented firms tend to encourage their employees to make decisions independently, introduce new innovations actively, bear calculated risks, act proactively and show some degree of aggressiveness in the competition with rivals (Lumpkin & Dess, 1996). A strong reason for examining the role of this peculiar strategic orientation within data-driven contexts is that entrepreneurial decision-making is normally characterised by a high degree of complexity, which can be tamed by resorting to appropriate decision-support logics and capabilities (e.g. BDAC) that may contribute to reinforce the firm's propensity to take disruptive and risky actions (Pappas & Brown, 2020).

The literature has outlined the significant impact of EO on product and process innovations (Kyrgidou & Spyropoulou, 2013; Lisboa et al., 2016). These peculiar characteristics make it possible to associate EO to DCs, which in fact imply sensing of market changes, learning and experimentation, as well as reconfiguration of resources and capabilities for innovation purposes (Teece, 2016). Based on the classification of DCs introduced by Grant (1996), EO can be assimilated to a higher-order DC, since it gains strength from lower-order DCs to dynamically guide the company towards the transformation of organisational processes and systems that are necessary for achieving sustainable competitive advantages (Jiang et al., 2018; Rehman et al., 2020).

2.5. Hypotheses

2.5.1. The impact of big data analytics capabilities on business model innovation

The widespread diffusion of BDA and Internet of Things (IoT) gives manufacturing and service companies the possibility to leverage on these technologies to renovate their strategies and redesign their BMs (Porter & Heppelmann, 2015) by creating or enhancing innovative product-service systems, optimising customer segmentation and pricing strategies, opening new delivery and communication channels and rethinking the existing revenue models and cost structures (Paiola & Gebauer, 2020). According to the DCV, the lack of DCs might hinder companies from exploiting the full potential of BDA as well as the opportunities to innovate their BMs and strengthen their competitive advantage, especially within a fast-changing environment (Bouncken et al., 2019). A firm's BM can be considered successful when it is able to stay relevant over time for its customers and other stakeholders (Gambardella & McGahan, 2010). This requires infrastructural, technical, managerial, and organisational capabilities to control and orchestrate the data resources which permit to dynamically innovate the business strategic logic. In particular, the availability of BDAC allows to exploit the potential of the valuable insights and knowledge extracted from large-sized, diverse and up-to-date data regarding customers, markets and competitors (Ghasemaghaei & Calic, 2019) in order to implement completely data-based BMs (Manyika et al., 2011). Through the expert utilisation of BDA techniques, firms can accurately predict market requirements and consequently evolve their structures and strategies to best meet emerging market needs and disclose future market aspirations (Gupta, Drave, Dwivedi, Baabdullah, & Ismagilova, 2019). The main advantage linked to data-driven BMI lies in the opportunity of rationalising management's intuitions and creativity through the immediate and continuous availability of fresh information concerning business stakeholders (Cheah & Wang, 2017). Different patterns based on the use of analytical data and tools can be followed in order to significantly trigger BMI (Schüritz & Satzger, 2016). Although the degree of innovativeness impacting the business architecture through the deployment of BD technologies is potentially very variable, digital technologies normally have disruptive effects, resulting in radical BM innovations (Arnold et al., 2016).

In light of an absence of literature analysing the impact of BDAC on BMI, we leveraged on some of the few existing empirical studies to build our hypothesis. First of all, Mikalef et al. (2019) find that corporate BDAC positively impact the firm's ability to develop not only incremental innovations, through which slight changes are made to existing products, services, and processes, but also radical ones, through which new products and services are created. Similarly, starting from the evidence of the beneficial role of IT infrastructure in facilitating new knowledge exploration and exploitation for innovation purposes (Benitez et al., 2018), Jimenez-Jimenez et al. (2019) demonstrate the positive influence of IT capabilities (which also include data collection and analysis capabilities; Wang et al., 2015) on both incremental and radical innovations. Finally, Ransbotham and Kiron (2017), leveraging on a survey-based study with practitioners and scholars, stress the importance of possessing adequate data governance skills in order to effectively innovate processes, products, services and also entire business configurations. Since BMI can be considered as an important category of radical innovation (Ritala & Hurmelinna-Laukkanen, 2013), our first hypothesis is:

H1. Big Data Analytics Capabilities have a positive and direct impact on Business Model Innovation.

2.5.2. The mediating role of Entrepreneurial orientation

According to Watson et al. (2018), BD-driven decision support systems foster knowledge access and sharing and support firms' analytical skills, thus increasing the strategic propensity to entrepreneurship. As a matter of fact, by successfully collecting up-to-date and real-time information on customers' profiles, behaviours and needs as well as on competitors' strategies and actions, organisations can dispose of a thorough representation of the current and potential future dynamics of the markets in which they operate, thus enhancing their ability to act as early movers in seizing promising innovation opportunities thanks to the less uncertainty and risk perceived (Côrte-Real et al., 2017).

Several BD and IT empirical studies address the existence of a positive impact of BDAC on EO and, in turn, on performance. Gnizy (2019) recognises that multinational companies have a higher chance of adopting entrepreneurial-oriented strategies if their BD systems are able to acquire new and reliable knowledge regarding future market trends continuously and in real time. Qosasi et al. (2019) find that IT capabilities have a positive influence on EO which, by allowing innovative, proactive, and risky decisions in dynamic market conditions, in turn enhances firms' competitive advantage. Similarly, Chen et al. (2015) find that corporate entrepreneurship, which is defined as the organisational attitude towards continuous and deliberate self-renewal through the identification and exploitation of new entrepreneurial opportunities and can be therefore assimilated to EO, is positively impacted by IT capabilities.

