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Big data analytics effect on competitive performance: Mediating role of business model innovation

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Purpose: Big Data Analytics Capabilities (BDAC) facilitate the generation of critical insights required for competitive performance. This study evaluates the relationship between Big Data Analytics Capabilities and competitive performance and argues the effect is mediated by Business Model Innovation (BMI). This is assessed through the theoretical lens of Dynamic Capabilities, where Big Data Analytics Capabilities enabled sensing identification opportunities that initiate the mobilisation of resources to transform firms' business models, via BMI, to enhance performance.

Design/methodology/approach: A quantitative research approach using a survey was utilised. Data from 272 firms were collected.

Findings/results: The research model is evaluated by Partial Least Squares Structural Equation Modelling. The findings show that Big Data Analytics Capabilities have a direct and indirect influence on competitive performance, where BMI mediates the latter. The results enrich Dynamic Capabilities, Big Data Analytics Capabilities and BMI literature by demonstrating that Big Data Analytics Capabilities have a positive effect on BMI and subsequently competitive performance, to create value for firms and their stakeholders.

Practical implications: Practitioners need to invest in Big Data Analytics Capabilities to enhance the probability of success of their BMI endeavours.

Originality/value: Firstly, organisations' efforts in nurturing big data infrastructure, human resources, and data-driven cultures drive actions that enhance both operational and strategic execution, leading to enhanced performance. Secondly, the positive effect of Big Data Analytics Capabilities is carried through BMI to influence competitive performance positively, thus suggesting that the sensing enabled by Big Data Analytics Capabilities leads to transformational activities that drive performance.

Keywords: big data analytics capability; business model innovation; competitive performance; dynamic capabilities; transformational activities.

Introduction

As technology has advanced, the ability for firms to sense, seize and transform opportunities and threats in dynamic environments has evolved, with big data analytics recognised as a key capability (Fosso Wamba et al., 2017; Grover et al., 2018; Mikalef et al., 2020). Big Data Analytics Capability (BDAC) represents firms' distinctive capabilities to deploy technology and human resources to generate value from big data, which is broadly characterised by the volume, variety and velocity at which it is generated (Fosso Wamba et al., 2015). This leads to the creation of insights that are disseminated across the business by placing equal focus on acquiring and developing technical assets, human competences and building a data-driven organisational culture (Gupta & George, 2016; Mikalef et al., 2019). Through this process, BDAC enables broad and in-depth understanding of market, customer and competitor trends (Fosso Wamba, Queiroz et al., 2020). These insights support firms to gain awareness of opportunities and threats in the market and, when required, transform their business models to be more competitive (Ciampi et al., 2021).

Business models represent capabilities by firms to conduct business in markets, which is embedded in their architecture, content and governance processes (Caputo et al., 2021; Geissdoerfer et al., 2018; Teece, 2010; Zott & Amit, 2010). Therefore business models enable firms to extract value from sales transactions and business opportunities through value creation, value proposition and value capture strategies (Clauss, 2017). Invariably when significant changes occur in the environment, such as technological advancements, changes in customer demands or heightened competitive intensity, it initiates the transformation of business models (Foss & Saebi, 2017; Teece, 2007, 2018). This process is referred to as Business Model Innovation (BMI), as an expansion of the business model concept (Zhang et al., 2021), which is defined as the purposeful organisational change process, where novel and non-trivial modifications are made to key components of business logic (Foss & Saebi, 2017; Zhang et al., 2021). Examples of BMI include investing in new technology, launching strategic partnerships, entering lucrative market and customer segments or designing novel revenue or cost models to increase profitability (Clauss, 2017; Foss & Saebi, 2017).

When comparing BMI to product, service and process innovation, it is a higher risk endeavour (Latifi et al., 2021). While it has the potential to generate significant new growth to surpass rivals (Zhang et al., 2021), and reshape industries (Mishra et al., 2019; Sorescu, 2017), it does not automatically lead to positive outcomes (Clauss et al., 2021; Kumar et al., 2018; Latifi et al., 2021). In fact, Christensen et al. (2016) found that 60% of BMI initiatives did not lead to expected outcomes based on the sample of organisations they assessed. As a result, it is important for firms to develop capabilities to enhance the probability of success of BMI to maintain their evolutionary fitness.

Yet, despite the important role that BDAC has in guiding operational and strategic decisions that lead to positive firm outcomes (Akter et al., 2016; Fosso Wamba et al., 2017; Fosso Wamba, Queiroz et al., 2020; Müller et al., 2018), research regarding BDAC's influence on BMI is nascent with only one empirical study existing (Ciampi et al., 2021). While Ciampi et al. (2021) confirmed that BDAC does have a positive and direct effect on BMI, they did not explore BMI's mediating role in the BDAC-competitive performance relationship. Thus, this study aims to address this knowledge gap and in doing so responds to Sorescu's (2017) call for further research to understand the effect of big data analytics on BMI and performance.

To address this gap, this study built upon Dynamic Capability (DC) theory, which suggests that firms should continuously evolve their capabilities, which leads to sensing, seizing and transformation activities, to enhance competitive advantage (Eisenhardt & Martin, 2000; Teece, 2007; Teece et al., 1997). This provides a relevant theoretical lens through which to study BDAC and BMI, as BDAC enables organisational sensing (Fosso Wamba, Queiroz et al., 2020), while BMI enables firm-level transformational activities (Foss & Saebi, 2017; Teece, 2018), both of which have an influence on performance (Akter et al., 2016; Bhatti et al., 2021; Clauss et al., 2021; Fosso Wamba et al., 2017; Fosso Wamba, Queiroz et al., 2020; Kumar et al., 2018; Latifi et al., 2021; Wei et al., 2017; Zhang et al., 2021). Specifically, the authors first investigated BDAC's direct influence on competitive performance. Next, they extended this knowledge by investigating BDAC's indirect influence on competitive performance, mediated by BMI.

The result of the study has both academic and practical implications as it confirms that BDAC does, indeed, have direct and indirect influence on competitive performance, with the indirect influence mediated by BMI. While the former confirms what is known in literature, the latter extends DC into the intersection of BDAC, and BMI literature by demonstrating that the sensing capability enabled by BDAC has a positive influence on the seizing and transformation activities of BMI, thereby contributing to enhanced performance. The study also provides guidance to practitioners to develop BDAC and facilitate its alignment to capabilities-based strategy to strengthen BMI success and competitive performance (Mikalef et al., 2020; Vidgen et al., 2017).

The article is arranged in the following manner. Section 'Literature review' reviews and summarises what is known in academia to establish the research hypothesis. Section 'Research methodology' discusses the research methodology, specifically data collection, measurement scales, statistical techniques, sample size and the measurement model. This is followed by section 'Empirical results' where the results are discussed in relation to the descriptive statistics and structural model results. Section 'Discussion' reflects on the results in terms of academic and practical implications, limitations and opportunities for future research. Finally, the article concludes with section 'Conclusion' where the primary contributions of the research are summarised.

Literature review

Dynamic capabilities theory

Dynamic Capability theory evolved from the resource-based view (RBV) theory (Lin & Wu, 2014; Peteraf et al., 2013; Schilke et al., 2018), which suggested prior to DC that firms can gain a sustained competitive advantage based on the value, rarity, inimitability and non-substitutability of their resources and capabilities (Barney, 1991). Subsequently, DC diverged from the static capabilities-based RBV theory by arguing that competitive advantage is not an equilibrium state, but rather the result of firms' continuous efforts to build, integrate and reconfigure their resources and capabilities to respond to changes in the market (Teece et al., 1997). Although it is worth mentioning that Eisenhardt and Martin (2000) believe that DC can only provide a competitive advantage to a limited extent in high velocity contexts. Consistent with extant DC literature (Mousavi et al, 2018; Peteraf et. al., 2013; Schilke et al., 2018; Shepherd et al., 2019), this study is aligned to the approach to dynamic capabilities as espoused by Teece et al. (1997).

