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The Source of SMEs' Competitive Performance in COVID-19: Matching Big Data Analytics Capability to Business Models

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Abstract

Literature notes that firms are keen to develop big data analytics capability (BDAC, e.g. big data analytics (BDA) management and technology capability) to improve their competitive performance (e.g. financial performance and growth performance). Unfortunately, the extant literature has limited understanding of the mechanisms by which firms' BDAC affects their competitive performance, especially in the context of small and medium-sized enterprises (SMEs). Using resource capability as the theoretical lens, this paper specifically examines how BDAC influences SMEs' competitive performance via the mediating role of business models (BMs). Also, this study explores the moderating effect of COVID-19 on the relationship between BDAC and BMs. Supported by Partial Least Squares-Structural Equation Modelling (PLS-SEM) and data from 242 SMEs in China, this study finds the mediating roles of infrastructure and value attributes of BMs in enhancing the relationship of BDAC on competitive performance. Furthermore, the improvement of financial performance comes from the matching of BDA management capability with infrastructure attributes of BMs, while the improvements in growth come from the matching of BDA management capability and BDA technology capability with value attributes of BMs. The result also confirms the positive moderating effects of COVID-19 on the relationship of BDA management capability and value attributes of BMs. This study enriches the integration of BDAC and BMs literature by showing that the match between BDAC and BMs is vital to achieve competitive performance, and it is helpful for managers to adopt an informed BDA strategy to promote widespread use of BDAs and BMs.

Keywords Big data analytics capability · COVID-19 · Business model · Competitive performance · Dual attributes

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1 Introduction

Since the advent of new digital technologies, almost all firms are increasingly challenged by the "big data era" (Gupta & George, 2016; Zhang et al., 2021). A significant number of government policies have been introduced to boost firms' big data analytics capability (BDAC), which is defined as the ability to generate business insights by utilizing big data (Akter et al., 2016; Mikalef et al., 2020; Wamba et al., 2020). As an important means to leverage the economic effects of big data, BDAC is seen as a core role in redefining new business competitive advantages for firms (Popovič et al., 2018; Liu et al., 2020; Dong & Yang, 2020; Mangla et al., 2020; Olabode et al., 2022). But surprisingly, some studies reveal that a large number of firms (more than 60%) fail to improve performance through big data, and sometimes, they fell into a survival crisis due to significant investments in BDAC projects (Marr, 2016; Gupta & George, 2016; Kiron et al., 2014; Liu et al., 2020; Dong & Yang, 2020; Wu et al., 2020; Xie et al., 2020; Wamba et al., 2017). This so called "IT productive paradox" drives scholars to urgently explore the impacting mechanism of BDAC on firms' competitive performance (Olabode et al., 2022; Ferraris et al., 2019), but so far this mechanism is still unclear (Mikalef et al., 2019; Popovič et al., 2018; Akter et al., 2016; Olabode et al., 2022).

Some exploratory studies attempt to investigate how BDAC influences big firms' performance by improving the dynamic capability (Wamba et al., 2017; Mikalef et al., 2020), supply chain management (Wamba et al., 2020), or knowledge management (Ferraris et al., 2019). But the wide adoption of BDAC among SMEs has largely been neglected by those studies. Actually, SMEs constitute about 90% of business and provide 60%-70% of the jobs in OECD countries (OECD, 2018; World Bank, 2020), and BDAC has been seen as an important means for SMEs to gain competitive performance (Desa & Basu, 2013; Latifi et al., 2021).

This study attempts to explore the effects of SMEs' BDAC on their competitive performance by considering the mediating factor, business models (BMs). Specifically, BMs describe the fundamental logic of how firms create and capture value, and can be seen as the key bridge for effective interaction between resource elements and organizational structure (Amit & Zott, 2001; Teece, 2010; Foss & Saebi, 2017). Abundant evidence has proved that competition between firms is not only limited to tangible products, but largely extends to their BMs (Casadesus-Masanell & Zhu, 2013; Ferreras-Méndez et al., 2021). The dual restrictions of resources and capabilities facing SMEs drive they to employ innovative BMs to overcome the survival trap (Yang et al., 2018; Latifi et al., 2021; Yuan et al., 2021). Some typical examples are JD and PDD,[1] which adopted creative business models to become successful when they were SMEs.

Additionally, it is meaningful to discuss the antecedents of BMs innovation from within an organization (e.g. BDAC), rather than the external factors, such as technological change, customer preferences, market competition (Yuan et al., 2021; Chesbrough, 2010; Patel et al., 2015; Foss & Saebi, 2017). BDAC is breaking down the traditional boundaries of resource acquisition, allowing the value creation and acquisition logic of SMEs to be constantly redefined (Santoro et al., 2019; Popovič et al., 2018). This change reveals that the significance and necessity of discussing BDAC with BMs is growing in importance among SMEs (Bouwman et al., 2018; Liu et al., 2020). Ciampi et al. (2020) also emphasize that simply focusing on the diversified generation, collection and storage of data is not enough to drive enterprises to become data-driven organizations. On the contrary, only when data is combined with other factors such as labor, technology, knowledge and management, can the final desired value output be achieved (Xie et al., 2020; Kwon et al., 2014), and this process cannot be separated from BMs (Bouwman et al., 2018). The rapid outbreak of the COVID-19 pandemic has illustrated the need for flexible BMs and presents a case for better integrating BDAC and BMs to increase viability and growth, and thus the competitive performance (Seetharaman et al., 2020). These arguments imply that exploring BDAC and its embeddedness in BM is a growing area; especially in the context of SMEs, it is a research topic that is under-researched. Although some studies (e.g., Ciampi et al., 2021; Olabode et al., 2022) have identified that firms' BDAC is generally positively associated with BM innovation, they fail to distinguish BDAC's sub-capabilities and BMs' sub-elements, which, as a result, leaves a lot of ambiguity on the specific affecting mechanisms of BDAC on BMs.

Thus, we aim to answer two closely related research questions: *(1) what role do BDAC and BMs play in improving SMEs' competitive performance? How are they related and embedded? (2) How do uncertainties like COVID-19 influence the effect of BDAC on BMs?* In order to study these research questions, the conceptual boundaries of BDAC, BMs and competitive performance are firstly defined. Specifically, BDAC is defined as the ability to develop business insight by using data management, technical foundations and talents (Kiron

[1] JD is regarded as one of the most popular and influential e-commerce sites in Chinese e-commerce sector, with a market value of over $93.1 billion in 2021. PDD is the e-commerce platform with the largest user base in China, with a market value of over $55.4 billion in 2021.

et al., 2014). It includes two dimensions: the organizational dimension integrating core business and operational functions (big data analytics (BDA) - management capability) and the basic dimension guaranteeing data acquisition and development (big data analytics (BDA) - technology capability) (Davenport et al., 2012; Sun & Liu, 2020; Akter et al., 2016). BMs refer to the basic theoretical logic to create and obtain value (Amit & Zott, 2001; Snihur et al., 2018; Teece, 2010), they generally consist of two dimensions: infrastructure attributes and value attributes (Yang et al., 2018). The infrastructure attributes describe the operational logic of how an enterprise does business (Amit & Zott, 2001), while the value attributes reflect the management logic of how to make profits (Yang et al., 2018). Furthermore, different from the traditional performance measurements, which mainly rely on financial indicators, SMEs' competitive performance has now been measured by the integration of financial and non-financial indicators (Aldrich & Martinez, 2001). Thus, we divide this competitive performance into two main aspects: growth performance and financial performance (Zott & Amit, 2007; Monferrer Tirado et al., 2019). Using these dimensions, we draw on 242 multi-point survey data from China and employ Partial Least Squares Structural Equation Modelling (PLS-SEM) to empirically test our theoretical hypotheses.

The research makes significant contributions to the literature on BDAC, BMs and competitive performance. First, this study theoretically explains why even after attracting numerous investments BDAC does not bring the expected benefits but significant burdens to SMEs. This is, the core internal mechanism of BMs in SMEs has been largely ignored in previous studies. By discussing BMs as the mediator, this finding empirically explains the reasons of the IT production paradox in the application of BDAC, which is helpful to expand the collaborative research of BDAC and BMs from the perspective of theoretical integration. Second, by focusing on matching types of BDAC (e.g. BDA management and technological capability) with types of BMs (e.g. infrastructure and value attributes), the proposed conceptual model theoretically answers the question "how do firms use BDAC to achieve competitive performance?", which provides a foundation for the development of avenues for practice and further research (Akter et al., 2016; Gupta & George, 2016). Third, by considering COVID-19 as the moderating factor, this study explores when the effects of BDAC would become stronger or weaker, which contributes to understanding the interaction of environment, BDAC and BMs.

