Big Data Analytics Capability and Market Performance: The Roles of Disruptive Business Models and Competitive Intensity

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Abstract

Research shows that big data analytics capability (BDAC) is a major determinant of firm performance. However, scant research has theoretically articulated and empirically tested the mechanisms and conditions under which BDAC influences performance. This study advances existing knowledge on the BDAC–performance relationship by drawing on the knowledge-based view and contingency theory to argue that how and when BDAC influences market performance is dependent on the intervening role of disruptive business models and the contingency role of competitive intensity. We empirically test this argument on primary data from 360 firms in the United Kingdom. The results show that disruptive business models partially mediate the positive effect of BDAC on market performance, and this indirect positive effect is strengthened when competitive intensity increases. These findings provide new perspectives on the business model processes and competitive conditions under which firms maximize marketplace value from investments in BDACs.

Keywords: Big data analytics capability, Market performance, Disruption, Disruptive business model, Competitive intensity, Knowledge-based view, Resource-based view, Contingency theory

1. Introduction

Estimates indicate that the global market for big data will increase from $193.14 billion in 2019 to $420.98 billion in 2027 (Borasi et al., 2020). Moreover, approximately 2.5 quintillion bytes of data are created every day, with 90% of the world's data generated within the past two decades. Several firms (e.g., Uber, Airbnb, Deutsche Postbank, and Amazon.com) are taking the opportunities provided by this big data revolution to pioneer innovative business models (Chaudhary et al., 2016). These data-driven firms are extracting, integrating, and optimizing large-scale data from a variety of data sources (e.g., Google Maps, Netflix accounts, online shopping charts) to generate new insights into consumers, competitors, and supply chains to disrupt almost every known driver of competitive advantage. A global survey by McKinsey reports that firms profit from big data investments at 6% and that this increases to 9% for investments over a five-year period (Bughin, 2016). Thus, investment in big data analytics capability (BDAC) may be a strong data-driven source of competitive advantage (Marshall et al., 2015; Pisano et al., 2015). For example, Hossain et al. (2021) show that organizations can create value from insights generated from data-driven customer analytics. Firms' ability to deliver superior value to consumers based on data analytics insights can, therefore, be a major determinant of competitive advantage (Gunasekaran et al., 2017). Empirical studies demonstrate that a stronger BDAC contributes to enhanced performance (e.g., Gunasekaran et al., 2017; Rialti et al., 2019; Wamba et al., 2017; Xu et al., 2016).

Although prior research has demonstrated a potential direct relationship between BDAC and performance, the mechanisms and conditions under which this relationship occurs are not fully understood. Importantly, theoretical articulation is limited on the mechanisms that explain how BDAC, as a data-driven knowledge-based resource, contributes to firm performance (Ferraris et al., 2019; Yasmin et al., 2020). In addition, prior research has largely ignored the conditions under which BDAC drives performance, thus failing to advance knowledge on when BDAC becomes an enabler of firm performance (Vitari & Raguseo, 2020). The present study addresses these two deficiencies by drawing insights from the knowledge-based view (KBV) and contingency theory to explain how disruptive business models (DBMs), defined as "activity systems that include new partners and activities configured in a way that is unprecedented in comparison to existing incumbents" (Snihur et al., 2018, p. 1279), act as a facilitating mechanism in the relationship between BDAC and performance and to assess the extent to which this relationship is dependent on different magnitudes of competitive intensity—that is "the behavior, resources, and ability of competitors to differentiate" themselves (Jaworski & Kohli, 1993, p. 60). By doing so, this study addresses three interrelated research questions: (1) How does BDAC contribute to improve market performance? (2) How do DBMs act as a facilitating mechanism in the BDAC–market performance relationship? and (3) To what extent does competitive intensity condition the relationship among BDAC, DBMs, and firm performance?

In addressing these interrelated research questions, this study extends the resource-based view (RBV) and KBV of the firm in three ways. First, the study draws insights from the tenets of these theories to conceptualize BDAC as a big data–driven knowledge resource that contributes to superior competitive advantage. From an RBV perspective, BDAC is a valuable, rare, idiosyncratic, and immobile resource that may explain differences among organizations (Vitari & Raguseo, 2020). As such, BDAC can be modeled as a determinant of market performance because it enables organizations to recognize potential market opportunities (Côrte-Real et al., 2017), identify suitable and profitable market segments (Wamba et al., 2015), advance product development (Xu et al., 2016), and achieve competitive advantages (Hossain et al., 2021).

Second, while some studies have drawn on the RBV (and dynamic capability theory) to argue that knowledge fusion (e.g., Xu et al., 2016) and process-oriented dynamic capabilities (Wamba et al., 2017) represent intervening forces between BDAC and performance, the present research extends these studies by drawing on the KBV to explain how DBMs serve as a channel through which BDAC influences market performance. This argument extents prior research that suggests that possession of knowledge resources drives development of and strengthens organizational capabilities (e.g., Hossain et al., 2021; Wu, 2006). In doing so, this study accounts for how firms deploy their BDACs to develop innovative business models that disrupt existing market order to boost market performance.

Third, this study argues that marketplace advantages may not accrue to firms as a result of greater capability in big data analytics if the competitive landscape is less cutthroat and increasingly benign. Similarly, a propensity to leverage BDACs to build DBMs may not result in superior market performance if the competitive imperative to do so is limited (Mikalef et al., 2019a). Thus, this study integrates insights from the KBV and contingency theory to argue that the relationship between BDAC and market performance through DBMs is likely to be amplified when competitive intensity in a firm's target market environment is high.

The next section discusses how extant literature has tried to untangle the nature of the BDAC–performance relationship, while also highlighting important empirical and theoretical lapses that warrant additional scholarly attention. This is then followed by an articulation of theoretical arguments to explain how DBMs and competitive intensity serve as contingencies to explain how and when BDACs influence performance. We then explain the approaches followed to obtain empirical data to test the relationships, after which we discuss key findings. We conclude with theoretical contributions and managerial implications.

2. Big data analytics capability: its conceptualization and consequences

Although a plethora of BDAC definitions exist, fundamentally it refers to “the ability of a firm to effectively deploy technology and talent to capture, store and analyze data, toward the generation of insight” (Mikalef et al., 2020, p. 2). Such insights usually come from analyzing a large variety and amount of customer data that help firms identify market opportunities and offer high-value product and service offerings to customers (Johnson et al., 2017). Research has conceptualized BDAC in various ways; key among these is the contention that BDAC is a unique organizational capability that confers firms the ability to store, manage, and analyze big data to generate market insights (e.g., Akter et al., 2016; Yasmin et al., 2020). For example, Akter et al. (2016) view BDACs as firm capabilities in big data analytics technology, management, and talent. Relatedly, Yasmin et al. (2020) argue that BDACs capture firms’ infrastructure, management, and human resources capabilities. Wamba et al. (2017) draw insights from the RBV to suggest that having firm-specific BDACs is a major enabler of competitive advantage.

However, other studies have modeled BDAC in terms of its dimensions (e.g., Liu, 2014; Johnson et al., 2017). While most studies have argued that the dimensions can be compressed into three components in what is often termed as the 3Vs (volume, variety, and velocity; Johnson et al., 2017), others have proposed various other dimensions. For example, some studies have proposed a four-dimensional BDAC construct with the component elements degree of volume, velocity, variety, and veracity of big data (Abbasi et al., 2016; Liu, 2015); others have gone further to propose a fifth (big data value; Ferraris et al., 2019), sixth (big data viability; Sun et al., 2015), and even seventh (big data visualization; Seddon & Currie, 2017) dimension. Despite the differences in conceptualization of the BDAC construct, most scholars seem to settle on a three-dimensional approach: volume, variety, and velocity (Chen & Zhang, 2014; Johnson et al., 2017; McAfee et al., 2012; Vitari & Raguseo, 2020). In following these studies, therefore, we conceptualize BDAC as a three-dimensional construct, with the component elements volume, variety, and velocity of big data.