Resources refer to the assets a firm has to create and implement strategies (Barney, 1991), while capabilities refer to the effective recombination of resources to achieve business objectives (Dutta et al., 2005). Thus, DCs are defined as 'higher-level competences that determine the firm's ability to integrate, build, and reconfigure internal and external resources and/or competences to address, and possibly shape, rapidly changing business environments' (Teece, 2012, p. 1395). This enables organisations to direct their efforts towards higher pay-off endeavours (Teece, 2014).

Dynamic Capability can be further segmented into base and higher-order tiers (Teece, 2007, 2018). Base DCs facilitate the recombination and adjustment of resources and capabilities and the creation of new ones (Teece, 2007), which results in innovation, market expansion and astute managerial decision-making (Teece, 2018; Winter, 2003). Higher-order DCs, which are based on repeated routinisation (Helfat & Peteraf, 2003, 2015; Mousavi et al., 2018) build upon this to inform and guide business strategy and operations at a macro level for long-term sustainability (Schoemaker et al., 2018; Teece, 2018). This includes sensing future opportunities and designing business models and organisational structures based on the optimum configuration for its existing and future paths (Teece, 2018).

The process by which DCs enable change in organisations is summarised by its disaggregation into sensing, seizing and transforming processes (Teece, 2007). Prior to the introduction of DC, Day (1994) suggested that sensing refers to the ability of a firm to gain awareness of its market environment and respond to this new knowledge by taking action. Dynamic Capabilities support this process by routinising the scanning, searching, exploring, learning and interpreting processes that transform information into knowledge that can be acted upon to create new opportunities (Helfat & Peteraf, 2003; Teece, 2007). Sensing also enables firms to improve their capability to predict future sources of competitiveness by assessing the value and rarity of capabilities and resources (Matysiak et al., 2018). Seizing refers to the ability to mobilise resources to capture value from opportunities (Teece, 2014). This is done by leveraging a firm's products, services and processes, and where required, investing in the development and commercialisation of opportunities (Teece, 2007). Finally, transforming refers to firms' capacities to enhance, combine and reconfigure the organisations' tangible and intangible resources and capabilities to remain competitive (Teece, 2012). This is required when a major change occurs in the market and technological environment.

According to the DC theory, successful sensing, seizing and transforming activities allow firms to sustain their competitive advantage by continuously reconfiguring and evolving their resources and capabilities to deviate from unfavourable, towards favourable, path dependencies and remain competitive in an ever-evolving environment of business (Matysiak et al., 2018; Teece, 2007).

Big data analytics capability

In the last two decades, digital networks have connected more people, devices and sensors, which has led to a notable increase in the scale and speed of data generation, and in turn to the big data phenomenon (Grover et al., 2018). Big data is defined according to its size (volume), the speed at which it is generated (velocity), its diverse formats (variety), its bias and abnormality (veracity) and the value it delivers (value) (Fosso Wamba et al., 2015), referred to as the 5V model.

As big data has become more prevalent, firms have increased efforts to develop capabilities to derive value from it, which is referred to as BDAC (Mikalef et al., 2020). Big Data Analytics Capability is defined as organisations' inimitable and distinctive capabilities to deploy technology and human resources to collect, store, process and analyse big data (Fosso Wamba et al., 2017; Gupta & George; 2016; Mikalef et al., 2019). The capability places equal focus on technical assets, human competences and organisational culture to generate and disseminate insights effectively across the business (Fosso Wamba et al., 2017; Gupta & George, 2016; Mikalef et al., 2019).

Technical assets, referred to as tangible resources, comprise the data, infrastructure and financial resources required to fund big data projects (Gupta & George, 2016; Mikalef et al., 2020). Human capabilities comprise the human skills related to technical, managerial and relational capabilities of big data employees (Gupta & George, 2016; Mikalef et al., 2020). Finally, organisational culture refers to the intangible resources related to embracing data-driven insights and organisational learning (Gupta & George, 2016; Mikalef et al., 2019).

Through this process of managing diverse internal and external information, BDAC enables organisational sensing, which supports both operational and strategic decisions regarding the effectiveness and efficiency of firms (Fosso Wamba et al., 2017; Fosso Wamba, Queiroz et al., 2020). From an operational perspective, BDAC supports firms' efforts in securing future revenue from existing customers and reducing operating costs by enhancing the efficiency of production operations (Fosso Wamba, Dubey et al., 2020; Grover et al., 2018; Holmlund et al., 2020; Rialti et al., 2019).

To enable the former, BDAC supports customer experience and customer satisfaction efforts by generating insights related to customers' behaviour, attitudes and preferences by integrating data from social, digital and physical interactions (Grover et al., 2018; Holmlund et al., 2020). These insights can be used to enhance user touch points, identify product optimisation opportunities and influence the personalisation of purchase recommendations and discounts (Grover et al., 2018). When customer experience is enhanced, it improves firms' business relationships with their customers, driving customer satisfaction and retention (Grover et al., 2018; Holmlund et al., 2020; Sorescu, 2017).

From a production perspective, efficiency can be achieved through the collection of historical data using complex BDAC infrastructure, which allows processes to be fine-tuned and fast-response mechanisms to be developed to address issues proactively (Grover et al., 2018; Rialti et al., 2019). This enhances the agility and adaptability of supply chains, as less time is spent on breakdowns, which contributes to optimised execution and competitive performance (Fosso Wamba, Dubey et al., 2020; Grover et al., 2018).

From a strategic perspective, BDAC facilitates the generation of insights that influence the value creation, value proposition and value capture strategies of firms (Ciampi et al., 2021). This is enabled by continual scanning, analysing and interpreting market, customer and competitor trends that highlight opportunities for growth (Grover et al., 2018). In fact, having access to information enables firms to gain a first-mover advantage, by reacting quickly to high potential opportunities (Côrte-Real et al., 2017). Furthermore, Mikalef et al. (2019) found that BDAC not only enables the development of incremental innovations based on existing products and services but also radical ones that result in new value propositions. Lehrer et al. (2018) had similar findings and found that it also enhances the likelihood of success of innovations.

Business model innovation

An organisation's business model is the architecture that summarises its structure, content and governance processes used to extract value from transactions and business opportunities (Teece, 2010; Zott & Amit, 2010). When major changes occur in the environment, such as shifts in technological innovation, customer demand and competitor intensity, it can result in transformational activities to remain competitive (Bhatti et al., 2021; Foss & Saebi, 2017; Zhang et al., 2021). This process is referred to as BMI, which is defined as the deliberate, novel and non-trivial modification, adaption or innovation of key components of the business logic (Foss & Saebi, 2017; Zhang et al., 2021). This leads firms to rally efforts towards reconfiguring and recombining their resources, assets and structures, and in some cases, creating entirely new break-out structures to maintain competitiveness (Teece, 2007).

Clauss (2017) suggested that BMI can lead to competitive advantage by optimising firms' value creation, value propositions and value capture strategies. New value creation opportunities can be achieved by enhancing the firms' resources and capabilities by launching new technology or infrastructure or creating new strategic partnerships (Clauss, 2017; Teece, 2010). Value propositions are related to firms' products and services that support targeting of new customer segments with higher willingness to pay or market expansion into more lucrative segments (Clauss, 2017; Teece, 2010). Finally, value creation refers to the strategies taken by firms to generate revenue and profit from business activities, which can be enhanced by launching new revenue models or adopting flexible processes that lead to cost reduction (Clauss, 2017; Foss & Saebi, 2017). In all instances, the goal of BMI is to transform key components of the firm's business logic to remain competitive in the long term (Foss & Saebi, 2017; Teece, 2018; Zhang et al., 2021).