This discussion leads us to hypothesise that:

H2a. Big Data Analytics Capabilities have a positive and direct impact on Entrepreneurial Orientation

The inner ambidextrous nature of EO is coherent with both the perspectives through which BMI can be analysed and achieved (i.e. the evolutive and the disruptive views; Paiola & Gebauer, 2020), though it better fits with BM radical innovations which require a higher level of entrepreneurship (S. Schneider & Spieth, 2013). A business mentality significantly oriented towards entrepreneurship represents a critical success factor for BMI (Foss & Saebi, 2018) as it allows companies to enhance their collaborative network with various stakeholders, exchange resources, competences and knowledge with them, thus facilitating the likelihood of innovation (Genc et al., 2019). According to Amit and Zott (2012), entrepreneurially-oriented firms even consider BMI as a better alternative than the mere product and service innovation, especially in the presence of scarce resources and uncertain market conditions.

Several empirical studies find or assume the existence of a positive relationship between EO and BMI. Kollmann and Stöckmann (2010) find that EO favours proactivity, propensity to innovate and risk appetite, thus stimulating ambidextrous organisations to both experiment new BMs and exploit the existing ones. Adopting the DCV, Bouncken et al. (2016) interpret EO as a DC and find that it can influence new value generation and value proposition formulas, thus positively impacting on BMI. Finally, Mütterlein and Kunz (2017) find that EO feeds the company's ability to evolve the different BM dimensions, i.e. value creation, value proposition and value acquisition.

Based on the previous considerations, our next hypothesis is:

H2b. Entrepreneurial Orientation has a positive and direct impact on Business Model Innovation.

While in Hypothesis 1 we suppose that BDAC have a positive and direct impact on BMI, in Hypotheses 2a and 2b respectively, we propose that BDAC have a positive and direct impact on EO and that EO has a positive and direct impact on BMI. This suggests that the relationship between BDAC and BMI may be both direct and indirect and that EO may mediate it.

Although prior research has highlighted the influence of BDAC on other several business strategic orientations (e.g. market orientation, learning orientation; Gnizy, 2019), EO seems to represent the ideal mediator between BDAC and BMI, as it reflects a propensity to contemporarily seek opportunities and competitive advantages (Zhang et al., 2016). Indeed, companies with robust BDAC are able to effectively collect and analyse data from the external environment, through which business opportunities may be sensed and shaped (Garmaki et al., 2016); this translates into the development of an EO that, capitalising on the valuable insights extracted, might allow firms to overcome the imperfections of their BMs by promoting innovative and steady new product and process development efforts usually involving a high level of risk (Marzi et al., 2020; Usai, Scuotto, Murray, Fiano, & Dezi, 2018).

The hypothesis of a positive mediation of EO in the BDAC-BMI relationship is grounded on the role played by the single behavioural components of EO. First of all, it is plausible to assume that companies that are capable of implementing effective BDA practices are naturally led to develop a propensity for innovation, creativity and future thinking (Lumpkin & Dess, 1996), as well as to continually pursue data-driven strategies which have the potential of disrupting their BMs (Wang et al., 2020). Secondly, organisations possessing robust skills for BD analysis are likely to be highly receptive to market signals and latent needs of both current and potential customers (Hughes & Morgan, 2007), which allow them to anticipate and even cause the changes in the external environment through radical modifications of their business logics. Finally, as BDAC improve corporate intelligence and data analysis systems, they favour the seeking of innovation opportunities outside the methods and thought patterns within which the organisation normally operates and competes, thus encouraging managers to bear more risks while at the same time being more open to adopt deep changes of the business value mechanisms (Roberts et al., 2016).

Consequently, we posit the following hypothesis:

H2c. Entrepreneurial Orientation mediates the positive effect of Big Data Analytics Capabilities on Business Model Innovation.

3. Methods

3.1. Data collection

To empirically test our hypotheses, we adopted a cross-sectional data collection system by administering an online questionnaire to managers and directors of UK companies operating in manufacturing, services, trade and financial industries. The use of a random stratified sampling method allowed us to obtain a selection of companies (2500) representative of the population of active UK companies with respect to their dimensional characteristics and industry. The choice to analyse UK companies is motivated by the fact that the United Kingdom is a

European country characterised by a high rate of technological innovation (Dutta et al., 2018; KPMG, 2019). As such these companies represent a suitable research target for investigating the variables object of our analysis. Data collection only involved top managers and directors of the sample companies, based on the assumption that only these subjects have a global vision of the business processes and are consequently able to assess the overall impact of BD and BDCA on EO and BMI.

We administered the questionnaire online to the random sample of 2500 companies in the period from September to October 2019. A total of 258 surveys were fully completed, corresponding to a response rate of 10.32%. Of these, 5 were eliminated as the compilation time was below the minimum threshold deemed reasonable to provide adequate responses, considering the number of questions. Thus, the final sample consisted of 253 valid respondents.

3.2. Measures

We measured the three constructs composing our conceptual model by using scales that have already been tested and validated in the literature (see Table 1).

We measured BDAC as a formative third-order construct depicted as a 25-item scale according to Mikalef et al. (2019). BDAC was composed of three second-order formative constructs: tangible resources (10 items), human skills (8 items) and intangible resources (7 items). Tangible resources were composed of three first-order formative construct: data (composed of 3 items), technology (5 items) and basic resources (2 items). Human skills construct was composed of two first-order reflective constructs: technical skills (4 items) and managerial skills (4 items). Finally, intangible resources construct was composed of two first-order reflective constructs: data-driven culture (3 items) and intensity of organisational learning (4 items). We measured EO as a first-order reflective construct consisting of a 9-item scale from Rank and Strenge (2018). Finally, BMI was measured as a first-order reflective construct consisting of a 5-item scale from Asemokha et al. (2019). Respondents rated the items on a 7-point Likert scale.

