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Business model innovation: harnessing big data analytics and digital transformation in hostile environments

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Abstract

Purpose – The literature mainly concentrates on the relationships between externally oriented digital transformation (ExtDT), big data analytics capability (BDAC) and business model innovation (BMI) from an intra-organizational perspective. However, it is acknowledged that the external environment shapes the firm's strategy and affects innovation outcomes. Embracing an external environment perspective, the authors aim to fill this gap. The authors develop and test a moderated mediation model linking ExtDT to BMI. Drawing on the dynamic capabilities view, the authors' model posits that the effect of ExtDT on BMI is mediated by BDAC, while environmental hostility (EH) moderates these relationships.

Design/methodology/approach – The authors adopt a quantitative approach based on bootstrapped partial least square-path modeling (PLS-PM) to analyze a sample of 200 Italian data-driven SMEs.

Findings – The results highlight that ExtDT and BDAC positively affect BMI. The findings also indicate that ExtDT is an antecedent of BMI that is less disruptive than BDAC. The authors also obtain that ExtDT solely does not lead to BDAC. Interestingly, the effect of BDAC on BMI increases when EH moderates the relationship.

Originality/value – Analyzing the relationships between ExtDT, BDAC and BMI from an external environment perspective is an underexplored area of research. The authors contribute to this topic by evaluating how EH interacts with ExtDT and BDAC toward BMI.

Keywords Digital transformation, Big data analytics, Dynamic capabilities, Business model innovation, Environmental hostility, SME

Paper type Research paper

1. Introduction

Digital transformation disrupted the previous competitive landscape (Verhoef *et al.*, 2021; Vial, 2019) and affected business processes, routines and capabilities (Matarazzo *et al.*, 2021). It also modified different industries by changing the nature of the competition (Barrett *et al.*, 2015; Dagnino *et al.*, 2021). We can disentangle digital transformation into its two main components, that is, internally and externally oriented (Li *et al.*, 2018; Matarazzo *et al.*, 2021). Companies that apply internal management information systems (e.g. customer relationship management) undertake an internally oriented digital transformation. Instead, externally oriented digital transformation (ExtDT) refers to the adoption of cross-boundary technologies (e.g. the Internet and social media) which enable the data-driven transformation of the value creation process and serve to find new ways to exchange value and interact with customers (Li *et al.*, 2018; Matarazzo *et al.*, 2021; Penco *et al.*, 2022). The intensive usage of smartphones, as a new permanent trend and the Covid-19 pandemic, which

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led customers to increase their trust in e-commerce, facilitated the proliferation and tracking of the data (Kim, 2020; Penco *et al.*, 2022), thus improving the potential of ExtDT. In this paper, we refer to ExtDT to indicate such digital transformation's components looking outside the organizational boundaries. They serve as enablers of value exchange, customer interaction, communication improvement, personalization and massive data collection (Matarazzo *et al.*, 2021). From an ExtDT perspective, websites and social media represent the most common tools to connect firms and customers. Firms deploy websites and social media as channels to advertise the brand and collect data about customer satisfaction, customer experience and customer engagement (Lee *et al.*, 2018). In addition, social media and websites enable millions of daily online transactions and communications that nurture the generation of big data (Dremel *et al.*, 2017; McAfee and Brynjolfsson, 2012). Overwhelmed by incessant customer data flows, firms must implement more advanced analytical systems to capitalize on this data (Barton and Court, 2012). In other words, firms need to re-organize their functions and internal processes to develop big data analytics capability (BDAC), thus becoming data-driven organizations (Anderson, 2015). Precisely, BDAC is defined as the firm's ability to generate strategic insights from data by orchestrating tangible, intangible and human resources synergistically (Mikalef *et al.*, 2019). Data-driven firms tend to be highly innovative (Duan *et al.*, 2020). The literature found that BDAC assists firms in developing superior innovation capabilities, innovating the value propositions through customer co-creation processes and adapting the business model's building blocks to emerging customer needs (Gebauer *et al.*, 2020; Mikalef *et al.*, 2019; Urbinati *et al.*, 2019). As demonstrated by a number of contributions, BDAC enables innovative forms of value creation, capture and delivery (Paiola *et al.*, 2021), thus playing a determinant role in influencing a business model's components. Since a firm's competitive advantage is rooted in its ability to implement a well-developed and differentiated business model (Teece, 2010), business model innovation (BMI) represents a critical source of value generation. It refers to multiple forms of innovation related to processes, products, or services (Foss and Saebi, 2017). Gaining a deeper understanding of the actual impact of ExtDT and BDAC on BMI can assist both academics and practitioners alike in identifying the critical factors that drive competitive advantage and enhance firm performance.

Therefore, an inextricable relationship appears to connect ExtDT, BDAC and BMI. We argue that ExtDT, promoted by the intensive use of social media and websites, facilitates BDAC development (Dremel *et al.*, 2017; Matarazzo *et al.*, 2021) while affecting customer demand-pull BMI. In this way, BDAC allows firms to leverage a greater volume of data collected through externally oriented digital technologies to strengthen BMI (Ciampi *et al.*, 2021).

Considering the entanglement between ExtDT, BDAC and BMI, another prominent issue emerges. Notwithstanding successful digital transformation should lead firms to pervasively redefine their business model's components (Volberda *et al.*, 2021), many firms limit their efforts at implementing ExtDT to maximize their capacity to gain data from external sources (e.g. e-commerce and social media). It is supposed this action is a sound investment to develop innovative business models able to increase future revenues. However, as the digital transformation pace is speeding up across many industries, it is questionable if a basic digital transformation, not supported by capabilities development, is still sufficient to achieve BMI (Li, 2020). Today's hostile competitive environments may require developing more advanced capabilities to innovate the business model and go beyond a basic digital transformation. In this regard, BDAC, a high-potential ability through which firms can leverage real-time data strategically, may represent a differentiating factor to achieve BMI more than ExtDT in the current competitive environments. Therefore, based on these assumptions, we aim to evaluate the effectiveness of BDAC as a mediator of the relationship between ExtDT and BMI and, by doing this, compare the direct effects generated respectively by ExtDT and BDAC on BMI.

At the same time, while the literature mainly analyzed the relationship between BDAC and BMI from an internal perspective (Ciampi *et al.*, 2021), it still lacks a clear understanding of the effects produced by the external environment. Our study aims to fill this gap by approaching the relationships between ExtDT, BDAC and BMI from an external perspective and investigating how environmental hostility (EH) changes the magnitude of the relationships between ExtDT-BMI, ExtDT-BDAC and BDAC-BMI. The concept of EH is defined as the degree to which threats from the external environment jeopardize a firm's survival (Breugst *et al.*, 2020; Miller and Friesen, 1982; Shirokova *et al.*, 2016). Previous literature shows that firms are more prone to transform their business models when they perceive a more hostile environment (Saebi *et al.*, 2017). EH triggers more intense reactions by firms since they must rapidly adopt countermeasures against rivals' moves to remain competitive (Porter, 2008). In this regard, we argue that ExtDT and BDAC facilitate the firms' reaction to the increasing level of EH by enabling real-time customer data analytics, reducing environmental complexity, facilitating decision-making, adopting ad hoc marketing strategies and satisfying emerging customer needs (Hitt *et al.*, 2020; Lee *et al.*, 2018; Matarazzo *et al.*, 2021). Therefore, the interaction between EH and BDAC generates a positive interplay in searching for BMI. Similarly, the perception of a higher EH may lead firms to implement more advanced digital technologies and develop new capabilities to escape an intense rivalry trap. As a result, EH may positively moderate the relationship between ExtDT and BDAC.