Competitive performance

In his seminal research, Porter (1985) suggested that competitive advantage is core to firms' performance in competitive markets and can be achieved through two competitive strategies. These strategies, namely, cost leadership and differentiation, consider the gap between the price charged for a product or service and its perceived value from customers relative to competitor strategies (Porter, 1985).

In the years following, RBV theory suggested an alternative approach to achieving competitive advantage, which was less related to the competitive strategy and more focused on firms' abilities to attain rare and valuable resources (Barney, 1991). Resource-based view theory argued that when these resources were not evenly distributed among competitors, firms could sustain a competitive advantage. Dynamic Capability theory shared the focus of RBV theory, based on high-quality resources and capabilities, but argued that competitive advantage was achieved through their continual reconfiguration to more complex, inimitable and distinctive states to remain competitive (Eisenhardt & Martin, 2000; Teece et al., 1997). The emergence of generative AI technologies made possible through new business models that make such technologies freely available to customers and competitors, while giving their developers a competitive advantage, further emphasises that rare and non-inimitable resources are not a sustainable source of competitive advantage (Budhwar et al., 2023). Unsurprisingly, the DC perspective has been endemic in management literature in the last three decades and has formed the theoretical foundation of this research (Eisenhardt & Martin, 2000; Teece 2007, 2010, 2012, 2014, 2018; Teece et al., 1997).

To measure competitive advantage, this research assessed competitive performance indicators related to financial and market performance (Behl et al., 2022). These indicators are commonly used in academia to assess firms' performance relative to competitors and were, thus, deemed relevant for this study (Akter et al., 2016; Behl et al., 2022; Fosso Wamba et al., 2017).

Hypotheses

The effect of big data analytics capability on competitive performance

The insights generated by BDAC provide firms with the knowledge required to understand the market, strengthen their customer relationships, identify opportunities to grow and enhance internal process efficiencies (Fosso Wamba, Dubey et al., 2020; Grover et al., 2018; Holmlund et al., 2020; Lehrer et al., 2018; Rialti et al., 2019; Sorescu, 2017). Recent empirical research has demonstrated that BDAC has a positive effect on competitive performance, moderated by either strategy alignment (Akter et al., 2016) or entrepreneurial orientation (Fosso Wamba et al., 2017). This was supported in later research where the effect of BDAC on productivity (Müller et al., 2018) and financial and market performance indicators (Fosso Wamba, Queiroz et al., 2020) was demonstrated. However, despite this progress in empirical research, some scholars argued that research on the topic is still rudimentary, and that many organisations still face tensions in realising performance gains from BDAC investments (Günther et al., 2017; Mikalef et al., 2020). Considering the developing nature of the research stream, the first hypothesis aimed to confirm results from prior empirical literature in this regard:

> **H1.** Big Data Analytics Capability has a positive and direct effect on competitive performance.

The mediating role of business model innovation

According to Fosso Wamba et al. (2017) and Mikalef et al. (2019), BDAC-enabled sensing fosters knowledge access and sharing to support both routine decisions required for the operational efficiency and radical new decisions that influence firms' strategies and value propositions. Major changes in firms' structures and cultures happen periodically to enable firms to strengthen their competitive performance in the long term (Teece, 2018), as summarised by BMI.

The effect of BDAC on BMI was recently empirically validated in literature (Ciampi et al., 2021); however, far more examples exist in practice where BDAC has influenced the creation and innovation of business models. Born-digital companies such as Amazon and Google were the first to pioneer the use of big data analytics to launch entirely new business models, while Netflix, Uber and Airbnb disrupted traditional industries by leveraging big data analytics to deliver value in more convenient and accessible ways (Mishra et al., 2019; Sorescu, 2017). For example, Amazon and Netflix have leveraged BDAC to innovate the way value is captured from customers by dynamically personalising recommendations based on previous search behaviour (Günther et al., 2017; Sorescu, 2017). Furthermore, manufacturing company Zara has leveraged BDAC to integrate store purchase with external fashion trends continually, thus ensuring that an ever-changing assortment of fashionable items is available for purchase while inventory remains low (Sorescu, 2017). This allows Zara to effectively deliver its fast fashion value proposition (Sorescu, 2017). Based on the limited empirical research available to validate this phenomenon seen in practice, the next hypothesis aimed to extend knowledge in this area:

> **H2a.** Big Data Analytics Capability has a positive and direct effect on Business Model Innovation.

Business Model Innovation is a process of renewal, where firms evaluate and strategically reconfigure business model components to align to customer demands and market contexts to remain competitive (Zhang et al., 2021). Thus, BMI is expected to have a positive influence on performance through the reconfiguring of external and internal resources to take advantage of opportunities (Zhang et al., 2021). However, existing empirical assessment of the effect of BMI on competitive performance has led to diverse results. In some cases, the results have demonstrated a moderate to strong relationship (Zhang et al., 2021), while others have found weak relationships (Bhatti et al., 2021; Wei et al., 2017) or no significant relationships at all (Kumar et al., 2018; Latifi et al., 2021). This may be driven by the complexity of BMI execution, where changes in one area have an effect on others or because of the lag time between BMI implementation and performance gains (Foss & Saebi, 2017). As research in this area is still developing, the next hypothesis sought to contribute to knowledge in this regard:

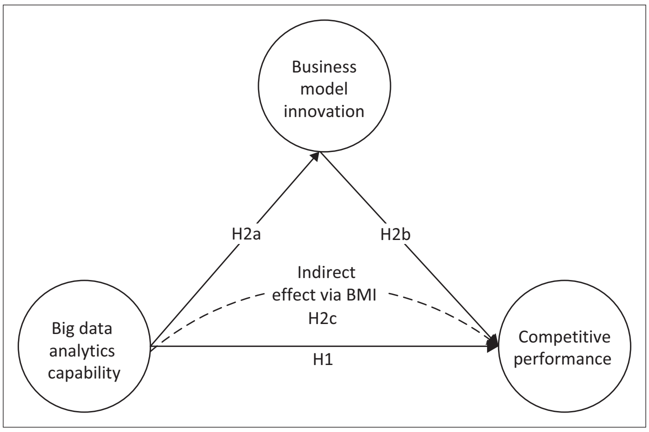
> **H2b.** Business Model Innovation in dynamic contexts has a positive and direct effect on competitive performance.

In the final hypothesis, the authors propose that BDAC has an indirect effect on competitive performance, mediated by BMI. This is driven by the understanding that BDAC-enabled sensing enables firms to gain awareness of changes in the market, customer and competitive environments (Fosso Wamba, Queiroz et al., 2020). This can spur organisations to evaluate their business models and undergo transformation activities (Ciampi et al., 2021; Teece, 2018).

When successful, BMI in turn can enhance organisations' competitive performance because of better alignment with the market context and customer demands (Bhatti et al., 2021; Foss & Saebi, 2017; Zhang et al., 2021). This process mirrors the sensing, seizing and transforming process summarised by DC theory, which occurs periodically in response to major changes in the environment (Teece, 2007, 2018). Consequently, the authors posit the final hypothesis:

> **H2c.** Big Data Analytics Capability has a positive and indirect effect on competitive performance mediated by Business Model Innovation.

Subsequently, the authors summarise the conceptual model in Figure 1 to indicate that a firm's BDAC has a positive and direct effect on a firm's ability to have a competitive advantage (H1); similarly, the authors hypothesised that BDAC has a positive and direct positive relationship with



H, hypothesis; BMI, business model innovation.

FIGURE 1: Conceptual model for research.

BMI (H2a), with BMI in dynamic contexts has a direct and positive relationship on a firm's competitive advantage (H2b). Finally, the authors argued that BDAC has a positive and direct effect on a firm's competitive performance and is mediated by BMI (H2c).

