An ambidextrous approach on the BA-competitive advantage relationship: exploring the moderating role of BA strategy

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ABSTRACT

This study aims to develop a theoretical framework to understand how the Business Analytics (BA) strategy moderates the relationship between BA and competitive advantage through innovative ambidexterity. Theorizing from the Dynamic Capability (DC) perspective, we develop a model to investigate how different BA (descriptive, predictive, prescriptive) influence innovative ambidexterity (exploration and exploitation) and competitive advantage. Besides, we propose the construct of "BA strategy" (innovator, conservative, undefined) to differentiate between firms in the way they adopt, use, and implement BA. Based on the PLS analysis of the 181 firm-level survey data, we assess the proposed model. The results show that innovative ambidexterity fully mediates the BA – competitive advantage relationship. We also find that BA innovator and conservative strategy moderate the BA-exploration and BA-exploitation links while such moderation is not observed for BA undefined strategy. This study enriches BA literature in various ways. First, it extends our understanding of the link from different BA categories to innovative ambidexterity, explorative innovation, and exploitative innovation. Second, this study provides empirical support of how BA strategy moderates BA – innovative ambidexterity – competitive advantage relationship and shows that to what degree BA innovator strategy leads firms to greater competitive advantage than BA conservative strategy.

Keywords: Business Analytics (BA); Business Analytics (BA) Strategy; Dynamic Capability (DC) View; Exploitation; Exploration; Innovative Ambidexterity

1. INTRODUCTION

The increasing amount of data from different sources highlights the prominent role of Business Analytics (BA). The term BA refers to *"the techniques, technologies, systems, practices, methodologies, and applications that analyze critical business data to help an enterprise better understand its business and market and make a timely business decision"* (Chen, Chiang et al. 2012). BA as an enabler allows firms to be agile in sensing market movements, making better decisions, and acting appropriately (Teo, Nishant et al. 2016, Ashrafi, Zare Ravasan et al. 2019). BA Investment is listed on top of cost-effective business applications, and a successful BA implementation can help firms create business value and gain a competitive advantage (Aydiner, Tatoglu et al. 2019). That is why BA is a topic of growing interest in both industry and academia (Wang, Yeoh et al. 2019).

While some past research confirmed the decisive role of BA on value creation considering different perspectives (e.g., Fink, Yogev et al. 2017, Seddon, Constantinidis et al. 2017, Grover, Chiang et al. 2018), there is an unexplored aspect of how firms should employ BA to fully realize the promised business value (Akter, Bandara et al. 2019, Mikalef, Krogstie et al. 2019). Thus, further investigation is recommended to grasp the mechanisms in which BA can create business value (Abbasi, Sarker et al. 2016, Günther, Mehrizi et al. 2017, Ashrafi, Zare Ravasan et al. 2019). Several attempts have been made to explore how BA leads firms to competitive gains (e.g., Akter, Wamba et al. 2016, Ashrafi, Zare Ravasan et al. 2019, Božič and Dimovski 2019, Rialti, Zollo et al. 2019). Despite the significant roles of ambidexterity (Božič and Dimovski 2019) and BA strategy (Grover, Chiang et al. 2018), few attempts have been done to explore their contribution in BA area. The proposed approach in this research differs in the following ways.

- First, this paper proposes the term innovative ambidexterity as a mediating construct in the context of BA. According to O'Reilly and Tushman (2013), ambidexterity means: *"The ability of an organization to both explore and exploit—— to compete in mature technologies and markets where efficiency, control, and incremental improvement are prized and to also compete in new technologies and markets where flexibility, autonomy, and experimentation."* Innovative ambidexterity means the concurrent development of both radical and incremental innovations (Jansen, Van Den Bosch et al. 2006, Kortmann, Gelhard et al. 2014). Thus, we postulate a model in which BA enables innovative ambidexterity and competitive advantage. We, therefore, intend to examine how BA may influence competitive advantage through the exploration and exploitation of business opportunities.
- Second, while previous studies highly recommend scholars to examine the moderating role of BA strategy on the link between BA and firms' outcomes (Grover, Chiang et al. 2018), no specific study was conducted to explore how BA strategy might intervene mentioned relationship. Therefore, we adopted a BA strategy typology to examine the role of different BA strategies on the link between BA and competitive advantage.
- Third, while there is a lack of knowledge on the types of employed BA technologies at the firm level (Ghasemaghaei 2019), we suggest a specific measurement metric based on three categories of BA (descriptive, predictive, prescriptive) as offered by Hazen, Skipper, Boone, and Hill (2018) to fill this gap. This approach will help firms understand the primary role of BA categories on ambidexterity and competitive advantage (Rouhani, Ashrafi et al. 2016).

- Forth, anecdotal evidence state that “resources rarely act alone in creating or sustaining competitive advantage” (Wade and Hulland 2004). This shows that lower-order dynamic capabilities (in here, BA) need higher-order capabilities as complementary resources (in here, innovative ambidexterity) to make synergy in creating desired business value. This assertion entirely aligns with previous research that information technology (IT) capabilities as lower-order constructs influence higher-order dynamic capabilities such as ambidexterity (Lee, Sambamurthy et al. 2015). While some authors have used this theoretical perspective in the BA context (Wamba, Gunasekaran et al. 2017, Torres, Sidorova et al. 2018), no specific study has been conducted to explore BA – competitive advantage relationship considering innovative ambidexterity and BA strategy. Hence, this study is theoretically grounded on the DC view, a well-known theory in the Information System (IS) area, especially in dynamic business contexts (Pavlou and El Sawy 2011).

To sum up, the present study aims at responding to the following research questions:

(1) What is the impact of BA on firm competitive advantage?

(2) How innovative ambidexterity and BA strategy contribute to the BA-competitive advantage link?

This study develops a survey-based instrument to empirically measure, test, and validate the proposed conceptual model using PLS (Partial Least Squares) to address these questions.

The paper is structured as follows. First, we build a theoretical background based on the DC view. Then, we propose the relationships between BA and competitive advantage, considering the two central concepts of innovative ambidexterity and BA strategy. Afterward, we hypothesize all the associations and propose the model. We develop a questionnaire-based survey to test the related hypotheses, gather the required data from our sample, and analyze it. Then, we present the results, and discussion, including the implications for theory and practice, in detail.

2. THEORY AND HYPOTHESIS

Dynamic capability (DC) means "the firm's ability to integrate, build, and reconfigure internal and external competencies to address a rapidly changing environment" (Teece, Pisano et al. 1997). This theory explains why some organizations are more successful than others in achieving competitive advantage considering market turbulence. As Ambrosini and Bowman (2009) stated, the key behind developing this perspective is related to identifying sources of sustainable competitive advantage. Firms that have highlighted developing DC will have a greater chance of achieving competitive advantage (Helfat and Peteraf 2009, Fainshmidt, Pezeshkan et al. 2016). This approach is proposed as a promising theoretical foundation for understanding the real value of IT/IS (Pavlou and El Sawy 2011, Tai, Wang et al. 2019) and BA (Wamba, Gunasekaran et al. 2017, Torres, Sidorova et al. 2018, Ghasemaghaei and Calic 2019, Mikalef, Krogstie et al. 2019).

DC is considered a higher-order capability advanced by lower-order capabilities to create business value (Liu, Ke et al. 2013). Regard, the notion of ambidexterity is defined as a type of higher-order DC that enables firms to create competitive advantage (Lee, Sambamurthy et al. 2015, Benitez, Castillo et al. 2018). The foundation of ambidexterity is structured on prior research conducted by March (1991) and Levinthal and March (1993). They intended to characterize the need to explore and exploit in an organizational learning context. March (1991) defines exploration as the efforts to pursue new knowledge, whereas exploitation means using and refining existing knowledge. Accordingly, while exploration shifts firms from current status to developing new skills or assets, exploitation leverages existing knowledge (Lavie, Stettner et al. 2010). In regards, the refinement nature of exploitative orientation seems good for short-term successes. In contrast, discovering new ways of doing business make explorative orientation appropriate for long-term performance (Chen 2017).

Previous research thoroughly discussed the contradictory logic of exploration and exploitation and proposed innovative ambidexterity as a way for firms to make a balance between the two in order to be responsive to the ongoing environmental changes (Gibson and Birkinshaw 2004, Birkinshaw and Gupta 2013). Innovative ambidexterity enhances the variety of products by developing incremental and radical innovations (Jansen, Van Den Bosch et al. 2006). Among different ambidextrous capabilities, innovative ambidexterity is argued as an essential capability (Kortmann, Gelhard et al. 2014), which remains relatively unexplored in the context of BA (Božič and Dimovski 2019), so it needs further investigation. To address the research gap and follow the DC theory, we define innovative ambidexterity as a higher-order capability, which is affected by lower-order capability (i.e., BA), to investigate the mechanisms in which firms can achieve sustainable competitive advantage. Based on the DC view, BA that works as a data-driven tool to capture, gather, and analyze the required information for the decision-making process, cannot be a source of firm-level value. Meanwhile, BA can merely provide unique values to create competitive value indirectly, since any organization can easily acquire BA tools (Larson and Chang 2016). Put simply, the BA reinforces higher-order capabilities to create competitive value. Hence, the present study proposes that BA (including descriptive, predictive, and prescriptive analytics) are lower-order capabilities that can be contributed to developing the mediation of higher-order capabilities (i.e., Innovative ambidexterity) that, in turn, leads to competitive advantage (Božič and Dimovski 2019). Reviewing the literature shows that previous scholars (e.g., Benitez-Amado and Walczuch 2012, Liu, Ke et al. 2013, Lee, Sambamurthy et al. 2015) used a similar approach in their studies.