The rest of this article is organized as follows: The second part introduces the core constructs involved in this study, namely BDAC and BMs with dual attributes. The third part puts forward hypothesis on how the two types of BDAC (e.g. BDA management capability and BDA technology capability) affect the two types of BMs (infrastructure attributes and value attributes). Additionally, we discuss the mediating role of BMs and the moderating role of COVID-19. The fourth part elaborates the research sample, data collection, variable measurement and statistical methods, and analyzes the common method bias. The fifth part explains the empirical results in detail, including the reliability and validity of the measurement scale, hypothesis testing and moderating test. The sixth part emphasizes our findings in terms of theoretical and managerial implications, limitations and some possible future research directions. Finally, the conclusion summarizes the main contributions of this study.

2 Theoretical Background

2.1 Big Data Analytic Capability as a New Enabler of Competitive Performance

The notion of big data analytics capability (BDAC) comes from the conception of big data. As Akter et al. (2016) mentioned in their study, the age of digitalization has led to the creation of vast amounts of data, which causes SMEs to be faced with ever increasing data generated from digital transactions, clickstreams, voice and video channels (Kauffman et al., 2012). Compared with traditional data, big data has three representative differentiating characteristics; "the three Vs", namely, Volume, Velocity and Variety (Johnson et al., 2017; Davenport et al., 2012; McAfee et al., 2012; Mikalef et al., 2019), and these features provide opportunities to broaden customer needs and reorganize resources. However, it is worth noting that data does not generate value on its own when it is separated from means of production (Xie et al., 2020). Instead, big data is likely to deliver performance only when the data is analyzed and refined (Chen et al., 2012; Huang et al., 2020; Mangla et al., 2020; Ciampi et al., 2020).

Furthermore, big data analytic capability (BDAC) is regarded as the ability to develop business insights by using data management, foundation information technology and talents (Kiron et al., 2014). Previous studies have noted that when exploited correctly, big data can result in competitive advantage and improved financial performance, and that the key lies in BDAC (Akter et al., 2016; Ciampi et al., 2021; Mikalef et al., 2020). More specifically, BDAC enables business to improve high performance and competitive advantages through the following aspects: improve product/data quality (Shan et al., 2019), digital

decision analysis model (Ghasemaghaei & Calic, 2019), market dynamic detection (Wielgos et al., 2021), customer demand forecasting (Liu et al., 2020), supplier defect tracking (Almohri et al., 2019) and generate new production innovation (Mikalef et al., 2020). The evidence indicates that the performance brought by BDAC are more competitive, not only in terms of current market share, but also in terms of future corporate growth (Monferrer Tirado et al., 2019). Ransbotham and Kiron (2017) also note that companies that are leading the way in adopting BDAC are more likely to launch new products and services than those who lag behind, which often brings high performance (Wamba et al., 2017). That is to say, BDAC plays an important role in the transformation of data from possible factors of production to actual means of production (Mikalef et al., 2019; Chen et al., 2020; Majhi et al., 2021).

Previous studies have discussed the conception and core dimensions of BDAC from perspectives of resources (Schroeck et al., 2012; Andersen & Ross, 2014), dynamic capabilities (Ciampi et al., 2021; Wamba et al., 2017), and socio-materialism (Akter et al., 2016; Barton & Court, 2012), and have conceptualized BDAC as a unidimensional construct (Srinivasan & Swink, 2018) or as a higher-order block with different dimensions (Akter et al., 2016; Gupta & George, 2016; Mikalef et al., 2020). This study holds the viewpoint of a higher-order block and focuses on two key dimensions: BDA management capability and BDA technology capability. First, BDA management capability refers to SMEs' organizational ability to utilize big data to plan, invest, co-ordinate and control (Sun & Liu, 2020; Akter et al., 2016). Barton and Court (2012) point out that BDA management capability ensures the interaction between data and the preset model, improves the identification of potential market opportunities, and thus improves the performance of enterprises. A distinguished obvious examples is Zhu Bajie company which is a Chongqing local start-up technology company providing brand marketing, software development, intellectual property, finance and taxation, scientific and technological consulting, office space and other solutions. It creates a billion-dollar market for itself by mining massive amounts of data on its platform, such as the monitoring of market changes, demand and supply connections, value analysis and other activities.

Second, BDA technology capability refers to the infrastructure modules that support data acquisition and development and achieve the flexibility of the BDA platform (Akter et al., 2016; Davenport et al., 2012), which comprises connectivity, compatibility and modularity. Connectivity is reflected in the connection between different business units and different functions within the same company, such as R&D department and customer management, supply chain management and finance department (Sun & Liu, 2020). Compatibility reflects the information sharing mechanisms established to implement decisions, such as health codes. Modularity refers to allowing digital systems to add or optimize default models to ensure the flexibility of the BDA platform, such as periodic system updates (Akter et al., 2016). In contrast to BDA management capability, BDA technology capability improves competitive performance from a more fundamental level. For example, Liu (2014) has pointed out that by capturing customer demands, BDAC reduced customer acquisition costs by approximately 47% and increased company revenue by approximately 8%. The same benefits can be seen in the supply chain, BDAC also achieves a sustainable robust layout by minimizing supply chain risks, designing distribution networks and facilitating supplier selection (Sharma & Routroy, 2016; Mishra & Singh, 2020; Lamba & Singh, 2019).

2.2 Business Models and their Dual Attributes

The changes in nature of value creation induced by digital technology drives SMEs to rely on business models (BMs) to gain competitive performance. BMs have gradually become an emerging topic of management research (Amit & Zott, 2001; Foss & Saebi, 2017; Snihur et al., 2018; Li et al., 2021). Since the 1990s, researchers have sought multiple pieces of evidence to explain the "fundamental logic of how companies do business" (Amit & Zott, 2001), and have gradually extended to entrepreneurship and organizational, strategic, cognitive perspectives (Amit & Zott, 2015; Teece, 2010; Morris et al., 2013; George & Bock, 2011). Some BMs succeed because they subvert the rules of the industry, such as with mobile payments, while some BMs, such as Luckin coffee and bicycle sharing, fail in the competition even if their logic holds (Zhang & Chen, 2020). BMs are widely recognized as the important source of performance differences between SMEs (Snihur et al., 2018).

From the perspective of essential attributes, BMs include not only infrastructure attributes of how to create value, but also value attributes of how to shape competitive advantages (Yang et al., 2018). The infrastructure attribute of BMs describes the main logic of how an enterprise operates and answers the source of value questions, such as by focusing on the adjustment of organizational structures and frameworks that affect the content and efficiency of transactions (Zott & Amit, 2008; Teece, 2010). The value attribute of BMs describes the logic of how Schumpeterian rents are generated, answering the source of advantage question (Amit & Zott, 2001; Yang et al., 2018). The reason why enterprises can obtain competitive advantage through BMs is not because of the basic logic of creating and obtaining value; on the contrary, it lies in the value attribute of how to shape the competitive advantage behind it. Value attribute focuses on the

management logic of how to bring benefits to the organization, which helps to reveal the internal logic of enterprises seeking subversive advantages (Yang et al., 2018; Morris et al., 2013; Latifi et al., 2021). Following the above viewpoints, this study focuses on the dual attributes of BMs: infrastructure attributes and value attributes.

3 Hypothesis Derivation

3.1 The Impact of BDAC on BMs

Mainstream research has broadly agreed that a new technology or technological change is one of the most important antecedents of BM innovation among firms (Chesbrough & Rosenbloom, 2002; Sorescu, 2017; Yuan et al., 2021). In the era of big data, more and more big and small firms rely themselves on big data analytics to capture business values and achieve competitive advantages, which proves the important value of BDAC in BMs (Bouwman et al., 2018; Ciampi et al., 2021; Sun & Liu, 2020). One typical business case is Netflix, which has upended the traditional video industry by mining user preferences through big data analysis and replacing advertising with paid subscriptions. Another instructive example is Clobotics, a startup that uses a cloud-based big data platform to analyze data and provide predictive data analysis services to enterprise users (International Data Corporation, 2019). These two cases all suggest that establishing BMs from big data analysis is the mainstream means for SMEs to undertake daily business activities (Wielgos et al., 2021). Compared with product innovation or service innovation, BMs created by BDAC are more helpful in achieving lasting competitive performance of SMEs (Spieth et al., 2019).