To conduct our investigation, we draw on the dynamic capabilities view (Teece, 2007; Teece *et al.*, 2016) combined with an external environment perspective. This perspective involves a twofold element: a digital one, associated with the externally oriented digital technology adoption to facilitate data tracking and a competitive one, associated with the hostility of the competition in the business environment. Hence, to fill the literature gap, we ask: *What are the effects of EH on the relationship between ExtDT and BMI?*

To answer this question, we developed a conceptual model linking ExtDT to BMI using the construct of BDAC as a mediating variable and EH as a moderator. We analyzed a cross-sectional sample of 200 Italian SMEs that declared to use analytics by performing partial least square-path modeling (PLS-PM). The results of our research are applicable in multiple literature streams, especially strategic management, innovation management and entrepreneurship. First, this paper contributes to the dynamic capabilities view. Since big data is a potential source of knowledge for innovative purposes (McAfee and Brynjolffsson, 2012; Grover *et al.*, 2018; Gupta and George, 2016; Mikalef *et al.*, 2020b), developing BDAC implies firms innovate their current modes of doing business. Specifically, this paper contributes to the debate about the relevance of building capabilities after ExtDT (Matarazzo *et al.*, 2021). This issue has received limited attention, despite covering a relevant area for the study of strategic change (Kristoffersen *et al.*, 2021). Second, this paper addresses the issue of hostile competitive environments characterized by intensified competition and complexity, short-term innovation cycles and high market volatility. In this regard, this paper aims to partially remedy the paucity of studies investigating possible antecedents and moderators of BMI (Foss and Saebi, 2017; Saebi *et al.*, 2017; Zhang *et al.*, 2021; Zott *et al.*, 2011). Third, this paper also contributes to the entrepreneurship literature by unveiling the crucial role of BDAC as a means to analyze and discover new business opportunities for BMI (Obschonka and Audretsch, 2020). Our study provides novel contributions to this field of inquiry by highlighting that BDAC, more than ExtDT, can equip firms with enhanced chances to achieve BMI. Entrepreneurial opportunities can arise from the analysis of big data through the discovery and generation of new business ideas, the anticipation of rivalry's competitive moves and the adoption of entrepreneurial strategies to launch and commercialize new products and services (Matarazzo *et al.*, 2021; Ndofor and Levitas, 2004). Such an effect is more pronounced as EH increases, demonstrating the uncertainty-reducing nature of BDAC (Van Rijmenam *et al.*, 2019).

The paper is structured as follows. Section 2 defines the theoretical background and reviews the literature. Section 3 develops the hypotheses. Section 4 describes the context of the analysis and the sample. Section 5 presents the methodology and the assessment. Section 6 presents the results. Section 7 discusses the findings and provides the theoretical and managerial implications. Section 8 concludes with the limitations and avenues for future research.

2. Literature review

2.1 Externally oriented digital transformation (ExtDT)

Digital transformation is a "change in how a firm employs digital technologies, to develop a new digital business model that helps create and appropriate more value for the firm" (Verhoef *et al.*, 2021, p. 889). Digital transformation involves two components, i.e. internal and external. We focus on the external component (ExtDT) to indicate the routines based on digital technologies that consistently modify the building blocks of the existing business models to create a unique newness. Therefore, ExtDT plays a crucial role in the logic of value creation and capturing through new business models. The research demonstrates that digital technologies have facilitated disruptive changes in many business models (Li, 2020). The transformations driven by the adoption of externally oriented digital technologies provoke drastic changes to business models, in terms of value creation and customer relationships (Penco *et al.*, 2022).

Firms can leverage ExtDT to improve communication with customers and better understand their needs. Subsequently, firms can customize the offering depending on the requirements suggested by the customer segments. The value co-creation process depends on this lean interaction between a firm and its clients.

2.2 Dynamic capabilities view: the relevance of the framework

Digital transformation requires both the adoption of technical resources and the development of dynamic capabilities (Matarazzo *et al.*, 2021). To provide a comprehensive understanding of this phenomenon, this study employs a construct related to technological resources, i.e. ExtDT, and dynamic-capabilities construct, i.e. BDAC. The dynamic capabilities view frames the conceptualization of this paper. Typically, the dynamic capabilities view refers to environments characterized by disruptive technological shifts. The firms integrate digital technologies to improve their internal activities and connections with customers (Karimi and Walter, 2015). Dynamic capabilities "extend, modify, change and/or create" (Drnevich and Kriauciunas, 2011, p. 255) new configurations of ordinary capabilities to address environmental changes (Matarazzo *et al.*, 2021; Rindova and Kotha, 2001).

The issue of building capabilities from the ExtDT process has often been overlooked, despite its absolute relevance to management (Matarazzo *et al.*, 2021; Warner and Wäger, 2019). Capabilities support firms in coping with unstable environments (Teece, 2007). As Teece and colleagues wrote in 1997, the term "dynamic capabilities" refers to "the capacity to renew competences so as to achieve congruence with the changing business environment" (Teece *et al.*, 1997, p. 515) by emphasizing "the key role of strategic management in appropriately adapting, integrating, and reconfiguring internal and external organizational skills, resources, and functional competences to match the requirements of a changing environment" (Teece *et al.*, 1997, p. 515).

Applying the notion of dynamic capabilities to the business model concept, dynamic capabilities can mix and orchestrate business model components or elements into new business models (Teece, 2018). In other words, dynamic capabilities shape the creation of new business models with an effect proportionate to their degree of development. Weaker dynamic capabilities are likely to incrementally adjust business models based on past investments and existing organizational processes. Incisive dynamic capabilities are more likely to generate radical shifts of resources or activities in a business model.

To explain the choice of hostility as an environmental condition, we apply the conceptualization by Chen (1996). A firm competing in a hostile industry does not have alternatives but to beat its competitors. In a hostile environment, a defensive strategy is a risky one. Contrarily, prospector strategies allow a firm to grasp opportunities (Calantone *et al.*, 1997). In other words, "Increased hostility forces executives to find innovative ways to reduce or manage the sources of hostility" (Zahra, 1993, p. 324). Therefore, in hostile environments, a firm must dynamically behave to find innovative business opportunities to prevent technological obsolescence or cope with radical changes in the industry (Zahra, 1993). For instance, a firm should engage in innovation activities to develop and offer novel or differentiated products/services. As a response to the need to find new solutions in hostile environments, firms are often motivated to adopt innovative strategies that involve making regular adjustments to their business models and exploring novel configurations in search of the most effective and innovative approaches. Therefore, based on the abovementioned arguments, we consider that EH consistently integrates into a framework whose BMI is the outcome.