2.1. BA and competitive advantage

Firms seek innovative ways to adapt to exceptionally complex business environments and differentiate themselves from competitors through data analytics, which is a primary asset for many organizations (Duan, Cao et al. 2020). BA solutions as a data-driven discovery approach can help companies transform raw data into insightful information and ultimately create business value (Janssen, van der Voort et al. 2017). Researchers (e.g., Mithas, Ramasubbu et al. 2011, Mithas, Tafti et al. 2012, Saldanha, Mithas et al. 2017) discussed the real value of a data-driven organization and shown that higher information management capabilities enhance firm performance. Senior executives need BA to exploit required information from existing data and advance in computational power to get smart and get ahead of their competitors in ways they could never before (Rouhani, Ashrafi et al. 2018). Grover et al. (2018) thoroughly reviewed the literature to build a value creation framework to figure out the direct/indirect values of using BA and what factors mediate/moderate the relationship between BA and value targets.

Several attempts have been made to figure out the black box between BA and competitive value (Fink, Yogev et al. 2017, Ashrafi, Zare Ravasan et al. 2019, Aydiner, Tatoglu et al. 2019, Ghasemaghaei and Calic 2019); however, two improvements might deserve some words. First, as far as we know, there is no published study that employs innovative ambidexterity as a higher-order DC in terms of the BA context. Because of the turbulent nature of today's business environments, innovative ambidexterity could be an excellent solution to mediate the relationship between BA and competitive advantage. Second, although past research extensively concentrates on BA from an evidence-based and problem-solving approach (Seddon, Constantinidis et al. 2017), there are limited studies (e.g., Aydiner, Tatoglu et al. 2019) that highlight the role of BA categories (descriptive, predictive, prescriptive). Following this approach addresses concerns about the nature of BA technologies used in each firm (Ghasemaghaei 2019) and improves our understanding of the potential consequences of BA (Rouhani, Ashrafi et al. 2016, Seddon, Constantinidis et al. 2017). The three categories of BA are:

- *Descriptive analytics*: descriptive analytics mainly focuses on answering what happened in the past through a set of tools, including key performance indicators (KPIs), dashboards, and descriptive statistics (Appelbaum, Kogan et al. 2017). It is the most common and purest form of analytics that opens up new avenues for firms from exploratory insight (Phillips-Wren, Iyer et al. 2015, Kunc and O'brien 2019).
- *Predictive analytics*: this type of analytics refers to using knowledge extracted from descriptive analytics to realize what will happen in the future. It goes through techniques such as statistical analysis, forecasting models, Natural Language Processing (NLP), text mining, and neural networks (Grover, Chiang et al. 2018). It allows users to predict future possibilities and discover hidden relationships to make the most likely patterns (Phillips-Wren, Iyer et al. 2015).
- *Prescriptive analytics*: it follows to find out what is the optimal solution based on the knowledge given from the descriptive and predictive analytics (Holsapple, Lee-Post et al. 2014). This makes value through the recruiting optimization approach, recommending solutions, and evaluating their influence regarding business consideration (Sivarajah, Kamal et al. 2017, Kunc and O'brien 2019).

2.2. Innovative ambidexterity

Ambidexterity is defined as an organizational theme in which successful firms effectively manage business issues and adapt to business environment changes. Organizational learning scientists (March 1991, Levinthal and March 1993) proposed exploration and exploitation as two substantially distinct means that firms can leverage their resources. Exploration refers to using resources in new ways to create new occasions, whereas exploitation concentrates on the efficient refinement of existing resources. There is an apparent tension between exploration and exploitation (Gibson and Birkinshaw 2004). Because of competition on scarce resources, previous studies widely highlight the importance of creating trade-offs between exploration and exploitation, which lead us to the undeniable role of ambidexterity (He and Wong 2004, Jansen, Van Den Bosch et al. 2006). This concept is a critical capability for firms responding to today's business changes (Cao, Gedajlovic et al. 2009, Birkinshaw and Gupta 2013, Lee, Sambamurthy et al. 2015).

Explorative activities emphasize new ideas for long-run success, so they are more susceptible to failure, as they try to explore more in an eternal cycle, which means a failure trap. In contrast, exploitative activities focus on short-run success, which means finding suitable ways to lead firms to early success, thereby creating a success trap (Gupta, Smith et al. 2006). This argument clearly articulates the foundation of March's (1991) logic that exploration and exploitation activities compete for capturing scarce organizational resources. In the simplest sense, he believed that exploration and exploitation conflict the two ends of a continuum. When an organization focuses more on new ideas, fewer rooms are available for exploitative activities (Cao, Gedajlovic et al. 2009).

In contrast to this approach, some researchers (i.e., Gupta, Smith et al. 2006, Jansen, Van Den Bosch et al. 2006) have considered a completely different view by mentioning that exploration and exploitation are independent activities and can be simultaneously achievable in a word orthogonal. Considering the twin concepts of exploitation and exploration demonstrates that ambidexterity intends to display a firm's ability to gain competitive advantages by simultaneously paying attention to short-term and long-term success in a dynamic environment (Gupta, Smith et al. 2006, O’Reilly and Tushman 2008).

Beyond these inconsistencies, some studies (He and Wong 2004, Cao, Gedajlovic et al. 2009) conceptualize balanced dimension (BD) and combined dimension (CD) of ambidexterity, which differs based on mechanisms and processes to create value. While BD believes in the trade-off between exploitative and explorative activities to prevent hazards in terms of competition, the main logic behind CD is that exploitative and explorative activities are not necessarily in competition to achieve the same resources, but they are investing in a complimentary domain (Gupta, Smith et al. 2006, Cao, Gedajlovic et al. 2009). To be sure that which approach would be helpful and play higher impacts on the BA field, we consider the ambidexterity issue in three different ways: (1) emphasizing exploration and exploitation as two distinct constructs, (2) highlighting the mediating role of BD of ambidexterity, and (3) highlighting the mediating role of CD of ambidexterity.

Even though ambidexterity is researched in different domains (Gibson and Birkinshaw 2004, He and Wong 2004, Im and Rai 2013, Lee, Sambamurthy et al. 2015, e.g., Benitez, Castillo et al. 2018), fewer attempts have been made to explore ambidexterity in the innovation context (Božič and Dimovski 2019, Rialti, Zollo et al. 2019). To delve more deeply into the research gap, we devise innovative ambidexterity as a dynamic organizational capability intended to increase competitive position. It is characterized as the firm's “learning-to-learn” ability that not only would be of great help to sense and seize new chances but reduce probable influences of path-dependence (O'Reilly and Tushman 2013). So, we believe that using BA helps firms improve their capability to use resources by applying new ideas or enabling firms to reuse the existing resources. In other words, BA enables firms and senior executives to realize what is going on in the business environment and helps them to increase their innovation competency in response to market changes (Ashrafi, Zare Ravasan et al. 2019). In addition, by employing a DC view, we define ambidexterity as a higher-order construct that focuses concurrently on exploration and exploitation within the business using different types of BA.

2.3. BA strategy

To cope fast-paced environment, firms have realized the significant role of information in their success. BA is introduced to transform raw data into meaningful information by applying highly sophisticated analytical tools and techniques to support organizational decision-making (Torres, Sidorova et al. 2018). Understanding from the literature, BA is emphasized as a generic viewpoint for managing, processing, and analyzing available data to create real-life patterns or ideas to achieve a competitive advantage (Ransbotham and Kiron 2017, Wamba, Gunasekaran et al. 2017). It is regarded as an enterprise-wide system that provides primarily long-term, strategic, and indirect benefits for firms (Fink, Yogev et al. 2017). That is why previous research (e.g., Wamba, Gunasekaran et al. 2017) stated that BA enables firms to analyze and manage their strategy through a data lens. Accordingly, it seems that BA is founded as a central point of focus among firms. Therefore, we should shed light on the fundamental IS strategy of firms in adopting and using BA.

Viewed from IS literature, IS strategy's critical impact is widely discussed from different points of view. For instance, Henderson and Venkatraman (1999) viewed IT from a strategic viewpoint and conceptualized a model considering the fundamental domains of IT and strategy. They declared that a lack of alignment between IT and business strategies might bring the inability to realize IT value. IS/IT strategic alignment is considered a critical concern of business and IT executives and is viewed as a fit between IS and business strategy (Preston and Karahanna 2009, Tallon and Pinsonneault 2011). The strategic alignment literature is of great importance, so Tanriverdi et al. (2010) mentioned it as a dominant quest of IS strategy research. Similarly, Akter et al. (2016) developed a research model to investigate how firms can gain performance by using BA regarding the moderating role of business strategy alignment. The outcome of their research revealed that alignment is a distinctive capability that allows firms to link overall capability with firm performance.