Big data volume refers to the ability of a firm to analyze large-scale data, such as the datasets available and number of observation parameters present for each variable under examination (George et al., 2016), to improve decision making processes (Johnson et al., 2017). The amount of data available to firms has exponentially increased in the past 20 years, facilitated by the growing use of information technology (IT), advancement of internet infrastructure, and willingness of customers to share information with firms (Ferraris et al., 2019).

Big data variety is the extent to which an organization has different sources and types of consumer data to analyze (Johnson et al., 2017). These data sources can range from primary data to secondary data obtained through the use of methodological tools such as surveys, interviews, and focus groups. Data variety can also emerge from customer databases generated from purchases, subscriptions, and loyalty schemes. Thus, big data variety refers to the ability of a firm to generate data from online, digital, and offline sources on information about consumer routines, demands, and preferences (Ferraris et al., 2019). An organization that possesses the ability to access different sources of consumer data can then triangulate findings using different approaches to make the best strategic decisions. By contrast, an organization that does not possess big data variety might be deficient in making accurate predictions about consumer purchase behavior, which can inhibit firm success.

Big data velocity refers to the speed with which data are generated (Ferraris et al., 2019), the speed with which data are analyzed and used (Johnson et al., 2017), and the speed with which the value of the data becomes outdated (George et al., 2016). The speed in generating, analyzing, and developing insights from large-scale data can boost organizational agility and facilitate quick and well-informed decision making. It can also help firms generate insights from big-scale data more quickly than competitors (Liu, 2014).

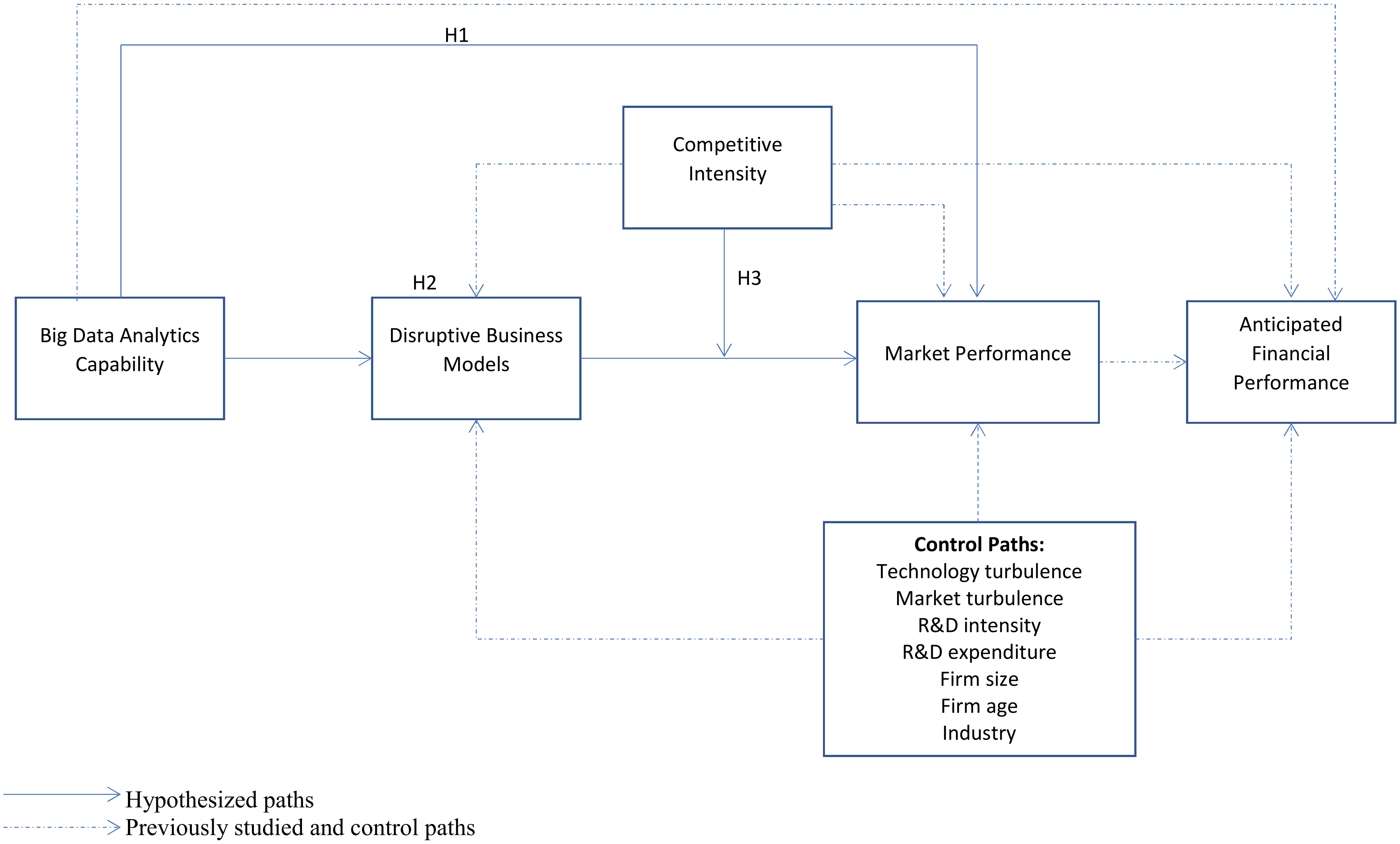
Prior research has used various theoretical lenses to examine the relationship between BDAC and firm performance. The RBV and dynamic capability perspective have dominated this line of research (e.g., Mikalef et al., 2019a; Yasmin et al., 2020). Studies drawing on the RBV perspective argue that BDAC is an enabler of competitive advantage, in that firms with greater capability in storing, managing, and analyzing (and possibly visualizing) big data are in possession of unique, valuable, and idiosyncratic resources that enable them to "manage strategy through a data lens" (Wamba et al., 2017, p. 357). In addition, Liu (2014) argues that BDAC enables firms to be proactive and forward looking in their decision-making processes, and this capability has the potential to decrease customer acquisition costs by as much as 47% and boost firm revenue by as much as 8%, thus affording firms with BDAC a superior marketplace advantage. Beyond the RBV and dynamic capability perspective, some studies suggest that KBV provides a stronger theoretical lens to explain the mechanism linking BDAC to firm performance. In particular, Xu et al. (2016, p. 1563) argue that "knowledge evolves quickly due to the availability of data, the significant reduction of cost for analytics, and the sharing of open knowledge insights on the Internet"; thus, firms with the capability to accumulate, protect, or create new knowledge from big data are likely to gain superior marketplace advantages. This argument is consistent with the tenet of the KBV that conceptualizes the firm as an institution that accumulates, integrates, shares, and uses knowledge in its possession to create unique value propositions. From this perspective, knowledge is "the understanding, awareness, or familiarity acquired through study, investigation, observation, or experience over the course of time" (Bollinger

& Smith, 2001, p. 9), which, when efficiently deployed and leveraged, can lead to superior value creation (Grant, 1996; Wang, 2013).