3.3. Statistical techniques

We used both Partial Least Squares Structural Equation Modelling (PLS-SEM) and fuzzy-set Qualitative Comparative Analysis (fsQCA), specifically the R software packages ‘plspm’ (Sanchez et al., 2017) and ‘QCA’ (Duşa, 2019). These two statistical techniques are based on different principles and have different focuses (Afonso et al., 2018). SEM analyses the net impact of the independent variable on the outcome as well as the competition among independent variables in explaining the dependent variable; furthermore, it is based on the rules of linearity, unifinality and additive effects (Woodside, 2013). On the contrary, FsQCA explores combinatorial effects and assumes the existence of asymmetries between variables, equifinality (different routes can generate the same outcome), multifinality (identical elements can generate different outputs) and conjunctural causation (Rihoux & Ragin, 2009; Woodside, 2013). In contrast to other QCA methods, in the case of fsQCA the variables are on a fuzzy (continuous between 0 and 1) and not on a dichotomous (binary) scale. Furthermore, it seeks combinations (configurations) of causal conditions leading to a specific outcome, rather than simple correlations between constructs (Mikalef & Pateli, 2017).

3.4. Common method and non-response bias

In order to address concerns regarding common method bias, we protected the privacy and confidentiality of respondents (Podsakoff et al., 2003), avoided item vagueness by using well-established scales, pre-tested the questionnaire and divided it into three parts, each of which was referred to one the three constructs (BDAC, EO and BMI)

Table 1
Constructs, codes and items used in this study.

BIG DATA ANALYTICS CAPABILITIES (BDAC; Mikalef et al., 2019)
TANGIBLE (TAN)
Data (D)
[D1] We have access to very large, unstructured, or fast-moving data for analysis
[D2] We integrate data from multiple sources into a data warehouse for easy access
[D3] We integrate external data with internal to facilitate analysis of business environment
Basic Resources (BR)
[BR1] Our ‘big data analytics’ projects are adequately funded
[BR2] Our ‘big data analytics’ projects are given enough time to achieve their objectives
Technology (T)
[T1] We have explored or adopted parallel computing approaches (e.g. Hadoop) to big data processing
[T2] We have explored or adopted different data visualisation tools
[T3] We have explored or adopted new forms of databases such as Not Only SQL (NoSQL)
[T4] We have explored or adopted cloud-based services for processing data and performing analytics
[T5] We have explored or adopted open-source software for big data analytics
HUMAN SKILLS (HUM)
Managerial Skills (MS)
[MS1] Our BDA managers are able to understand the business needs of other functional managers, suppliers, and customers to determine opportunities that big data might bring to our business
[MS2] Our BDA managers are able to coordinate big data-related activities in ways that support other functional managers, suppliers, and customers
[MS3] Our BDA managers are able to understand and evaluate the output extracted from big data
[MS4] Our BDA managers are able to understand where to apply big data
Technical Skills (TS)
[TS1] Our ‘big data analytics’ staff has the right skills to accomplish their jobs successfully
[TS2] Our ‘big data analytics’ staff is well trained
[TS3] We provide big data analytics training to our own employees
[TS4] Our ‘big data analytics’ staff has suitable education to fulfil their jobs
INTANGIBLE (INT)
Data-driven Culture (DD)
[DD1] We base our decisions on data rather than on instinct
[DD2] We are willing to override our own intuition when data contradict our viewpoints
[DD3] We continuously coach our employees to make decisions based on data
Intensity of Organisational Learning (OL)
[OL1] We are able to acquire new and relevant knowledge
[OL2] We have made concerted efforts for the exploitation of existing competencies and exploration of new knowledge
[OL3] We are able to assimilate relevant knowledge
[OL4] We are able to apply relevant knowledge
ENTREPRENEURIAL ORIENTATION (EO; Rank & Strange, 2018)
[EO1] In general, top managers of my company favour a strong emphasis on R&D, technological leadership and innovations
[EO2] In the last five years, my company has marketed many new product lines or services
[EO3] In my company, changes in product or service lines have been quite dramatic
[EO4] In the last years, my company has typically initiated actions which the competition then responds to
[EO5] In the last years, my company was very often the first business to introduce new products/services, administrative techniques, and operating technologies
[EO6] In the last years, my company has typically preferred a competitive “undo-the-competitors” posture
[EO7] In the last years, my company had a strong proclivity for high risk projects (with chances of very high return)
[EO8] In the last years, my company believed that owing to the nature of the environment, wide-ranging acts are necessary to achieve the company’s objectives
[EO9] When confronted with decision-making situations involving uncertainty, my company has typically adopted a bold, aggressive posture to maximise the probability of exploiting potential opportunities
BUSINESS MODEL INNOVATION (BMI; Asemokha, 2019)
[BMI1] When necessary, we are able to carry out massive internal reconfigurations to enhance our overall value proposition to our customers
[BMI2] When we sense an opportunity, we are quick at re-organising our operating processes
[BMI3] When necessary, we are able to reorganise our partner network to improve our value proposition to our customers
[BMI4] New opportunities to serve our customers are quickly understood
[BMI5] We regularly consider innovative opportunities for changing our existing pricing models

being part of our conceptual model (Akbar et al., 2016). We also performed the Harman's one-factor test (Fuller et al., 2016) and found that the first factor accounted for 45.5% of the variance (which is lower than the 50% threshold; Fuller et al. (2016). Finally, we conducted the marker variable and common factor tests, without finding evidence of common method bias.

With regard to non-response bias, we compared organisation age and size of the participating and non-participating firms in our initial sample of 2500 UK companies. ANOVA provided p-values equal to 0.951 and 0.562, respectively, indicating no statistically significant differences. Furthermore, following Armstrong and Overton (1977), we performed t-tests comparing organisation age and size of early and late respondents, without finding any statistically significant difference (p-values 0.609 and 0.405, respectively).