Furthermore, BDA technology capability pays more attention to connectivity, compatibility and modularity (Akter et al., 2016; Sun & Liu, 2020), which largely influences BMs' construction by breaking traditional resource isolation mechanisms and connecting new value creation activities (Burgelman & Grove, 2007; Ciampi et al., 2021). First of all, in the traditional "Production—Supply—Marketing" linear model, the value activities of firms are largely influenced by information barriers and geographical boundaries (Yang et al., 2018; Foss & Saebi, 2017), which makes it difficult for SMEs to build a profitable business model (Yuan et al., 2021; Latifi et al., 2021). Yet, the obvious feature of BDA technology capability effectively breaks down these barriers by providing a broad information integration platform, such as gathering data and information from multiple business units, partners, external markets and consumers (Mikalef et al., 2020; Sun & Liu, 2020). A sample case in China is ByteDance's ability to accurately promote product information by analyzing consumers' short video data in real time. In the process of understanding and digesting multi-party data, SMEs gradually adjust their value proposition, value creation interaction and value acquisition mechanism, thus promoting the establishment of transaction content and transaction structure in BMs (Sorescu, 2017). Secondly, the infrastructure attributes of BMs focus on describing the basic logic of how to operate business, while the connectivity of BDA technology capability effectively reduces the ambiguity of management activities and plays an important role in promoting the division of labor and assistance between different business units and the understanding between participants (Wamba et al., 2017). Finally, modularity can help related technical personnel to adjust the previous cost-benefit model, product service system, pricing strategy, which not only improves resource utilization efficiency and reduces management costs, but also is a clear BMs' source of value creation (Akter et al., 2016).

By contrast, the technical analysis barriers of BDA technology capability also guarantee the value acquisition process based on BMs, which can effectively explain why BMs are full of competitive force. That is, due to the acquisition and analysis of real-time multidimensional data caused by technological progress, SMEs' BMs are no longer a 'relatively open closed system', but a 'relatively closed open system' (Yang et al., 2018). This means that the business focus of SMEs is not only focused on a few niche markets, on the contrary, it focuses on the value co-creation of multiple subjects and resources (Sorescu, 2017). This effectively explains the source of Schumpeter rent in the value attribute of BMs (Nambisan et al., 2017; Olabode et al., 2022). More specifically, BDAC technology capabilities promote the interaction between data and strategy, marketing, organizational structure and other elements by mining customer needs and identifying potential opportunities, thus realizing the knowledge spillover effect (Sun & Liu, 2020; Soluk et al., 2021). For example, more and more SMEs pay attention to the establishment of customers' electronic files in their daily operation (Chen et al., 2020). Additionally, PDD, a third-party social e-commerce platform focusing on C2M group shopping, achieves personalized prediction, recommendation and matching of marketing scenes based on the extraction of key information such as user characteristics and product attributes (Wang et al., 2020). What is more, SMEs can easily and conveniently connect with other information platforms and realize the possibility of leveraging large businesses at a small cost through the flexibility and connectivity of BDA technology capability, which is of great significance for SMEs to build new

competitive advantages (Sun & Liu, 2020; Olabode et al., 2022). This discussion leads us to hypothesize that:

- **H1a:** BDA technology capability is positively related to infrastructure attribute of BMs;
- **H1b:** BDA technology capability is positively related to value attribute of BMs.

BDA management capability refers to the organizational ability of taking advantage of big data to plan, invest, coordinate and control (Sun & Liu, 2020; Akter et al., 2016). Santhanam and Hartono (2003) pointed out that data resources can be easily copied among enterprises (such as information system and customer management system), but the configuration and integration of data are not easily copied. In other words, the analysis and management of data is the key basis for differences in competitive performance (Wamba et al., 2017). Unlike large firms, SMEs do not have the comparative advantage of capability and resources, and most of time they tend to improve the utilization rate of resources, which undoubtedly indicates the importance of organizational management (Desa & Basu, 2013).

Specifically, BDA management capability focuses on objectively grasping resources, stakeholders, environment, and risks through data management (Gupta et al., 2019), which promotes the flow of data and resources among participating entities and broadens the channels of value sources. This not only provides a clear direction for who and how to create value, but also lays the foundation for SMEs to build value creation logic in the future (Sun & Liu, 2020). For example, Tik Tok started with a focus on short video sharing, but with the analysis of consumer behavior data, it is now able to capture consumer preferences and accurately push videos in seconds. Today, Tik Tok is positioned not just as a short-video social app, but as a product revolution that will change consumer habits. This example confirms that BDA management capability has strengthened the identification of market opportunities, market risk monitoring, cost-benefit analysis, and value chain activity analysis for SMEs (Woerner & Wixom, 2015), helping them to understand risks and benefits more comprehensively. The relationship between them enhances the evaluation and selection of their own value creation and value acquisition methods.

From the perspective of the operation logic of BMs, the core of BMs is to reveal the value logic of how firms to business (Amit & Zott, 2001), that is, the transaction activity system connected by the target firms and their partners and the interaction mechanism behind these transaction activity systems (Amit & Zott, 2015). Therefore, it not only depends on its own process arrangement for value creation, value transmission and value acquisition, but also needs cross-boundary collaboration from different participants (Foss & Saebi, 2017). Especially for SMEs, BDA management capability realizes asymmetric links between them and large firms, such as the informal innovation network of *MIUI* (Wei et al., 2021). In other words, the synergy of BDA management capability improves the mechanism system including transaction content, transaction structure and transaction governance (Akter et al., 2016) by docking the demands of different entities, ensuring the smooth operation of BMs and value acquisition. Meanwhile, BDA management capability has strengthened the cultural orientation with data-driven operations as its core, effectively alleviating rigid routine processes, and thereby promoting the emphasis on efficiency and quality, which are important sources of competitive advantages (Mikalef et al., 2020; Gupta et al., 2020). Based on the above analysis, this research proposes the following hypotheses:

- **H2a:** BDA management capability is positively related to infrastructure attribute of BMs;
- **H2b:** BDA management capability is positively related to value attribute of BMs.

3.2 The Impact of BMs on Competitive Performance

Mainstream research has agreed that BMs are an important motive for inducing competitive advantage (Amit & Zott, 2001; Snihur et al., 2018; Li et al., 2021). However, there is still a big debate in academia on the deep-seated issue of "which BM can better promote the growth of firms" (Rietveld, 2018; Foss & Saebi, 2017). The competitive performance of SMEs is not only reflected in quantifiable financial indexes, but also needs to pay attention to its growth (Zott & Amit, 2007; Monferrer Tirado et al., 2019). Therefore, their competitive performance consists of two important parts: growth performance and financial performance.

The infrastructure attributes of BMs focus on describing the operational logic of how an enterprise does business, aiming to clarify the transaction content and improve the transaction efficiency (Zott & Amit, 2008), so as to achieve benefit optimization. Therefore, the infrastructure attributes of BMs play an important role in enhancing SMEs' competitive performance. First of all, the core of infrastructure attributes is to build a fully input-output model, which helps SMEs to identify participants, transaction content and transaction mode in the value chain (Amit & Zott, 2001; Teece, 2010; Li et al., 2021), and to promote the complete value delivery process and significantly improve the market share, profit level and return on investment (Loon & Chik, 2019). This process enables the daily business logic of SMEs to be completed. At the same time, the improvement

of transaction efficiency helps to expand the efficiency of resource utilization and reduce management costs (Chesbrough, 2010), which has a significant promoting effect on improving short-term financial performance among SMEs.

In addition, infrastructure attributes answer the question of the source of value, which can be embodied in customer orientation and customer value optimization (Brettel et al., 2012). Products innovation induced by customer participation further deepens the chain of value creation, delivery, and acquisition, which is of great significance to the growth of SMEs. Finally, the improvement of transaction content and transaction efficiency helps to enhance the system stickiness to stakeholders, thus realizing deeper cooperation and attracting more participants (Amit & Zott, 2015), so as to promote SMEs' growth. Xiaomi, for example, dominates the smartphone industry with a strong innovation ecosystem. Consequently, this study posits the following hypotheses:

H3a: Infrastructure attribute of BMs is positively related to growth performance;
H3b: Infrastructure attribute of BMs is positively related to financial performance.

The value attributes of BMs focus on the management logic that describes how to generate revenue, and focuses on the key competitive forces that generate the source of value advantage (McGrath, 2010; Yang et al., 2018). Therefore, value attributes enhance SMEs' competitive performance by innovating value propositions, products and services, and management processes (Zott & Amit, 2008). First, value attributes broaden the scope of value creation by changing transaction content and introducing new transaction rules and participants (Yang et al., 2018). Facebook, for example, revolutionized the social media and sparked consumer demand. The new value proposition can bring additional benefits to SMEs and significantly improve their financial performance and growth performance.

Secondly, value attributes help SMEs to establish differentiated organizational structures and profit models, such as connecting resources of multiple participants and restructuring cross-border transactions and governance structures (Teece, 2010; Yang et al., 2018), which lay a foundation for market expansion and financial gains. Thirdly, value attributes effectively break the current industry "cognition mode" (Foss & Saebi, 2017). The introduction of new products, new technologies and new services helps to shorten the product-market gap, which largely stimulates potential customer demand and enhances customer value (Kim & Min, 2015; Li et al., 2021). It provides favorable evidence for the acquisition of the competitive performance. Thus, this study proposes the following hypotheses:

H4a: Value attribute of BMs is positively related to growth performance;
H4b: Value attribute of BMs is positively related to financial performance.