2.3 Big data analytics capability (BDAC)

BDAC is the ability of a firm to exploit big data to reap strategic insights (Grover *et al.*, 2018). BDAC gains strategic relevance through new information exploitation, increasing the synergies between business areas and seizing new business opportunities (Akter *et al.*, 2016; Dremel *et al.*, 2017; Matalamäki and Joensuu-Salo, 2021; Sestino *et al.*, 2020). Therefore, a firm can pursue a better framing of the strategic options and anchor this process to the numbers' rationality through BDAC. BDAC also facilitates environmental scanning to identify new business opportunities (Duan *et al.*, 2020) and reduces complexity and uncertainty by extracting meaning from data to improve strategic decision-making (Chen *et al.*, 2015). In addition, BDAC allows firms to address market changes and customers' needs and optimize their internal operations (Dubey *et al.*, 2020; Kitchens *et al.*, 2018). BDAC enables the personalization of services and offers through advanced consumer analytics (Matarazzo *et al.*, 2021). Hence, big data systems may lead to increased customer-centricity and business model experimentation (Dezi *et al.*, 2018).

Gupta and George (2016) distinguish the three dimensions of the BDAC. The tangible resources dimension indicates the technological architecture that a firm adopts to integrate, store, process, analyze and visualize data, the amount of data at its disposal and basic resources (i.e. money, time) (Dubey *et al.*, 2020; Gupta and George, 2016). The intangible resources dimension refers to the culture of a data-driven organization. They enable organizational decision-making pervasively connected to the data. Intangible resources also refer to the intensity of organizational learning, indicating a process of exploration, sharing and knowledge application derived from data (Chen *et al.*, 2015). The human resources dimension embraces the employees' technical skills, managerial skills to understand information from data and coordinate workmates and relational competencies linking different hierarchical levels and professionals within an organization (Anderson, 2015).

In this paper, BDAC represents the capability of channeling the potential of ExtDT toward BMI. The development of specific dynamic capabilities helps avert the so-called capabilities gap (Karimi and Walter, 2015), which arises when, following a change process, the firm lacks the necessary capabilities to capitalize on the change.

2.4 Business model innovation (BMI)

A business model indicates a firm's "design or architecture of the value creation, delivery, and capture mechanisms" (Teece, 2010, p. 172). A business model describes how a firm delivers value to customers, persuades them to pay and converts payments into profit (Sjödin *et al.*, 2020). It represents the managerial beliefs about customer needs, how they want customers to be satisfied and how the firm can organize the best arrangement to meet those needs (Teece, 2010). A well-developed business model is essential for innovators to not fail in delivering or capturing value from their innovations (Chesbrough, 2007; Miller *et al.*, 2021). A business model differentiating from the competitors and hard to imitate is more likely to yield profits (Teece, 2010). A business model must continuously address the changes in the competitive environment. To marry the new conditions, a firm must innovate its business model (Johnson *et al.*, 2008; Teece *et al.*, 2016). The definition of BMI differs depending on the theoretical framework adopted. This paper adopts the BMI definition proposed by Foss and Saebi (2017), according to which BMI is "designed, novel, nontrivial changes to the key elements of a firm's business model and/or the architecture linking these elements" (Foss and Saebi, 2017, p. 201). Therefore, from the perspective adopted in this paper, the BMI is the outcome of transformative processes and an innovative result itself (Snihur and Wiklund, 2019).

2.5 Environmental hostility

Firms must sense the environment to timely seize the window of opportunity. Firms need capabilities that allow them to plumb the external environment. Specifically, this paper deals with EH (Kreiser *et al.*, 2020; Michaelis *et al.*, 2022). It refers to the action of external forces that threatens a firm (Breugst *et al.*, 2020). These forces can simultaneously involve aspects of the industry, competition, customers and market (Covin and Slevin, 1989; Green *et al.*, 2008). High firms' failure rates, incessant competitive intensity, low customer loyalty and reduced profit margins in the industry are examples of threats affecting competitive environments. The joint action of such exogenous factors undermines the executive's ability to control the firm fate (Michaelis *et al.*, 2022). Depending on multiple factors, high hostility is perceived differently from firm to firm. An organization may see lights, like opportunities, in the hostile dark, while others may see only shadows. The manner firms approach the market mainly depends on these perceptions (Hitt *et al.*, 2020).

3. Hypotheses development

3.1 Digital transformation influencing business model innovation

Firms use digital technologies to structure new business models to create value and capitalize on it (Verhoef *et al.*, 2021). The literature suggests that ExtDT contributes to BMI by changing the value propositions and networks, launching new digital channels and enabling agility and ambidexterity (Li *et al.*, 2018; Dezi *et al.*, 2018; Vial, 2019). Empirical evidence suggests that firms can innovate their business model by leveraging digital technologies to create and deliver value to new and specific customer segments (Matarazzo *et al.*, 2021). The more frequent use of mobile devices, social media and e-commerce has radically changed the interactions between firms and customers (Muninger *et al.*, 2019). Literature also shows that social media improves and changes customer value propositions and contributes to shaping innovative delivery mechanisms (Matarazzo *et al.*, 2021; Penco *et al.*, 2022).

Based on the abovementioned arguments, we hypothesize that:

H1. ExtDT significantly and positively affects BMI.

3.2 Digital transformation effects on big data analytics capability

In 2017, Dremel *et al.* found that the advancement of the ExtDT process is necessary to develop a proper BDAC. Analytics was implemented through a more advanced technology infrastructure to perform data analytics with innovative methods. Information technology and big data departments work side by side to meet the analytics needs. Externally oriented digital technologies allow a firm to generate and store more data. These devices connect people to businesses by aligning customer needs with business priorities (Jones *et al.*, 2015). ExtDT generates large and varied volumes of data on customers at a higher velocity (George *et al.*, 2014). If sustained by the appropriate technological architecture, BDAC represents the bundle of attitudes, skills and competencies to exploit the latent values of data. Digital technologies equip firms with advanced systems to monitor real-time data, recognize new trends and renew their strategy (Iansiti and Lakhani, 2014). BDAC provides the keys to opening them and supporting data acquisition, storage and analysis (Hanelt *et al.*, 2021). Matarazzo *et al.* (2021) show that new externally oriented digital technologies lead SMEs to change their interactions with customers promoting value co-creation. These changes imply that firms reconfigure existing routines and resource through dynamic capabilities development (Matarazzo *et al.*, 2021). Customer data acquisition from social media and websites encourages firms to develop BDAC.

Therefore, we posit that:

H2. ExtDT significantly and positively affects BDAC.

3.3 Big data analytics capability effects on business model innovation

BDAC allows firms to predict market requirements, adjust their strategies and architecture to meet emerging market needs and anticipate the competitors' moves. BDAC supports massive reconfigurations to continuously nurture innovative value propositions for customers (Kitchens *et al.*, 2018). BDAC can enable the adoption of a non-easily-copiable business model (Loebbecke and Picot, 2015). Ciampi *et al.* (2021) highlight that a manager may intuit a new business model but not be able to rationalize and consistently articulate it. Starting from these assumptions, Ciampi *et al.* (2021) demonstrated that BDAC positively influences BMI. BDAC allows firms to extract hidden insights about consumer behaviors, expectations and opinions on social media. BDAC helps firms to exploit customer data. Employees and managerial capabilities support the interpretation of the results from analytics. This process shapes customer value creation based on their different profiles. Firms cluster customers through BDAC to reveal different buyer segments. Therefore, firms can personalize the customer experience, launch tailored promotions and apply varying prices depending on the demand changes (Matarazzo *et al.*, 2021). Overall, BDAC supports BMI through massive and multiple reconfigurations. The mediation mechanism enabled by BDAC allows firms to identify customer behavior patterns from multiple data sources. This allows for the creation of information asymmetries over rivals, which the firms can exploit to their advantage to pursue ad hoc competitive strategies. Possessing valuable and exclusive knowledge enhances the firm's ability to implement tailored-made business models by leveraging that knowledge to better satisfy customer needs (Ndofor and Levitas, 2004).