3.5. Sample size requirements for PLS-SEM

The minimum sample size at which PLS-SEM path coefficients become significant depends on the magnitude of path coefficients at the population level: the lower this magnitude is, the bigger is the needed sample size. In the case of PLS-SEM, the most widely used criterion to determine minimum sample size is the '10-times rule', according to which the sample size should be greater than 10 times the maximum number of inner or outer links received by any construct (Peng & Lai, 2012). In our study the construct with the maximum number of links was BDAC, with 25 links, leading to a minimum sample size requirement of 250. Two alternative approaches, the inverse square root and the gamma-exponential criteria (Kock & Hadaya, 2018), were also applied: assuming a minimum magnitude for path coefficients equal to 0.2 (corresponding to a small effect size; Cohen, 1988), we found that a minimum sample size of 215 and 199, respectively, was needed in order to obtain a statistical power of 0.9 at a significance level of 0.05. Our final sample of 253 firms exceeded all of the above requirements.

3.6. Measurement model

We used different validation criteria depending on the nature (reflective or formative) of the constructs contained in our model.

Specifically, the validation of the reflective constructs (which, in our study, are all first-order constructs) was carried out by conducting the tests of convergent validity, discriminating validity, internal consistency and composite reliability (see Table 2). To test the convergent validity of the reflective constructs, we verified that the Average Variance Extracted (AVE) index was greater than 0.50; the lowest observed value of 0.54 is substantially higher than this threshold.

The discriminant validity of reflective constructs was tested in three ways. We first verified that the AVE value of each construct exceeded its highest quadratic correlation with any other reflective construct (Fornell-Larcker criterion). Secondly, we verified the outer loadings for each item to be higher than the cross-loadings (Farrell, 2010). Thirdly, we checked the heterotrait-monotrait (HTMT) ratios to be lower than 0.85 (Henseler et al., 2015). In order to test the internal consistency of the reflective constructs, we verified that the value of Cronbach's Alpha index exceeded 0.7; the lowest observed value of 0.75 widely exceeds this threshold. Finally, we calculated the composite reliability values for the reflective constructs, confirming their validity with respect to the minimum threshold of 0.70 (Nunnally, 1978).

We assessed the reliability of the indicators of all constructs (both reflective and formative) considering the saturation values of each item with respect to the corresponding construct (outer loadings). All these values were above the threshold of 0.70.

These results suggest the validity of the reflective constructs used in our analysis as well as the adequacy of the items used as construct indicators.

With regard to formative constructs, we first examined the significance of weights. For all first-order constructs (i.e. Data, Technology, Basic Resources) all items show positive and highly significant weights. For all the second order (i.e. Tangible, Human Skills, Intangible) and third order (BDAC) constructs, all lower level constructs show positive and highly significant weights. Following MacKenzie et al. (2011) we then estimated the adequacy coefficient (R^2_a) of Edwards (2001). For all first, second and third order constructs the R^2_a values were higher than 0.50. Subsequently, by calculating the Variance Inflation Factors (VIF), we examined the possible presence of multicollinearity between the indicators of the formative constructs and between the first and second order formative constructs. All values were below 10, confirming the absence of multicollinearity.

4. Empirical results

The results of our study are based on a sample of 253 respondents whose characteristics are described in Table 3. Specifically, it is composed of 59.7% males, 19.8% up to 30 years old (71.5% up to 45), 49.8% with an expertise in the industry of more than 10 years (77.1% higher than 5 years) and 73.5% holding a top management position (15.0% with a board of director position, 11.5% with a chief executive officer position). Furthermore, 79.8% of the firms in the sample have less than 500 employees (63.6% less than 250 employees). Responses

Table 2
Correlation matrix and assessment of convergent validity, discriminating validity, internal consistency, and composite reliability of reflective constructs.

		1	2	3	4	5	6	7	8	9	10	11	12	13
1	Data (D)	1.000												
2	Basic resources (BR)	0.714	1.000											
3	Technology (T)	0.792	0.654	1.000										
4	Managerial skills (MS)	0.788	0.779	0.732	1.000									
5	Technical skills (TS)	0.811	0.831	0.754	0.870	1.000								
6	Data-driven culture (DD)	0.713	0.672	0.690	0.758	0.776	1.000							
7	Intensity of organisational learning (OL)	0.672	0.634	0.589	0.715	0.692	0.709	1.000						
8	Tangible (TAN)	0.927	0.878	0.900	0.850	0.889	0.768	0.702	1.000					
9	Human (HUN)	0.827	0.837	0.773	0.966	0.967	0.793	0.722	0.902	1.000				
10	Intangible (INT)	0.762	0.717	0.703	0.805	0.806	0.934	0.910	0.808	0.830	1.000			
11	Big data analytics capabilities (BDAC)	0.887	0.848	0.847	0.904	0.906	0.871	0.804	0.955	0.940	0.918	1.000		
12	Entrepreneurial orientation (EO)	0.585	0.505	0.603	0.505	0.518	0.511	0.406	0.626	0.539	0.515	0.635	1.000	
13	Business model innovation (BMI)	0.521	0.524	0.481	0.566	0.523	0.552	0.545	0.566	0.569	0.597	0.636	0.651	1.000
	Mean	4.852	4.721	4.489	4.965	4.864	4.851	5.408	4.645	4.915	5.169	4.878	4.154	4.938
	Standard deviation	1.662	1.631	1.768	1.462	1.687	1.591	1.337	1.717	1.579	1.477	1.623	1.707	1.481
	Cronbach's Alpha*	–	–	–	0.923	0.898	0.747	0.860	–	–	–	–	0.892	0.876
	AVE*	–	–	–	0.809	0.779	0.665	0.713	–	–	–	–	0.538	0.670
	HTMT ratio*	–	–	–	0.818	0.811	0.796	0.704	–	–	–	–	0.617	0.714
	Composite reliability*	–	–	–	0.944	0.934	0.856	0.909	–	–	–	–	0.913	0.910

* Only relevant for reflective constructs.