While previous research argued on strategic alignment (Tanriverdi, Rai et al. 2010, Akter, Wamba et al. 2016), the real value and content of BA strategy remains unclear and needs further investigation (Dallemule and Davenport 2017, Grover, Chiang et al. 2018). Thus, the present research explores the BA strategy's moderating role in the relationship between BA –Innovative ambidexterity. Previous studies tried to define what the real meaning of BA strategy is and introduced different types of strategy in the BA area. For instance, Dallemule and Davenport (2017) proposed two different strategies, including defensive vs. offensive, as two ends of a continuum to differentiate between firms to apply data into their business processes. For our purpose, we used a typology of three IS strategies (innovator, conservative, undefined), which is firstly developed by Chen, Mocker, Preston, Teubner (Chen, Mocker et al. 2010), as it brings the common view of the IS role in the firm and also differs from the business strategy. According to Chen et al. (Chen, Mocker et al. 2010), BA strategy means "the organizational perspective on the investment in, deployment, use, and management of BA" In regards, the firm's BA strategy can be classified into three categories, as follows:

- *BA Innovator*: it is defined as "an organizational perspective to continuously seek to be innovative through new IS initiatives, i.e., this strategy seeks to *explore* new, uncertain alternative" (Chen, Mocker et al. 2010). Like the prospector strategy in Miles and Snow typology, this strategy intends to discover new market opportunities through continuous scanning of the business environment. The innovator strategy's main goal is to enable and drive business strategy (Leidner, Lo et al. 2011).

- *BA Conservative*: it represents "an organizational perspective to create value through effectively refining and improving existing IS practice" (Chen, Mocker et al. 2010). In contrast with the innovator strategy, this strategy follows a more stable viewpoint by operationalizing BA innovations when others successfully applied them in the industry (Leidner, Lo et al. 2011).
- *BA Undefined*: As Chen et al. (Chen, Mocker et al. 2010) argued, it refers to the situation in which there is no articulated approach towards either explorative or exploitative IS use. In essence, BA undefined does not have clear long-term goals concerning the BA investment, deployment, use, and management.

2.4. Hypotheses development

Regarding the theoretical framework of higher-order capabilities presented by Grant (1996), previous IS research widely tried to switch the approach from the direct influence of IS resources on performance to how and under what mechanism IS resources impact higher-order capabilities, which results in performance (Mithas, Ramasubbu et al. 2011, Mithas, Tafti et al. 2012). This issue is of high value because a recent research report from MIT Sloan review showed a downward pattern about the degree that managers believe using BA can bring them a competitive advantage (Ransbotham, Kiron et al. 2016). Thus, several attempts have been made to develop BA firm-level models to pursue competitive advantage that help managers find ways to achieve desired benefits (Seddon, Constantinidis et al. 2017, Wamba, Gunasekaran et al. 2017, Torres, Sidorova et al. 2018, Ashrafi, Zare Ravasan et al. 2019). Despite the extensive research in this research line, there are still rooms for future research (Günther, Mehrizi et al. 2017, Akter, Bandara et al. 2019). So, through the adoption of previous research and industry practices in the BA and DC view, we proposed a conceptual framework that consists of BA, innovative ambidexterity, BA strategy, and competitive advantage, as illustrated in Fig. 1.

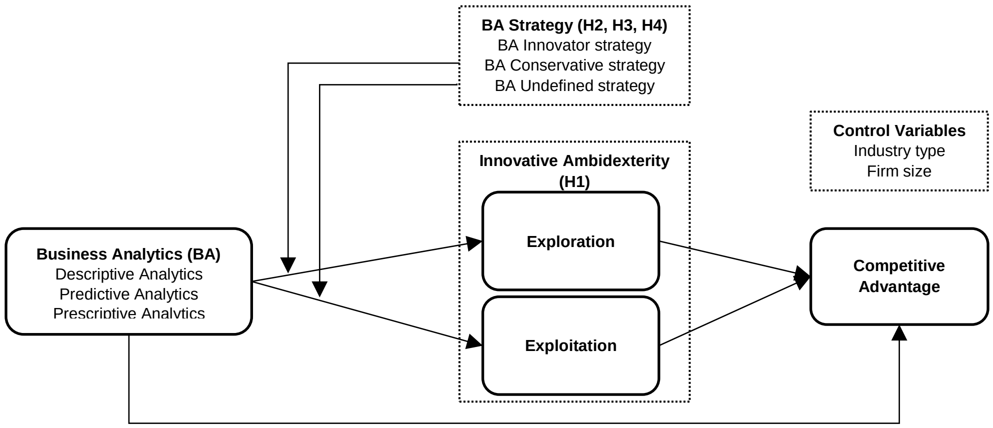


Fig. 1. Nomological model

Undoubtedly, IT capabilities do not increase firm performance per se. Nevertheless, they can enable higher-order capabilities or interact with business resources to create a competitive value (Benitez-Amado and Walczuch 2012, Chae, Yang et al. 2014). Building relentless innovation in products, services, or channels, are vital for higher-performing firms. Thus, firms integrate IT with the key processes to nurturing innovation in domains such as customer relationships, manufacturing, procurement, and supply chains (Sambamurthy, Bharadwaj et al. 2003). Similarly, Holsapple et al. (2014) and Mithas (2013) proposed innovation as one of the main primary pathways for firms to achieve competitive advantage through using analytics-based capabilities. The real key to success or mere survival in the complex global marketplace is to become more innovative in response to its customers' evolving needs (Teo, Nishant et al. 2016, Akter, Bandara et al. 2019, Aydiner, Tatoglu et al. 2019). For instance, Wang et al. (2018) argue that using BA in business processes results in detailed reports on different subjects, such as market trends. Such knowledge allows firms to make timely decisions for product development and utterly more effectively commercialize innovative ideas into new products. As such, Google is capable of determining whether an ad displayed on a user's smartphone during a search resulted in a store visit (Côrte-Real, Ruivo et al. 2019). Thus:

Hypothesis (H1). *BA enhances competitive advantage by facilitating greater innovative ambidexterity*.

Having a clear understanding of customer behavior advances current marketing practices, resulting in innovation. Therefore, to be more innovative, organizations leverage BA insights to find hidden patterns in data and understand potential growth opportunities (Roberts and Grover 2012). Using BA allows firms to capture related data from market demands, leading them to extract new ideas for building entirely new products/services or refining the existing ones (Tan, Zhan et al. 2015). In other words, discovering complex data relationships within the market enables firms to sense capability better. So, senior executives must understand what is happening in the marketplace from the consumers’ demands or competitors’ movement perspective and decide to refine the current processes or make radical innovations (Atuahene-Gima 2005).

From the BA perspective, using data-driven insights might be beneficial by providing credible information for senior executives. Descriptive analytics uses historical data and applies simple statistics to answer what happened in the past. The results enable firms to equip themselves by considering an appropriate strategy, such as establishing a new product or refining the existing product based on the achieved insights. Predictive and prescriptive analytics use more sophisticated analytic techniques on real-time data to predict future trends and prescribe the most appropriate solution to gain higher business value. For example, analyzing real-time and near real-time data allows firms to anticipate consumers' buying patterns, use customized recommendation techniques to show similar products (such as Amazon or NETFLIX), and finally improve sales positions. In detail, Google tracks tailor-made advertisements or Walmart's BA algorithm to analyze credit card purchases to provide specific recommendations to its customers based on their purchase history. Therefore, the firm's dual capacity for innovative exploration and exploitation is critical to managing consumers' demands by designing innovative processes or improving the current processes simultaneously. Based on the above argument, we propose:

Hypothesis (H1a, H1b). *BA enhances competitive advantage by facilitating greater Exploration (H1a) and Exploitation (H1b).*

Past studies promised that BA provides different competitive values such as firm performance (Ashrafi, Zare Ravasan et al. 2019), agility (Park, El Sawy et al. 2017), innovation (Saldanha, Mithas et al. 2017, Mikalef, Boura et al. 2019), business process performance (Aydiner, Tatoglu et al. 2019), operational performance (Chae, Yang et al. 2014), among others. As discussed, one of the main pathways of these benefits is through strengthening a firm's ability to innovate and differentiating itself from the rivals (Kiron, Prentice et al. 2014). Although it is widely discussed that BA generates valuable insights for decision-makers to take a competitive advantage, there is a dearth of academic and practice knowledge about the distinct types of BA strategy on the firm level. Recently, some scholars focused on the research question of how BA strategy might influence the relationship between BA and competitive advantage (Akter, Wamba et al. 2016, Grover, Chiang et al. 2018). For instance, Akter et al. (2016) articulated how BA strategy moderates the link between BA and firm performance. The approach used in this study to measure BA strategy was based on approved IS literature about strategic alignment and intended to show that the presence of strategic alignment between BA and business strategy is of great importance.

Contrary to this picture, no specific studies have highlighted the role of BA strategy from an IS perspective and how firms think, adopt, implement, and use BA across departments and business processes. This gap is highlighted by Grover et al. (2018) and is suggested as an important contextual factor that needs further investigation. In general, having a defined BA strategy is critical for firms to the extent that without this, any achievements are likely to be attributed to the circumstances than a planned objective (Galliers and Leidner 2014).

Generally, it is believed that it may be difficult for firms to concurrently focus on creating new knowledge and reusing the existing ones (Wu, Hitt et al. 2019). Hence, there is a need for an appropriate strategy to support this ambidexterity. In our case, it is reasonable to state that a firm with a BA innovator strategy not only supports creativity and facilitates innovations but also supports innovative activities to gain a competitive advantage (Chen, Mocker et al. 2010). This type of strategy fosters innovative activities by spending a massive amount of money and continuous supports to achieve superior results (Leidner, Lo et al. 2011). As Piccoli and Ives (2005) mentioned, scholars should view the IS strategy as a perspective for strategic IS use. Thus, we argue that IS innovators is not necessarily the leader in introducing and applying innovations. However, those who have a consistent strategic perspective to seamlessly find innovative ways with IS can be leaders (Chen, Mocker et al. 2010).