Methodology

Data collection

To test the hypotheses, data were collected using a cross-sectional approach via an online questionnaire. The units of analysis were organisations that use data and analytics as part of their business processes, while the sampling unit was employees that either work in data and analytics departments or interact regularly with them. Regular interaction was required for respondents that do not work in data and analytics departments because of the focus on big data analytics questions within the survey that necessitated an understanding of the topic. Respondents with seniority of manager level and above were targeted as these respondents have a broad understanding of strategic decisions and business processes to assess the effect of advanced analytics and BMI on performance (Ciampi et al., 2021). No restrictions were placed on the country of residence, because of the pervasive nature of BDAC and the ubiquitous adoption of big data analytics technologies, tools and infrastructure supported globally by the growth in mobile phones, social media, cloud-enabled platforms and the Internet of Things (Grover et al., 2018). This resulted in responses from 42 countries, which allowed greater generalisability of the results (Ciampi et al., 2021).

The questionnaire was administered online from August to September 2022. A total of 277 surveys were attained. During data screening, five respondents were eliminated as the variability in their responses did not exceed the threshold of 0.25 standard deviation (Collier, 2020). All responses exceeded the minimum completion time threshold of two seconds per question (Huang et al., 2012). No missing values were present in the questionnaire because of limitations imposed in the questionnaire design. Thus, the final sample size comprised 272 valid responses.

Measures

Three constructs were measured as part of the conceptual model by using previously validated scales from academic literature (see Table 1). Big Data Analytics Capability was measured as a third-order formative construct consisting of 25 indicators based on the validated scale of Mikalef et al. (2019). Big Data Analytics Capability comprised three second-order formative constructs, namely, tangible resources, human skills and intangible resources, with 10, 8 and 7 indicators, respectively. Tangible resources comprised three first-order formative constructs including data, technology and basic resources with three, five and two indicators, respectively. Human skills comprised two first-order reflective constructs including managerial skills and technical skills both with four indicators. Finally, intangible resources comprised two first-order reflective constructs including data-driven culture and organisational learning with three and four indicators.

Business Model Innovation was assessed as a first-order reflective construct with indicators evaluating organisations' foci on new or existing activities related to the nine elements of the business model canvas (Bhatti et al., 2021; Osterwalder & Pigneur, 2010). These included key resources, activities, partnerships, channels, customer relationships, customer segments, value propositions, cost structure and revenue streams (Bhatti et al., 2021; Osterwalder & Pigneur, 2010).

The final construct, competitive performance, was also a first-order reflective construct comprising five financial and market indicators. These included revenue, profit, operating costs, market share and service and product quality (Behl et al., 2022). Respondents assessed the indicators of the constructs on a seven-point Likert scale. Screening and demographic questions were assessed using categorical responses.

Statistical techniques

The analysis was conducted using Partial Least Squares Structural Equation Modelling (PLS-SEM) using SmartPLS 3.0 software. The same approach was taken by Ciampi et al. (2021), who assessed the relationship of BDAC with BMI and Akter et al. (2016), Mikalef et al. (2020) and Fosso Wamba et al. (2017), who assessed the relationship of BDAC with competitive performance.

Partial Least Squares Structural Equation Modelling was selected as it is recommended for research where structural models contain both formative and reflective constructs and where latent variable scores are required to develop higher-order constructs (Hair et al., 2011). The assessment of the hypotheses required evaluating the significance of the total, direct and indirect path coefficients (Hair et al., 2017). This was assessed using a bootstrapping technique with 5000 random samples with a 95% confidence interval.

Common method bias

To mitigate the effects of common method bias, the confidentiality and privacy of respondents were protected by using an anonymous survey (Podsakoff et al., 2003). Furthermore, indicator vagueness was avoided by using validated scales from literature, dividing the questionnaire into separate parts for each of the constructs and conducting a pilot on the questionnaire before administering it to the research respondents (Ciampi et al., 2021).

The pilot was conducted in two phases. The initial phase included five respondents where feedback was received that the questionnaire length, which exceeded 80 questions, was too long. This resulted in shortening the questionnaire by shifting to more succinct scales for BDAC and BMI (Bhatti et al., 2021; Mikalef et al., 2019). In the second pilot,

TABLE 1: Constructs, codes, and indicators used in the study.

Constructs measured	Factor loadings	VIF
Big Data Analytics Capability (BDAC; Mikalef et al., 2019)	-	-
Tangible resources [Tan]	-	-
Data [D]	-	-
[D1] We have access to very large, unstructured, or fast-moving data for analysis	†	1.28
[D2] We integrate data from multiple sources into a data warehouse for easy access	†	1.56
[D3] We integrate external data with internal to facilitate analysis of business environment	†	1.49
Basic resources [BR]	-	-
[BR1] Our 'big data analytics' projects are adequately funded	†	2.33
[BR2] Our 'big data analytics' projects are given enough time to achieve their objectives	†	2.33
Technology [T]	-	-
[T1] We have explored or adopted parallel computing approaches (e.g. Hadoop) to big data processing	†	1.75
[T2] We have explored or adopted different data visualisation tools	†	1.25
[T3] We have explored or adopted new forms of databases such as Not Only SQL(NoSQL)	†	1.60
[T4] We have explored or adopted cloud-based services for processing data and performing analytics	†	1.42
[T5] We have explored or adopted open-source software for big data analytics	†	1.55
Human skills [HS]	-	-
Managerial skills [MS]	-	-
[MS1] Our 'big data analytics' managers are able to understand the business need of other functional managers, suppliers, and customers to determine opportunities that big data might bring to our business	0.93	4.04
[MS2] Our 'big data analytics' managers are able to coordinate big data-related activities in ways that support other functional managers, suppliers, and customers	0.91	3.45
[MS3] Our 'big data analytics' managers are able to understand and evaluate the output extracted from big data	0.89	3.01
[MS4] Our 'big data analytics' managers are able to understand where to apply big data	0.89	3.10
Technical skills [TS]	-	-
[TS1] Our 'big data analytics' staff has the right skills to accomplish their jobs successfully	0.88	3.58
[TS2] Our 'big data analytics' staff is well trained	0.90	3.90
[TS3] We provide big data analytics training to our own employees	0.80	1.79
[TS4] Our 'big data analytics' staff has suitable education to fulfil their jobs	0.85	2.17
Intangible resources [INT]	-	-
Data-driven culture [DD]	-	-
[DD1] We base our decisions on data rather than on instinct	0.89	2.16
[DD2] We are willing to override our own intuition when data contradict our viewpoints	0.88	2.14
[DD3] We continuously coach our employees to make decisions based on data	0.83	1.68
Organisational learning [OL]	-	-
[OL1] We are able to acquire new and relevant knowledge	0.84	2.15
[OL2] We have made concerted efforts for the exploitation of existing competencies and exploration of new knowledge	0.87	2.40
[OL3] We are able to assimilate relevant knowledge	0.89	2.96
[OL4] We are able to apply relevant knowledge	0.88	2.81
Business model innovation (BMI; Bhatti et al., 2021)		
[BMI1] Focus is on developing radically NEW products and/or services	0.78	2.25
[BMI2] Focus is on identifying and serving entirely NEW market and customer segments	0.78	2.23
[BMI3] Focus is on developing and/or acquiring NEW resources and competences (technology, people, IT systems, etc.)	0.75	2.04
[BMI4] Focus is on developing NEW core processes and activities (design, logistics, marketing, etc.)	0.70	1.72
[BMI5] Focus is on establishing relationships with NEW strategic business partners (suppliers, distributers, end user, etc.)	0.72	1.85
[BMI6] Focus is on developing NEW tools for building customer relationships (personal service, memberships, bonus systems, etc.)	0.68	1.75
[BMI7] Focus is on selling products and/or services through NEW channels (own stores, partner stores, online, etc.)	0.70	1.86
[BMI8] Focus is on making MAJOR changes in the combination of costs incurred when operating the company	0.70	1.78
[BMI9] We have developed NEW ways of generating revenue (products, services, leasing, sponsorships etc.)	0.69	1.69
Competitive performance (CP; Behl et al., 2022)		
[CP1] Compared with our competitors, we have higher profit growth rate	0.84	2.71
[CP2] Compared with our competitors, we have higher sales revenue growth rate	0.87	3.16
[CP3] Compared with our competitors, we have lower operating costs	0.62	1.24
[CP4] Compared with our competitors, we have better product and service quality	0.65	1.34
[CP5] Compared with our competitors, we have increasingly higher market share	0.82	2.06

VIF, variance inflation factor.
†, Not relevant for formative constructs.

comprising 10 respondents, the questionnaire length was deemed appropriate. Feedback was received to add definitions for uncommon terms to ensure understanding across industries. This was implemented to strengthen the accuracy of responses.