3.3 The Moderating Effect of COVID-19

The COVID-19 pandemic has created unprecedented crises, such as disruption of business operations, accelerated environmental change, and frequent and unknown threats (Seetharaman et al., 2020; Kraus et al., 2020). There is a general agreement that COVID-19 will accelerate the reshaping of the business landscape, not only outside the organization, but also within it (Montani & Staglianò, 2021). SMEs are generally more flexible than large firms (Miroshnychenko et al., 2021), so when faced with restrictions and control measures (such as strict community isolation measures, travel restrictions, home isolation, etc.), they are more likely to rely on digital technologies, represented by artificial intelligence, and big data, etc., to mitigate the impact of COVID-19 (Leswing, 2020; Ameen et al., 2021). Firstly, the COVID-19 pandemic presents a high degree of uncertainty, for example, the features are mainly characterized by uncertain economic recovery (expected to end in 2025), wide-spread loss of life (global pandemic) and vague a recovery pattern (McKinsey, 2020), which largely threatens the survival of SMEs. In order to survive in a highly mutated environment, one of the quickest, most effective ways for SMEs to innovate new value creation and acquisition logic is to rely on big data resources and digital technologies. Thus, SMEs may pay more attention to the vital role of BDA technology capability in exploring the new sources of value, which makes the relationship of BDA technology capability and BMs more inter-associated (Seetharaman et al., 2020; Leswing, 2020).

Secondly, the connectivity and compatibility of BDA technology capability are more active under COVID-19, with online office, online shopping, cross-department collaboration and other activities gradually replacing the traditional offline activities. A large amount of diversified information accumulated on the BDA platform not only saves the search cost and management cost (Sun & Liu, 2020; Akter et al., 2016), but at the same time promotes multi-stakeholder understanding of customer needs and corporate governance to facilitate the optimization of existing business models and the introduction of new value propositions. Finally, COVID-19 reinforces the modular block of BDA technology capability, allowing SMEs to quickly adapt existing business scenarios, pricing strategies, and product and service systems to meet existing needs, such as health codes, community group buying, and face mask production lines (Ma et al., 2021). Thus, this adjustment

clarifies the source of value, and on the other hand, it forms a whole set of new income generation routes.

In summary, COVID-19 has pushed SMEs to enhanced the flexibility, connectivity, compatibility, and modularity of BDA technology capability, which accelerates the information docking between supply and demand sides, reducing costs and innovating transaction methods. Thus, this study proposes the following hypothesis:

H5a: COVID-19 strengthens the positive effect of BDA technology capability on the infrastructure attribute of BMs;
H5b: COVID-19 strengthens the positive effect of BDA technology capability on the value attribute of BMs.

In addition, if BDA technology capability needs hardware technological support, then BDA management capability highlights the smart power of organizational coordination. That is, the COVID-19 pandemic has strengthened the importance of BDA management capability among SMEs' organizational operations (Clauss et al., 2021). More specifically, BDA management capability is oriented towards scientific planning and coordinated control (Sun & Liu, 2020), emphasizing the improvement of collaboration and information sharing among participants in the business ecosystem (Foss & Saebi, 2017; Gupta et al., 2019) to ensure the operation and efficiency of BMs. This critical path has re-emerged because of COVID-19. From the perspective of value creation, in order to break through the dilemma, SMEs under the epidemic situation will strengthen the emphasis on customer-orientation (Brettel et al., 2012), meet customer needs through customization and individualization, and improve customer perceived value. Meanwhile, customer participation in product design has gradually become an important means to retain customers (Amit & Zott, 2015). Customers with a high sense of experience are more likely to bring sustainable value to SMEs. What is more, the strong impact of COVID-19 drives them to expand more transaction participants into their business network, and gain additional benefits by discovering and satisfying potential demand (Shamim et al., 2020).

From the perspective of value acquisition, the epidemic impact strengthens the efficiency of resource utilization and data mining (Awan et al., 2021). Optimizing existing BM networks is easier than developing new ways to capture value (Mikalef et al., 2020). Thus, SMEs will increase the overall analysis of environment, input-output, value chain, and improve their performance by innovating resource management and reducing transaction costs (Woerner & Wixom, 2015). Secondly, under the epidemic situation, SMEs have a stronger sense of networking and the synergistic effect of BDA management capability enhances the stickiness among various subjects in the business system, which helps to optimize and adjust the institutional system of transaction content, transaction structure, transaction governance and other aspects (Akter et al., 2016). Finally, diversified data driven by the epidemic has become an important territory to explore new market opportunities. Data-driven management makes value analysis more efficient and high-quality, which also helps them to identify the strengths and weaknesses of their BMs.

In conclusion, by enhancing participant collaboration, customer orientation and digital decision-making, COVID-19 can not only strengthen the value evaluation in BMs, but also enhance customer value and value acquisition through scientific planning and coordinated control, thus promoting the construction of BMs. Thus, this study proposes the following hypotheses:

H6a: COVID-19 strengthens the positive effect of BDA management capability on the infrastructure attribute of BMs;
H6b: COVID-19 strengthens the positive effect of BDA management capability on the value attribute of BMs.

Based on the above theoretical analysis, this paper constructs the following theoretical framework, as shown in Fig. 1:

4 Methodology

4.1 Data Collection and Sample

To empirically test our hypotheses, we adopted cross-sectional survey data collected from SMEs in China as Chinese government provides a significant number of policy supports to foster the development of digital economy, boosting the digitalization of Chinese companies. First, EMBA and MBA students in several universities in Chongqing and Chengdu were contacted to complete the survey questionnaire. Second, senior managers who were alumni of Chongqing University were contacted. Third, other interviewees were selected from the Chamber of Commerce by a snowball process. In China, most EMBA and MBA students work in CEO, senior management or departmental management positions of companies, and have a good understanding of the company's strategy, BMs, and operating performance (Yuan et al., 2021). Thus we included them in our study. A sampling frame was formed based on the Ministry of Industry and Information Technology, the National Bureau of Statistics, the National Development and Reform Commission, and the Ministry of Finance notifications on classification of SMEs. The questionnaire was developed based on the constructs identified in the literature and is presented in Appendix.

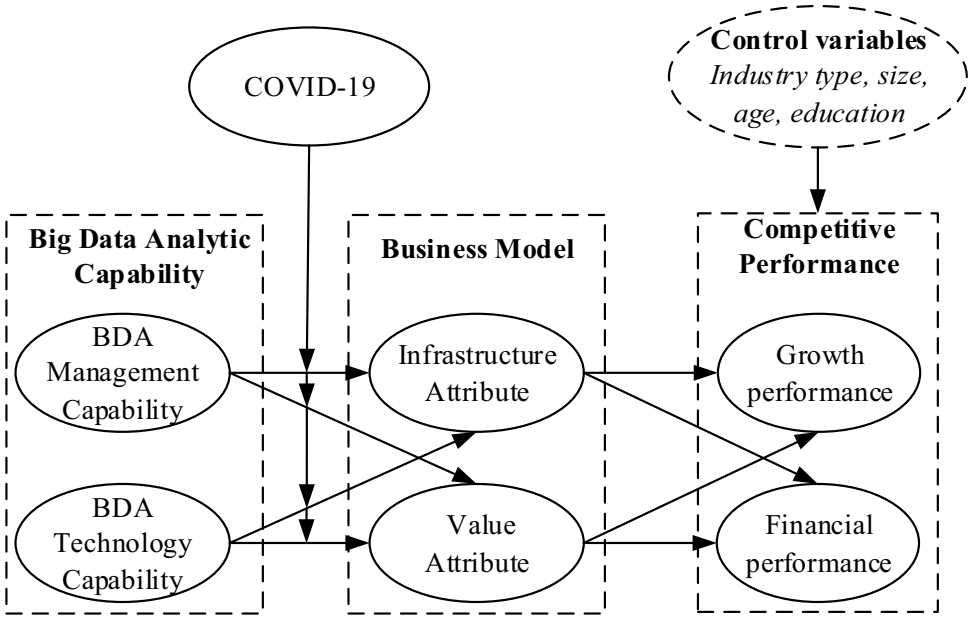

Fig. 1 Theoretical research model

The study used both an offline paper questionnaire and an online questionnaire to collect research data. The research team distributed paper questionnaires to students during class after obtaining the teacher's consent, and collected the questionnaires after they were filled in. To ensure the quality of the questionnaire and reduce the systematic errors caused by Common Method Variance (CMV), the research team members explained the original intention and purpose of the study to the participants and adopted the information hiding method (anonymity) when designing the questionnaire. For those in the alumni association and chamber of commerce that could not fill in on the spot, we collected data by sending electronic questionnaires. Meanwhile, the quality of the recovered sample data was reviewed and cleaned. The review criteria were as follows: firstly, unfilled and incomplete paper questionnaires were deleted, secondly, online responses which were answered in less than 5 minutes were deleted Thirdly, invalid questionnaires and questionnaires with inconsistent screening items were also deleted.