While firms may possess different types of knowledge (e.g., propositional, heuristic), they may also possess stocks of automated knowledge that enhance their ability to process natural language and extract and integrate information from multiple databases and machine learning sources (Xu et al., 2016). We argue that in today's internet era, possession of such customized knowledge resources may be a new enabler of marketplace advantage, in that firms can accumulate, integrate, and share not only real-time information and data with various stakeholder groups but also possess an enhanced ability to act quickly to transform information and data into valuable pioneer innovative business models and strategies to enhance marketplace advantage (Nickerson & Zenger, 2004). This growing importance of building and using customized knowledge from big data to boost marketplace advantage has enabled many firms to build capabilities from a variety of big data analytics (e.g., social media analytics, supply chain analytics, search engine optimization, customer analytics, pay-per-click management) and techniques (e.g., split testing, data fusion and data integration, data mining, machine learning, natural language processing, statistics) to create innovative business models that are capable of disrupting existing sources of competitive advantage (Hämäläinen & Inkinen, 2019).

A case in point is how global business giants such as Facebook, Twitter, LinkedIn, Amazon, Netflix, Starbucks, General Electric, American Express, and Capital One are using BDAC to pioneer unique and difficult-to-imitate business models to generate advantages in their respective markets. Indeed, studies have shown that firms such as IBM (Chaudhary et al., 2016); Facebook, Boeing, General Electric, and Rolls-Royce (Jiang & Chai, 2016); Saarstahl AG, Staples, and Daimler FleetBoard (Schuritz & Satzger, 2016); and Amazon and Fitbit (Sorescu, 2017) are taking advantage of the golden opportunities created by big data analytics to build DBMs to enhance their marketplace advantages. With firms' increasing use of sophisticated big data analytics to generate real-time information and market insights in today's social media era, understanding the processes that connect

Fig. 1: Conceptual model



BDAC to superior market performance is important. To accomplish this task, we integrate insights from the KBV, contingency theory, and in-depth interviews with managers to develop a conceptual model (see Fig. 1) that proposes that the extent to which BDAC contributes to market performance is dependent on firms' ability to use BDACs to create DBMs to earn superior market performance under varying degrees of competitive intensity.

3. Hypotheses development

3.1 Big data analytics capability as an enabler of market performance

A firm's ability to develop a strong BDAC can contribute to superior market performance (Liu, 2014; Wamba et al., 2017). This argument is predicated on the assumption that BDAC enables firms to view the market using a different lens (Liu, 2014). This is especially important, because the amount of data now available to firms is ever increasing and provides an avenue for them to generate new insights from a wide array of data to understand the market, meet consumer needs, and exceed consumer expectations. Thus, the ability of firms to access high amounts of consumer data, access a variety of data types, and analyze data quickly can lead to enhanced marketplace advantages.

As mentioned previously, drawing on the tenets of the RBV and KBV, we conceptualize BDAC as a big data–driven knowledge resource that can help firms achieve superior competitive advantage. BDAC cannot be easily exchanged between firms and can be the differentiating factor between organizations that successfully introduce DBMs and those that do not. We can also define BDAC as the ability of an organization to acquire knowledge that facilitates its strategic decision making and results in positive market performance outcomes. This is in line with KBV tenets that argue that knowledge is an integral resource available to organizations and can be maximized to enhance competitive advantages (Grant, 1996).

The importance of BDAC is also reflected in its impact on market performance. Market performance depends on how successful an organization's products, markets, businesses, and future positioning are (Kandemir et al., 2006) and captures its ability to gain a competitive advantage over competitors (Mithas et al., 2011). An organization can be deemed to have positive and high market performance outcomes if its market share, market share growth, sales volume, sales growth, and product development are higher than those of its competitors (Sarkar et al., 2001; Vitari & Raguseo, 2020). BDAC plays a major role in enhancing the market performance outcomes of organizations by helping them recognize potential market opportunities (Côrte-Real et al., 2017), identify suitable and profitable market segments (Wamba et al. 2015), and advance product development (Xu et al., 2016).

Yasmin et al. (2020) find that BDAC has a positive relationship to market performance outcomes such as market share, sales growth, and product development. In addition, various studies have examined the relationship between BDAC and market performance outcomes, such as sales growth, market share, product development, sales volume, and market share growth (Akter et al., 2016). Furthermore, Mikalef et al. (2020) examine the relationship between BDAC and competitive performance among 202 chief information officers and IT managers in Norwegian firms. Their findings show that the defining and essential characteristics of BDAC (volume, variety, and velocity) play a significant role in building competitive advantages for firms.

BDAC aims to provide organizations with valuable insights to facilitate competitive advantages, performance outcomes, and customer value (Wamba et al., 2015). As such, BDAC provides firms with a unique ability to generate new insights into emerging new market opportunities early and ahead of competitors. This enables them to implement business strategies to address the needs of new groups of customers and the emerging needs of existing customers and, as a result, generate more sustainable new revenue streams ahead of the competition. Therefore, firms with greater BDAC should outperform their marketplace competitors in terms of market share, market share growth, sales volume, sales growth, and product development (Sarkar et al., 2001). Thus:

H1. BDAC is positively related to market performance.

3.2. Disruptive business model as an intervention force

Yovanof and Hazapis (2008) argue that though possessing BDAC may lead to superior market performance, the process through which this relationship occurs is not well understood. Although some studies argue that knowledge fusion (e.g., Xu et al., 2016) and process-oriented dynamic capabilities (Wamba et al., 2017) serve as intervening forces, research has paid little attention to explaining how DBMs may serve as a channel through which BDAC influences market performance. A DBM explains a firm's ability to use a novel business model (or technology) to "move upmarket without emulating the incumbents' high costs—that is, to follow a disruptive path" (Christensen et al., 2015, p. 53). It also explains a firm's ability to craft a business strategy with the goal of reshaping its industry or market (Yovanof & Hazapis, 2008), and the incentive to initiate DBM strategies is often triggered when firms are faced with major paradigm shifts caused by disruptive technologies.

As such, firms use DBMs to challenge dominant industry logics by creating "frame-breaking change within the industry or market" (Menon & Menon, 1997, p. 57), with the goal of altering customer perceptions and preferences, performance metrics, industry operations, existing business models, the basis for competition, organizational resources, and capabilities required for business success (Christensen et al., 2002; Dewald & Bowen, 2010). Karimi & Walter (2016, p. 343) argue that a DBM encapsulates a firm's ability to replace an "old business model with a new one for offering products or services not previously available" and may also entail use of innovations that incorporate disruptive technologies strategically combined to achieve maximum impact (Christensen & Raynor, 2003).

In drawing on KBV logic, we hypothesize that BDAC provides the required competences required to develop DBMs. Theoretically, the KBV suggests that firms focus on solving valuable problems that have the potential to generate valuable knowledge and competences (Fidel et al., 2015). To actualize this KBV logic in a big data era, firms may use big data generation mechanisms to quickly gain new insights into consumer perceptions and preferences, as well as competitor behaviors, to proactively pioneer DBMs to earn marketplace advantages (Weber & Rohracher, 2012). A case in point is how Netflix uses big data and matrices on the customer life cycle to pioneer a DBM of selecting and creating movie content for customers online (Xu et al., 2016). Thus, the positive effect of BDAC on market performance may be strengthened when it is channeled through DBM development. This argument finds support in previous studies that suggest that BDAC must be targeted to developing firm knowledge and competences (e.g., Mikalef et al., 2019b; Xu et al., 2016; Yasmin et al., 2020); a greater competence in developing and deploying DBMs can then serve as a source of competitive advantage that translates into market performance. Thus:

H2. A DBM positively mediates the relationship between BDAC and market performance.