Harman's single factor test was also conducted to assess whether the first factor accounted was below the threshold of 50% (Fuller et al., 2016). This was the case as the first factor accounted for 35.94% variance, concluding that common method bias was not a risk.

Sample size requirements for partial least squares structural equation modelling

The ‘ten times rule’ was used to determine the minimum sample size, which suggests that the size should be 10 times greater that the number of indicators of the largest construct (Peng & Lai, 2012). In this research, BDAC has the greatest number of indicators with 25 measures, which led to a minimum sample size of 250. This sample size exceeded the critical sample size of 200 for Structural Equation Modelling, which provides stable parameter estimates and adequate power to test structural models (Collier, 2020). The final sample size of 272 exceeded both criteria.

Measurement model

The validation and reliability criterion used to assess the measurement model differed for reflective and formative constructs. This was because the internal consistency assessments that underpin reflective model assessment are not relevant for formative constructs as they do not necessarily co-vary (Hair et al., 2017).

The reliability and validation of the reflective constructs, which comprised all first-order constructs apart from data, basic resources and technology, were verified by conducting tests for multi-collinearity, factor loadings, internal consistency reliability, convergent reliability and discriminant validity. Variance inflation factor (VIF) was used to evaluate whether multi-collinearity exists. All constructs fell below the threshold of five, indicating that no collinearity issues existed (Hair et al., 2017). The factor loading results demonstrated that most indicators exceeded the threshold of 0.7, apart from five factors that fell between 0.6 and 0.7. For complex constructs, as is the case in this research, it is recommended that indicators that have factor loadings that exceed 0.6, and average variance extracted (AVE) values higher than 0.5 should be retained in the model (Collier, 2020). While these indicators may have a weaker contribution, they may capture a unique component of the construct (Collier, 2020). Table 1 summarises the factor loadings for reflective indicators and VIF results.

The internal consistency reliability was tested via Cronbach’s alpha and composite reliability. In both cases, the constructs exceeded the threshold of 0.7, verifying their reliability (Nunnally, 1978; Nunnally & Bernstein, 1994). The convergent validity was assessed through AVE where all constructs exceeded the threshold of greater than 0.5 verifying convergent validity (Fornell & Larcker, 1981).

The discriminant validity was assessed through three tests, namely, Fornell and Larcker criterion, cross-loadings and the Heterotrait-Monotrait (HTMT) ratio. The cross-loadings demonstrated that the indicators loaded most strongly on their parent constructs (Farrell, 2010). The Fornell and Larcker criterion illustrated that the square root of the AVE of a construct was greater than its correlation with other constructs (Fornell & Larcker, 1981). Finally, the HTMT ratio tested that the ratio of between-trait and within-trait correlations of constructs had a threshold of less than 0.85 (Henseler et al., 2015). In all three cases, the discriminant validity was verified. Table 2 and Table 3 summarise the construct correlation matrix, internal consistency reliability, convergent reliability and discriminant validity (specifically HTMT ratio) results.

To assess the measurement model of the formative constructs, namely data, basic resources, technology, tangible resources, human skills, intangible resources and BDAC, the significance of the outer-weights, the size of the outer-loadings and the collinearity of the constructs was assessed. Most of the outer weights were significant apart from the indicators T2 and T3 and the construct human skills. This required further assessment of the size of the outer loadings to establish whether they exceeded 0.5. As this was the case, the constructs

TABLE 2: Correlation matrix and validity and reliability results for reflective constructs.

Construct	Variable	1	2	3	4	5	6	7	8	9	10	11	12	13
1	Data (D)	1.00	-	-	-	-	-	-	-	-	-	-	-	-
2	Basic resources (BR)	0.54	1.00	-	-	-	-	-	-	-	-	-	-	-
3	Technology (T)	0.66	0.76	1.00	-	-	-	-	-	-	-	-	-	-
4	Managerial skills (MS)	0.43	0.50	0.64	1.00	-	-	-	-	-	-	-	-	-
5	Technical skills (TS)	0.35	0.35	0.50	0.46	1.00	-	-	-	-	-	-	-	-
6	Data-driven culture (DD)	0.56	0.62	0.73	0.46	0.37	1.00	-	-	-	-	-	-	-
7	Organisational learning (OL)	0.49	0.55	0.85	0.52	0.44	0.51	1.00	-	-	-	-	-	-
8	Tangible resources (Tan)	0.54	0.91	0.70	0.44	0.35	0.57	0.54	1.00	-	-	-	-	-
9	Human Skills (HS)	0.39	0.63	0.86	0.56	0.43	0.47	0.60	0.55	1.00	-	-	-	-
10	Intangible resources (INT)	0.61	0.59	0.70	0.47	0.29	0.58	0.44	0.57	0.52	1.00	-	-	-
11	Big data analytics capability (BDAC)	0.46	0.93	0.69	0.48	0.30	0.58	0.46	0.69	0.61	0.52	1.00	-	-
12	Business model innovation (BMI)	0.49	0.66	0.96	0.61	0.49	0.55	0.88	0.61	0.91	0.54	0.61	1.00	-
13	Competitive performance (CP)	0.82	0.69	0.82	0.53	0.40	0.88	0.57	0.66	0.54	0.83	0.62	0.62	1.00
-	Mean	5.77	5.21	5.76	5.72	5.59	5.41	5.78	5.65	5.66	5.62	5.65	5.21	5.01
-	SD	1.45	1.60	1.60	1.29	1.41	1.38	1.13	1.57	1.35	1.26	1.42	1.56	1.35
-	AVE†	-	-	-	0.82	0.73	0.75	0.75	-	-	-	-	0.52	0.59
-	Cronbach’s alpha†	-	-	-	0.93	0.88	0.83	0.89	-	-	-	-	0.88	0.82
-	Composite Reliability†	-	-	-	0.95	0.92	0.90	0.92	-	-	-	-	0.91	0.88

AVE, average variance extracted; SD, standard deviation.
†, Only relevant for reflective constructs.

TABLE 3: Discriminant validity results via Heterotrait-monotrait ratio.

Construct	BMI	CP	DD	MS	OL	TS
BMI	-	-	-	-	-	-
CP	0.55	-	-	-	-	-
DD	0.60	0.54	-	-	-	-
MS	0.48	0.40	0.62	-	-	-
OL	0.63	0.49	0.69	0.60	-	-
TS	0.54	0.35	0.54	0.76	0.69	-

BMI, business model innovation; CP, competitive performance; DD, data-driven culture; MS, managerial skills; OL, organisational learning; TS, technical skills.

TABLE 4: Higher-order construct validation.