As such, we can hypothesize that:

H3. Through its impact on BDAC, ExtDT will be positively related to BMI.

3.4 The moderating effect of environmental hostility

It has been demonstrated that environmental uncertainty, i.e. a set of external phenomena that involves EH, moderates the relationship between BMI and its antecedents (Foss and Saebi, 2017; Zhang *et al.*, 2021). Some authors argue that BMI is a reaction process to environmental changes (Zhang *et al.*, 2021). Firms leverage digital technologies to renew their business model components as a response to external changes. For instance, in unpredictable competitive environments, firms may use their digital capabilities to collect data and information identifying the current trends in market development and customer preferences according to which innovating their business models (Matarazzo *et al.*, 2021; Verhoef *et al.*, 2021). The literature shows that SMEs incorporate digital technologies into their business models in an innovative effort to face increasingly competitive environments (Paiola *et al.*, 2022). Leveraging externally oriented digital technologies (e.g. customer relationship management systems) enables particular combinations of business model design able to support the firm's competitiveness against the threats of fierce rivalry through enhanced management of customer relationships (Zhao *et al.*, 2020).

Therefore, when the competitive landscape becomes more hostile, firms appear to be more prone to leverage ExtDT to innovate their business models. Being ExtDT exposed to contingency effects and able to influence BMI, one may argue that when the degree of EH is higher, the relationship between ExtDT and BMI is strengthened.

H4a. The relationship between ExtDT and BMI is positively moderated by EH.

External triggers affect dynamic capabilities building (Teece, 2007; Teece *et al.*, 2016). External factors are associated with the disruptive digital competition enabled by the more intensive use of externally oriented digital technologies (Warner and Wäger, 2019). Specifically, more hostile competitive environments may trigger firms to implement more advanced digital technologies and develop specific capabilities. For instance, Volberda *et al.* (2021) highlight that firms tend to adopt a transformative approach to face fierce competition by upgrading their digital routines. In these terms, firms perceive environmental hostility as an external condition to be coped with regular digital advancements. For instance, by investigating the transformation journey of a high-tech small and medium-sized enterprise (SME), Ates and Acur (2022) found that firms should move through different digital transformation steps to escape the obsolescence trap. This manifests in incremental phases of digital technology implementation. They also found that developing dynamic capabilities is an effective approach to thrive in unpredictable competitive environments. Therefore, the perception of greater EH may lead firms to regularly implement advanced digital technologies and develop inimitable capabilities, avoiding their technological advantage being deteriorated by competitors.

Therefore, one may argue that the interaction between ExtDT and EH generates higher positive effects on BDAC.

H4b. The relationship between ExtDT and BDAC is positively moderated by EH.

Saebi *et al.* (2017) empirically demonstrate that firms are more likely to adapt their business model when they perceive more threats than opportunities in the external environment. We argue that, when high levels of EH interact with higher BDAC, the intensity with which a firm tends to innovate its business model increases. For instance, BDAC reduces the action time since it replaces harsh marketing research and enables more frequent and rapid adjustments of marketing strategies (Lee *et al.*, 2018). Therefore, the positive interplay between BDAC and EH can aid firms in timely discovering new trends and innovating their business model. BDAC contributes to unraveling a hostile and uncertain competitive environment (Hitt *et al.*, 2020) by providing rational information to make decision-making processes more effective in an unclear context. Under high environmental turbulence, the impact of BDAC on innovation capabilities amplifies (Mikalef *et al.*, 2019). When complexity and uncertainty underlying EH increase, BDAC contributes to averting information overload (Eppler and Mengis, 2004). Specifically, under these circumstances, BDAC supports managerial decisions (Mikalef *et al.*, 2019) when heuristics may decrease in effectiveness. BDAC unveils the complexity of fuzzy context by making sense of unstructured data, providing causal or correlational evidence and enabling the management of multiple collaborations in a flexible way (Grover *et al.*, 2018).

Therefore, we hypothesize that:

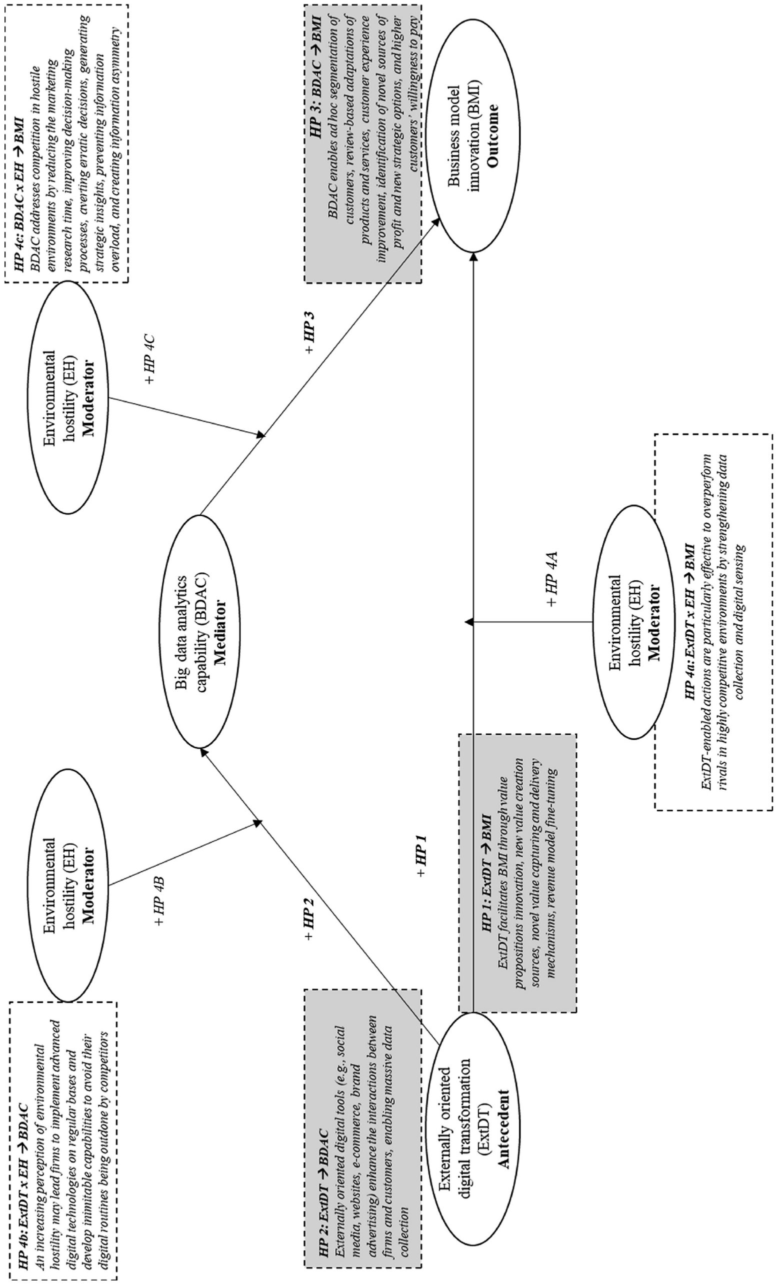
H4c. The relationship between BDAC and BMI is positively moderated by EH.