3.3. Competitive intensity as a contingency factor

Previous studies (e.g., Mikalef et al., 2019b; Wilden & Gudergan, 2014) have argued that organizational capabilities, such as the ability to develop DBMs, are vital during times of high competition, competitive turbulence, and unpredictable market conditions. As such, the economic benefits of investing in BDAC and DBMs might not be realized in an environment characterized by low and predictable competitive behaviors. Under conditions of low and benign competition, firms are better off operating well-tested business models, and they rarely have any incentive to build capabilities to glean new insights from big data given the alternative cost of developing such a data-driven capability. Thus, ownership of BDAC per se might not confer a firm a new type of competitive advantage when competition is limited.

This argument is support by Mikalef et al.'s (2019a) suggestion that BDAC is more valuable under conditions of high market uncertainty. Thus, the need for BDAC is heightened in highly competitive environments, as in these environments BDAC affords a firm a unique advantage over its market rivals in terms of insights into current and emerging market dynamics (McAfee et al., 2012; Mikalef et al., 2019b). As such, when competition is cutthroat, when competitors are introducing new and innovative strategies on a regular basis, and when the market is difficult to predict because of intensive and dynamic competitive activities, firms have greater incentives to invest in cutting-edge BDACs to accurately predict future market trends to earn unique competitive advantages.

Under conditions of increased competitive intensity and dynamism, the incentive to use big data capabilities to drive DBMs becomes elevated. This is because the only way to survive in a heightened competitive landscape is perhaps to abandon existing earning competitive advantages and move to a new competitive territory by pioneering a big shift in the form of a new revenue generation model that takes the market by surprise. Similarly, Li & Liu (2014) argue that firms operating in highly competitive environments need to make constant modifications to their business strategies to satisfactorily address consumer needs, market changes, competitive pressures, and market demands. Therefore, under conditions of intense competition, firms with greater BDACs can generate new insights that enable them to introduce new business models to disrupt the existing competitive arrangement and create a new form of competitive advantage to earn superior market performance. We posit that BDAC's positive effect on market performance is strengthened when it is channeled through a DBM and under conditions of heightened competitive intensity. Thus:

H3. The positive effect of BDAC on market performance through DBMs is strengthened when competitive intensity increases.

4. Methodology

4.1 Empirical setting

Extant literature suggests that qualitative research should precede quantitative studies because of the ability to make valuable contributions to the development of research questions, refine conceptual models, and aid data collection and analysis (Malhotra et al., 2012). The exploratory nature of qualitative research makes it invaluable to quantitative research, which is principally confirmatory and deductive in nature (Trochim, 2006). Thus, we followed both qualitative and quantitative approaches to obtain empirical data to examine the relationships proposed herein.

The first stage of the data collection process involved conducting in-depth interviews with 15 small, medium-sized, and large organizations in the United Kingdom (UK). Typical informant titles were chief executive officer, managing director, marketing officer, and head of strategy. The number of employees ranged from five to 32,000, and the organizations traded in industries such as business software and IT, fast-moving consumer goods, pharmaceuticals, airline, and automotive. The interviews helped explicate the conceptual domain of DBMs and facilitated the development and refinement of the study's conceptual model. Each interview lasted for approximately 40 minutes to one hour, and the interviews were semi-structured to enable the informants to express their views and opinions within the boundaries of the study's research questions. We specifically asked the informants about the conceptual domain of DBMs, how they were implemented within the organization, the driving forces, and organizational outcomes obtained.

We then proceeded to the quantitative approach based on findings from the exploratory study to ensure empirical testing of the study's conceptual framework. We opted for a cross-sectional survey design, which is the most common method used in management, business, and marketing strategy studies because of its strength when using large sample sizes to make inferences (Jap & Anderson, 2004). Our research design assumes that BDAC is an objective reality that manifests in causal relationships and therefore can be measured empirically with reliable and valid data collection instruments (Straub et al., 2004). From this standpoint, this study addresses the research questions by capturing the objective and social reality of BDAC by means of survey-based data from senior executives of UK companies operating in manufacturing and service industries. Following precedent (e.g., Wamba et al., 2017), we began by assessing extant literature on the dimensionality of BDAC and its performance outcomes using KBV and contingency theory as theoretical lenses. Following the specification of the study's conceptual model and research hypotheses, we obtained primary data from key informants in each organization and analyzed these data using ordinary least squares (OLS) regressions, confirmatory factor analysis (CFA), and covariance-based structural equation modeling (CB-SEM) to validate the study's hypotheses.

We undertook this study in the UK for three reasons. First, the UK is an advanced economy with highly competitive industries that face external pressures from innovative practices. Second, the UK is among the top three most "promising countries in the world to introduce technological breakthroughs which will have a global impact" (KPMG, 2019, p. 3). This is especially important because DBMs generally comprise disruptive technologies and can facilitate greater application of BDACs. Third, the UK is among the top 10 most competitive countries in the world and the fourth most competitive economy in Europe (Schwab, 2018), providing a sound setting to examine the role of competition implications of investing in BDACs.

We first pretested the data collection instrument to ensure that the questionnaire was well understood by top managers. Twenty-five managers completed the questionnaire and provided feedback on the clarity of words and general comments on how the survey could be improved. To facilitate the response rate for the pretest, we offered a monetary incentive of donation of £1.00 per completed survey to Children's Aid to potential respondents. The results from the pretest enabled us to make some modifications and corrections. For example, we changed the reference for the items on performance from comparison with "major competitors" to comparison with "a major competitor," as organizations have different major competitors and performance outcomes can be higher or lower than those competitors. The changes helped remove any ambiguity of and confusion on the items related to performance. In addition, the pretest proposed some corrections to the questionnaire's flow, content, and structure.

We compiled data from Fame (Bureau van Dijk), a database of more than 11 million companies in the UK and Ireland that provides detailed information about firms' financials, industry descriptions, organizational profile, directors, managers, and up-to-date contact details. We checked whether the organizations were operational in the UK and were involved in either manufacturing or services. From this, we identified 7,585 firms and randomly selected 1,450 firms to administer the online questionnaire. As an incentive to complete the survey, respondents had the option to obtain a summary of the research findings. After two reminders via email and telephone calls, 458 surveys were completed, representing an initial response rate of 31.5%. Forty responses with excessive missing data were deemed unusable for data analysis.

In addition, 58 completed surveys failed to meet the competency requirements and attention checks included in the survey. The survey included three items to evaluate key informant competency and knowledgeability to answer the questions and the extent to which the answers reflected the firm's situation. The items were (1) "The questionnaire deals with issues I am very knowledgeable about," (2) "I am completely confident about my answers to the questions," and (3) "I am confident that my answers reflect the firm's situation." Only responses that scored above the scale midpoint were retained (M = 5.98, SD = 0.896). Consequently, we excluded an additional 98 defective responses from the data, which left 360 effective responses for analysis. The firms studied were manufacturing only (130 firms), service only (175 firms), and manufacturing and services (55 firms). They also operated in the domestic market (139 firms), international markets (166 firms), and both domestic and international markets (55 firms).

4.2. Method bias assessment

To address the measurement challenges commonly associated with single-informant data, we took various steps to minimize biases. Following the key informant method proposed by Phillips (1981), the study included questions about respondents' position in their organizations; their level of knowledge about organizational strategies, capabilities, and activities; and their confidence in answering the survey questions. The findings from the survey suggest that the respondents were competent with the issues raised in the survey.