Construct	Measures	Weight	Significance (*p*)	Outer loadings	VIF
Data (D)	D1	0.39	< 0.001	0.74	1.28
	D2	0.39	< 0.001	0.82	1.57
	D3	0.47	< 0.001	0.83	1.49
Basic resources (BR)	BR1	0.75	< 0.001	0.98	2.33
	BR2	0.30	< 0.050	0.87	2.33
Technology (T)	T1	0.36	< 0.050	0.78	1.75
	T2	0.21	0.135	0.60	1.25
	T3	0.07	0.621	0.62	1.60
	T4	0.31	< 0.050	0.72	1.42
	T5	0.41	< 0.010	0.82	1.55
Tangible resources (Tan)	Data (D)	0.35	< 0.001	0.83	1.78
	Basic resources (BR)	0.51	< 0.001	0.88	1.68
	Technology (T)	0.32	< 0.050	0.83	1.81
Human skills (HS)	Managerial skills (MS)	0.53	< 0.001	0.91	1.91
	Technical skills (TS)	0.56	< 0.001	0.92	1.91
Intangible resources (INT)	Data-driven culture (DD)	0.53	< 0.001	0.88	1.55
	Organisational learning (OL)	0.59	< 0.001	0.91	1.55
BDAC	Tangible resources (Tan)	0.34	< 0.001	0.82	2.19
	Human skills (HS)	0.04	0.720	0.76	2.32
	Intangible resources (INT)	0.72	< 0.001	0.96	1.95

VIF, variance inflation factor; BDAC, big data analytics capability.

were retained in the measurement model (Hair et al., 2017). A VIF assessment was conducted to test for multi-collinearity. All values fell below the threshold of five, indicating an absence of multi-collinearity (Hair et al., 2017) (see Table 4). Based on these assessments, all reflective and formative models met their required criterion, and the measurement model was verified to be reliable and valid.

Figure 2 summarises the structure of the measurement model and its indicators, illustrating the BDAC third-order construct dimensions, the factor loadings for reflective constructs and the significance of outer weights for formative constructs.

Ethical considerations

Ethical clearance to conduct this study was obtained from the University of Pretoria's Gordon Institute of Business Science Research Ethics Committee.

Empirical results

Descriptive statistics

The empirical results of the study are based on 272 respondents whose demographics are summarised in Table 5. The demographics section comprised seven respondent questions and two company questions. The dominant respondent groups were males, aged 30 years to 39 years, with post-graduate education, with more than 10 years' work experience, at management position, working in data and analytics departments, and residing in the Netherlands, United States, United Kingdom or South Africa. From a company perspective, the dominant industries were professional services and technology industries, and the dominant company size was large.

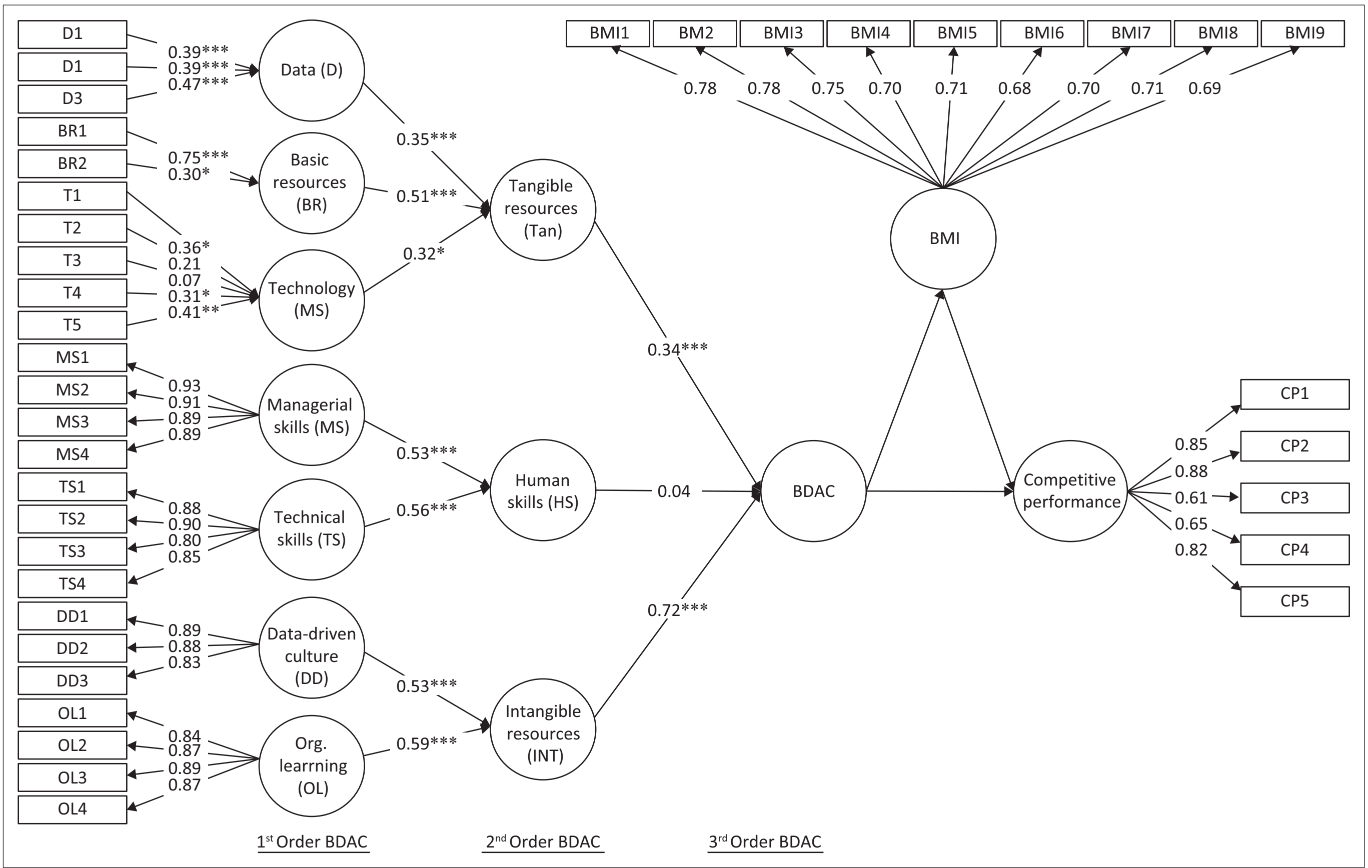
Structural model results

Figure 3 and Table 6 summarise the structural model from the PLS-SEM analysis by providing the standardised path coefficients (β), their significance (*t*-value) and the explaining variance of the endogenous variables (R^2). The analysis was conducted using a bootstrap method based on 5000 random samples.

The results demonstrated that all the hypotheses were supported. Big Data Analytics Capability had a significant relationship with competitive performance ($\beta = 0.343$, $t = 4.768$, $p < 0.001$; Hypothesis 1 was confirmed). Big Data Analytics Capability also had a significant relationship with BMI ($\beta = 0.640$, $t = 15.672$, $p < 0.001$; Hypothesis 2a was confirmed). Business Model Innovation had a significant relationship with competitive performance ($\beta = 0.245$, $t = 3.048$, $p < 0.01$; Hypothesis 2b was confirmed).

Finally, the indirect relationship of BDAC→BMI→CP was also found to be significant indicating a mediation path ($\beta = 0.156$, $t = 2.974$, $p < 0.01$; Hypothesis 2c was confirmed). The combined effect of BDAC on competitive performance, based on the sum of the direct and indirect effect, was 0.500 ($t = 10.603$, $p < 0.001$). Thus, the direct effect and indirect effect accounted for 69% and 31%, respectively. As both the direct and indirect effects were in the same direction and significant, the nature of the median is complementary partial mediation (Collier, 2020; Hair et al., 2017).