Table 3
Sample characteristics.

Variables	Number (N)	Percentage (%)	Variables	Number (N)	Percentage (%)
Respondent Variable					
Age			Gender		
18–30	50	19.76%	Male	151	59.68%
31–45	131	51.78%	Female	102	40.32%
46–60	60	23.72%			
>60	12	4.74%			
Industry expertise			Company position		
<1 year	2	0.79%	Chief executive officer	29	11.47%
1–5 years	56	22.14%	Board member	38	15.02%
6–10 years	69	27.27%	Line manager	61	24.11%
>10 years	126	49.80%	Senior manager	53	20.95%
			Functional manager	58	22.92%
			Other top management position	14	5.53%
Company variables					
Industry			Size (employee number)		
Manufacturing	79	31,23%	1–50	43	17.00%
Services	91	35,97%	51–150	65	25.68%
Trade	25	9,88%	151–250	53	20.95%
Bank and Financials	58	22,92%	251–500	41	16.21%
			>500	51	20.16%

were collected from companies operating in manufacturing (31.2%), services (36.0%), trade (9.9%) and financial industries (22.9%).

4.1. Structural model results

Fig. 1 and Table 4 synthesise the structural model from PLS analysis by showing the standardised path coefficients (β) and their significance (t-values) as well as the explained variance of endogenous variables

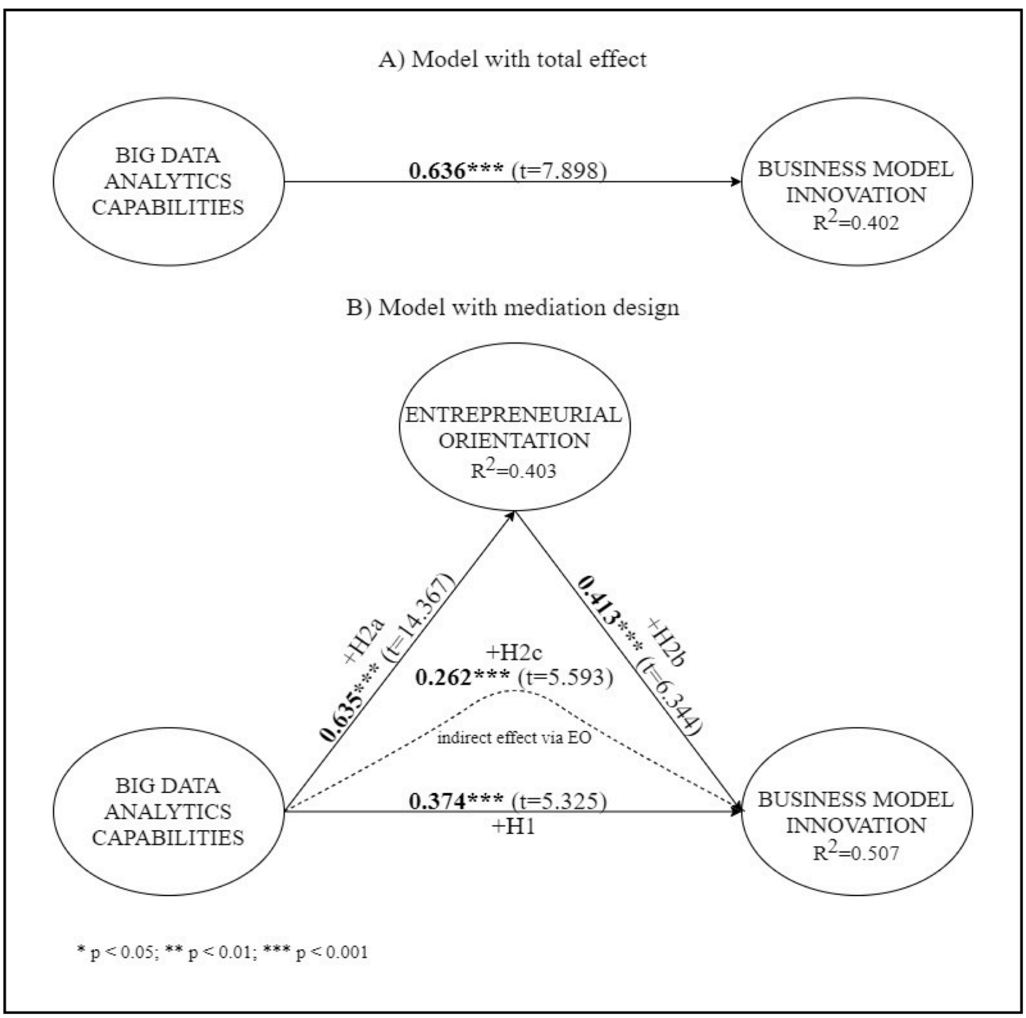

Fig. 1. Estimated causal relationships of the structural model.

Table 4
Mediation results.

Model A - Total effect			
Path	Estimate	t-value	95% CI
BDAC → BMI	0.636***	7.898	(0.478, 0.794)
Model B - Direct effect			
Path	Estimate	t-value	95% CI
BDAC → BMI	0.374***	5.325	(0.246, 0.503)
Model B - Indirect effect			
Path	Estimate	t-value	95% CI
BDAC → EO → BMI	0.262***	5.593	(0.170, 0.354)

BDAC: Big Data Analytics Capabilities, EO: Entrepreneurial Orientation, BMI: Business Model Innovation, 95% CI: Bias corrected bootstrap 95% confidence interval. Bootstrapping 15% confidence interval based on 5000 samples. *** $p < 0.001$.