The formal questionnaire survey was divided into two periods, lasting for two months. In the first stage, offline paper questionnaires were issued and recovered. A total of 242 questionnaires were issued and 221 questionnaires were returned, of which 38 were blank questionnaires, and 183 were completed questionnaires. Of these, 138 valid questionnaires were collected, with valid response rate of 57.02%. In the second stage, online distribution and collection were carried out. A total of 218 questionnaires were collected, of which 104 were valid, and the valid response rate was 47.71%. In conclusion, a total of 460 questionnaires were sent out in this study, and 242 were effectively returned with a valid response rate of 52.60%. The details of samples are shown in Table 1.

Table 1 Descriptive statistics of samples (N = 242)

Indexes	Category	Frequency	Per (%)	Indexes	Category	Frequency	Per (%)
Firm size (Number of employees)	1-50	49	20.2%	Firm property	State-owned business	71	29.3%
	51-150	50	20.7%		Private enterprises	120	49.6%
	151-250	27	11.2%		Joint ventures	21	8.7%
	251-500	37	15.3%		WFOE	20	8.3%
	Above 500	79	32.6%		Others	10	4.1%
Industry	Manufacturing	70	28.9%	Firm Age	<1 years	7	2.9%
	Retailing	24	9.9%		1-4 years	50	20.7%
	Foodservice	28	11.6%		5-8 years	46	19.0%
	IT	38	15.7%		>8 years	139	57.4%
	Others	82	33.9%				

4.2 Measures

As all measures used in this study were originally derived from mature measurement tools, we chose Brislin's (1980) "translation and back–translation" procedure to translate them into Chinese with Chinese context. All the scales were assessed using a 7-point Likert-type scale (1 = strongly disagree, 7 = strongly agree).

Independent variable. Following previous studies on BDAC (Akter et al., 2016; Sun & Liu, 2020), we used a five-item scale to measure BDA technology capability and a six-item scale to measure BDA management capability.

Dependent variable. We evaluated the competitive performance from two aspects: growth performance and financial performance. Growth performance was measured from three aspects: sales volume, market share and number of employees by following Monferrer Tirado et al. (2019) and Brinckmann et al. (2011). Financial performance was measured from three aspects of profit level, return on investment and market share by following Covin et al. (2006), and Zhang & Li (2021).

Mediator variable. Following previous studies on business models (Zott & Amit, 2007; Yang et al., 2018), we used a six-item scale to measure both infrastructure attributes and value attributes.

Moderator variable. Since a measure of COVID-19 did not exist, we followed the practice of previous studies by Montani & Staglianò (2021), Hochwarter et al. (2008), and adopted a six-item scale.

Control variable. Differences in property of enterprises would lead to different cultural styles, and different industries could also drive enterprises to adopt different response strategies in response to environmental changes (Vorhies & Harker, 2000). At the same time, the perception of the environment of enterprises in different periods and sizes also shows obvious differences (Zhou et al., 2010). In order to ensure "net effect" of the research topic, we controlled for four variables: firm size, firm age, industry type and firm property.

4.3 Statistical Techniques

Partial Least Squares Structural Equation Modelling (PLS-SEM) was employed to support our analysis. Compared with Covariance-Based Structural Equation Modelling (CB-SEM), PLS-SEM not only overcomes the harsh requirements of large samples (generally the sample size should be greater than 200), but also verifies the theoretical model with the help of small samples (Afthanorhan, 2013; Marsh et al., 1998; Fornell & Bookstein, 1982); Furthermore, PLS-SEM can simultaneously deal with complex models and path relationships of multiple indicators (Hair et al., 2011). In addition, PLS-SEM is more suitable for exploratory forecasting research and can effectively deal with non-normal sample data. In recent years, more and more studies have used PLS-SEM to study issues of organization, strategy, and entrepreneurship (Ali, 2021; Ciampi et al., 2021; Lee & Tang, 2018; Ameen et al., 2020). The theoretical model constructed in this study includes multivariate and multipath relationships. PLS-SEM can intuitively provide the factor loading, significance, effect size and R^2 of latent variables. Moreover, the purpose of this research model is to predict and explain the difference in the impact of key dimensions. Therefore, this study decided to use PLS-SEM.

4.4 Common Method and Non-response bias

This study carried out an extremely detailed test on Common Method Variance (CMV), including: first, analysis of variance on the multi-time point questionnaire, and the results showed that there was no significant difference between the samples, so the influence of time effect was excluded. Secondly, Harman's single – factor analysis was conducted for all questions (Podsakoff et al., 2012), and the results showed that: the cumulative variance contribution rate of the first factor without rotation factor was 31.629%, slightly lower than the threshold value of 50% (Fuller et al., 2016). Third, collinearity diagnosis was performed on all questions, and the results (see Table 2) showed that all VIF values were lower than 4, which indicated that the samples selected in this study did not have serious CMV problems.

5 Empirical Results

5.1 Reliability and Validity

We employed three indexes of Cronbach's α, CR (component reliability) and SMC to evaluate the reliability of core constructs. The results show (see Table 2): Cronbach's α and CR values of core blocks were all greater than the standard value of 0.7, and SMC values of all measurement questions were greater than the standard value of 0.36. Furthermore, Dijkstra-Henseler's rho (ρ_A) was recommended to assess reliability, and the results indicated that the lowest value of ρ_A was for FP (0.877) and the highest value of ρ_A was for BDAT (0.936). Overall, the indices of four types of reliability exceeded the threshold value, supporting the suggestion that all seven constructs were acceptable.

Table 2 Results of reliability of measurement model (N = 242)

Constructs	Items	SFL	SE	t-value[a,b]	SMC	VIF	α	CR	ρ_Ac	AVE
BDAT	BDAT01	0.883	0.017	51.421	0.780	3.014	0.932	0.949	0.936	0.787
	BDAT02	0.918	0.012	79.289	0.843	3.927				
	BDAT03	0.896	0.013	70.790	0.803	3.307				
	BDAT04	0.875	0.016	55.283	0.766	2.900				
	BDAT05	0.862	0.025	34.375	0.743	2.756				
BDAM	BDAM01	0.773	0.031	25.032	0.598	1.837	0.899	0.922	0.900	0.664
	BDAM02	0.831	0.024	34.811	0.691	2.267				
	BDAM03	0.817	0.025	32.883	0.667	2.235				
	BDAM04	0.852	0.020	41.696	0.726	2.597				
	BDAM05	0.781	0.028	28.036	0.610	1.954				
	BDAM06	0.833	0.024	35.180	0.694	2.327				
BMI	BMI01	0.798	0.033	24.703	0.637	2.001	0.892	0.917	0.913	0.648
	BMI02	0.851	0.020	42.933	0.724	2.600				
	BMI03	0.858	0.021	40.174	0.736	2.851				
	BMI04	0.827	0.021	38.450	0.684	2.098				
	BMI05	0.739	0.048	15.254	0.546	1.959				
	BMI06	0.749	0.039	19.352	0.561	1.970				
BMV	BMV01	0.846	0.021	39.575	0.716	2.557	0.920	0.938	0.922	0.715
	BMV02	0.866	0.016	55.682	0.750	2.869				
	BMV03	0.882	0.015	57.837	0.778	3.708				
	BMV04	0.846	0.019	45.381	0.716	2.886				
	BMV05	0.858	0.023	37.837	0.736	2.765				
	BMV06	0.771	0.035	22.151	0.594	2.048				
GP	GP01	0.877	0.029	30.504	0.769	2.694	0.871	0.919	0.904	0.792
	GP02	0.904	0.017	52.980	0.817	2.604				
	GP03	0.888	0.018	48.904	0.789	1.978				
FP	FP01	0.898	0.016	57.361	0.806	2.159	0.865	0.917	0.877	0.787
	FP02	0.871	0.020	42.684	0.759	2.225				
	FP03	0.893	0.015	59.961	0.797	2.355				
COVID-19	COV01	0.823	0.026	31.822	0.677	2.340	0.915	0.934	0.916	0.702
	COV02	0.866	0.018	47.959	0.750	2.927				
	COV03	0.871	0.016	54.988	0.759	3.040				
	COV04	0.838	0.017	49.005	0.702	2.497				
	COV05	0.786	0.026	30.721	0.618	1.942				
	COV06	0.840	0.020	41.722	0.706	2.562				

SFL = Standardized factor loading; SE = Standard error; α = Cronbach's Alpha; C.R = Composite reliability; AVE = Average variance extracted; SMC = Square Multiple Correlations; Dijstra-Henseler's rho;

a = Test-statistics are obtained by 5000 Bootstrapping runs;

b = Absolute *t*-values >1.96 are two-tailed significant at 5% level;

BDAT = BDA technology capability; BDAM = BDA management capability; BMI = infrastructure attribute of BMs; BMV = value attribute of BMs; GP = growth performance; FP = financial performance; COVID-19 = COVID-19.