In addition, the adoption of a cross-sectional design may lead to common method bias (CMB) in the data (Podsakoff et al., 2003) and undermine the ability to make causal inferences between independent and dependent variables (Rindfleisch et al., 2008). To address this problem, we undertook several procedural and post hoc remedies proposed by Podsakoff et al. (2003). One procedural remedy undertaken was the use of different response formats for the scales of predictor and criterion variables, because different common-scale anchors were used (Lindell & Whitney, 2001). Furthermore, we assured respondent anonymity in written form on the first page of the online survey and mixed up the variables (independent and dependent variables) to ensure that respondents could not easily guess the relationships under examination (Podsakoff et al., 2003). In addition, the survey asked respondents to answer questions retrospectively with a focus on actual behaviors rather than belief systems (Golden, 1992).

Moreover, we used two post hoc statistical approaches for detecting possible CMB. First, we conducted a CFA version of the Harman single-factor test using the EQS 6.2 software package. Specifically, we estimated a single superordinate construct reflected by all the study's manifest variables (Podsakoff et al., 2003). The model fit statistics showed poor fit to the data ($\chi^2(276)$ = 3221.933, normed fit index [NFI] = .478, non-normed fit index [NNFI] = .455, comparative fit index [CFI] = .498, standardized root mean square residual [SRMR] = .187, root mean square error of approximation [RMSEA] = .172), suggesting that CMB is not a major issue. The second approach was a marker-variable test (Lindell & Whitney 2001), which employed a theoretically unrelated measure of respondent negative affectivity as a marker variable measured with three items adapted from (Menguc et al., 2014). Thereafter, we used the average correlation for negative affectivity with the other model variables ($r = .03$) to compute the CMB-adjusted correlations between all the study variables using the equation $r_A = (r_u - r_M)/(1 - r_M)$, where r_A is the CMB-adjusted correlation, r_u is the original correlation, and r_M is the marker variable.

The results of this procedure revealed negligible differences between the original and CMB-adjusted correlations ($\Delta r < .05$), while the pattern of significant and non-significant relationships remained unchanged. Following Hultman et al. (2009), we extended the method further by estimating the study's structural model on the basis of the CMB-adjusted correlations and comparing the emerged path coefficients with those obtained from the unadjusted correlation matrix. This procedure yielded comparable results between the original and adjusted path coefficients ($\beta \leq .02$) without changes in significant and non-significant paths, thus enhancing confidence in the absence of severe CMB.

4.3. Measure development

We measured the study's constructs using existing tested and validated scales in the literature (see the Appendix). We measured the BDAC construct as a second-order construct (Johnson et al., 2017) comprising big data volume (four items), big data variety (four items), and big data velocity (four items). The questionnaire provided a definition of disruption and a specific example of a disruption (i.e., cellular phones), adapted from Govindarajan & Kopalle (2006), to ensure that no ambiguities were present. As such, we measured the construct "disruptive business model" with five items adapted from Zott and Amit (2007); this construct appeared after the definition and example of disruption in the questionnaire.

We measured competitive intensity with three items adapted from Jaworski & Kohli (1993). Next, we measured market performance with five items adapted from Sarkar et al. (2001) that evaluated firms' current performance relative to their major competitors. To estimate potential long-term performance outcomes, we added anticipated financial performance to the model as a control variable. This measure evaluated the expected performance of the firm in the next financial year relative to major competitors and was measured with four items adapted from Katsikeas et al. (2006) and Vorhies & Morgan (2005).

We also added various other control variables to the model, including industry (manufacturing/services; B2B/B2C), technological turbulence (Jaworski & Kohli, 1993), market turbulence (Guo et al., 2018), firm size measured as the number of full-time employees, firm age measured as the number of years the firm had been in operation (Assadinia et al., 2019), research and development (R&D) expenditure (previous year's R&D spend), and R&D intensity measured as the percentage of sales spent on R&D annually (Adomako et al., 2021).

5. Analyses and results

5.1. Measurement model validation

We evaluated the measurement properties of the multi-item constructs in the conceptual model using CFA. We used the elliptical reweighted least squares (ERLS) procedure as an estimation method because it is less constrained by normality assumptions and can provide unbiased parameter estimates for both multivariate normal and non-normal data (Sharma et al., 1989). We restricted the items to load on their pre-assigned factor and set the latent factors to correlate freely (Gerbing & Anderson, 1988). Overall, we estimated two CFA models for the first- and second-order factors, respectively, to maintain acceptable observation-to-parameter ratios. The CFA results reveal overall good fit indices based on Bagozzi & Yi's (2012) model fit criteria (first CFA model: $\chi^2_{(260)} = 494.324$, NFI = .958, NNFI = .977, CFI = .980, SRMR = .066, RMSEA = .050; second CFA model: $\chi^2_{(51)} = 87.966$, NFI = .986, NNFI = .992, CFI = .994, SRMR = .034, RMSEA = .045).

As Tables 1 and 2 show, Cronbach's alphas and composite reliability scores for each multi-item construct are greater than .600 (Bagozzi et al., 1991). In addition, discriminant validity is established for each construct as the square root of the lowest average variance extracted ($\sqrt{AVE} = .704$) is higher than any inter-construct correlation between each pair of constructs (Fornell & Larcker, 1981).

Table 1: CFA for first-order factors

Construct	β	t-value	AVE	CR	α	M	SD
Disruptive Business Models			.628	.837	.890	4.444	1.453
Our business model offers new combinations of products, services and information that are disruptive.	.798	15.695***				4.411	1.778
Our firm is the pioneer of the current business model in the industry.	.667	12.343***				4.792	1.698
This firm has continuously introduced disruptive innovations in its business model.	.895	18.604***				4.408	1.698
This firm's disruptive business model has been imitated by competitors.	.748	14.343***				4.422	1.752
This firm's business model depends on disruptive technologies.	.835	16.781***				4.189	1.792
Competitive Intensity			.602	.742	.817	4.827	1.365
In our industry, there are many "promotion wars" in our industry.	.821	15.129***				4.744	1.706
In our industry, price competition is a hallmark of our industry.	.740	13.350***				5.111	1.472
In our industry, one hears of a new competitive move almost every day.	.765	13.882***				4.625	1.601
Technological Turbulence			.613	.831	.886	5.454	1.097
In our industry, the technology is changing rapidly.	.834	16.644***				5.406	1.501
In our industry, technological changes provide big opportunities.	.788	15.357***				5.556	1.261
In our industry, a large number of new product ideas have been made possible through technological breakthroughs	.810	15.966***				5.411	1.353
In our industry, the diversity in technology has dramatically increased over the past 5 years.	.746	14.214***				5.536	1.246
In our industry, the leading firms have introduced state-of-the-art products (services) over the past 5 years.	.733	13.881***				5.361	1.232
Market Turbulence			.496	.627	.700	5.15	1.021
In our industry, customers' product preferences change quite a bit over time.	.744	12.934***				5.322	1.294
In our industry, it is difficult to product market and customer preference changes.	.512	8.397***				4.858	1.546
In our industry, it is very difficult to forecast where customer demand in our industry will be in 5 years.	.690	11.882***				5.236	1.116
Market Performance			.672	.855	.909	4.841	1.168
Market share	.823	16.546***				4.783	1.390
Market share growth	.855	17.534***				4.808	1.313
Sales volume	.853	17.472***				4.867	1.447
Sales growth	.846	17.263***				4.892	1.394
Product development	.716	13.637***				4.856	1.321
Anticipated Financial Performance			.774	.867	.931	5.035	.133
Profit margin	.847	17.393***				5.013	1.252
Return on assets	.880	18.419***				4.989	1.253
Return on investment	.914	19.571***				5.002	1.225
Profit growth	.876	18.290***				5.133	1.246

Model fit indices: $\chi^2_{(260)}$ = 494.324, NFI = .958, NNFI = .977, CFI = .980, SRMR = .066, RMSEA = .050 (90% CI: .043, .057). CR = composite reliability, α = Cronbach's alpha.
****p* < .001 (two-tailed).