Figure 1 shows the conceptual framework hypothesized. It involves the causal relationship between the different concepts and clarifies through which actions the causal relationships are realized. Overall, the configuration of this model derives from the systematic conceptualization proposed by Schilke *et al.* (2018) that reveals an antecedent-consequence model pivoting around the dynamic capabilities. The model also involves a moderator, i.e. the environmental factor. Mikalef *et al.* (2019) demonstrate that BDAC triggers the sensing, seizing and transforming properties of the higher-order dynamic capabilities (Teece, 2007). In the specific, firms sense opportunities and threats using big data-generated insights combining multiple data sources (Kiron, 2017). Firms seize opportunities by exploiting the big data capacity to improve decision-making and resource orchestration (Mikalef *et al.*, 2019). In addition, data-driven firms learn from previous successes or failures concerning products, services, or marketing campaign launches to transform their current capabilities, processes and business models (Matalamäki and Joensuu-Salo, 2021; Mikalef *et al.*, 2019). Customer data analysis is essential to convert user review-based information into action. Figure 1 deductively shows how ExtDT affects BMI through the mediating role of BDAC. The environmental factor of hostility is supposed to positively interplay with ExtDT and BDAC toward BMI. Previous literature shows that BDAC can aid firms in responding to EH. As complexity increases due to radical industry changes, intense regulatory burdens and hard-to-beat competitors, data-driven firms stand out by obtaining a better knowledge of the strategic alternatives (Dutot *et al.*, 2014).

4. Data

4.1 The context of analysis

Italy is the birthplace of SMEs. SMEs cover 99.9% of the entire Italian entrepreneurial fabric (European Commission, 2019) and generate a value-added of 490.9 billion (66.9% of all enterprises). We analyze a sample of 200 Italian SMEs by adopting a cross-sectional design. Data collection occurred in October 2021. We considered a database containing 1,707 firms that would potentially meet the selection criteria (for example, SMEs using analytics as a unit of analysis and professionals of strategic management as a respondent). We sent an e-mail to potential candidates asking about their willingness to participate in a survey for research purposes. The survey was administered through Computer-Assisted Telephone Interviewing (CATI). Data were collected via Google Forms and exported to an Excel spreadsheet. An essential requirement of the research is that only firms using analytics were considered valid respondents because of their better knowledge of advantages, disadvantages and related difficulties in the analytics implementation, ExtDT and capabilities development. The questionnaire has a specific filter at the first stage: "Do you make use of big data analytics systems within your company?". If the response was negative, the profile could not participate in the survey. Finally, we received 200 useable and valid questionnaires corresponding to a response rate of 12%. Concerning the respondent profile, 70% are top managers, 20.9% are family members involved in business management and 9% are entrepreneurs. The respondents are professionals committed to the firm strategic management. These profiles better know the business model, activities and vision. Table 1 shows the characteristics of the firms and respondents interviewed.



Source(s): Our elaboration

Figure 1.
Conceptual framework

Variables	Number (N = 200)	Percentage (%)
Respondent's age		
35–49	87	43.5
50–64	106	53
≥65	7	3.5
Gender		
Female	40	20
Male	160	80
Position		
Top Manager	140	70
Entrepreneurs	16	8
Family member	42	21
Other	2	1
Industry		
Agriculture, livestock, fishing	5	2.5
Service to businesses (consulting, IT, etc.)	13	6.5
Service to people (hotels, restaurants, sports, entertainment)	10	5
Wholesale and retail trade	48	24
Finance, banking, insurance	3	1.5
Process industry	12	6
Manufacturing industry	98	49
Health services	4	2
Transportation and logistics	6	3
Utilities	1	0.5
Firm's size (employees)		
<49	116	58
50–99	53	26.5
100–249	27	13.5
250–499	4	2

Source(s): Authors' own elaboration

Table 1.
Characteristics of the sample

5. Methodology

We tested the hypotheses through the partial least square path modeling (PLS-PM) method (Sanchez *et al.*, 2017). The PLS method supports research based on not normally distributed variables and reinforces the predictive nature of the analysis (Galindo-Martín *et al.*, 2019). The PLS method is a usual method to analyze cause-effect relationships. Bootstrap validation based on 5,000 resamplings supports the PLS-PM application to test the significance of the relationships of the structural model. We used the R software package "plspm" (Sanchez *et al.*, 2017) to perform the analysis.

5.1 Measurement scales

We measured the constructs through 7-point Likert scales (1 = strongly disagree, 7 = strongly agree). All the scales had been tested and validated in the literature. We performed a principal component analysis (PCA) on each latent construct to verify the factor structure of the corresponding set of observed variables. Following this, we excluded the items having a weak correlation to the factor. The removal suggested by PCA implied a reduction of the scales' dimensionality in the case of ExtDT (Galindo-Martín *et al.*, 2019), BMI (Asemokha *et al.*, 2019), EH (Green *et al.*, 2008) and BDAC (Mikalef *et al.*, 2019). Table 2 describes the items selected after the factor analysis for each construct.

Constructs	Items	Sources
ExtDT	Use social networks (for example, Facebook, LinkedIn, Xing, Viadeo, Yammer, etc.) Having a web	Galindo-Martín *et al.* (2019)
BDAC	*Basic resources* Our "big data analytics" projects are adequately funded Our "big data analytics" projects are given enough time to achieve their objectives *Technology* We have explored or adopted parallel computing approaches (for example, Hadoop) to big data processing We have explored or adopted new forms of databases such as Not Only SQL (NoSQL) *Managerial skills* Our BDA managers are able to coordinate big data-related activities in ways that support other functional managers, suppliers, and customers Our BDA managers are able to understand and evaluate the output extracted from big data Our BDA managers are able to understand where to apply big data *Technical skills* Our 'big data analytics' staff has the right skills to accomplish their jobs successfully Our "big data analytics" staff has suitable education to fulfill their jobs *Data-driven culture* We base our decisions on data rather than on instinct We are willing to override our own intuition when data contradict our viewpoints *Organizational learning* We are able to assimilate relevant knowledge We are able to apply relevant knowledge	Mikalef *et al.* (2019)
BMI	When necessary, we are able to carry out massive internal reconfigurations to enhance our overall value proposition to our customers We regularly consider innovative opportunities for changing our existing pricing models	Asemokha *et al.* (2019)
Environmental hostility	The failure rate of firms in my industry is high Low profit margins are characteristic of my industry	Green *et al.* (2008)

Source(s): Authors' own elaboration

Table 2.
Measurement scales

5.2 Measurement model

We tested the validity of the formative constructs by calculating the Adequacy Coefficient (R^2) (Mackenzie *et al.*, 2011). All the constructs show an R^2 higher than the threshold of 0.5, in line with those the literature prescribes. The constructs do not suffer from multicollinearity since the Variance Inflation Factors (VIFs) are lower than 10. Finally, the weights between the items and the latent constructs are statistically significant (Petter *et al.*, 2007).