This study examined the convergent validity and discriminative validity of the measurement tools. First of all, the standardized factor loads of all the dimension's measurement questions were higher than the threshold value of 0.7, and the AVE values of the seven dimensions were all higher than the standard value of 0.5 (see Table 2), which indicates that the convergence validity of the core dimensions selected in this study is ideal. Secondly, the square root of AVE values of all dimensions was greater than the correlation coefficient of the row and column in which they were located, and the correlation coefficient between any dimension was less than 0.8 (see Table 3), which indicates that the discriminative validity of construct construction was acceptable. Finally, the results of HTMT between constructs were also lower than the standard value of 0.85 or 0.9 (Henseler et al., 2014), as shown in Table 3.

Table 3 Results of convergence and discriminate validity (N = 242)

	1	2	3	4	5	6	7
1. BDAT	**0.887**	0.506	0.094	0.670	0.202	0.115	0.469
2. BDAM	0.466**	**0.815**	0.168	0.713	0.441	0.202	0.467
3. BMI	−0.066	0.142	**0.805**	0.125	0.110	0.396	0.078
4. BMV	0.624**	0.649**	0.096	**0.846**	0.360	0.121	0.570
5. GP	0.187**	0.406**	−0.095	0.338**	**0.890**	0.059	0.304
6. FP	0.100	0.176**	0.368**	0.107	−0.043	**0.887**	0.070
7.COVID-19	0.437	0.424**	0.061	0.524**	0.274**	0.031	**0.838**

significance level: $p<0.05^{*}$; $p<0.01^{**}$; $p<0.001^{***}$;

Diagonal elements are the square roots of the AVE;

The elements appearing in the lower-left are the Pearson correlation coefficient between constructs;

The elements appearing in the upper-right are the HTMT values;

BDAT = BDA technology capability; BDAM = BDA management capability; BMI = infrastructure attribute of BMs; BMV = value attribute of BMs; GP = growth performance; FP = financial performance; COVID-19 = COVID-19.

5.2 Structural Model Assessment

Before testing our hypothesis, we assessed the structural model by blindfolding procedure. To set omission distance = 7, the results suggested that (see Table 4) values of Q^2 were higher than 0, which indicated that the PLS path model received satisfactory in-sample power (Khan et al., 2018; Razzaq et al., 2019). Furthermore, this study also employed the index of standardized root mean square residual to evaluate the model fit of the PLS path model, and the results showed that the value of SRMR was 0.055, which is significantly less than the threshold value of 0.08 (Hair et al., 2016; Henseler et al., 2014), indicating that the overall model has a good degree of fit.

5.3 Test for Path Analysis

Smart PLS 3.0 software was used in this study to establish the path relationship between latent variables. As shown in Table 4 and Fig. 2, BDA technology capability is significantly negatively related to infrastructure attribute of BMs ($\beta = -0.169$, $p < 0.05$), and positively related to value attribute of BMs ($\beta = 0.411$, $p < 0.001$), demonstrating that H1a was not supported, but H1b was supported. BDA management capability was both positively associated with infrastructure attribute of BMs ($\beta = 0.223$, $p < 0.01$) and value attribute of BMs ($\beta = 0.458$, $p < 0.001$), and so H2a and H2b were supported. Infrastructure attribute of BMs was negatively associated with growth performance ($\beta = -0.128$,

Table 4 Results of path analysis (N = 242)

Structural path Hypothesized links (direct effect)	Path coefficients	Supported or not?	95% BCa confidence interval	Effects size (f^2)
BDAT → BMI	−0.169*	Not supported	[−0.308, −0.026]	0.023
BDAT→ BMV	0.411***	Supported	[0.266, 0.553]	0.296
BDAM→ BMI	0.223**	Supported	[0.064, 0.373]	0.041
BDAM→ BMV	0.458***	Supported	[0.311, 0.599]	0.367
BMI→FP	0.361***	Supported	[0.255, 0.470]	0.151
BMI→GP	−0.128*	Not supported	[−0.237, −0.016]	0.019
BMV→FP	0.072	Not supported	[−0.037, 0.185]	0.006
BMV→GP	0.351***	Supported	[0.251, 0.465]	0.141
$R^2_{(BMI)} = 0.043$		$Q^2_{(BMI)} = 0.022$		
$R^2_{(BMV)} = 0.553$		$Q^2_{(BMV)} = 0.367$		
$R^2_{(GP)} = 0.141$		$Q^2_{(GP)} = 0.096$		
$R^2_{(FP)} = 0.131$		$Q^2_{(FP)} = 0.086$		

significance level: $p<0.05^{*}$; $p<0.01^{**}$; $p<0.001^{***}$; BCa = Bias-corrected and accelerated;

R^2 = Determination coefficients; Q^2 = Predictive relevance of endogeneity (omission distance = 7);

BDAT = BDA technology capability; BDAM = BDA management capability; BMI = infrastructure attribute of BMs; BMV = value attribute of BMs; GP = growth performance; FP = financial performance.

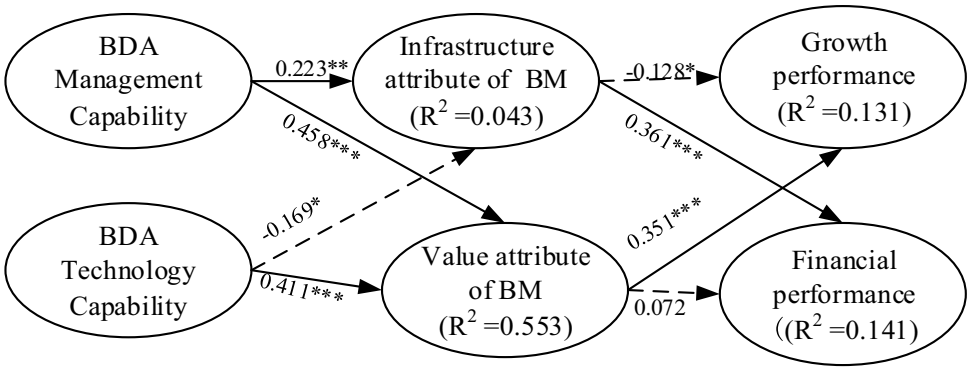

Fig. 2 Path relationship model. *Note:* significance level: $p<0.05$*; $p<0.01$**; $p<0.001$***

$p < 0.05$), but positively associated with financial performance ($\beta = 0.361$, $p < 0.05$), therefore H3a was not supported, while H3b was supported. Value attribute of BMs was only positively associated with growth performance ($\beta = 0.351$, $p < 0.001$), but has no significant effect on financial performance ($\beta = 0.072$, $p > 0.1$), showing that H4a was supported, but H4b was not supported.

The PLS path model in this study was a partial mediation model (see in Fig. 2). To further shed light on this issue, this study examined whether infrastructure attributes of BMs and value attributes of BMs mediated in the model. As suggested by Hayes and Preacher (2013), non-parametric bootstrapping was used to assess the mediating effect. As shown in Table 5, the direct relationship between BDA technology capability and growth performance ($\beta = 0.166$, $p < 0.001$) was significant, but only the indirect effect of value attribute of BMs was significant ($\beta = 0.144$, $p < 0.001$), which indicated that value attribute of BMs had a partial mediating effect between BDA technology capability and growth performance. Similarly, value attribute of BMs had a partial mediating effect between BDA management capability and growth performance ($\beta = 0.161$, $p < 0.001$). Further, the infrastructure attribute of BMs had a total mediating effect between BDA technology capability and financial performance ($\beta = -0.061$, $p < 0.05$), and a partial mediating effect between BDA management capability and financial performance ($p = 0.081$, $p < 0.05$), as shown in Table 5.

5.4 Test for Moderation

This study conducted hierarchical regression to test moderating effect of COVID-19 (see in Table 6). Synthesizing the estimated results of Model 2 and Model 4, COVID-19 had no moderated effect on the relationship between BDA technology capability and infrastructure attribute of BMs ($\beta = -0.029$, $p > 0.1$), and so H5a was not supported. Similarly, synthesizing the results of Model 7 and Model 9, COVID-19 had no moderated effect on the relationship between BDA technology capability and value attribute of BMs ($\beta = -0.045$, $p > 0.1$), and so H5b was not supported.

Synthesizing the estimated results of Model 3 and Model 5, COVID-19 had no moderated effect on the relationship between BDA management capability and infrastructure attributes of BMs ($\beta = 0.021$, $p > 0.1$), therefore H6a was not supported. Similarly, synthesizing the results of Model 8 and Model 10, COVID-19 played a positive moderator role in the relationship between BDA management capability and value attribute of BMs ($\beta = 0.109$, $p < 0.05$), so H6b was supported.

In order to clarify the direction of moderating, we plotted moderating effects of COVID-19 (see in Fig. 3).

