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ORIGINAL PAPER

Big data analytics management capability and firm performance: the mediating role of data-driven culture

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Abstract

The effect of big data analytics on firm performance and the effects of intermediary variables on this relationship are not yet clearly understood. Drawing on the dynamic capability view (DCV), this study investigates the mediating effect of a data-driven culture on the relationship between big data analytics management capability and firm performance (i.e., operational and financial performance). Drawing on survey data from 432 big data experts across 132 firms operating in Turkey, our findings indicate that big data analytics management capability and a data-driven culture have significant positive effects on both the operational and financial performance of a firm. In addition, a data-driven culture significantly mediates the links between big data analytics management capability and the measures of both operational and financial performance. Hence, our findings offer a valuable guide for managers utilizing big data or making big data investments to increase firm performance.

Keywords Big data analytics capability · Data-driven culture · Dynamic capability view · Operational performance · Financial performance

1 Introduction

Today, the growth and performance of businesses depend on the active use of digital technologies spread throughout the organization (Andrade and Techatassanasoontorn, 2020). For this reason, many businesses are trying to maintain their growth and sustain their competitiveness by implementing some forms of digitalization. Big data is one of the digital forms that enable the digital transformation of a business (Bouncken et al. 2021a). The rise of big data has increased firms' demand for data analytics to enhance data-driven management in decision-making processes and

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organizational actions (Davenport and Harris 2007; Raguseo 2018). As a result, firms have started to make substantial investments in big data analytics (BDA) to gain precious insights from large sets of big data (Constantiou and Kallinikos 2015). BDA technologies are used to benefit from digital trace data, and BDA tools enable businesses to generate valuable information from large numbers of digital data sets. In this way, BDA facilitates the generation of insight into customers' needs, preferences, interests, and behaviors from various data sources related to people's daily activities (Lehrer et al. 2018). Such data-generated information is crucial, especially for firms that operate in a turbulent, dynamic, and highly competitive business environment (Wamba et al. 2017). Although BDA is vital for firms in the new data age, there is little research on how firms should be organized to gain business value from big data initiatives and the interaction of third variables that enhance performance outcomes (Mikalef et al. 2018; Vidgen et al. 2017). Despite progress in explaining how BDA improves performance, we still know little about the underlying mechanisms and capabilities that enable firms to translate their BDA into greater performance, especially in dynamic and fluid environments.

Although significant progress with BDA has been made in developed countries, its application in emerging countries mainly relies on organizations' ability to manage, process, and analyze data sets in various business domains (Chen et al. 2015). We, therefore, conceptualize BDA as an essential organizational capability that provides the opportunity to take advantage of state-of-the-art knowledge in a dynamic environment. Wamba et al. (2017, p. 358) adapted BDA capabilities from the information technology (IT) capabilities literature as a third-order construct of "BDA personnel expertise capability, BDA infrastructure flexibility capability, and BDA management capability." We build on and extend the work of Wamba et al. (2017) by examining the underlying mechanisms/capabilities that enable firms to convert their BDA into performance outcomes in emerging markets—where the rapid change in the institutional, technological, and social landscape may shape the extent of the organizing, administering, and structuring of big data. For instance, firms operating in emerging markets find it difficult to structure and manage data due to weak technical skills and inadequate institutions (Shamim et al. 2020), necessitating a combination of non-technical capabilities to enhance decision-making. Building on this view, we provide a theoretical argument and accompanying evidence that, through the dynamic capability of a data-driven culture (DDC), BDA management capability (BDAMC) improves the operational and financial performance of a firm with data-oriented coordination and control functions through proper data-oriented planning and investment abilities (Wamba et al. 2017). This aids firms in systemizing routine management processes and optimizing their decision models (Barton and Court 2012; Ferraris et al. 2018).

Drawing upon the dynamic capability view (DCV) of firms, this study examines how BDAMC can contribute to firm performance under the mediating effect of a DDC. The dynamic nature of BDAMC calls for the adoption of a DCV to analyze its underlying mechanisms and outcomes. This approach offers a suitable theoretical foundation for our research, as digital transformation endures as a meta-capability to help firms reconfigure change in the external environment (Endres et al. 2020; Schilke et al. 2018). The potential power of BDAMC rests on its ability to generate new resources and digital transformation (Braganza et al. 2017; Mikalef et al. 2019a). We argue that BDAMC affects performance, but the relationship is an indirect one mediated by DDC.

In a continuously changing environment, dynamic capabilities can be viewed as vital channels enabling firms to manage big data successfully and convey it into superior performance (Conboy et al. 2020). The prior literature suggests that a DDC is essential for gaining value from BDA initiatives (Kiron and Shockley 2011). In a DDC, managers make decisions depending on the information derived from data rather than based on their intuitions. Without cultural adaptation to data-driven working habits, developing BDAMC cannot create higher performance alone (McAfee et al. 2012; Wang et al. 2016). Therefore, a DDC becomes vital to enhancing the impact of BDAMC on firm performance. Based on survey data from 432 big data experts across 132 firms operating in a key emerging market, Turkey, this study explores the following two central research questions: (i) Does BDAMC influence the effect of BDA on the operational and financial performance of a firm? (ii) Does the DDC of a firm mediate the relationships between BDAMC and these two measures of firm performance (i.e., operational and financial performance)?