We calculated Cronbach's alpha to evaluate the scales' internal consistency of the reflective constructs. Three constructs reach the threshold of 0.7. The only exception is the technical skill construct, with a value equal to 0.628. For this reason, we performed the additional test of Dillon–Goldstein's rho (DG rho) to evaluate the internal consistency. All these values are higher than 0.843, exceeding the threshold of 0.7. This test supports the consistency of the inner constructs. In addition, all the outer loadings exceed the cross-loadings. Average variance extracted (AVE) demonstrates an overall good discriminant validity. The minimum AVE value obtained is 0.727 (minimum threshold of 0.5). We concluded that the measurement model validation ensures adequate standards for a model analyzing relationships between higher-order formative constructs. Table 3 shows the correlation matrix and assessment for the reflective constructs. We assessed the model by considering the goodness of fit (GOF). The GOF value of 0.69 is in line with the recommended threshold (Wetzels *et al.*, 2009).

6. Results

First, we preliminarily run structural equation models to test firm sectors and size as control variables on the endogenous variables (i.e. BDAC and BMI). To include the control variables, we followed the indications provided by Becker (2005), Becker *et al.* (2016) and Barrett *et al.* (2015). We obtain that the control variables do not have a significant effect on endogenous variables.

Second, we tested the hypotheses of the main research model. Table 4 summarizes the results, including the standardized path coefficients (β), their significance (t-values) and the explained variance of endogenous variables (R^2). We calculated these values through a bootstrapping validation based on 5,000 random resamples. BMI and BDAC, as endogenous variables, explain a portion of the variance equal to 40.2% and 19.0%. Hypothesis 1 confirms the significant and positive relationship between ExtDT and BMI ($\beta = 0.192$, t-value = 2.345). The significance of the relationship is also confirmed by bootstrapping (perc. 0.25 = 0.028; perc. 0.75 = 0.341). The results show that hypothesis 2 is not confirmed because ExtDT does not significantly affect BDAC ($\beta = -0.012$; t-value = −1.285). The results show that the intensity and significance of the relationship between BDAC and BMI ($\beta = 0.252$, t-value = 3.264) are higher than ExtDT-BMI. Contrary to our expectations, ExtDT does not appear to influence BDAC. This result could find *a-posteriori* justification in the absence of many decisive factors that the relationship between ExtDT and BDAC does not consider. Such factors would appear determinant in the construction of BDAC to the extent that their absence could inhibit the significance of the relationship between ExtDT and BDAC. These factors may include existing data infrastructure, lack of skilled personnel and ineffective data management practices. Although a company may have already implemented ExtDT, it is possible that additional digital technologies (e.g. cloud computing, machine learning) are necessary to support the development of BDAC. In addition, while ExtDT can enable organizations to collect and store large volumes of data, the ability to analyze data and extract insights from that data requires highly skilled personnel. The lack of these professionals may partially explain why ExtDT does not significantly impact a firm's BDAC. Finally, the implementation of the latest technologies should go hand-in-hand with the adoption of effective data management practices. Such practices lead firms to capitalize on data through the definition of a proper data governance framework, including the assignment of roles and responsibilities for data management and the mobilization of multiple data sources (i.e. data integration) to gain more accurate and exclusive strategic insights. Hypothesis 3 is confirmed. Bootstrapping positively validates the effect of BDAC on BMI (perc. 0.25 = 0.066; perc. 0.75 = 0.333). Therefore, the direct effect of BDAC on BMI is higher than that of ExtDT on BMI ($\beta_{\mathrm{BDAC}\rightarrow\mathrm{BMI}} - \beta_{\mathrm{EXTDT}\rightarrow\mathrm{BMI}} = 0.060$). The previous findings show that ExtDT is not a direct antecedent of BDAC. The interaction with EH does not change the result. The model does not show a significant effect of EH on the relationship between ExtDT and BMI ($\beta = -0.086$, t-value = −0.909). Therefore, hypothesis 4a is not confirmed. When EH increases, so does the complexity and uncertainty associated with the external environment. As a result, in the absence of BDAC, which may reduce the level of environmental complexity,

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
Firm industry (1)	1.00														
Firm size (2)	0.11	1.00													
ExtDT (3)	−0.04	0.15	1.00												
Resources (4)	−0.04	0.19	0.34	1.00											
Technology (5)	−0.07	0.11	0.23	0.55	1.00										
Managerial Skills (6)	−0.00	0.14	0.27	0.73	0.53	1.00									
Technical Skill (7)	0.01	0.21	0.24	0.59	0.30	0.66	1.00								
Culture (8)	0.10	0.18	0.19	0.53	0.37	0.57	0.54	1.00							
Learning (9)	0.05	0.18	0.18	0.37	0.14	0.52	0.51	0.41	1.00						
Tangible (10)	−0.06	0.18	0.33	0.91	0.84	0.73	0.53	0.53	0.31	1.00					
Human (11)	0.00	0.19	0.28	0.74	0.47	0.93	0.90	0.61	0.56	0.71	1.00				
Intangible (12)	0.10	0.21	0.22	0.55	0.32	0.65	0.63	0.87	0.81	0.51	0.70	1.00			
BDAC (13)	0.02	0.23	0.33	0.87	0.68	0.85	0.77	0.74	0.60	0.89	0.90	0.80	1.00		
BMI (14)	0.10	0.17	0.34	0.47	0.37	0.45	0.42	0.44	0.28	0.49	0.48	0.43	0.55	1.00	
Environmental hostility (15)	−0.13	−0.03	0.17	0.19	0.36	0.13	0.17	0.08	0.08	0.30	0.17	0.10	0.25	0.23	1.00
Cronbach's alpha						0.84	0.63	0.72	0.69						
AVE						0.76	0.73	0.78	0.76						
DG rho						0.90	0.84	0.88	0.87						

Source(s): Authors' own elaboration

Table 3.
Correlation matrix and assessment of reflective constructs

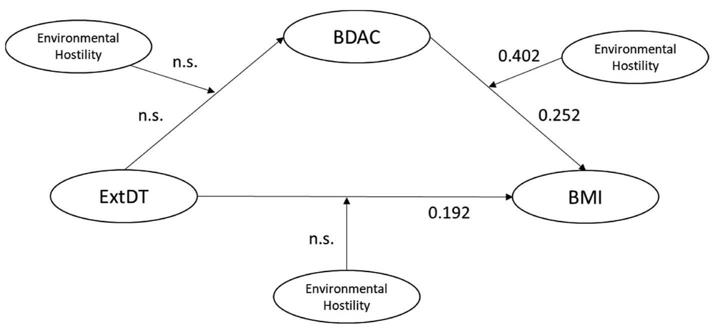
Table 4.
Summary of the results

Hypothesis	Hypothesis testing	Relationship	Estimate	*t*-value	Bootstrapping confidence interval
Hypothesis 1	Supported	ExtDT → BMI	0.192*	2.345	(0.028; 0.341)
Hypothesis 2	Not supported	ExtDT → BDAC	−0.012	−1.285	(−0.031; 0.044)
Hypothesis 3	Supported	BDAC → BMI	0.252***	3.264	(0.066; 0.333)
Hypothesis 4a	Not supported	ExtDT x EH → BMI	−0.086	−0.909	(−0.213; 0.030)
Hypothesis 4b	Not supported	ExtDT x EH → BDAC	0.025**	2.665	(−0.003; 0.087)
Hypothesis 4c	Supported	BDAC x EH → BMI	0.402****	4.543	(0.395; 0.634)