Table 5 Mediation analysis results (N = 242)

	Direct effect on GP	Direct effect on FP	Indirect effects on GP		Indirect effects on FP	
			Through BMI	Through BMV	Through BMI	Through BMV
BDAT	0.166***	−0.031	0.022 [0.000, 0.052]	0.144*** [0.095, 0.205]	−0.061* [−0.121, −0.008]	0.030 [−0.016, 0.079]
BDAM	0.132**	0.114**	−0.029 [−0.060, −0.002]	0.161*** [0.090, 0.257]	0.081* [0.022, 0.151]	0.033 [−0.016, 0.092]

significance level: $p<0.05$*; $p<0.01$**; $p<0.001$***;

[] is 95% BCa confidence interval; bootstrapping set is 5000;

BDAT = BDA technology capability; BDAM = BDA management capability; BMI = infrastructure attribute of BMs; BMV = value attribute of BMs; GP = growth performance; FP = financial performance

Table 6 Results of hierarchical regression (N = 242)

	BMI					BMV				
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8	Model 9	Model 10
Industry	−0.029	−0.021	−0.017	−0.019	−0.018	−0.018	0.028	0.058	0.032	0.053
Firm Property	−0.011	−0.004	−0.021	−0.003	−0.020	0.089	0.013	0.032	0.015	0.033
Firm age	0.113	0.111	0.127	0.109	0.130	−0.147	−0.110*	−0.082	−0.114*	−0.066
Firm size	−0.024	−0.008	−0.012	−0.007	−0.011	−0.019	−0.031	0.045	−0.030	0.050
BDAT		−0.125		−0.126			0.489***		0.487***	
BDAM			0.142*		0.149*			0.514***		0.551***
COVID-19		0.110	0.064	0.107	0.001		0.302***	0.307***	0.297***	0.319***
BDAT ×COVID-19				−0.029					−0.045	
BDAM×COVID-19					0.021					0.109*
R^2	0.011	0.027	0.030	0.027	0.031	0.036	0.484	0.505	0.486	0.515
Adj-R^2	−0.005	0.002	0.006	−0.002	0.002	0.019	0.471	0.492	0.470	0.500
ΔR^2		0.016	0.019	0.016	0.020		0.448	0.469	0.450	0.479
F value	0.671	1.073	1.226	0.944	1.059	2.197	36.705***	39.970***	31.575***	35.491***

significance level: $p<0.05^{*}$; $p<0.01^{**}$; $p<0.001^{***}$; BDAT = BDA technology capability; BDAM = BDA management capability; BMI = infrastructure attribute of BMs; BMV = value attribute of BMs; GP = growth performance; FP = financial performance; COVID-19 = COVID-19

6 Discussion

In China, the digital economy has become an important force in economic transformation, and both large firms and SMEs are searching for progress in digital transformation (Chen et al., 2020; Xie et al., 2020). Compared with the resource advantages of large firms, there is still a lot of confusion among SMEs about how and when to play the positive role of BDAC in competitive performance. To fill this research gap, this paper explores the mechanism by which BDAC can influence BMs to promote SMEs' competitive performance and investigates the moderating role of COVID-19 based on 242 multi-point survey data on SMEs in China. The conclusions of this study are as follows:

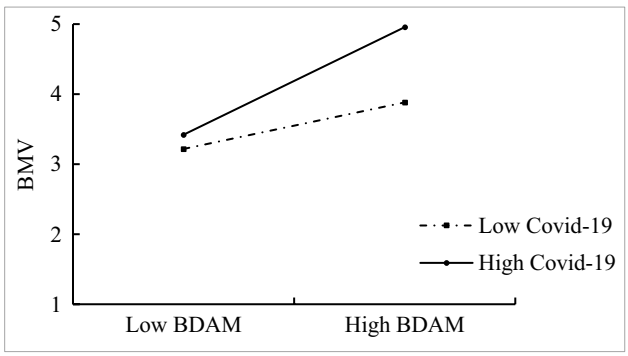

Fig. 3 Moderating effect of COVID-19. *Note:* BDAM = BDA management capability; BMV = value attribute of BMs; COVID-19 = COVID-19

First, BDA management capability is positively associated with both infrastructure attribute of BMs and value attribute of BMs. BDA management capability is broadly defined as the organizational ability of taking advantage of big data to plan, invest, coordinate and control (Akter et al., 2016; Sun & Liu, 2020). By analyzing the market opportunities, market risks, cost-effectiveness and value chain activities of SMEs, we can objectively and comprehensively understand resources, stakeholders, environment and risks, so as to build a logical business model (Woerner & Wixom, 2015). Meanwhile, BDA management capability can improve the mechanism system including transaction content, transaction structure and transaction governance by connecting with the needs of different subjects to ensure the smooth operation and value acquisition of BMs, thus promoting the improvement of efficiency (Akter et al., 2016; Mikalef et al., 2020).

Second, BDA technology capability is only positively associated with value attribute of BMs, while is significantly negatively related to infrastructure attribute of BMs. The technical analysis barriers of BDA technology capability also guarantee the value acquisition process based on BMs. In other words, BDA technology capability realizes the knowledge spillover effect of data and strategy, marketing, organizational structure and other elements by promoting a relatively closed open system among SMEs, which is of great significance for SMEs to build a new competitive

BM (Sun & Liu, 2020; Soluk et al., 2021). However, BDA technology capability may break existing business logic in the process of building new BMs, and thus may negatively impact existing infrastructure attributes of BMs.

Third, infrastructure attribute of BMs is positively associated with financial performance, while it is negatively associated with growth performance. As infrastructure attribute of BMs focuses on describing how an enterprise does business, it can help SMEs to identify participants, transaction content and transaction mode in the value chain (Amit & Zott, 2001; Teece, 2010), which helps to promote the complete value delivery process and significantly improve the market share, profit level and return on investment (Loon & Chik, 2019). However, we should also realize that just because a BM is viable does not mean it is competitive. For example, group-buying may be a great business, but it doesn't mean it can't be copied. In general, the more profitable companies' BMs are, the more rigid they become. Therefore, infrastructure attribute of BMs may have a negative impact on future growth performance.

Fourth, value attribute of BMs is only positively associated with growth performance, but has no significant effect on financial performance. Value attributes of BMs focus on the management logic that describes how to generate competitive force (Yang et al., 2018), which effectively breaks the current industry "cognition mode" and establishes differentiated organizational structures and profit models, such as connecting resources of multiple participants and restructuring cross-border transactions and governance structures (Teece, 2010; Foss & Saebi, 2017). Thus, value attribute of BMs may be associated with growth performance of SMEs. However, financial performance is more reflected in short-term indicators, while value attribute of BMs emphasizes breaking existing norms and regulations, so it may have not a significant effect on short-term financial performance.

Fifth, COVID-19 only plays a positive moderator role in the relationship of BDA management capability and value attribute of BMs but has no significant effect on other relationships. This finding reveals that compared with BDA technology capability, SMEs are limited by weak ability and can only play a positive effect of BDA management capability to a certain extent, through scientific allocation of existing resources and management of participants to achieve superiority (Woerner & Wixom, 2015). Thus, the causal relationship of BDA management capability and value attributes of BMs is more significant.

6.1 Theoretical Implications

This study aims to explore, theoretically and empirically, the internal mechanism of BDAC on competitive performance and the moderating role of COVID-19 in this relationship. The objective is to extend resource-based view (RBV) in BDAC field, which brings several theoretical contributions. First, this study deeply discusses the causal relationship by exploring BMs as the core mediator, giving theoretically evidence for explaining the phenomenon of IT production paradox in SMEs. From a theoretical standpoint, this finding emphasizes that BMs played an important role in facilitating the transformation of data from possible factors of production to actual means of production (Amit & Zott, 2001), which echoes the research of Wamba et al. (2017) and Olabode et al. (2022), and extends the research of Akter et al. (2016). Specifically, value attributes of BMs play a partial mediating role in the relationship between BDA management capability and BDA technology capability and growth performance. Yet, infrastructure attributes of BMs have a total mediating effect between BDA technology capability and financial performance, and a partial mediating effect between BDA management capability and financial performance. This result, therefore, helps to reconcile an influential academic debate, in which BDAC is confirmed to have a positive impact on SMEs' competitive performance (Gupta & George, 2016; Wamba et al., 2017).

Second, by discussing the matching between BDAC and their BMs, this study provides sufficient evidence to answer the question "how do SMEs use BDAC and BMs to achieve competitive performance?", which extends the literature on discussing the antecedent factors of BMs. For example, although BMs are seen as the important source of performance differences between SMEs, much evidence asserts that more than 60% of firms do not reach the expected outcome though business model innovation (Christensen et al., 2016), which demonstrates that BMs can be seen as a double-edged sword (Latifi et al., 2021; Casadesus-Masanell & Zhu, 2013; Foss & Saebi, 2017). Hence, this study revealed that the improvement in financial performance is largely related to the matching of BDA management capability with infrastructure attributes of BMs (Gupta et al., 2019; Sun & Liu, 2020), while the improvement of growth performance comes from the matching of BDA management capability and BDA technology capability with value attributes of BMs (Burgelman & Grove, 2007). This outcome expands the collaborative research of BDAC and BMs from the perspective of theoretical integration.