Hypothesis (H2). *BA innovator strategy leads to a greater competitive advantage because it strengthens the link from BA to innovative ambidexterity.*

Hypothesis (H2a, H2b). *BA innovator strategy leads to a greater competitive advantage because it strengthens the link from BA to exploration (H2a) and exploitation (H2b)*

While the BA conservative strategy's nature, similar to the BA innovator strategy, focuses on sensing business changes; however, a defensive approach uses BA in less innovative activities and mostly tends to use existing knowledge and provide some improvements continuously. BA conservative strategy focuses on small and continuous innovative steps to improve business processes by using the existing knowledge and finding innovative ways to make efficient outputs.

Hypothesis (H3). *BA conservative strategy leads to a greater competitive advantage because it strengthens the link from BA to innovative ambidexterity*.

Hypothesis (H3a, H3b). *BA conservative strategy leads to a greater competitive advantage because it strengthens the link from BA to exploration (H3a) and exploitation (H3b)*

To conclude, the degree to which a firm may advantage from BA - innovative ambidexterity - competitive advantage relationship will depend on the founded way and specific strategy to which a firm uses BA in its business processes. We believe that whereas the BA innovator strategy seeks to be innovative through new BA initiatives continuously, BA conservative strategy intends to generate value by improving existing BA practices. Similar to Chen et al. (2010), we believe that undefined strategy has no clear effect and role on the link between using BA and ambidexterity. Thus, we posit:

Hypothesis (H4). *BA undefined strategy does not influence competitive advantage because it has no impact on the link from BA to innovative ambidexterity*

Hypothesis (H4a, H4b). *BA undefined strategy does not influence competitive advantage because it has no impact on the link from BA to exploration (H4a) and exploitation (H4b)*

3. METHOD

3.1. Survey procedure

The research model was validated using a firm-level survey of key informants, a method successfully used in research on the BA domain (e.g., Ashrafi, Zare Ravasan et al. 2019). Our survey instrument requires knowledgeable BA professionals with adequate business tenure. Hence, we targeted Chief Information Officers (CIOs) of European firms as their opinions should reflect the BA strategy and business issues (Božič and Dimovski 2019, Tai, Wang et al. 2019, Wang, Yeoh et al. 2019).

A market research firm administered the online survey to CIOs whose roles within firms were verified. To ensure data validity, only CIOs of firms that reported on using BA tools were allowed to take the survey. Besides, at the beginning of the questionnaire, we asked participants how they were familiar with the BA use within their firms. If their answer was 'no opinion' or 'are uncertain,' they were excluded from the dataset. We provided definitions of all questionnaire items with specific examples for categories of BA (descriptive, predictive, and prescriptive) to make the questionnaire more explicit.

Out of 480 questionnaires distributed to sample firms from May to July 2020, 181 valid and 12 invalid questionnaires were returned. The response rate equals 37.7%. Having the 181 usable questionnaires satisfies the sample size requirement as the minimum sample size needed to detect a medium effect size at alpha of .05, and a power of .80 is 91 cases (Roldán and Sánchez-Franco 2012). The respondents' profile is shown in Table 1. As the table depicts, there is an adequate diversity in the industry type, firm age, and firm size over the participated firms.

We assessed the non-response bias by looking for differences between early responders and late responders. We correlated the order of survey responses to firm size and firm age. The yielded correlations were non-significant for both, suggesting that non-response bias is not a matter in our dataset. Further assessment of the Common Method Variance (CMV) bias threat is presented in section 3.2.

Table 1. The profile of respondent firms (number = 181)

Category	(%)	Category	(%)
Industry type		**Firm size (number of employees)**	
Manufacturing	19.3%	Small (50<)	17.7%
IT	16.6%	Medium (51–250)	37.0%
Electrical and Electronics	13.3%	Large (251 >)	44.8%
Chemical and Pharmaceuticals	11.0%	**Firm age (in years)**	
Finance, Banking, and Insurance	9.9%	10<	26.0%
Oil and Gas	8.8%	11-20	34.8%
Dairy and Foods	7.7%	>21	39.2%
Healthcare	4.4%		
Others	8.8%		

3.2. Measurement development

The survey instrument included items for measuring the model's constructs and firms' demographic information. We adapted previously validated measurement items in the main part of the questionnaire. To measure BA use, we adopted IS use measures of Hartwick and Barki (1994). We asked the respondents how often and to what extent their organizations use different BA types (i.e., descriptive, predictive, and prescriptive) in their business processes. Following prior research (e.g., Jeyaraj 2020), we focused on frequency and extent of use to capture BA use intensity for competitive gains.

To estimate innovative ambidexterity as a composed measure of exploration and exploitation, we followed the approach proposed by Cao et al. (2009). Accordingly, we adopt the Balance

Dimension (BD) and Combined Dimension (CD) of Ambidexterity. BD relates to a balance in the magnitudes of exploration and exploitation in a firm. We follow Cao et al. (2009) approach to operationalizing BD. First, we obtained the means for exploration and exploitation for every single sample and then the absolute difference between the two mean values. The achieved values range from zero to 3.64. To facilitate interpretation, this measure was reversed by subtracting the difference score from 5. Therefore, a greater value indicates a higher BD.

On the other hand, the CD is estimated using a combined magnitude of exploration and exploitation in a firm. Followed by Cao et al. (2009), we multiply exploration and exploitation to operationalize CD. Mean-centered values of exploration and exploitation were used to estimate the product that mitigates the threat of multi-collinearity.

We measured the BA strategy based on IS literature and used nine items presented by Chen et al. (2010). According to the literature Leidner et al. (2011), we categorized BA strategy into the innovator, conservative, and undefined strategy and presented three items for each. Finally, we used previously developed perceptual measures of competitive advantage, which considered both absolute and relative assessments of a number of financial performance dimensions regarding competitors over three years (Bhatt, Emdad et al. 2010). This approach is previously applied in prior research (e.g., Bhatt and Grover 2005). A seven-point Likert scale was used to measure all items.

We have also captured the firm size and industry sector as control variables (CVs) (e.g., Seddon, Constantinidis et al. 2017, Mikalef, Boura et al. 2019). We utilized dummy variables of the firm size (small as 1, medium as 2, and large as 3). We also controlled industry type since the industry-specific context may influence the proposed relationships. Industry type was also coded as a dummy variable (e.g., 1: Manufacturing, 2: IT). Furthermore, firm age, measured by years in operation, has been employed as the research marker variable. The main questionnaire items are included in Appendix A. Furthermore, reliability and validity of the questionnaire were carried out using two approaches. Feedback was gathered after each approach and the questionnaire was refined in response to the feedback. Firstly, the questionnaire was sent to the ten subject-matter experts in order to gauge their reaction on the wording and content of the items. The questionnaire was then pilot tested in ten firms to assess construct validity.

Finally, we assessed the Common Method Variance (CMV) bias threat as the self-reported survey approach adopted in this research can be threatened by this bias. There are some remedies to overcome this challenge as follows. First, to deal with procedural remedies, as suggested in Podsakoff et al. (2012), besides above mentioned reliability and validity checks, we followed further crosschecks to ensure the questionnaire's reliability. It is performed by, for instance, employing clear language, avoiding complex syntax, defining vague or unclear terms, and labeling all scale points. Respondents were ensured of their responses and identities' anonymity, which could diminish the likelihood of editing their responses. Second, the recommendation of Simmering et al. (2015) to deal with the CMV is followed here by including a marker variable. We employed the correlational technique of Lindell and Whitney’s (2001), which indicates the degree to which CMV bias the PLS results. Accordingly, “firm age” (coded as “company newness” in Simmering et al. (2015, p.482) as an ideal marker variable) was used for which we do not expect a significant relationship with the model’s main constructs. The marker variable (firm age) is assessed using a three-point Likert variable (i.e., dummy variables of one for <10, two for 11-20, and three for >21 years old). Because a marker variable is unrelated to our principal constructs, the correlations must be minor. Nevertheless, any high correlations could be considered as a threat to CMV. The resulted correlation matrix outlines that the highest correlation between the marker variable and the model's primary constructs does not exceed 0.05, a level that is far below the threshold level of 0.90 (Tehseen, Ramayah et al. 2017). Therefore, CMV bias is not a serious concern in this research.

4. DATA ANALYSIS

This study uses PLS with SmartPLS (v. 3.3.2) (Ringle, Wende et al. 2015) to test and validate the proposed research model. PLS has the advantages such as a) high level of flexibility relating to theory and practice, b) less dependency to sample size, and c) having fewer assumptions on multivariate normality (Hair, Hult et al. 2017).

4.1. Assessment of the measurement model

First, the full model's measurement model (including moderating variables) was assessed using SmartPLS to check for reliability and validity measures (see Tables 2 and 3).

The instrument shows adequate indicator reliability based on the results, as all the loadings are higher than 0.7. Composite reliability coefficient values are all above 0.7, indicating that the constructs are reliable. Using "rho_" instead of Cronbach's alpha and composite reliability has been suggested by Dijkstra and Henseler (2015). The "rho_" values between 0.7 and 1.0 exhibit excellent composite reliability, ranging from 0.806 to 0.905. The Average Variance Extracted (AVE) should be above 0.5 to ensure convergent validity (Hair, Hult et al. 2017) met according to Table 2.