Table 2: CFA for second-order factor

Construct	β	t-value	AVE	CR	α	M	SD
First-order factors of big data analytics capability (BDAC) dimensions							
Big Data Volume			.804	.879	.942	5.383	1.379
We analyze large amounts of data about our customers.	.899[a]					5.494	1.441
The quantity of data we explore about our customers is substantial.	.895	20.638***				5.364	1.467
We use a great deal of customer data.	.906	21.241***				5.444	1.481
We scrutinize large volumes of customer data.	.888	20.238***				5.230	1.587
Big Data Variety			.756	.860	.924	5.320	1.353
We use several different sources of customer data to gain customer insights.	.854[a]					5.403	1.391
We analyze many types of customer data.	.901	18.409***				5.378	1.503
We have many customer databases from which we can run data.	.836	16.081***				5.203	1.587
We examine customer data from a multitude of sources.	.886	17.857***				5.297	1.512
Big Data Velocity			.742	.856	.917	4.841	1.429
We analyze customer data as soon as we receive it.	.871[a]					4.908	1.550
The time period between when we get and analyze customer data is short.	.745	13.531***				4.883	1.547
We are lightning fast in exploring our customer data.	.917	19.572***				4.678	1.668
We analyze customer data very quickly.	.902	18.987***				4.894	1.618
Second-order factor							
BDAC			.779	.849	.954	5.181	1.247
Big data volume	.924	14.062***				5.383	1.379
Big data variety	.990	14.172***				5.320	1.353
Big data velocity	.710	10.327***				4.841	1.429

Model fit indices: $\chi^2_{(51)}$ = 87.966, NFI = .986, NNFI = .992, CFI = .994, SRMR = .034, RMSEA = .045 (90% CI: .028, .050). CR = composite reliability, α = Cronbach's alpha.
****p* < .001.
[a] Parameter is fixed to one.

5.2. Hypotheses testing

To ensure robust results, we used dual methods consisting of both CB-SEM and a series of OLS regressions to test the hypotheses. While research has established SEM as a useful approach to confirm theoretically established relationships (Akter et al., 2017), comparable results across multiple methods would enhance confidence in the stability of the results (Hultman et al., 2021). Following Ping (1995), we employed a multiplicative CB-SEM approach using the ERLS method to test the moderating effect hypotheses. We mean-centered constructs involved in the interactive analysis before calculating their loading and error variances using Ping's (1995) equations. For purposes of model

Table 3: Inter-construct correlations

	1	2	3	4	5	6	7	8	9	10	11	12	13
1. Firm size	1												
2. Firm age	.540**	1											
3. Industry 1‡	-.127*	-.049	1										
4. Industry 2#	-.100	-.046	.139**	1									
5. R&D expenditure	.376**	.310**	-.062	-.024	1								
6. R&D intensity	.020	-.227**	.040	-.047	-.125*	1							
7. Technological turbulence	.139**	-.080	-.029	.031	-.069	.408**	1						
8. Market turbulence	0.077	-.199**	.024	.016	-.144**	.294**	.498**	1					
9. Disruptive business models	.117*	-.138**	.095	.028	-.090	.390**	.393**	.232**	1				
10. Big data analytics capability	.187**	-.032	.029	-.073	.015	.338**	.548**	.295**	.470**	1			
11. Competitive intensity	.020	-.023	.070	-.099	-.142**	.171**	.339**	.462**	.266**	.298**	1		
12. Market performance	.184**	-.006	.047	.019	-.056	.309**	.297**	.112*	.463**	.389**	.099	1	
13. Anticipated financial performance	.148**	-.078	.020	.061	-.034	.345**	.326**	.100	.390**	.331**	.078	.763**	1

N = 360; $^{*}p < 0.05$; $^{**}p < 0.01$ (two-tailed).

‡ = Industry 1 = B2B versus B2C.

= Industry 2 = Manufacturing versus services.

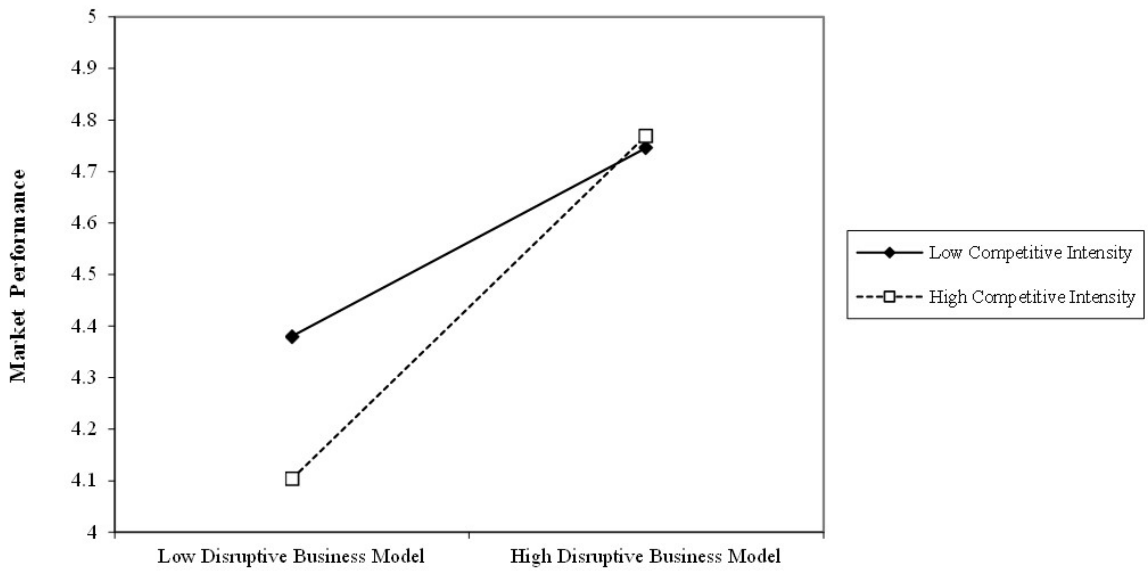
estimation, we assumed that the single-item constructs (i.e., firm size, firm age, industry, R&D intensity, and R&D expenditure) had an error of .10 (Anderson & Gerbing, 1988) and used the mean values for the three first-order constructs rather than full-information to model the second-order BDAC construct. The results in Table 3 indicate acceptable model fit ($\chi^2_{(528)}$ = 1186.916, NFI = .980, NNFI = .986, CFI = .988, SRMR = .098, RMSEA = .066) and show both the standardized parameter estimates and the directional significance levels for the CB-SEM and OLS models. As Table 3 shows highly similar patterns of significant and non-significant results, we can conclude that the results have a high degree of stability.