Third, this study adds new insights into the impacts of COVID-19 on SMEs. It is acknowledged that SMEs have suffered a huge impact from COVID-19 (Seetharaman et al., 2020), but we do not have a good understanding of how COVID-19 affects SMEs' application of BDAC in the digital era. This leads to the inability to use BDAC to improve SMEs' competitive performance. Our finding suggests that COVID-19 positively moderates only the relationship between BDA management capability and value attributes of BMs, while the moderating effects on other pathways are

not significant. This result is meaningful to help SMEs pay more attention to the development and matching of BDAC management capability and value attributes of BMs under the high degree of environmental uncertainty.

6.2 Managerial Implications

The results of our study also have several interesting implications for practitioners. First, since our study highlights BMs as the mediating factor, managers should focus on the unique role of BMs as a bridge for BDAC in promoting competitive performance (Snihur et al., 2018). Therefore, managers should clearly improve the business model design based on the value creation logic and value acquisition mechanism under the BDAC by means of resource allocation, organizational structure adjustment, participants' collaboration, value chain analysis and other ways (Yang et al., 2018; Latifi et al., 2021). On the one hand, SMEs should carry out business model design based on value attributes when pursuing growth performance, such as creating new trading systems, networks, and products. On the other hand, business model design based on infrastructure attributes should be considered when acquiring financial performance, such as improving transaction efficiency and reducing costs (Li et al., 2021).

Second, by considering the matching degree of BDAC and BMs, this study suggests how managers can put balanced investments into the development of BDAC and BMs. Specifically, as BDAC and BMs have undoubtedly become the vital strategic asset of SMEs (Sun & Liu, 2020; Sheng et al., 2017), managers need carefully to assess their BDAC types and BMs types, in order to make appropriate matches to improve the effect of BDAC on their competitive performance (Mikalef et al., 2020; Christensen et al., 2016). Additionally, we can focus carefully on development of BDA management capability and infrastructure attributes of BMs when concentrating on improving financial performance, while paying more attention to matching of BDA management and technology capability and value attributes of BMs when improving growth performance.

Lastly, by considering COVID-19 as moderating factor, SMEs should attach importance to the impact of exogenous shocks in order to stimulate the positive utility of BDAC. Specifically, SMEs' managers are suggested to establish a data-driven market monitoring system in order to achieve timely cost-benefit analysis in an uncertain environment. Moreover, as COVID-19 plays a positive moderator role in the relationship between BDA management capability and value attribute of BMs, SMEs should take the chance to develop BDA management capability and value attributes of BMs to maintain their competitive performance.

6.3 Limitations and Future Research

Despite the contributions of the present study, there are still several limitations to address. First of all, although considerable efforts are undertaken to ensure data quality, self-reported data is still subjective. In view of data privacy, emotional exclusion and other reasons, there are still some errors in the questionnaire data (such as homologous variance and collinearity). Future research should try to optimize measurement by means of situational experiment, case study, experience sampling and so on (Mikalef et al., 2020; Ciampi et al., 2021). Secondly, the data in this study are primary cross-sectional data rather than longitudinal tracking data, which limits the explanatory power of the research conclusions. Thirdly, this study only explains the single matching impact of BDAC and BMs, but there are still other explanatory mechanisms for this relationship, such as resource integration and organizational learning. Future research could introduce new perspectives to further explain this pathway. Fourth, this study only selects SMEs in Chengdu-Chongqing area as samples, and the number of samples is relatively limited, which may affect the universality of the research conclusion. Future research should further expand the data range of samples to enhance the scientific nature of the research conclusions. Fifth, Chinese context is different from developed countries. Specifically, the unique characteristic of Chinese economy is characterized by both transition and digitalization, while the economy of developed countries has passed the transition period. Also, Chinese market is significantly affected by government polies while the developed economy is not (Xiong & Xia, 2020; Xia et al., 2020). Therefore, our research conclusions may not be perfectly generalizable to developed countries. Future research can do some comparative studies between emerging and developed economies.

7 Conclusion

This study is helpful to enrich and expand the literature on BDAC and BMs, and provide theoretical guidance for SMEs to carry out digital transformation in the COVID-19 context. First, this study emphasizes that matching the degree of different types between BDAC and BMs attributes is a key foundation for improving SMEs' competitive performance, which makes up for the deficiency of existing research on BMs. Second, this study explains the internal mechanism regarding BDAC's influence on SMEs' competitive performance via the mediating role of BMs. Finally, COVID-19 has a differentiated moderating effect on the relationship between BDAC and BMs, which can help guide the development of the design of BDAC and BMs in different contexts from a dynamic perspective.

Appendix

Scale Items for Key Constructs

To what extent do you agree with the following statements?
(*1 = strongly disagree; 7 = strongly agree*)

Big data analytics capability (Akter et al., 2016; Sun & Liu, 2020):								
BDA technology capability	-The rest of offices are connected to the core central office for sharing analytics insights.	1	2	3	4	5	6	7
	-Our organization utilizes open systems network mechanisms to boost analytics connectivity.	1	2	3	4	5	6	7
	-Software applications of our organization can be easily used across multiple analytics platforms.	1	2	3	4	5	6	7
	-Employees can access all platforms through the company's user interface.	1	2	3	4	5	6	7
	-To meet the various needs of data analysis, our organization will adjust its internal process system.	1	2	3	4	5	6	7
BDA management capability	—We continuously examine innovative opportunities for the strategic use of business analytics.	1	2	3	4	5	6	7
	—We perform business analytics planning processes in systematic ways.	1	2	3	4	5	6	7
	—When we make business analytics investment decisions, we estimate the effect they will have on the productivity of the employees' work.	1	2	3	4	5	6	7
	—When we make business analytics investment decisions, we project how much these options will help end users make quicker decisions.	1	2	3	4	5	6	7
	—In our organization, information is widely shared between business analysts and line people so that those who make decisions or perform jobs have access to all available know-how.	1	2	3	4	5	6	7
	—In our organization, the responsibility for analytics development is clear.	1	2	3	4	5	6	7
Dual attributes of business model (Zott & Amit, 2007; Yang et al., 2018):								
Infrastructure attribute	-Our organization introduces new operational processes into their business models.	1	2	3	4	5	6	7
	-Our organization adopts novel trading methods.	1	2	3	4	5	6	7
	-Our organization adopts new ways to connect with stakeholders.	1	2	3	4	5	6	7
	-Our organization's business model builds a variety of distribution channels.	1	2	3	4	5	6	7
	-Our organization set up a special organization to keep in touch with customers.	1	2	3	4	5	6	7
	-Our organization has built a perfect partner network.	1	2	3	4	5	6	7
Value attribute	-Our organization reduces inventory, marketing, sales and other costs through the business model.	1	2	3	4	5	6	7
	-Through the business model, our organization reduces mistakes in the process of business transactions.	1	2	3	4	5	6	7
	-Our organization's business model creates new ways to make money.	1	2	3	4	5	6	7
	-Our organization's business model creates new profit points.	1	2	3	4	5	6	7
	-Our organization provides customers with novel value experience through business model.	1	2	3	4	5	6	7
	-Our organization has a unique mode of operation, creating novel products/services.	1	2	3	4	5	6	7
Competitive performance (Monferrer Tirado et al., 2019; Brinckmann et al., 2011; Covin et al., 2006; Zhang & Li, 2021)								
Growth performance	-The sales growth of our organization is relatively satisfactory.	1	2	3	4	5	6	7
	-The market share growth rate of our organization is relatively satisfactory.	1	2	3	4	5	6	7
	-The growth rate of new employees is still satisfactory.	1	2	3	4	5	6	7
Financial performance	-The market share of our organization is still relatively satisfactory.	1	2	3	4	5	6	7
	-The rate of return on investment of our organization is still satisfactory.	1	2	3	4	5	6	7
	-The profit level of our organization is still satisfactory.	1	2	3	4	5	6	7
Covid-19 induced stress (Hochwarter et al., 2008)								
	—The COVID-19 epidemic has had an adverse impact on our organization.	1	2	3	4	5	6	7
	—The COVID-19 has made daily work even more challenging.	1	2	3	4	5	6	7
	—The COVID-19 epidemic has added to concerns about their future development.	1	2	3	4	5	6	7
	—The COVID-19 epidemic has inspired our organization to take the initiative to expand business.	1	2	3	4	5	6	7
	—The COVID-19 epidemic has caused me to work longer hours.	1	2	3	4	5	6	7
	—The COVID-19 epidemic has made work more demanding.	1	2	3	4	5	6	7

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Declarations

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