We also evaluated the model's discriminant validity, which is the extent to which measurement items of the model's constructs are distinct from each other. We employed Heterotrait-Monotrait (HTMT) ratio that must be below 0.85 (Dijkstra and Henseler 2015). According to Table 3, our HTMT ratios for each pair are satisfactory, representing that all constructs in the model are independent of others. Utterly, based on these measures, we conclude that the model entails good reliability and validity. Therefore, the model can be considered for the structural model and further assessments.

Table 2. Construct's reliability and validity

Constructs	Loading range	Rho_A	Cronbach's Alpha	Composite Reliability	AVE
Business Analytics	0.71-0.88	0.90	0.89	0.92	0.66
Exploitation	0.72-0.86	0.82	0.82	0.88	0.65
Exploration	0.71-0.87	0.81	0.81	0.87	0.64
Competitive Advantage	0.81-0.928	0.89	0.87	0.94	0.76
BA Innovator Strategy	0.83-0.91	0.86	0.83	0.89	0.74
BA Conservative Strategy	0.84-0.85	0.85	0.84	0.88	0.72
BA Undefined Strategy	0.82-0.94	0.90	0.90	0.91	0.77

Table 3. Discriminant validity of the constructs (HTMT ratios)

Constructs	1	2	3	4	5	6	7
1. BA		0.848	0.162	0.821	0.833	0.474	0.599
2. Competitive Advantage			0.065	0.768	0.821	0.587	0.838
3. BA Conservative Strategy				0.056	0.279	0.783	0.301
4. Exploitation						0.410	0.596
5. Exploration						0.695	0.647
6. BA Innovator Strategy							0.240
7. BA Undefined Strategy							

4.2. Assessment of the structural model

To test the structural model, we considered 20 models to precisely observe individual direct and indirect effects. M1, M5, M9, M13, and M17 were conducted to estimate the effects of control variables on exploration, exploitation, innovative ambidexterity (BD and CD), and competitive advantage. M2, M6, M10, and M14 evaluate the effects of BA on exploration, exploitation, and innovative ambidexterity (BD and CD), respectively. M3 is developed to evaluate the moderating effects of BA strategy (innovator, conservative, and undefined) on the link from BA to exploration, which provides inputs to test H2a, H3a, and H4a. M7 provides the same input for the link from BA to exploitation, providing inputs to test H2b, H3b, and H4b. Similarly, M11 and M15 present the input to test H2, H3, and H4. M4, M8, M12, and M16 were conducted to estimate the effects of descriptive analytics, predictive analytics, and prescriptive analytics on exploration, exploitation, and innovative ambidexterity (BD and CD). M18, M19, and M20 are proposed to estimate the effects of BA, exploration, exploitation, and innovative ambidexterity (BD and CD) on competitive advantage, providing input to test H1, H1a, and H1b. Table 4 summarizes the PLS analysis results.

Regarding the research CVs (industry type, firm size), direct effects of CVs on exploration, exploitation, innovative ambidexterity (BD and CD), and competitive advantage, have been examined through M1, M5, M9, M13, and M17. The control variables are also repeated in all other models. The results point out that CVs do not influence the model’s constructs. To put it simply, companies of a distinct industry type or size do not significantly differ concerning the relationships within the model. Thus, it can be assumed that BA can be equally supportive of diverse industries and firm sizes to boost competitive advantage.

Based on M2, BA has a significant positive relationship with exploration ($\beta=0.516$, $p<0.001$). The explained variance in exploration is 19.3%. M6 suggests a significant positive relationship between BA and exploitation ($\beta=0.541$, t $p<0.001$) with an explanatory power of 16.6%. Similarly, M14 presets a strong relationship between BA and innovative ambidexterity (CD) ($\beta=0.566$, t $p<0.001$), while, according to M10, such relation is not observed for innovative ambidexterity (BD).

M3 depicts the moderating role of BA innovator strategy ($\beta=0.161$, $p<0.001$), BA conservative strategy ($\beta=0.119$, $p<0.01$), and BA undefined strategy ($\beta=-0.018$, $p>0.10$) on the link from BA to exploration, confirming H2a, H3a, and H4a, respectively. Likewise, through M7, the moderating effects of BA innovator strategy ($\beta=0.219$, $p<0.001$) and BA conservative strategy ($\beta=0.123$, $p<0.01$) are confirmed for the link from BA to exploitation, while no moderating effect is confirmed for BA undefined strategy ($\beta=0.050$, $p>0.10$) confirming H2b, H3b, and H4b, respectively. M11 and M15 assess the effect of the same moderating effects on innovative ambidexterity (BD) and innovative ambidexterity (CD). We observed a significant moderating role of BA innovator strategy ($\beta=1.344$, $p<0.01$) and BA conservative strategy ($\beta=0.682$, $p<0.10$) on the link from BA to innovative ambidexterity (CD).

Table 4. Summary of the PLS results

	Exploration				Exploitation			
	M1	M2	M3	M4	M5	M6	M7	M8
Control/Marker Variables								
Firm age	0.030	0.039	0.022	-0.040	-0.035	-0.068	0.071	0.049
Firm size	0.098	0.046	-0.026	-0.033	0.095	-0.008	-0.047	0.014
Industry type	0.034	-0.020	0.025	-0.094	-0.064	0.068	-0.080	-0.047
Dependent Variables								
BA		0.516***	0.385**			0.541***	0.457***	
Descriptive analytics				0.168**				0.201**
Predictive analytics				0.405**				0.336**
Prescriptive analytics				0.241**				0.129*
Mediating Variables								
Exploration								
Exploitation								
Innovative Ambidexterity (BD)								
Innovative Ambidexterity (CD)								
Moderating Variables								
BA×BA Innovator Strategy			0.161***				0.219***	
BA×BA Conservative Strategy			0.119**				0.123***	
BA×BA Undefined Strategy			-0.018				0.050	
R^2	0.020	0.193	0.231	0.209	0.031	0.166	0.205	0.187

†p<0.1; ∗p<0.05; ∗∗p<0.01; ∗∗∗p<0.001, two-tail test.

Table 4. Summary of the PLS results (continued)

	Ambidexterity (BD)				Ambidexterity (CD)				Competitive advantage			
	M9	M10	M11	M12	M13	M14	M15	M16	M17	M18	M19	M20
Control/Marker Variables												
Firm age	0.032	-0.017	0.075	0.034	-0.033	0.044	0.023	0.054	-0.077	-0.073	0.003	-0.039
Firm size	-0.089	0.012	-0.051	0.024	0.085	0.011	0.037	0.014	-0.039	0.079	0.042	-0.054
Industry type	-0.065	0.072	0.081	-0.051	0.072	0.074	-0.072	0.047	0.079	0.066	0.071	0.064
Dependent Variables												
BA		0.128	0.101			0.566**	0.471**			0.069	0.056	0.048
Descriptive analytics				0.027				0.231**				
Predictive analytics				0.064				0.438*				
Prescriptive analytics				-0.001				0.262*				
Mediating Variables												
Exploration										0.238**		0.201**
Exploitation										0.568***		0.528**
Innovative Ambidexterity (BD)											0.115	0.094
Innovative Ambidexterity (CD)											0.772*	0.640*
Moderating Variables												
BA×BA Innovator Strategy			0.061				1.344***					
BA×BA Conservative Strategy			0.032				0.682†					
BA×BA Undefined Strategy			0.044				0.047					
R^2	0.013	0.032	0.035	0.033	0.027	0.221	0.261	0.338	0.025	0.310	0.325	0.437

†p<0.1; ∗p<0.05; ∗∗p<0.01; ∗∗∗p<0.001, two-tail test.

Additionally, M4 supports the positive link from descriptive analytics (β=0.168, p<0.01), predictive analytics (β=0.405, p<0.01), and prescriptive analytics (β=0.241, p<0.01) to exploration. Alike, significant positive links from descriptive analytics (β=0.201, p<0.01), predictive analytics (β=0.336, p<0.01), and prescriptive analytics (β=0.129, p<0.05) to exploitation are observed via M8. Moreover, strong relationships from descriptive analytics (β=0.231, p<0.01), predictive analytics (β=0.438, p<0.05), and prescriptive analytics (β=0.262, p<0.05) to innovative ambidexterity (CD) are observed, according to M16. However, given M12, innovative ambidexterity (BD) is not significantly correlated with any of them.

Moreover, M18 supports the direct significant positive effect of exploration (β=0.238, p<0.01) and exploitation (β=0.568, p<0.001) on competitive advantage. Conversely, such a relationship is not confirmed for the direct link from BA to competitive advantage (β=0.069, p>0.10). M19 assesses the impact of innovative ambidexterity (BD) (β=0.115, p>0.10) and innovative ambidexterity (CD) (β=0.772, p<0.05) on competitive advantage. Finally, M20 implies a positive effect of exploration (β=0.201, p<0.01), exploitation (β=0.528, p<0.01) and innovative ambidexterity (CD) (β=0.640, p<0.05) on competitive advantage. Table 4 provides data for further analysis of mediating and moderating effects, which will be discussed further in the sub-sections 4.3 and 4.4.

4.3. Assessment of the moderating effects

M3 estimates the moderating effects of BA innovator, conservative, and undefined strategy on the link between BA and exploration. Regarding the observed path coefficients and the significance levels, BA innovator strategy (β=0.161, p<0.001) and BA conservative strategy (β=0.119, p<0.01) moderate the link, while such moderation effect is not observed for BA undefined strategy (β=-0.018, p>0.10). Thus, H2a, H3a, and H4a are confirmed.