(R^2). We calculated t-values through a bootstrap approach based on 5000 random resamples.

Results show that all of our hypotheses are supported. BDAC have a significant and positive impact on EO ($\beta = 0.635$, $t = 14.367$, $p < 0.001$; Hypothesis 2a is confirmed). BMI is significantly and positively influenced by EO ($\beta = 0.413$, $t = 6.344$, $p < 0.001$; Hypothesis 2b is confirmed). BMI presents a significant and positive direct effect from BDAC ($\beta = 0.374$, $t = 5.325$, $p < 0.001$; Hypothesis 1 is confirmed). The structural model explains a variance rate of 40% for EO ($R^2 = 0.403$) and 50% for BMI ($R^2 = 0.507$). These R^2 values indicate a predictive accuracy of the model between moderate and strong (Hair et al., 2016).

Finally, the BDAC → EO → BMI mediation path was also found positive and significant ($\beta = 0.262$, $t = 5.593$, $p < 0.001$), thus confirming Hypothesis 2c. The total effect of BDAC on BMI, calculated as the sum of the direct and indirect effect, was 0.636 ($t = 7.898$, $p < 0.001$). As a result, the direct and indirect effects account for 59% and 41% of the total effect, respectively.

Beside examining R^2, we also tested the predictive validity of the model by analysing the predictive relevance of the exogenous variables Q^2 (Chin, 1998), as well using a cross-validation hold-out procedure (Hair et al., 2012).

With regard to Q^2, we found that both EO ($Q^2 = 0.188$) and BMI ($Q^2 = 0.309$) have values greater than zero, indicating a satisfactory predictive relevance (Hair et al., 2016). With regard to the second test following Cepeda Carrión et al. (2016) we randomly divided the sample into two sub-samples: a training sample ($n = 152$) and a holdout sample ($n = 101$). The weights and path coefficients of the regression were then estimated by using only the training sample data. Subsequently, we normalised the hold-out sample observations and calculated the construct scores based on the training sample estimates. Then we normalised the holdout sample construct scores and used these scores to calculate the path coefficients and the R^2 value of each endogenous construct. Finally, we compared these R^2 values with those obtained from the path coefficients estimated using the training sample data. The similarity between the R^2 values for the holdout sample (EO: $R^2 = 0.416$; BMI: $R^2 = 0.500$) and the training sample (EO: $R^2 = 0.440$, BMI: $R^2 = 0.543$) confirmed the predictive validity of our model.

The analysis of the composite-based standardised root mean square residual (SRMR) gave a value (0.089), below the 0.10 threshold, which confirmed the overall goodness of fit of the model (Henseler et al., 2014).

Finally, we found that the weights of both company size and industry (our two control variables) were not statistically significant for the BMI construct.

4.2. FsQCA results

FsQCA aims to find out all the combinations of causal conditions that potentially lead to a certain result (outcome). In our study high levels of BMI represent the outcome, while the causal conditions are the combinations of high and low levels of the antecedents of BMI, i.e., BDAC and EO. In fsQCA dependent and independent variables must be preliminarily calibrated, i.e., transformed into fuzzy sets with values ranging from 0 to 1, where 1 represents full set membership, 0.5 represents the crossover point and 0 denotes no set membership (Ragin, 2008).

Following Ordanini et al. (2014) while using the direct method for calibrating (Ragin, 2008), the following threshold values were adopted: 6 for full membership, 2 for full non-membership, and 4.5 for the crossover point. The calibrated constructs were obtained by averaging the corresponding calibrated indicators.

FsQCA analyses causal conditions and configurations of causal conditions through the metrics of consistency and coverage. Consistency indicates the degree to which a subset relation has been approximated and is analogous to the notion of statistical significance (Schneider & Wagemann, 2010), while coverage measures how empirically relevant the consistent subset is, analogously to R-squared in regression analysis (Mendel & Korjani, 2012).

The analysis of sufficiency is certainly the most important part of fsQCA. Nevertheless, it is good practice to precede it with a necessity analysis (Schneider & Wagemann, 2010). Therefore, we applied fsQCA to verify whether any of the two antecedent conditions (BDAC and EO) are always present (or absent) in all the cases where the outcome (BMI) is present (or absent; Rihoux & Ragin, 2009). According to the literature, to be considered as 'necessary' or 'almost always necessary', a condition should have consistency (the level to which the cases comply with the necessity rule) above 0.9 or 0.8 respectively and coverage (the degree of empirical relevance) above 0.75 (Ragin, 2000). Our results of the fsQCA on necessary conditions show that only high levels of BDAC give consistency above 0.8, precisely 0.864 (with coverage of 0.886), confirming that high levels of BMI 'almost never' can be achieved without the presence of BDAC.

We began sufficiency analysis by using the fsQCA algorithm in order to produce the truth table (Ragin, 2008). In order to avoid including less significant configurations, a ten observations frequency threshold was adopted (Rihoux & Ragin, 2009), which did not cause the exclusion of any case in the sample. Subsequently, in order to identify the sufficient configurations of conditions for companies to achieve high levels of BMI, this study applied the thresholds proposed by Skarmeas et al. (2014) for determining sufficiency and coverage: 0.74 and 0.27, respectively. Our results of the fsQCA test on sufficiency conditions are described in Table 5.

Our analysis produced three possible solutions leading to high level of BMI. Solution 1a, high levels of BDAC and high levels of EO, has the highest consistency (0.965) and explains the highest number of cases (coverage = 0.670). It also has the highest unique coverage (0.237 against 0.116 and 0.022 of solutions 2a and 3a, respectively), indicating that the combination of high levels of BDAC and high levels of EO mostly contributes to high levels of BMI compared to all other solutions. This result gives confirmation to the existence of an indirect effect of BDAC

Table 5
Results of the fsQCA on sufficient conditions.