Note(s): ****p-value <0.001; *** p-value <0.005; ** p-value <0.01; * p-value <0.05; bootstrapping based on 5,000 samples
Source(s): Authors' own elaboration

a firm's ability to oversee evolving market and customers' preferences), as well as their ability to predict and react to rival initiatives and discover new business opportunities, may decrease. Finally, such premises may be the prelude to failure in the BMI process. Hypothesis 4b is partially not confirmed by bootstrapping. EH would not appear to moderate the relationship between ExtDT and BDAC (β = 0.025; t-value = 2.665). Despite the t-value (2.665) being close to an ideal threshold of significance, the bootstrapping validation definitively demonstrates it is not significant (perc. 0.25 = −0.003; perc. 0.75 = 0.087). The lack of significance in the relationship between ExtDT and BDAC under the moderation of EH might be due to negative side effects generated by highly competitive and uncertain environments, such as risk aversion, which may discourage firms from investing further resources in strengthening their BDAC while relying on existing routines. This may lead firms to prioritize short-term strategic paths over long-term and costly process of BDAC development. Such arguments may partially clarify why our empirical evidence does not support the influence of ExtDT on a firm's BDAC. Hypothesis 4c is confirmed since the positive effect of BDAC on BMI significantly increases when EH plays as a moderator (β = 0.402, t-value = 4.543). Bootstrapping confirms the validity of this finding (perc. 0.25 = 0.395; perc. 0.75 = 0.634).

Figure 2 represents the path coefficients for each relationship between the higher-order constructs.



Source(s): Our elaboration

Figure 2.
Path coefficients between higher-order constructs

7. Discussions and conclusions

This paper aims to answer the research question of whether ExtDT contributes to BMI. Considering BDAC as a mediator variable between ExtDT and BMI, we develop and test an empirical model. The analysis shows that ExtDT significantly and positively affects BMI. According to our hypotheses, the implementation of externally oriented digital technologies enables firms to access vast amounts of data from external sources, such as customers, suppliers and competitors. As a result, this culminates in a better understanding of customer needs and preferences, market trends and competitor strategies, which can inform the development of innovative business models. Taking it a step further, from our empirical analysis, it would appear that the effectiveness of digital technologies in achieving BMI is contingent on the business environment in which a firm competes. As the level of EH increases, the external environment becomes more complex and uncertain. In hostile environments, the risk to make erratic decisions significantly increases (Mitchell *et al.*, 2011), especially if firms do not have the capabilities to make sense of such uncertain and rapidly-changing environments and make more informed decisions (Mikalef *et al.,* 2019). In other words, without a well-established BDAC, which can help reduce the level of environmental complexity, a firm's ability to stay abreast of evolving market and customer preferences, predict and respond to rival initiatives and identify new business opportunities may decrease. Ultimately, these factors can increase the risk of failure in the BMI process.

It is noteworthy that the strength of the relationship is lower than those between BDAC and BMI. An explanation may be that many more firms decide to use digital technologies to adequate to the new trends. Today, innovating the business model only through the adoption of digital technologies is more difficult for a firm. For many industries, a specific level of ExtDT could be a minimum requirement to remain competitive. To increase the likelihood of BMI, firms must adopt more complex technologies and develop dynamic capabilities to shape their functions in a differentiated and original manner compared to their rivals. It would explain the higher effect of BDAC on BMI than ExtDT does. BDAC nourishes the competitive armory of a company by conferring tools, diversified and complementary competencies and adequate knowledge with a high degree of specialization to exploit customer data toward BMI. This specialization marks the difference in the resources and capabilities possessed by competitors, leading some firms to innovate more than others, overperforming their counterparts. This finding appears to support previous literature according to firms need non-imitable and non-replicable capabilities to define their activities (Schilke *et al.*, 2018; Teece, 2007). Digital transformation is a journey that implies regular development steps (Ates and Acur, 2022; Volberda *et al.*, 2021). Therefore, it is fundamental that firms upgrade their technological systems and capabilities over time to increase the likelihood of achieving BMI.

Contrary to our hypothesis, ExtDT does not significantly influence the BDAC. It means that ExtDT solely does not contribute to enhancing a firm's analytical capabilities. First, the development of BDAC may require additional investments in a different array of digital technologies to upgrade the existing data infrastructure according to analytics needs (Dremel *et al.*, 2017). Therefore, the development of BDAC is not a mere issue of technology (Gupta and George, 2016) but requires an all-around transformation to combine multiple capabilities and skills (Anderson, 2015). For instance, firms running toward a data-headed reconversion must cover functional needs by seeking and hiring highly skilled professionals (De Mauro *et al.*, 2018), such as data scientists able to extract, manipulate and manage big data. Moreover, data-driven firms are used to adopt ad hoc managerial data practices (Mikalef *et al.*, 2019). Such practices include establishing solid procedural and structural governance adjustments in order to marry the leadership style, effective talent management, appropriate technologies and innovative decision-making processes based on cross-functional cooperation and problem-solving approaches (McAfee and Brynjolfsson, 2012; Mikalef *et al.,* 2020a). In addition, firms must feed a new organizational culture by instilling a sense of job security in all employees (Sestino *et al.*, 2020) through an ethical approach (Vial, 2019). Even when considering the moderation of EH, the relationship between ExtDT and BDAC does not appear to be significant. This could be attributed to the side effects associated with hostile environments such as risk aversion which may discourage firms from investing further resources in strengthening their BDAC. Expanding on this line of reasoning, when firms perceive themselves as entities not able to navigate hostile environments due to limited technological infrastructure and the lack of capabilities, they may develop an aversion to investing additional resources to upgrade their assets. In such a situation, perceptions of hostile environments and growing uncertainty encourage managers to rely on existing routines (Chattopadhyay *et al.*, 2001; Shimizu, 2007). Said differently, the lack of enabling routines may reduce a firm's attitude to take action and implement more advanced technologies and capabilities (Chattopadhyay *et al.*, 2001). Under this condition, firms may prioritize strategic momentum (i.e. repeating previous strategic actions; see Amburgey and Miner, 1992) and short-term survival over the long-term process of capabilities development.

Our results indicate that BDAC leads to BMI. This result is consistent with prior literature showing that BDAC positively affects BMI (Ciampi *et al.*, 2021) and, from a general perspective, dynamic capabilities lead to BMI (Randhawa *et al.*, 2021; Teece, 2018). Dynamic capabilities favor BMI, especially in environments characterized by high hostility (Teece *et al.*, 2016). Practically, BDAC allows ad hoc segmentation of customers, stimulating firms to effectuate more precise adaptations of products and services, improving the customer experience and willingness to pay (Grover *et al.*, 2018). It leads to BMI, often performed through trial and error (Randhawa *et al.*, 2021).

When the hostility grows, the impact of BDAC on BMI increases. BDAC application could aid in hindering the rival ascendant or being a first mover in more hostile environments. This finding could claim the effectiveness of BDAC in addressing hostile environments to capture insights leading to innovative outcomes. Hostility denotes complex environments with intense competitive pressure and enhanced uncertainty. Under such challenging conditions, the ability to process information and make assessments of the decision-makers may fail (Chen *et al.*, 2015; Dubey *et al.*, 2020). Therefore, developing a BDAC becomes relevant to avoid erratic decisions when decision-makers face hostile environments (Mitchell *et al.*, 2011). In these terms, this research supports that BDAC is a capability linked to complex environments, where possessing dynamic capabilities is crucial to overperform rivals and innovate the business model.