Moreover, the moderating effects of the three mentioned constructs were evaluated for the relationship between BA and exploitation, using M7. Again, we observed positive moderating effects of BA innovator strategy ($\beta=0.219$, $p<0.001$) and BA conservative strategy ($\beta=0.123$, $p<0.01$) with no moderation effect for BA undefined strategy ($\beta=0.050$, $p>0.05$), confirming H2b, H3b, and H4b. In a similar vein, M11 and M15 assess the same moderating effects on innovative ambidexterity (BD) and innovative ambidexterity (CD). We observed the significant moderating role of BA innovator strategy ($\beta=1.344$, $p<0.01$), BA conservative strategy ($\beta=0.682$, $p<0.10$) on the link from BA to innovative ambidexterity (CD).

To further interpret the significant moderating effects (BA innovator and BA conservative strategy on the link from BA to exploration, exploitation, and innovative ambidexterity (CD)), we plot the interaction effects, employing the Interaction software package[3]. This package plots the interaction effects using −3 to +3 Standard Deviation (SD). Regarding the positive moderating effects (M3, M7, and M15), the steeper slope of the purple line (+3 SD) compared to the red line (-3 SD) (e.g., in Fig. 2, part a) demonstrates that an increase in BA contributes to a superior increase in exploration, in higher levels of BA innovation strategy. Likewise, an increase in BA is associated with a superior increase in exploitation when the BA conservative strategy is high (e.g., in Fig. 2, part e).

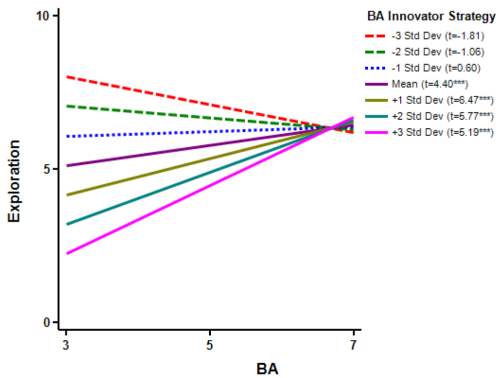
To further analyze whether the moderating effects of BA innovator strategy on the link from BA to exploration, exploitation, and ambidexterity (CD) are higher than those for BA conservative strategy (i.e., P ($b^{(\text{BA innovator})} > b^{(\text{BA conservative})}$), PLS Multi-Group Analysis (MGA) is conducted. To do so, firstly, we need to create the groups in SmartPLS. More specifically, we set two subsamples based on the means of BA innovator and conservative strategy variables. Meanwhile, if the mean

[3] See www.danielsoper.com

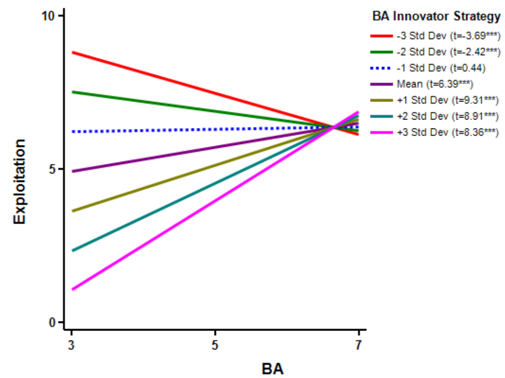
of BA innovator strategy for a firm exceeds four (out of seven), we considered that firm (i.e., a record of data) in subsample 1. Likewise, if the associated mean for the BA conservative strategy is above four, it is labeled as subsample 2. Secondly, we conducted bootstrapping using 10,000 sub-samples for analyzing the differences.

The achieved p-value for the BA and exploration relationship is 0.042, denoting that the BA innovator strategy, compared to the BA conservative strategy, has a higher moderating effect on the relationship between BA and exploration. The same approach is also followed to investigate the moderating effect of BA innovator and conservative strategies on the link from BA to exploitation and from BA to innovative ambidexterity (CD). We did not consider innovative ambidexterity (BD) here, as, according to Table 4, the moderating effects were not significant.

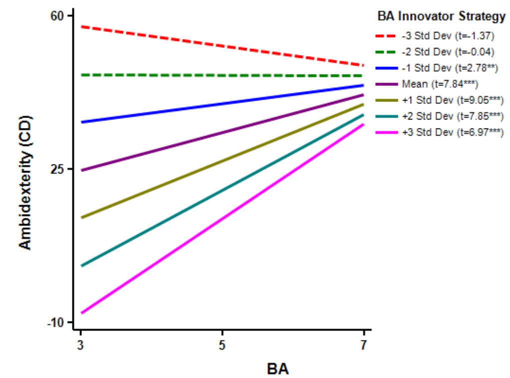
The derived p-value for the BA and exploitation relationship is 0.039. Again, it shows that the BA innovator strategy, compared to the BA conservative strategy, has a higher moderating effect on the relationship between BA and exploitation. As well, the obtained p-value for the case of ambidexterity (CD) is 0.048, proposing a significantly higher moderating effect of innovator strategy on the link from BA to innovative ambidexterity (CD), compared to the BA conservative strategy.



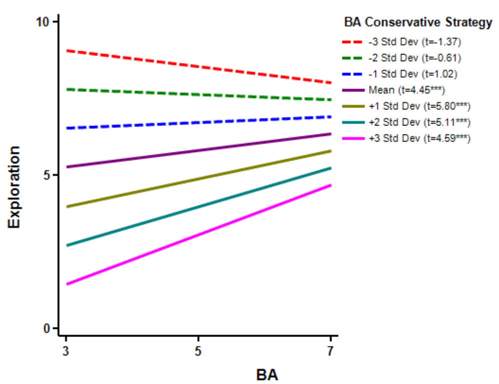
a) BA × BA Innovator Strategy→ Exploration



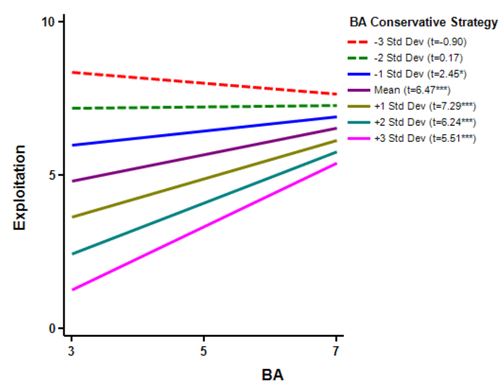
b) BA × BA Innovator Strategy→ Exploitation



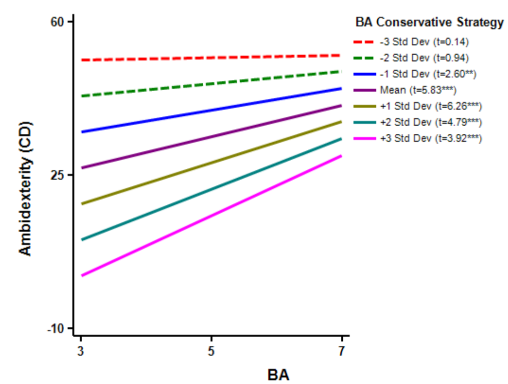
c) BA × BA Innovator Strategy→ innovative Ambidexterity (CD)



d) BA × BA Conservative Strategy→ Exploration



e) BA × BA Conservative Strategy→ Exploitation



f) BA × BA Conservative Strategy→ innovative Ambidexterity (CD)

Note: The bold lines indicate significant relations, whereas the dashed lines refer to non-significant ones. T-values and significant levels are also presented for each line (*p<0.05; **p<0.01; ***p<0.001)

Fig 2. Plots of simple slopes to account for the interaction effects

4.4. Assessment of the mediating effects

The data in M2, M6, M12, M18, M19, and M20 suggests that there may be some mediation effects in the model. We ran further analyses on SmartPLS to determine whether the impact of BA on competitive advantage is mediated through exploration, exploitation, and innovative ambidexterity (CD). To this end, we ran both PLS and bootstrapping procedures to derive path coefficients and significant levels for relevant direct and indirect paths. The bootstrapping test was run using 10,000 sub-samples to test the path coefficients' statistical significance. Accordingly, we confirmed that the mediated paths of BA → exploitation → competitive advantage ($\beta = 0.287$, $p < 0.001$), and BA → exploration → competitive advantage ($\beta = 0.132$, $p < 0.01$) are significant. Considering the non-significant direct path from BA to competitive advantage ($\beta = 0.069$, $p > 0.05$), full mediation is observed (Hair, Hult et al. 2017), confirming both H1a and H1b. Likewise, noting the positive mediated paths from BA to competitive advantage (i.e., through innovative ambidexterity (CD) with $\beta = 0.437$, $p < 0.001$), and the non-significant direct path there (from BA to competitive advantage, ,with $\beta = 0.069$, $p > 0.05$), full mediation is apparent through innovative ambidexterity (CD), confirming H1. In other words, the link from BA to competitive advantage is fully mediated with innovative ambidexterity (CD).

4.5. Assessment of the model fit

We assessed the model fit (full model with BA, exploration, exploitation, and competitive advantage constructs) using StoneGeisser's Q^2, Standardized Root Mean Residual (SRMR), RMS_theta, Goodness-of-Fit (GoF), and coefficient of determination (R^2). The blindfolding procedure was employed to estimate predictive relevance (Q^2), revealing how well the model reproduces the observed values. Positive Q^2 values suggest that the structural model has adequate predictive relevance, while negative values indicate improper predictive relevance (Hair, Hult et al. 2017). Q^2 values for exploration, exploitation, and competitive advantage constructs are estimated as 0.172, 0.192, and 0.551, respectively, ranging from moderate (above 0.15) to high (above 0.35), revealing an adequate predictive relevance.