5.3. Mediation tests

H1 posits that BDAC is positively related to market performance. Both the CB-SEM and OLS results show that BDAC is positively associated with market performance ($p < 0.05$); thus, H1 is supported. H2, as an alternative argument to H1, proposes that BDAC contributes to market performance improvement through DBMs. To account for the mediating path, we conducted a mediation test using the SPSS macro syntax PROCESS, which allows use of bootstrapping procedures to estimate indirect effect paths (Hayes, 2009, 2017). Mediation is supported if the confidence interval (CI) does not include zero and is rejected if the CI includes zero values (Zhao et al., 2010). The results show support for H2, as the conditional indirect effect does not contain zero values (Preacher & Hayes, 2004; Yoshida et al., 2014). Therefore, the conditional indirect effect of BDAC on market performance through DBMs is positive and significant at –1SD below the mean (LLCI = .0213; ULCI = .1236), at the mean (LLCI = .0503; ULCI = .1592), and +1SD above the mean (LLCI = .0699; ULCI = .2076).

H3, which argues that the positive association between BDAC and market performance through DBMs is strengthened when competitive intensity increases, offers an alternative argument to H1 and H2. The SEM results ($\beta = .16$, $p < 0.001$), OLS results ($\beta = .07$, $p < 0.05$), and SPSS process results all show support for H3, as the index of moderated mediation does not contain zero values (β = .028; LLCI = .0072; ULCI =.0484). Thus, the indirect association between BDAC and market performance through DBMs is strengthened, as competitive intensity has larger values above the mean (see Fig. 2).

Fig. 2: Interaction effect of competitive intensity



5.4. Additional analyses

We carried out additional analyses to rule out reverse causality and address any endogeneity concerns. First, we rule out the contention that performance may cause firms to increase BDAC levels, generating a reverse-causality problem. The results show that performance does not significantly cause variation in BDAC (b = –.043, $p > .10$), and thus reverse causality is unlikely. Second, we used a three-stage least squares analysis (Poppo et al., 2016) to correct for any potential endogeneity with regard to the DBM. Multiple factors can influence an organization's decision to adopt a DBM, including the level of managerial commitment to innovation, competitive intensity, technological turbulence, market turbulence in the industry of operation, BDAC, the level of R&D intensity, R&D expenditure, firm size, firm age, and industry of operation.

Table 4: Standardized estimates of Stage 1 regression analysis

Independent Variables	DBMs (β)
Competitive intensity	.126*
Big data analytics capability	.278***
Industry 1 (B2B/B2C)	.072
Industry 2 (manufacturing/services)	.068
Technological turbulence	.068
Market turbulence	-.038
Management commitment to innovation	.208*
R&D intensity	.067
Firm size	.143*
Firm age	-.121*
R&D expenditure	-.049
Adjusted R^2	.325
Model F	16.731
df	359

****p* < 0.001; **p* < 0.05 (two-tailed)

Accordingly, in stage 1, we regressed the DBM on all these variables to obtain a predicted value of DBM. The results (Table 4) indicate that DBM is significantly related to competitive intensity (b = .126, $p < .05$), BDAC (b = .278, $p < .001$), management commitment to innovation (b = .208, $p < .05$), firm size (b = .143, $p < .05$), and firm age (b = –.121, $p < .05$). We then obtained a residual value that is free of influence from management commitment to innovation, competitive intensity, BDAC, technology turbulence, market turbulence, R&D intensity, R&D expenditure, firm size, firm age, and industry of operation. In stage 2, we used the DBM residual (DBMr) as an indicator and regressed performance (market performance and anticipated financial performance) with it along with the controls. In stage 3, we added the interaction terms to test the moderating effects. We mean-centered the variables before constructing the interaction terms to reduce the effects of multicollinearity (Ping, 1995). We assessed multicollinearity by checking for the size of the variance inflation factors associated with each predication. The highest value of these factors is 2.44, which is well below the threshold of 10. Table 5 reports the regression results of the controls-only model, as well as the second- and third-stage models. The DBMr measure displays the same pattern of results as the original DBM measure (Table 6), so endogeneity is not a major concern.

Table 5: Standardized estimates of endogeneity test

	Dependent Variables					
Independent variables	**Market performance**	**Anticipated financial performance**	**Market performance**	**Anticipated financial performance**	**Market performance**	**Anticipated financial performance**
Constant	2.935***	3.236***	2.621***	3.047***	2.635***	1.227***
Technological turbulence	.198**	.239***	.068	.158*	.071	.109*
Market turbulence	-.057	-.107	-.066	-.113*	-.046	-.063
R&D intensity	.222***	.249***	.187***	.228***	.186***	.094*
R&D expenditure	-.086	-.034	-.095	-.039	-.099	.029
Firm size	.208**	.182**	.171**	.159*	.168**	.036
Firm age	-.033	-.107	-.020	-.099	-.018	-.085*
Industry 1 (B2B)	.033	1.566	.055	.090	.059	.052
Industry 2 (MANUFAC)	.060	.509	.042	.014	.046	-.016
BDAC			.279***	.174**	.282***	-.026
DBM					.237***	-.011
Competitive intensity					-.034	-.001
DBMr × competitive intensity					.070†	.018
Market performance						.714***
Adjusted R^2	.149	.177	.199	.195	.256	.597
R^2 change	.168	.195	.051	.020	.061	.396
Highest VIF	1.665	1.665	1.885	1.885	1.895	1.901
Model F	8.853***	10.623***	10.925***	10.647***	11.289***	41.861***

N = 360; VIF = variance inflation factor; BDAC = Big Data Analytics Capability; DBM = Disruptive Business Models
† $p < 0.1$ * $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$ (two-tailed).

Table 6: Results

Independent Variables	**Dependent Variables**											
	DBMs				**Market performance**				**Anticipated financial performance**			
Control paths	**Coefficient (t-value)**		**SE**		**Coefficient (t-value)**		**SE**		**Coefficient (t-value)**		**SE**	
	OLS (r^2=.318)	SEM (r^2=.324)	OLS	SEM	OLS (r^2=.308)	SEM (r^2=.296)	OLS	SEM	OLS (r^2=.612)	SEM (r^2=.684)	OLS	SEM
Constant	-1.514 (-2.634)**	–	.584	–	4.014 (8.153)***	–	.490	–	1.082 (2.77)**	–	.393	–
Technological turbulence	.133 (1.653)	.083 (.758)	.085	.119	.047 (.694)	.112 (1.036)	.062	.097	.113 (2.401)**	.144 (1.796)	.055	.066
Market turbulence	.004 (.058)	.099 (.917)	.072	.154	-.028 (-.352)	.038 (.281)	.067	.160	-.073 (-1.422)	-.074 (-.733)	.052	.110
R&D intensity	-.693 (3.947)***	.293 (3.747)***	.173	.345	.331 (2.325)*	.222 (2.656)***	.142	.302	.260 (2.452)**	.124 (2.086)**	.110	.197
R&D expenditure	-.029 (-1.526)	-.067 (1.379)	.013	.016	-.020 (-1.572)	-.081 (-1.652)	.012	.013	.012 (.754)	.039 (1.080)	.011	.009
Firm size	.193 (2.625)**	.165 (3.230)**	.077	.058	.116 (1.966)*	.172 (3.302)***	.065	.049	0.030 (.841)	.021 (.536)	.042	.033
Firm age	-.374 (-2.273)*	-.194 (-2.955)**	.168	.222	.083 (.591)	.037 (.560)	.137	.186	-0.19 (-1.972)*	-.106 (-2.222)*	.102	.122
Industry 1 (B2B)	.164 (1.195)	.073 (1.127)	.139	.224	.098 (.772)	.018 (.274)	.114	.184	.125 (1.528)	.079 (1.653)	.085	.125
Industry 2 (MANUFAC)	.252 (1.800)	.113 (1.732)	.132	.221	.069 (.588)	.055 (.845)	.113	.182	-.033 (-.404)	-.026 (-.551)	.084	.123
BDAC	.278 (5.843)***	.288 (4.289)***	.061	.072	.172 (3.217)**	.162 (2.166)**	.051	.066	-.013 (-.484)	-.045 (-.834)	.041	.044
DBM					.252 (5.891)***	.288 (4.093)***	.042	.058	-.010 (-.180)	-.026 (-.551)	.039	.123
Competitive intensity					-.060 (-1.332)	-.041 (-.533)	.041	.062	-.001 (-.002)	-.011 (-.194)	.032	.042
DBM × competitive intensity					0.075 (3.162)**	.160 (3.218)***	.027	.021	.023 (1.098)	.038 (1.032)	.023	.014
Market performance									.675 (17.602)***	.737 (12.452)****	.042	.054

BDAC = Big Data Analytics Capability; DBMs = Disruptive Business Models

Model fit indices: $\chi^2(528)$ = 1186.9164, NFI = .980, NNFI = .986, CFI = .988, SRMR = .098, RMSEA = .066 (90% CI: .061, .070). n = 360.