This study offers major contributions to BDA research. First, our study investigates the effect of BDAMC on firm performance using DCV as a theoretical lens. The reason for adopting DCV as a theoretical basis is that it contributes to firm performance by adapting technological capabilities and resources to changing conditions in environments with high uncertainty and complexity (Bouncken et al. 2016; Endres et al. 2020). The idea of successfully managing BDA capability at the firm level requires dynamic and collective capabilities (e.g., DDC) to yield effective results in emerging markets.

While several studies have investigated the direct relationship between BDAMC and firm performance, there is a noticeable gap in BDA literature that attempts to unpack the link between various types of BDAMC and firm performance. To fill this lacuna, our study offers a new conceptual framework to consider the influence of DDC as a mediator on the link between BDAMC and the effect of BDA on firm performance. Second, partial least squares-structural equation modeling (PLS-SEM) is used to test the effect of BDAMC on firm performance. PLS-SEM is a variance-based approach for SEM and has been increasingly used in management research to explain complex relationships with more relaxed assumptions (Esposito et al. 2010; Hair et al. 2017; Ratzmann et al. 2016). The firm is selected as the unit of analysis, and BDAMC is linked with firm performance under the mediating effect of a DDC, providing an important contribution to BDA literature.

Finally, this study is conducted in an emerging market, Turkey, which is fast-growing and similar to other emerging markets like Brazil, India, Pakistan, and Mexico. BDA research is generally conducted in developed countries with an apparent lack of research in the context of emerging markets (Aydiner et al. 2019a; Peng et al. 2016; Yasmin et al. 2020). Turkey values technological infrastructure investments to adopt big data technologies because it is becoming crucial for firms in all sectors to develop BDA capabilities. Although emerging countries are generally considered to be insufficient in terms of economic, legal, and financial infrastructure (Autio et al. 2021), BDA researchers argue that big data can help both private and public sector firms to cope with global competition by facilitating decision-making and achieving developmental goals. Therefore, our choice of Turkey as a survey setting offers a valuable contribution to the BDA literature in understanding the dynamics of the BDAMC and firm performance relationship within an emerging country context.

The rest of the study is organized as follows. In the next section, we provide a review of the theoretical background of BDA capabilities and DCV. Then, we present the research methodology, followed by the data analysis and results. The conclusion and implications are discussed in the final section.

2 Theoretical background and hypothesis development

2.1 BDA management capability and the dynamic capability view

Firms that use BDA are heterogeneous in terms of their business environment and operations. The resource-based view (RBV) suggests that firms gain a competitive advantage with firm-specific resources and capabilities (Barney 1991). Early studies in the IT and BDA literature are highly fed from the RBV to enhance firm competitiveness and performance with distinctive IT-based organizational capabilities and resources (Kwon et al. 2014; Wade and Hulland 2004). With rapid changes and increasing uncertainties in the business environment, the RBV became inadequate for explaining how and in what way businesses can gain competitive advantages (Eisenhardt and Martin 2000). Therefore, the DCV was developed as an extension of the RBV and included difficult-to-replicate capabilities to maintain competitiveness by responding to rapid changes in highly dynamic environments (Teece 2007). With a rapid realignment of resources and capabilities, firms can respond to IT-based analytical developments to sustain firm performance (Braganza et al. 2017).

The extension of the RBV into dynamic markets provides a fresh perspective for explaining why some firms are better at managing their BDA. Defined as the "learned and stable patterns of collective activity through which the organization systematically generates and modifies its operating routines in pursuit of improved effectiveness" (Zollo and Winter 2002, p. 340), DCV determines the capacity of an organization to change (Eisenhardt and Martin 2000). Accordingly, the ability to adapt and reconfigure internal and external resources and competencies to address rapidly changing environments rests at the epicenter of BDAMC (Endres 2018). The core argument here is that DCV can serve as the internal process through which firms manage and govern large volumes of both structured and unstructured data to match market demand. This forces the firm to rethink its existing managerial mechanisms and adapt and transform its digital resources and capabilities to achieve a sustainable competitive advantage (Endres et al. 2020).