SRMR value of 0.071 depicts a good fit, as it is below 0.08 (Hair, Hult et al. 2017). RMS_theta, which evaluates the extent to which the outer model residuals correlate, must be ideally below 0.12 (Hair, Hult et al. 2017). The estimated value for RMS_theta equals 0.115, indicating a well-fitting model. Furthermore, the overall model's Goodness-of-Fit (GoF) equals 0.43 estimated employing the equation: GoF=$\sqrt{\overline{AVE} \times \overline{R^2}}$ (Alolah, Stewart et al. 2014). The average AVE of the model's four latent variables (moderating variables are not included) and average R^2 of the three endogenous latent variables are used to estimate the overall GoF. Moreover, this index has been estimated for each endogenous variable using the respective AVE and R^2. GoF values equal 0.37, 0.35, and 0.57 for exploration, exploitation, and competitive advantage, respectively, suggesting a large overall fit (Alolah, Stewart et al. 2014). Finally, regarding the R^2 coefficients in the structural model, the proposed constructs explain a 43.7% variance of competitive advantage. R^2 coefficients of exploration and exploitation and innovative ambidexterity (CD) are also estimated as 19.3%,16.6%, and 22.1%, respectively. Considering R^2 = 0.02 as small; R^2 = 0.13 as medium; and R^2 = 0.26 as large (Hair, Hult et al. 2017), all R^2 values lie around the large level.

5. DISCUSSION

Given the undeniable BA role in our volatile business environment, scholars and practitioners have a great interest in discovering how using BA might affect firms' competitive advantage. In this way, previous research extensively discussed different theoretical foundations and mechanisms that BA influences competitive advantage (e.g., Akter, Wamba et al. 2016, Ashrafi, Zare Ravasan et al. 2019, Aydiner, Tatoglu et al. 2019, Božič and Dimovski 2019). However, reviewing the literature showed that innovation, as one of the main primary pathways to competitive advantage, has rarely been examined. Besides, most prior research has been founded on DC theory, and a few attempts have been made to see this picture from other possible points of view, such as ambidexterity theory. Combining the above, the influence of BA on competitive advantage through innovative ambidexterity needs further investigations. To address this issue, this research draws on the ambidexterity theory to find out how innovative ambidexterity would mediate the relationship between BA and competitive advantage. Furthermore, we propose that different BA strategy types would moderate the link between BA and innovative ambidexterity. The result confirms that the BA has a significant positive relationship with both exploration and exploitation. The results also demonstrate that the relationship between BA and competitive advantage is fully mediated with innovative ambidexterity. We also estimate the moderating effects of BA innovator, conservative, and undefined strategy on the link between BA-exploration and BA-exploitation. Our findings approve that both BA innovator and BA conservative strategy moderate the mentioned links, while such moderation effect is not observed for the BA undefined strategy.

5.1. Theoretical Implications

First, this study extends the BA literature by distinguishing different BAs and their influence on competitive advantage. Besides considering BA as a holistic variable, we also used a specific measurement metric (i.e., descriptive, predictive, prescriptive) to better articulate which one plays a more crucial role in exploration and exploitation practices within firms. BA can provide a decision support environment that not only facilitates the different types of innovative practices across business departments but also makes an appropriate balance between exploitation and exploration, which results in an ambidextrous environment (Božič and Dimovski 2019, Hindle, Kunc et al. 2020). Using BA allows firms to capture related data from the market, leading them to extract new ideas for building new products/services or improving the existing ones (Tan, Zhan et al. 2015). Based on M2 and M6, BA has a significant positive relationship with exploration (β=0.516, $p<0.001$) and exploitation (β=0.541, t $p<0.001$). This finding can be considered a theoretical confirmation for what is mentioned in the BA literature (Mikalef, Boura et al. 2019). The path coefficient for the BA-exploitation relationship is higher than that for the BA-exploration link. One possible explanation is that senior managers and executives mostly intend to use resources in reliable and predefined ways to reach quick wins. According to Gupta and George (2016), firms must exploit current knowledge besides exploring a new one to cope with turbulent market conditions. To be clear, while exploitation stress enhancing adjustment to the current environment, exploration aims at improving future adaptability (Lavie, Stettner et al. 2010, Chen 2017). Similarly, firms have more tendency to engage in exploitative activities because of the greater and faster returns of valuable resources than exploratory innovations. Thus, it is entirely logical that firms pay an increasing attention to applying and improving exploitative practices (Popovič, Hackney et al. 2018). Besides, that would be much easier for firms to improve their product offering than generate innovative products/services (Ghasemaghaei and Calic 2019). So, managers highlight more on exploitative practices for promptly seizing the opportunities (O'Reilly and Tushman 2008).

Second, previous research (e.g., Aydiner, Tatoglu et al. 2019) developed empirical models to investigate the impact of BA on firms' outcomes considering various categories of tools and techniques. However, their findings on how different BA categories might result in different consequences have not shed sufficient light on both business and academics. In response, we consider BA categories (i.e., descriptive, predictive, prescriptive) to figure out possible impacts on innovative ambidexterity. Comparing the M4 and M8, we find that descriptive analytics has a stronger influence on exploitation than exploration. This finding is entirely consistent with the nature of exploitative activities. Exploitative orientation is expected to work within well-established problem-solution frameworks with detailed and sufficient information with less uncertainty. These assumptions are aligned with the purpose of descriptive analytics techniques, which are mainly focused on what has happened. Thus firms have enough information to provide descriptive reports to answer questions about previous events (Appelbaum, Kogan et al. 2017). It also provides the overall view of the company's current status, so senior executives can utilize descriptive reports as a basis to recommend the optimal solutions (Hazen, Skipper et al. 2018). Therefore, firms mostly intend to use descriptive analytics to see an overview of what happened in the past, then make small changes based on any changes in the markets and customers' preferences to achieve their short-run objectives. Both predictive and prescriptive analytics are still novel, and most managers and senior decision-makers have little knowledge of applying them in practice. Thus, they prefer to rely on descriptive reports to reach predefined goals in a timely manner. Adding to the above, the impacts of both predictive and prescriptive analytics are higher on exploration than exploitation. Generally, exploratory activities center of the belief that a firm may not have complete information about all possible opportunities, so it needs to sense and seize new opportunities (Teece 2007). In other words, firms believe that they have not yet reached their maximum capabilities. Hence, they need to develop their existing capabilities (Wang and Chen 2018) or transform existing capabilities (Teece 2007). Generally, using advanced reports based on predictive and prescriptive analytics techniques enable firms to develop predictive models for future events to make predictions and alter strategic execution to maximize performance results (Chen, Chiang et al. 2012). As an example, analyzing real-time and near real-time data allows firms to anticipate consumers' buying patterns, use customized recommendation techniques to show similar products (such as Amazon or NETFLIX), and finally improve sales positions. In addition, using predictive data analytics techniques help organizations improve their capability to quickly identify areas for growth.

Third, contrary to past research that indicated the direct relationship between BA and firm outcomes (e.g., Wamba, Gunasekaran et al. 2017, Rialti, Zollo et al. 2019), the results found no significant influence, which is precisely consistent with Aydiner et al. (2019). In this study, we tested the mediating effect of innovative ambidexterity, which helps explain how BA value is delivered to the firm. As discussed by Cao et al. (2015), we believe that BA would positively influence firm outcomes through unique complementarities and dynamic capabilities. Specifically, this finding is essential for firms to understand the different mechanisms that using BA might help them make a synergistic effect the outcomes. Based on DC theory, BA that works as a data-driven software cannot be merely a source of firm-level value but may provide unique values to indirectly make competitive value (Conboy, Mikalef et al. 2020). Therefore, BA needs higher-order capability as complementary resources (e.g., innovative ambidexterity) to make synergy in creating desired business value. This claim is entirely aligned with previous research that IT capabilities influence agility through the mediating effect of ambidexterity (Lee, Sambamurthy et al. 2015). In other words, firms need to focus on more significant factors than just data and technology to sense market changes and respond to them to achieve their predefined goals (Ashrafi and Zare Ravasan 2018, Ashrafi, Zare Ravasan et al. 2019).

Fourth, we find that the mediating effect of exploitative practices between the BA and competitive advantage is somewhat stronger than that for explorative orientation. One possible explanation is that the use of predictive and prescriptive techniques as the main predictors of exploration are much lower than basic level analytics. Thus, most firms focus on analyzing past data to interpret what happened, then exploit new practices into their products or services. The other explanation relates to the firms' lack of BA expertise, which stops them from using advanced tools and techniques to create higher-level reports for managers and senior executives. It might be because of the lack of support from executive teams who always want to focus on financial numbers rather than on research and development to generate new ideas that take time to come to the surface and show competitive gains.