The structural model explained a variance rate of 41% for BMI ($R^2 = 0.409$) and 29% for competitive performance ($R^2 = 0.285$). This indicated a weak to moderate predictive accuracy as the values exceeded 25% but were less than 50% (Hair et al., 2017). To further understand the predicative relevance of the exogenous variable, BDAC, on the endogenous variables, BMI and competitive performance, a Q^2 analysis was conducted using a blindfolding procedure (Shmueli et al., 2019). The results indicated that satisfactory predictive relevance was achieved (Shmueli et al., 2019). Big Data Analytics Capability had a large predictive relevance for BMI as the



BMI, business model innovation; BDAC, big data analytics capability.
Formative constructs; *p < 0.05, **p < 0.01, ***p < 0.001.

FIGURE 2: Measurement model with factor loadings (reflective constructs) and significance of outer weights.

result of 0.406 exceeded 0.35, and a medium predictive relevance for competitive performance as the result of 0.246 exceeded 0.15 (Hair et al., 2017).

Discussion

This research aimed to validate that BDAC had both a direct and indirect effect on competitive performance, with BMI mediating the latter. In both cases, the results indicated that a significant effect was established, with a combined path coefficient of 0.50. This indicated that BDAC had a substantial influence on competitive performance because of a strong path coefficient (Pallant, 2020). These results aligned with findings from Akter et al. (2016) and Fosso Wamba et al. (2017), who also found a strong effect, and Fosso Wamba, Queiroz et al. (2020), who found a moderate to strong effect. The positive and substantial effect of BDAC on performance was likely because of BDAC's role in highlighting market expansion and innovation opportunities and generating insights used to strengthen customer satisfaction and operational efficiency (Fosso Wamba, Dubey et al., 2020; Grover et al., 2018; Holmlund et al., 2020; Lehrer et al., 2018; Rialti et al., 2019).

While the results confirmed what is known in empirical research, it was noted that existing literature is still nascent in explaining how organisations realise value from BDAC investments to enhance performance (Günther et al., 2017; Mikalef et al., 2020). Seddon et al. (2017) and Günther et al. (2017) suggested that the ability to achieve value from BDAC is influenced by effectively balancing human and algorithmic intelligence, as human actors can influence trust in relying on data and the subsequent dissemination of insights across the business. Furthermore, the effectiveness of BDAC departments may be hindered if they are not adequately integrated into the organisation, making it challenging to align the insights from big data analytics to the strategy of the organisation (Vidgen et al., 2017). If the mechanisms by which BDAC delivers value are not well understood, it may cause tensions in realising performance gains, as only 20% of big data analytics investments are expected to yield returns in practice (White, 2019).

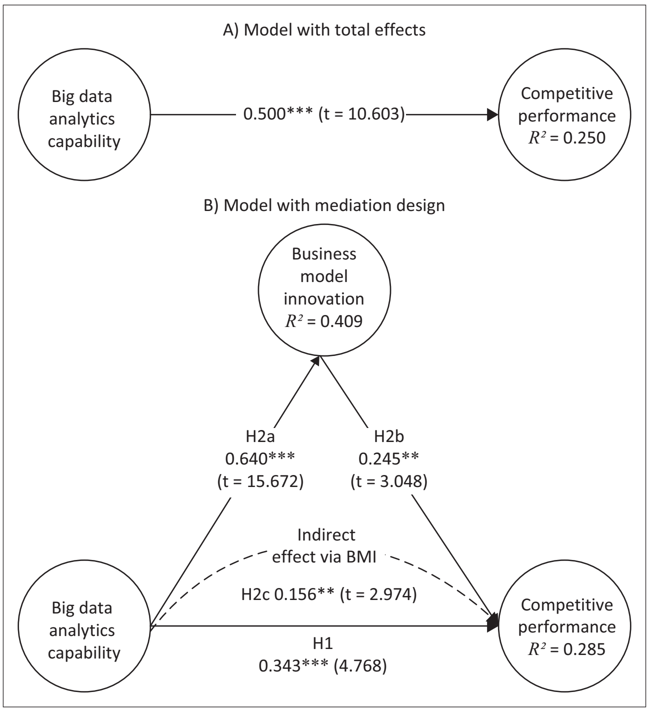
As part of the mediation analysis, the relationship between BDAC and BMI, and BMI and competitive performance, was also assessed. In both cases, a positive direct relationship was established. Big Data Analytics Capability demonstrated a strong effect on BMI with a path coefficient of 0.64 (Pallant, 2020), which confirmed empirical research by Ciampi et al. (2021), who also found a strong relationship. This aligns with literature that suggests that BDAC-enabled sensing provides firms with knowledge regarding shifts in the market, customer and competitive environments (Fosso Wamba, Queiroz et al., 2020), which can spur organisations to make changes to their business logic based on high potential opportunities (Ciampi et al., 2021; Teece, 2007).

TABLE 5: Sample characteristics.

Respondent variables and company variables	*N*	%
Gender		
Male	224	82.35
Female	47	17.28
Other	1	0.37
Age (years)		
20–29	8	2.94
30–39	126	46.32
40–49	75	27.57
> 50	63	23.16
Education		
Undergraduate degree	59	21.69
Postgraduate degree	202	74.26
Other	11	4.05
Work experience		
≤ 5	3	1.10
> 5 but ≤ 10	40	14.71
> 10 but ≤ 15	73	26.84
> 15 but ≤ 20	50	18.38
> 20 but ≤ 25	42	15.44
> 25	64	23.53
Company position		
Senior manager; line manager; functional manger	186	68.38
CEO; MD; Partner and Other top management position	86	31.62
Department		
Data & analytics; Advanced Analytics; Big data analytics	142	52.21
Information; IT; and technology	44	16.18
Finance	17	6.25
Commercial operations	13	4.78
Sales	13	4.78
innovation	10	3.68
Marketing	8	2.94
Other	25	9.19
Country		
The Netherlands	45	16.54
United States	40	14.71
United Kingdom	32	11.76
South Africa	28	10.29
India	15	5.51
Germany	13	4.78
Brazil	10	3.68
Other	89	32.72
Industry		
Professional services	107	39.34
Technology	55	20.22
Financial services	41	15.07
Retail and Wholesale	20	7.35
Manufacturing	15	5.51
Healthcare	10	3.68
Travel, transport & logistics	6	2.21
Other	18	6.62
Company size		
Small (< 100 employees)	17	6.25
Medium (100 to 2499 employees)	38	13.97
Large (> 2500 employees)	217	79.78

CEO, chief executive officer; MD, managing director.

It also validated phenomena seen in practice where BDAC supported digital companies to create new business models and disrupt traditional industries (Mishra et al., 2019; Sorescu, 2017). As empirical research on the relationship between BDAC and BMI is still emerging, with only one



H, hypothesis; BMI, business model innovation.

FIGURE 3: Relationships of the structural model.

TABLE 6: Mediation results.

Path	Estimate	*t*-value	95% CI	Conclusion
Model A Total effect path: BDAC→CP	0.500***	10.603	(0.403, 0.586)	-
Model B Direct effect path: BDAC→CP	0.343***	4.768	(0.199, 0.482)	Direct effect, H1 supported
Model B Indirect effect path: BDAC→BMI→CP	0.156**	2.974	(0.047, 0.257)	Partial mediation, H2c supported

Note: 95% CI, Bias corrected bootstrap 95% confidence interval. Bootstrapping 15% confidence interval based on 5000 samples.

BDAC, big data analytics capability; BMI, business model innovation; CP, competitive performance.

**, $p < 0.01$; ***, $p < 0.001$.

known prior empirical study existing (Ciampi et al., 2021), these results extended knowledge in this area and strengthened the foundation for future research.