Configurations for achieving high levels of BMI					
Solution	BDAC	EO	Consistency	Raw coverage	Unique coverage
1a	●	●	0.965	0.670	0.237
2a	●	○	0.902	0.531	0.116
3a	○	●	0.962	0.342	0.022
Overall consistency: 0.911. Overall coverage: 0.808.					
Configurations for achieving low levels of BMI					
Solution	BDAC	EO	Consistency	Raw coverage	Unique coverage
1b	○	○	0.789	0.756	0.141
2b	○	●	0.744	0.522	0.022
Overall consistency: 0.758. Overall coverage: 0.778					

● denotes the presence of a causal condition (i.e., high levels of a construct).
○ denotes the absence of a causal condition, (i.e., low levels of a construct).

on BMI through the mediation of EO (Hypothesis 2c).

Solution 3a, namely low levels of BDAC and high low levels of EO, indicates the sufficiency of high levels of EO for achieving high levels of BMI, which is also coherent with our mediation hypotheses (H2b and H2c). Finally, solution 2a indicates that high levels of BDAC and low levels of EO are also sufficient to achieve high levels of BMI, thus supporting the existence of a direct effect of BDAC on BMI (Hypothesis 1).

Differently from the SEM analysis, the fsQCA assumes the existence of asymmetries between variables. As a consequence, it is possible to explore whether configurations leading to the inverse of the outcome (low levels of BDAC) are different from those leading to the outcome (high levels of BDAC; Ragin, 2008).

Our analyses of the inverse of the outcome (Schneider & Wagemann, 2010) produce two informative solutions (1b and 2b). Solution 1b, low levels of both BDAC and EO, confirms the indirect effect of BDAC on BMI through the mediation of EO (Hypothesis 2c), while solution 2b, namely low levels of BDAC and high levels of EO, supports the existence of a direct effect of BDAC on BMI (Hypothesis 1). These results show the presence of causal asymmetry as three causal configurations consistently lead to high levels of BMI, while only two configurations are consistently associated with low levels of BMI.

The robustness of these findings was verified across three different calibration choices. First, we changed the full membership (5.75 instead of 6) and full non-membership thresholds (2.25 instead of 2), then we changed the crossover point from 4.5 to 4.25, and finally we changed the crossover point from 4.5 to 4.75. All three analyses produced the same results obtained using our initial calibration choice.

5. Discussion

While the theoretical literature on BD has shown the opportunity for firms to leverage on digitalisation to innovate their BMs in order to achieve superior performance (Bouwman et al., 2018; Lokshina et al., 2018; Sorescu, 2017; Woerner & Wixom, 2015), no empirical study has so far investigated whether and the extent to which BDAC impact on the capacity of a firm to innovate its BM. Recent empirical literature has recognised how BDAC facilitate innovations in different business contexts (Fosso Wamba et al., 2017; Hooi et al., 2018; Mikalef et al., 2019; Pappas et al., 2018). However, to the best of our knowledge, there is still no research exploring whether and how these changes favoured by BD utilisation are actually exploitable to guide BMI (Wang & Hajli, 2017). This study aims to fill this gap. Specifically, we leveraged on the DCV to examine if (1) BMI may represent an outcome of organisation-wide BDAC, and (2) EO might mediate the BDAC-BMI relationship, considering the radical changes that are usually implied with data-driven innovations.

5.1. Theoretical implications

The theoretical contributions of this study are twofold. Firstly, it finds the existence of a direct and positive relationship between BDAC and BMI, thus demonstrating how BDAC, besides representing enabling capabilities for co-innovation and new product development (Hooi et al., 2018), also have a significant impact on BMI. This finding enriches the DCV literature by showing that distinctive DCs created through an attentive orchestration of BD resources can favour effective adaptations and evolutions of companies' BMs aimed at achieving longer-lasting competitive advantages, especially in turbulent environments (Heider et al., 2020; Garmaki et al., 2016). It brings about the opportunity for companies to nurture BDAC by specifically investing in the basic resources on which these capabilities are based, i.e. tangible resources, human skills, and intangible resources (Gupta & George, 2016). In fact, this set of distinctive resources makes it possible to extract new valuable knowledge from raw data which permits companies to stay up-to-date on current and potential transformations occurring in the competitive context (Mikalef et al., 2019). In addition to being used to reengineer business processes, create new products and ways of serving customers as well as to develop new ways of engaging stakeholders and communities (Marzi et al., 2020; Xie et al., 2016), this knowledge can be effectively deployed for developing new BMs (Lee, 2018). In particular, the presence of a trained staff who has the ability to technically handle BD and recognise its importance as a valuable source of business information, together with the widespread diffusion of a data-driven corporate culture and knowledge management systems capable of collecting, storing, sharing and utilising the obtained information, gives firms the opportunity to implement new value creation mechanisms through which customised value propositions can be shaped and value capture methods introduced and enhanced (Teece, 2010).

Furthermore, this study gives a contribution to the strategic and innovation management literature by demonstrating for the first time the positive mediating role exerted by EO in the BDAC-BMI relationship. This finding suggests two principal considerations. First, the availability of adequate BDAC improves the degree of alertness and reactiveness of corporate information systems and decision-makers to the internal and external stimuli (Huber, 1991), thus allowing firms to be proactive in grasping market opportunities and trends (Bouncken et al., 2019) and avoid the selective bias phenomena usually connected to BD's high perceived complexity and risk (Fischer et al., 2000). In particular, the presence of a modular technological infrastructure (an essential component of BDAC; Akter et al., 2016) usually increases business decision-making flexibility, which in turn promotes research, discovery, experimentation and risk-taking behaviours possibly directed to the quick update and effective reconfiguration of BMs (Del Giudice, 2016). Secondly, the availability of appropriate BDAC allows the sharing of valuable insights and knowledge inside and outside the firm which, being normally associated with an increasing engagement in entrepreneurial initiatives (Chen et al., 2015), can facilitate the discovery and adoption of new BMs. On the one hand, the presence of a corporate data-driven culture stimulates the internal collaboration on joint projects based on the creative experimentation of BD usage within the company, which in turn facilitates the integration of ideas, the disruption of old thought patterns and ultimately the rethinking of existing BMs (Zeng & Khan, 2019). On the other hand, BDAC usually encourage the cooperation with external business partners, potentially resulting in innovation and renewal strategies concerning products, processes and organisational structures (Kunz et al., 2017).