Fifth, the current paper is the first attempt to incorporate BA strategy into a BA model, innovative ambidexterity, and competitive advantage. Here, we used different BA strategies and attempted to test this typology's moderating roles in the relationship between BA and innovative ambidexterity. Regarding the observed path coefficients and the significance levels, we find that BA innovator and conservative strategy moderate the BA-exploration and BA-exploitation links, while such a moderation effect is not observed for the BA undefined strategy. It shows that while BA benefits can be varied, substantial, and the basis for competitive advantage, to realize the benefits, firms have to carefully establish and execute BA strategy (Watson 2014). As previously mentioned, the BA strategy means the organizational perspective on the investment in, deployment, use, and management of BA (Chen, Mocker et al. 2010). Thus, regardless of the BA innovator or conservative approach, the presence of a defined BA strategy plays a great role for a firm's IT strategic level to determine the pathway and approach to market changes. We also find that the moderating effect of innovator strategy on the link from BA to exploration and exploitation is larger than that for the conservative strategy. One explanation for this finding is that whereas BA innovator strategy seeks to be innovative through new BA initiatives continuously, BA conservative strategy intends to make value through improving current BA practices (Chen, Mocker et al. 2010, Birkinshaw and Gupta 2013). Our finding demonstrates that firms with BA conservative strategy have some limitations in their ability to respond quickly and flexibly to the environment (Martinez-Simarro, Devece et al. 2015). Hence, they attempt to experience short-run advantages through the best usage of existing resources.

Finally, we concurrently consider both BD and CD as the most common ambidexterity approaches to determine how they might play between the BA-competitive advantage relationship. In this study, we found that the positive mediated paths from BA to competitive advantage (i.e., through innovative ambidexterity (CD) with $\beta = 0.437$, $p < 0.001$), and the non-significant direct path there (from BA to competitive advantage, with $\beta = 0.069$, $p > 0.05$), full mediation is apparent through innovative ambidexterity (CD), confirming H1. It means that using BA tools to obtain a higher level of exploitation and exploration will enhance competitive advantage. This finding clearly shows that mere exploration or exploitation is not enough to create value in the context of BA. Managers must consider this issue to achieve the highest value they want to get from analytics. On the one hand, overemphasizing innovative exploitative activities might hinder firms from focusing on future market trends, which means losing a competitive position in the turbulent market because of a lack of new knowledge. On the other hand, high concentration on explorative activities could decrease the effectiveness of current knowledge, cause extensive risks for firms, and might inhibit existing resources to be considered as a basis to deep firm's understanding of market information for future actions. To sum up, this finding demonstrates that the combination of exploitative and exploratory innovation is the impediment mediator for getting competitive value from BA.

5.2. Practical Implications

This study also has several interesting implications for practice. Firstly, the empirical evidence clearly shows the non-significant direct relationship between BA and competitive advantage. Given this finding, companies should understand that using BA techniques alone will not automatically generate competitive value to cope with market changes and challenges. In other words, they should highlight the mediating roles of exploration and exploitation orientations as a significant ambidextrous pathway for firms to gain competitive advantage. Therefore, managers must develop and pursue both exploitation and exploration and balance the two orientations to achieve sustained performance. On the one hand, top-level managers should advertise policies and scenarios for departments, and mid-level managers to consider the existing resources to create short-term advantages. This approach will be useful when the environment changes gently. While firms need to continuously increase quality or reduce costs, they also must create novel products/services to cope with uncertain and dynamic conditions. On the other hand, managers need to allow their workers to think out of the box to evolve new scenarios for developing new products/services or processes. Preparing special motivational programs for workers to engage themselves in exploration and exploitation activities could facilitate the proposed pathway.

Secondly, we find that the mediating effect of exploitative practices between the BA-competitive advantage is stronger than that for the explorative orientation. It means that CIOs or IT executives tend to use existing knowledge or refine current business processes instead of focusing on radical changes. This finding could be a warning point for firms because of two main possible reasons. One possible reason for this finding is that factors like business culture and strategy might hinder CIOs from taking risks to establish new ideas based on analyzing market data. This strategy would be good enough for a stable environment. However, to cope with the turbulent market challenges, managers need to turn their minds to explorative practices; otherwise, they will be out of the market in the future. The other possible reason is the lack of internal expertise to use advanced analytics techniques to create predictive models. To resolve this issue, managers can think about cloud services such as using analytics-as-a-service, a cost-effective option to help firms achieve their objectives. More, firms do not need to hire several IT and BA specialists familiar with machine learning techniques to work with various tools and techniques. However, they need to deal with system reliability and information confidentiality issues.

Thirdly, to achieve a higher level of ambidexterity and competitive value, managers and IT executives must realize the crucial role of a well-defined BA strategy. So, firms' senior executives need to know that the degree to which a firm may benefit from BA - innovative ambidexterity - competitive advantage relationship will depend on the founded way and specific strategy to which a firm uses BA in its business processes. The research outcome demonstrates that firms need to adopt either BA innovator or conservative to enhance the effects of using BA on exploration and exploitation. For instance, in a highly competitive environment, firms require to explore and rapidly respond to market opportunities. To do so, following a BA innovator strategy will support a higher level of radical innovations and enhance dynamic capabilities that are necessary to achieve a competitive advantage. Besides, BA practitioners should grasp that to contribute significantly to ambidexterity and firms' competitive advantage, the IT department should strive to take either a BA innovator or a conservative approach to align with business strategy. By nature, firms with an innovator business strategy tend to focus on radical innovations that are consistent with the BA innovator strategy.

In contrast, a conservative approach in firms' business strategy instills that the firm only follows its industry leaders' best practices. This safe approach will significantly limit a firm's ability to respond to market conditions promptly. Thus, CIOs or IT executives should build an appropriate

BA strategy considering business strategy and culture to extract higher benefits. Lack of consistency between business and BA strategy may bring huge problems at the strategic level. For instance, building a BA innovator strategy in a firm with a common conservative approach means that plans and data analysis for radical innovations will be banned from top-level managers who prefer to encourage a culture based on incremental actions. Besides, CEOs should fully support the IT department and provide a creative environment for the staff to generate their radical or incremental ideas to align with the business context. Finally, the lack of a particular strategy may cause several difficulties for practitioners to understand how they must adopt or employ BA, which results in damaging nature on business development. Therefore, managers should choose a well-defined strategy, even the conservative approach, and plan based on the chosen approach.

5.3. Limitations

Here, we mentioned some limitations of the paper. First, we utilized a cross-sectional approach that naturally limits the study of the causal relationships among the research constructs. Therefore, future studies need to conduct longitudinal research or case-based research to make further support. Second, we did not consider organizational mindset related to exploration and exploitation. We believe that organizational routines for firms highly focusing on exploitative activities are completely different from those concentrated on exploratory issues. Thus, future research can focus on organizational culture and mindsets as moderating variables and determine the difference between firms. Third, we only examined the moderating role of BA strategy on the relationship between BA and innovative ambidexterity. Future research could explore other possible moderating variables (e.g., data-driven culture, firms' strategic orientation) and how they might influence the BA-innovative ambidexterity relationship. Forth, we proposed and validated a nomological model based on a combination of DC and ambidexterity theories. Therefore, future studies could apply other well-known IS theories, such as information processing view or institutional theory, and provide other exciting food for thought.

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Appendix A. Measurement Items

Constructs and items

Business Analytics (BA) (Hartwick and Barki 1994)

- *Descriptive Analytics*
  1) Please indicate to what extent does your organization use descriptive analytics tools?
  2) Please indicate how often does your organization use descriptive analytics tools?
- *Predictive Analytics*
  1) Please indicate to what extent does your organization use predictive analytics tools?
  2) Please indicate how often does your organization use predictive analytics tools?
- *Prescriptive Analytics*
  1) Please indicate to what extent does your organization use prescriptive analytics tools?
  2) Please indicate how often does your organization use prescriptive analytics tools?

BA Strategy (Chen, Mocker et al. 2010)

- *BA Innovator strategy*
  1) Our organization is a leading BA innovator in our industry.
  2) Our organization believes in being the first in the industry to develop new BA initiatives, even if not all of these efforts prove to be highly profitable.
  3) Our organization responds rapidly to early signals concerning areas of opportunity for BA.
- *BA Conservative strategy*
  1) Our organization follows a safe and stable approach to developing new BA initiatives.
  2) Our organization adopts promising BA innovations once these initiatives have been proven in our industry.
  3) BA innovations are carefully examined before they are chosen by our organization.
- *BA Undefined strategy*
  1) Our organization does *not* have definitive long-term BA goals.
  2) Our organization does *not* have an articulated BA strategy.
  3) Our organization does *not* have a consistent pattern of behavior regarding BA.

Innovative ambidexterity (Jansen, Tempelaar et al. 2009)

- *Exploration*
  1) Our organization responds to demands that go beyond existing products and services.
  2) We commercialize products and services that are completely new to our organization.
  3) We frequently seek out new opportunities in new markets.
  4) Our organization regularly uses new distribution channels.
- *Exploitation*
  1) We frequently make small adjustments to our existing products and services.
  2) We continuously improve our production efficiency of products and services.
  3) We continuously increase economies of scale in existing markets.
  4) Our organization frequently expands services for existing clients.

Competitive Advantage (Bhatt, Emdad et al. 2010)

1) Over the past three years, our organization’s financial performance has been outstanding.
2) Over the past three years, our organization’s financial performance has exceeded the competitor’s performance.
3) Over the past three years, our organization’s sales growth has been outstanding.
4) Over the past three years, our organization’s profitability has been higher than our competitor’s profitability.
5) Over the past three years, our organization’s sales growth has exceeded the competitor’s sales growth.

* We used a seven-point Likert scale for all measurement items (i.e., 1: Strongly low, to 7: Strongly high for the BA construct and 1: Strongly disagree, to 7: Strongly agree for the rest)