Finally, the effect of BMI on competitive performance was found to be significant; however, the influence was weak with a path coefficient of 0.25 (Pallant, 2020). The weak correlation contrasted with the findings of Zhang et al. (2021) who found a moderate to strong relationship with a path coefficient of 0.48 based on their meta-analytic research spanning 74 studies from 2007 to 2017. When reflecting on the dichotomy of results related to BMI's effect on performance in prior literature, Zhang et al. (2021) argued that they have 'settled this dispute and shown that BMI has a moderate to strong and significant correlation with firm performance' (Zhang et al., 2021, p. 811).

Conversely, scholars have demonstrated results that align with those of this study, namely, a significant relationship but with a weak influence (Bhatti et al., 2021; Wei et al., 2017). Bhatti et al. (2021) assessed the effect of BMI on performance, while Wei et al. (2017) assessed the effect of two business model types, namely, novelty-based and efficiency-based, on performance. In both cases, weak effects were established. Furthermore, in some cases, scholars have found a negative influence of BMI sub-constructs, namely value capture, on performance (Clauss et al., 2021), or no significant relationship between BMI and performance at all (Kumar et al., 2018; Latifi et al., 2021).

The wide variety of results in existing literature might be linked to the high-risk nature of BMI endeavours when compared to product or service innovation (Latifi et al., 2021). While BMI is expected to lead to positive outcomes such as market and customer segment expansion, launching strategic partnerships and optimising the revenue and cost models (Clauss 2017; Foss & Saebi, 2017; Teece, 2010), it does not automatically trigger significant performance gains (Latifi et al., 2021). In fact, restructuring key components of organisations' business models requires the coordination of various functions, people and partners, which can disrupt the system and lead to adverse consequences if not handled properly (Christensen et al., 2016; Clauss et al., 2021). This could negatively impact stakeholders such as suppliers and employees, ultimately, impeding customer retention (Latifi et al., 2021).

Furthermore, Foss and Saebi (2017) suggested that the lack of clarity regarding BMI's effect on competitive performance could be driven by a lag time between implementation of BMI and the performance gains. The ambiguity in the link between BMI and performance could also be driven by the complex nature of business model components, where changes in one component can influence others (Foss & Seabi, 2017).

Theoretical implications

The study has theoretical contributions in BDAC, BMI and DC literature. From a BDAC perspective, it validated direct and indirect positive relationships between BDAC and competitive performance. This brings about the opportunity for organisations to foster the development of BDAC by specifically investing in big data infrastructure, attaining relevant human skills and the development of a data-driven corporate culture to translate insights to action (Gupta & George, 2016; Mikalef et al., 2019). It also demonstrated the central role that BDAC has in informing strategic decisions aimed at sustaining competitive advantage in the long term. This supported emerging research that suggests that big data analytics is not subordinate to strategy, but a key enabler in defining the future path of the organisation, illustrating the fusion and integration between data, technology and strategy (Mikalef et al., 2020).

Furthermore, the study contributed to BMI literature by illustrating, for the first time, the positive mediating role of BMI in the BDAC-competitive performance relationship. This finding demonstrated two principles; firstly, that the availability of BDAC resources and capabilities advanced the alertness of firms to internal and external triggers, thus allowing them to proactively respond to opportunities (Ciampi et al., 2021). This was because of the scanning, searching, researching, interpreting, experimenting and discovering that sensing enables (Day, 1994; Teece, 2007), which leads to transformational activities that drive BMI (Teece, 2018). Secondly, when business models were effectively reconfigured, competitive performance was enhanced (Bhatti et al., 2021; Foss & Saebi, 2017; Teece, 2018; Zhang et al., 2021). While the relationship found by this research was weak, it remains significant.

Finally, the validated mediation path extended DC literature by demonstrating the role that BDAC-enabled sensing had in generating insights that influence the transformation of business models, which in turn enhance competitive performance. This reflects the sensing, seizing and transforming process of DCs (Teece, 2007).

Managerial implications

From a managerial perspective, the results suggested that to support the effective transformation of business models, organisations should foster the development of BDAC. This includes hiring and training skilled employees, adopting organisation knowledge sharing and learning practices and supporting the development and adoption of a data-driven culture (Mikalef et al., 2019). This requires the support from leadership to develop and execute dedicated plans regarding investment in big data infrastructure, the recruitment of relevant skills to advance the big data analytics department and relevant training programmes to shift the corporate culture.

Once BDAC resources and capabilities are established, leadership are encouraged to create a strong integration between BDAC departments and the strategy of the organisation. As a result, it is recommended that BDAC management should form part of the leadership team responsible for strategy development, and big data analytics employees should be incentivised to balance the generation of insights that benefit both the short term and long term.

Limitations and future research directions

The research presented some limitations that might be areas to explore in future research. When considering the structure of the research, the survey approach, the scales and the cross-sectional nature of the research, each introduced limitations. The questionnaire relied on self-reported responses, which were subjective, and might have undermined the objectivity of the results because of bias (Ciampi et al., 2021). In terms of the scales, a shorter set of scales were selected to measure BMI to optimise the survey length based on feedback from the pre-testing phase. While this had a positive impact on drop-out rate, it may have reduced the comprehensiveness of the questionnaire related to BMI. An opportunity exists to strengthen insights related to the dimensions of BMI, namely, value proposition, value creation and value capture, using the more comprehensive scales by Clauss (2017).

The cross-sectional nature of the study provided insights that were relevant to a specific point in time and would not adapt with time (Saunders & Lewis, 2018). Longitudinal research could be conducted in the future to overcome this limitation, as it is less likely to be impacted by temporary factors, and therefore would be more robust (Köhler et al., 2017). Finally, the generalisability of the results might be limited because of the purposive non-probability sampling approach used where judgement was applied to source respondents.

Despite the limitations discussed, the research brought about possible future research opportunities. As discussed, while the research validated that BDAC has an influence on competitive performance, the mechanisms through which it acts could be investigated in the future (Mikalef et al., 2020). Furthermore, based on the focus on BMI, an opportunity exists to assess the effect of moderating variables on the structural model. Foss and Saebi (2017) suggested that macro-level, firm-level and micro-level moderators might influence the antecedents and outcomes of BMI. Macro-level influence includes changes to the external environment, firm-level influence refers to organisational culture, structure and leadership characteristics, and micro-level influence refers to management cognition, open mindedness and adversity to change (Foss & Saebi, 2017).

Conclusion

This research contributed to the evolving empirical research on the significance of BDAC in driving competitive performance. Firstly, it demonstrated that organisations' efforts in nurturing big data infrastructure, human resources and data-driven cultures drive actions that enhance both operational and strategic execution, leading to enhanced performance. Secondly, it discovered that the positive effect of BDAC is carried through BMI to influence competitive performance positively, thus suggesting that the sensing enabled by BDAC leads to transformational activities that drive performance. These insights demonstrate that BDAC is not subordinate to business strategy, but rather a key enabler of it, illustrating the need for effective fusion and integration of data and technology with business strategy to drive positive performance outcomes.

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Competing interests

The authors declare that they have no financial or personal relationships that may have inappropriately influenced them in writing this article.

Authors' contributions

N.J. and M.D.C., were involved in the conceptualisation and methodology. N.J., conducted the research from a data collection, data curation, resources and analysis perspective as required for her masters degree, and M.D.C., supervised the collection and analysis, and provided guidance on the above. The writing was conducted by N.J., with assistance from M.D.C., M.M., and A.H.V., contributed to the strengthening of the article during the review process and were invaluable in addressing the comments and strengthening the theoretical base of the review and resubmit.

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Data availability

The data that support the findings of this study are available from the corresponding author, M.D.C., upon reasonable request.

Disclaimer

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