This paper contributes to the research stream that considers the disruptive impact of BDA on the traditionally presumed linear relationship between company strategy, firm structure and information systems architecture, in favour of a new perspective that advocates the central role of BD resources and capabilities in directly informing the strategic actions aimed at maintaining the competitive advantage in the long run (Mazzei & Noble, 2017). In other words, it stresses the role of BDAC as an enabling factor for firms to shape strategies based on the "fusion between technology and business", rather than a "subordinate of business strategy" (Mikalef et al., 2020, p. 11).

Moreover, our results extend the DCV literature by demonstrating the positive mediating effect of higher-order DCs (hereby represented by EO, a strategic orientation that can be assimilated to a DC (Teece, 2016) in the relationship between BDAC (hereby considered as lower-order DCs; Grant, 1996) and innovation outcomes (Mikalef et al., 2019; Xiao et al., 2020).

5.2. Managerial implications

From a managerial point of view, our results suggest that in order to make BMs effectively evolve, companies should nurture valuable organisation-wide BDAC by hiring and training skilled personnel, adopting organisational learning and knowledge sharing practices, and promoting the diffusion of a corporate data-driven and evidence-based culture (Mikalef et al., 2019). This requires the engagement of top management in the development of dedicated actions and processes, e.g.

technical decisions about evolutionary changes concerning the IT infrastructure in collaboration with Chief Information Officers, recruitment of skilled data analysts and data scientists, arrangement of temporary teaching task forces and development of leader role modelling programs (Barton & Court, 2012).

Secondly, since our study highlights how a great proportion of the effect of BDAC on BMI is influenced by the mediation of EO, we argue that top managers should take actions for better leveraging BDAC to favour entrepreneurial initiatives. For instance, the introduction of monetary or not-monetary incentives for the employees engaged in creative BD-based experimentation and exploration activities may encourage the internal collaboration on joint innovative projects based on data that require the assumption of high risks and responsibilities. Besides, the availability of common data platforms representing the "single source of truth" for the firm and its external partners (Fosso Wamba et al., 2015, p. 242) can stimulate knowledge sharing processes outside the organisation and, in turn, may favour corporate entrepreneurship processes oriented to product, process and BM renewal.

Lastly, coming back to the positive impact of BDAC on BMI, we recommend business managers to perform their attempts towards BD-driven BMI by resorting to a checklist of sequential questions allowing them to rationally and consciously adopt decisions concerning the desired degree of 'data-drivenness' of the desired new business logics, the selection of the data sources from which to obtain data, and whether to employ the data collected to support or transform the existing core business (Zaki, 2019).

5.3. Limitations and future research directions

Our paper presents some limitations which may act as starting points for future empirical studies. First, the survey-based structure of this research, combined with the perceptive nature of the selected variables, can cause cognitive bias that can undermine its objectivity. Therefore, future contributions could analyse the same topic using multiple informant and case-based methodologies. Another limitation concerns the first-order construct used for measuring BMI. Although the construct can be considered adequate for an exploratory study, future empirical research could use more complex scales taking into account the single value dimensions of BMI, i.e. value creation, value proposition and value capture (Clauss, 2017). Furthermore, the fact that this study only looks at firms based in one country (UK) limits the generalisability of the results obtained, as country-specific characteristics might influence how BDAC have impact on EO and BMI, as well as the size of these impacts. Future research should therefore perform cross-country analyses, in order to verify whether our findings are also valid for other national economic settings. Finally, although our study controlled for business size and industry, we believe that these variables do not cover all the possible contextual differences capable of affecting the relationships examined in our conceptual model. Hence, the opportunity for future studies to include other potentially significant control variables, such as the degree of firm internationalisation and the types of customers served (e.g. business customers or final consumers).

Regardless of the limitations described above, our study brings out some possible future research avenues. For instance, it could be interesting to investigate the role of further strategic orientations (e.g. technology orientation, market orientation, learning orientation) as mediating variables within the BDAC-BMI relationship. Likewise, it could also be stimulating to replicate this study by including moderating variables associated with environmental (e.g. the degree of market dynamism and technological turbulence), managerial (e.g. the level of management's intuitive and creative abilities) or behavioural (e.g. the level of trust and/or conflict between employees) factors.

6. Conclusion

This study contributes to the emerging empirical literature on the importance of an effective BD utilisation within the context of strategic and innovation management. First, it shows how firms' efforts towards the implementation of flexible technological platforms and advanced software for BD analysis, the training of general and specialist staff, and the promotion of a corporate data-driven culture (BDAC) favour the implementation of effective BMI processes.

Second, it discovers the existence of a positive partial mediation role played by EO within the relationship between BDAC and BMI, thus suggesting that the availability of adequate BD resources and capabilities encourages the adoption of a strategic propensity towards decision-making characterised by high degrees of innovativeness, proactivity and risk-taking, which, in turn, facilitates the identification and implementation of the effective changes regarding the BM and its essential dimensions.

Acknowledgements

This article is based on a study funded by the Basic Research Program of the National Research University of Moscow and by the Russian Academic Excellence Project '5-100'.

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