7.1 Theoretical implications

This paper unfolds several theoretical implications. First, it mainly contributes to the strategic management and innovation literature by capturing the mediation effect of BDAC between ExtDT and BMI and the moderation of EH in these relationships. To the best of our knowledge, no previous study has applied a comprehensive model to interpret the relationships between these variables. This fills an academic gap because the literature contributions on BDAC and BMI from an external environment perspective are scant. In particular, we contribute to the dynamic capabilities view by demonstrating that BDAC effectively leads to BMI. We strengthen this perspective by highlighting the positive interplay between BDAC and EH toward BMI. In sum, the paper conceives the capabilities development as an effort harbingering more effective BMI. BDAC channels the potential of ExtDT toward BMI. BDAC supposes a specialization in digital sensing that is a valuable gift for firms that compete in hostile, changing and unpredictable environments. The findings show that managers are more prone to take risky actions when a firm perceives a threat than under favorable circumstances (Saebi *et al.*, 2017). These results are consistent with Saebi *et al.* (2017), confirming that entrepreneurs tend to take more risks under uncertain conditions.

The current paper shows that a higher degree of EH encourages BMI. In other words, the perceived threats stimulate firms to innovate if they possess the right capabilities to nurture this ambition. Alternatively, it could mean that BDAC allows firms to sense opportunities and capture them in hostile environments. Therefore, BDAC contributes to converting risks into opportunities by plumbing the environment.

Second, this paper provides some reflections on the role of EH, which remains a neglected area of research. In the wake of strategic management and innovation management literature, this work underlines the crucial role of the hostile environment in adopting a BMI. The empirical evidence according to which the interaction between BDAC and EH strengthens the path to BMI, while the interplay between ExtDT and EH fails, is symptomatic of how BDAC does represent a competitive boost in conditions of high EH. On the contrary, interrupting the digital transformation journey before developing advanced and inimitable capabilities may compromise the firm's ability to innovate the business model when the hostility of competitors increases, reducing competitiveness and profitability in the medium and long term.

Third, we aim to contribute to the development of entrepreneurship theory by investigating the understudied area at the intersection between big data and BMI (Obschonka and Audretsch, 2020). BDAC can assist a firm's aim to accomplish entrepreneurial activities such as identifying business opportunities and creating new products or services, giving rise to innovative business models (Matarazzo *et al.*, 2021). BDAC can be especially effective under conditions of EH by providing an analytical foundation to capture, in a timely manner, difficult-to-interpret changes in the competitive landscape. Our results are in line with influential literature supporting the view that big data analytics can assist firms in detecting, anticipating and responding to uncertainty, industry disruption and conditions of high EH that undermine firms' survival (Mikalef *et al.*, 2020a; Van Rijmenam *et al.*, 2019). To face this challenging trend, data-driven firms can leverage their BDAC to improve their ability to sense opportunities, decision-making processes and internal processes, identify changes in customers' behaviors and anticipate changes through assets' transformation (Mikalef *et al.*, 2019; Van Rijmenam *et al.*, 2019). In these terms, BDAC appears to play as a complexity reducer through which firms can achieve expected entrepreneurial outcomes.

7.2 Managerial implications

The results of the present study provide some interesting managerial implications. ExtDT appears as an upstream process to nurture by developing specific capabilities (Karimi and Walter, 2015). This link may be the key to capitalizing on the efforts and placing the planning nearer the medium-term objective. Practically, the literature suggests that experimentation, quick learning and adaptation are fundamental to facilitating BMI. Therefore, one may recommend carrying out a trial-and-error process during the ExtDT process (Muninger *et al.*, 2019). Reminding we are dealing with an iterative process, that sequence of attempts could occur in specific business units, isolated from each other to avoid cascade effects (Christensen *et al.*, 2016; Verhoef *et al.*, 2021).

However, the findings show that ExtDT alone does not enable BDAC development. A firm must align all the internal factors that play a role in developing capabilities (Vial, 2019). For example, BDAC is a multifaceted capability composed of tangible, human and intangible resources. A firm focusing all its efforts exclusively on the technological dimension is doomed to fail. Therefore, executives must exert their efforts to support a data-driven organizational culture, train their employees and adopt best data management practices based on the search for high-quality data (Fainshmidt and Frazier, 2017). Managers must also adjust the decision-making processes to put data at the center (McAfee and Brynjolfsson, 2012). Data-driven organizations require a collaborative approach and coordinated efforts to pursue a common objective. Indeed, the success of data-driven decision-making lies in the managers' ability to incentivize an open, bottom-up and inclusive internal debate. In addition, management must mix experience and insights from data to make decisions and avoid the former hindering the latter (Anderson, 2015).

Managers should consider innovating communication systems with customers. They should also use ExtDT and BDAC to improve post-purchase customer services and monitor client satisfaction (Kim, 2020) as a key to enhancing customer loyalty. However, strategists must consider that social media and website-intensive usage is not an antecedent of BDAC. BDAC depends on multi-level factors. Specifically, managers should put social media and websites at the center to interact with customers to create an emotional connection (Lee *et al.*, 2018). Studies demonstrate that clients emotionally connected to a brand generate much higher lifetime value (Kim, 2020). Strategists should realize that investing in BDAC is fundamental to maximizing the potential of ExtDT toward BMI. Specifically, BDAC is effective in hostile environments. Firms could perform activities through BDAC to differentiate from the competitors. For instance, they could predict customer behaviors based on sophisticated analytics. In addition, BDAC assists firms in the optimization of customer experience, pricing and revenues (Matarazzo *et al.*, 2021). Developing a more sophisticated BDAC (e.g. artificial intelligence (AI-powered big data analytics) allows firms to reduce flaws and biases during the decisional process. For instance, machine learning enables the technology to learn independently (Verma *et al.*, 2021). These technologies raise the competitiveness of firms in hostile environments, where timing is crucial to overperform rivals. Contrarily to the work-repeating technologies, powered BDAC improves decision-making by detecting user-generated content on social media and brand websites to understand preferences and emotions and discover customer polarity (Verma *et al.*, 2021). Future managers should merge their business knowledge with a psychological understanding of customer profiles. Sustained by technically skilled employees and disruptive technologies, strategists will be able to predict consumer behaviors.

7.3 Limitations and further research

Although this contribution provides several theoretical and practical implications, this research is also characterized by different limitations that future works should address.

First, ExtDT, BMI and EH scales used in this work, although explaining a sufficient percentage of variance and showing adequate robustness, have only two items that could partially capture the complexity of these phenomena. Future work could use multidimensional scales to reveal the many facets of these complex constructs. Second, the cross-sectional design of the study limits its generalizability. Researchers may test this framework over time by conducting longitudinal analyses. A longitudinal design is proper to evaluate the impact of technological renewal in competitive environments characterized by frequent systemic shifts (Hanelt *et al.*, 2021). Third, this study focuses on a single-respondent survey. It is acknowledged that such a survey design may generate bias to solve by differentiating the profile of the units of analysis. For instance, interviewing two or more respondents for each firm could equip the researcher with a broader perspective and cross-validation. Fourth, a future research avenue looks at the search for the multi-level antecedents and moderators that can lead to BDAC together with ExtDT. One may argue that the non-significant effect of ExtDT on BDAC is due to the lack of antecedents or moderators who, interacting with the ExtDT, can successfully drive BDAC development (Dremel *et al.*, 2017). For instance, organizational trust, commitment, transparency, coordination, agility and flexibility may positively affect BDAC (Clauss *et al.*, 2019; Fainshmidt and Frazier, 2017).

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