$^{*}p < 0.05$; $^{**}p < 0.01$; $^{***}p < 0.001$ (two-tailed)

6. Discussion

6.1 Theoretical contributions

This study aimed to examine, theoretically and empirically, the mechanisms and contingencies that explain the extent to which BDAC contributes to market performance. The objective was to extend the long-established contention in the RBV that BDACs are associated with stronger competitive advantage and superior performance (e.g., Akter et al., 2016; Gunasekaran et al., 2017; Xu et al., 2016; Yasmin et al., 2020). However, despite the contributions of previous research in advancing knowledge on the performance implications of BDACs, theoretical articulation of the extent to which BDAC constitutes a knowledge-based resource and the competitive environment conditions under which BDAC contributes to market performance is limited (Ferraris et al., 2019; Vitari & Raguseo, 2020; Yasmin et al., 2020). This deficiency in the literature limits insight into how and when BDAC becomes an enabler of market performance. Thus, the findings from the present study help extend big data analytics and RBV literature in two ways.

First, in an extension to the RBV, we drew on KBV logic and empirical data to demonstrate that beyond the widely accepted direct association between BDAC and market performance, BDAC is also indirectly related to market performance by contributing to firms' ability to develop DBMs. From a theoretical standpoint, this finding of an indirect relationship between BDAC and market performance provides empirical support for the contention that firms can use insights from big data to introduce disruptive innovations and new combinations in their target markets to subsequently enhance market performance. As Xu et al. (2016) and Chaudhary et al. (2016) suggest, a higher level of BDACs per se might not contribute to competitive advantage; rather, from a KBV perspective, sustained competitive advantage may emerge when firms leverage their BDACs to develop data-driven customized knowledge and insights to proactively develop disruptive technologies and innovations to provide new combinations of solutions that market rivals find unrealistic to duplicate.

This study, therefore, extends the KBV to new contexts of analysis by evaluating the role of DBMs as a facilitating mechanism in the relationship between BDAC and market performance.

Second, an additional deficiency in BDAC literature is a lack of articulation on the conditions under which investment in big data analytics pays off. Research in this area seems to suggest that investing more in BDAC is a good thing because big data provide firms with useful economic benefits (Mills, 2019). However, some studies have raised doubt about whether big data are always a useful determinant of business success (Côrte-Real et al., 2017; Ross et al., 2013). For example, Ross et al. (2013) argue that investments in big data may not pay off because firms already have trouble managing existing data. To contribute to this scholarly discourse, we draw on contingency theory to argue that the economic benefits of investing in BDACs and DBMs might not be realized in an environment characterized by low and predictable competitive activities. We contend that the potency of BDAC as a determinant of market performance is strengthened when the intensity of competition among market players is cutthroat, competition to understand and address customer needs is stiff, and operating data to inform customer value creation decision making are paramount (McAfee et al., 2012; Mikalef et al., 2019b). In addition, the economic benefit for DBMs is predicated on finding a new basis for competing in the market; thus, the extent to which DBMs influence market performance may be dependent on the degree of competitive intensity. We find that under conditions of high competitive intensity, BDAC gives a firm a unique advantage over market rivals that informs development of new and innovative business models to drive improvement in market performance.

6.2 Managerial implications

This study provides useful insights into the processes managers can use to generate greater returns from investments in BDACs. While prior research (e.g., Gunasekaran et al., 2017) highlights the vital roles of organizational leaders and managers in building BDACs in organizations, we find that beyond the widely accepted direct benefits captured in extant literature (e.g., Akter et al., 2016;

Gunasekaran et al., 2017; Mikalef et al., 2020; Yasmin et al., 2020), managers can harness BDAC to develop DBMs to improve market performance. This finding of an indirect effect extends previous research showing that BDAC can help firms create innovative business models to generate improved marketplace advantages (Chaudhary et al., 2016; Ciampi et al., 2021). An important implication for big data managers is the importance of mobilizing resources within and beyond the organization to build BDACs to pioneer new business models to generate sustained sales growth. This recommendation is consistent with Ciampi et al.'s (2021) suggestion that organizations can facilitate development of innovative business models by investing in personnel expertise in big data analytics. It is also in line with previous research that suggests that organizational culture that prioritizes data-driven and evidence-based decision making can facilitate development of innovative business models (Mikalef et al., 2019a).

Finally, we find evidence to support our contention that BDAC and DBMs may not always be beneficial for firms under all competitive environment conditions, insofar as firms benefit more from BDACs when intensity of competitive activities is high. We argue that organizations that operate in highly competitive environments are more likely to enjoy greater performance benefits when possessing BDACs and DBMs. Greater competitive intensity requires greater innovative initiatives from competing industry actors, and under such conditions, a capability to develop DBMs may enable firms to reinvent their business models to outwit and leapfrog industry competitors (Voelpel et al., 2004).

6.3 Limitations and future research avenues

Some limitations associated with this study may be starting points for further research. First, while this study focused on volume, variety, and velocity components of BDAC, following prior research, it would be useful to examine the IT infrastructure, management, and human resources components of BDAC. Second, BDAC could have a combinative effect on other capabilities (e.g., human resources, marketing). For example, we suggest that firms need complementary human resources to gain a competitive advantage from BDAC, as having the right personnel with the right expertise to develop algorithms and to design and operate meaningful experiments may be necessary to generate insights from big data. Similarly, given that big data are more beneficial when used to generate insights into evolving customer needs and demands, rather than simply to understand historic big data, marketing capability might be a useful complementary capability. Third, future studies might draw on organizational information processing theory to examine how BDAC (an information-processing capacity) interacts with firm resilience (the ability to absorb and quickly recover from disruptions) to shape firm performance.

Methodologically, this study is limited by its reliance on cross-sectional data from a sample of UK firms. Future research might improve on this research design by obtaining longitudinal data from a wider range of firms from multiple geographic locations to improve generalizability of the findings. Such studies could also make stronger causal inferences about how BDAC contributes to performance. In addition, our use of perceptual indicators, instead of objective measures, of market performance is a weakness. Future research might address this weakness by obtaining objective data from firms either to use as a proxy for market performance and/or to cross-validate the perceptual data.

7. Conclusion

The findings from this study suggest an increased need for organizations to not only access different types of data but also develop capabilities to analyze and interpret predictive trends in data to inform strategic decision making. In line with KBV logic, the study shows that BDACs enable firms to develop DBMs to enhance market performance. Thus, DBMs play a pivotal role in gleaning insights from big data analytics to boost market performance outcomes, especially when competitive activities are increasingly cutthroat and unforgiving.

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