Later researchers used the DCV to conceptualize BDA capabilities that enhance the competitiveness of firms in a highly complex and dynamic business environment (Chen et al. 2015; Dubey et al. 2017). The growth of uncertainty and complexity in the business environment has forced firms to rely on BDA to create effective analytical strategies and plans for the management of uncertainties (Sun et al. 2016; Wang et al. 2015). As dynamic capabilities are used to adapt to environmental changes, BDA capabilities are also regarded as dynamic capabilities for sustainable business performance. BDA capabilities are theoretically based on IT capabilities and have been adopted by many researchers as a new IT innovation that offers firms higher competitiveness and performance (Enders et al., 2021; Garmaki et al. 2016). In this context, Wamba et al. (2017, p. 358) adapted BDA capabilities from IT capabilities, considering BDA capabilities as a multi-dimensional construct with three underlying dimensions: "BDA management capability, BDA infrastructure flexibility capability, and BDA personnel expertise capability."

In this study, we conceptualized BDAMC as a dynamic capability for two main reasons. First, in today's data-driven environment, BDAMC is a data-oriented dynamic analytical capability that allows firms to systematize and organize routine management activities depending on the objective information extracted from organizational data sets (Ferraris et al. 2018). The DCV not only considers big data as a value-creating resource and investigates various usage methods but also focuses on the continuous restructuring of big data assets and processes to support the dissemination and use of information obtained from large data sets within the organization for diverse operational and strategic purposes (Ciampi et al. 2021). In this way, traditional managerial routines are adapted to changing data-driven organizational conditions to examine multiple sourced data sets and maintain competitiveness. The management functions of planning, coordination, investment decision-making, and control capabilities are systematized to optimize the decision models of businesses (Barton and Court 2012). With these capabilities, firms can also quickly gain insight into market changes and amend their resources and strategies accordingly (Wang et al. 2019).

Second, the use of BDAMC reflects the characteristics of dynamic capabilities: commonalities in features with idiosyncratic details. In the BDA literature, there are many industry reports and academic studies that describe the "best practices" for firms in exploring and implementing BDAMC for different purposes (Chen et al. 2015; Mandal 2018, 2019). BDAMC also cannot be used by different firms in precisely the same way, which makes BDAMC idiosyncratic across firms. The use of BDAMC can be embedded into IT and integrated with different IT management processes to optimize management decisions systematically. Therefore, theoretically, it is significant to use BDAMC as a dynamic capability to understand the effects on firm performance.

Wamba et al. (2017) classify BDAMC under four dimensions of capability: planning, investment decision-making, coordination, and control. BDA planning capability refers to creating strategies, making plans, and designing processes for the effective use of data analytics across the enterprise. Therefore, a well-planned IT infrastructure in BDA positively influences the performance outcomes of a firm (Mandal 2019; Wu et al. 2017; Barton and Court 2012) state that BDA planning capability is related to identifying potential opportunities for the business and predicting how big data-based business models can contribute to business performance. For example, Amazon has a suggestion system for every product bought or visited through the Amazon website that gives its customers a referral to something that "you may also want." This system uses big customer data, and Amazon realizes 30% of its sales with this recommendation system (Manyika et al. 2011).

BDA investment decision capability is related to having an optimal IT resource with various structured financing models to balance the investment cost of an enterprise and strengthen its strategic stance on IT investments (Kim et al. 2012). The failure of many BDA investments is actually due to poorly planned investment decisions. Therefore, profit and loss calculations should be conducted with various evaluation methods, and BDA investment decisions should be made according to these results (Hitt and Brynjolfsson 1996; Ryan and Gates 2004; Ramaswamy 2013) has argued that companies that make the correct investments in big data provide above-average returns and gain competitive advantages. For example, Netflix invested in a suggestion system that recommends movies and TV series to customers by analyzing the big data sets from customer profiles, including likes, dislikes, and comments given to the movies. In this way, Netflix has reached over 221 million paying subscribers worldwide as of 2021 (Statista 2022).

BDA coordination capability refers to the cross-functional synchronization of activities related to big data analytics across the enterprise (Mandal 2019). Coordination capability is crucial to ensuring the accessibility of big data whenever needed by all business units. For example, Procter and Gamble uses big data synchronously in many areas, such as sales, marketing, product development, supply chain, and market research (Davenport 2006). BDA control capability is essential for checking whether financial and human resources are used appropriately in a firm (Wamba et al. 2017). For example, within Amazon, assessing the compliance of BDA schemes with BDA plans, clarifying the roles and responsibilities of the BDA unit, developing performance monitoring criteria, and continuously monitoring performance are essential control practices (Schroeck et al. 2012).

In this regard and in light of the DCV, we argue that dynamic BDAMC positively affects firm performance. BDAMC is essential to gather, transform, and reorganize resources with BDA-based analytical procedures to respond to changing business needs in different industries. The proper use of data analytics for the right management routines or processes can accelerate a firm's response to rapid technological changes, improve the data-driven objective decision-making ability of managers, and ultimately result in higher operational and financial performance.

2.2 Hypothesis development

2.2.1 BDAMC, DDC, and firm performance

Digital technologies increase the resilience of companies in the face of sudden and disruptive events and support business transformation by adopting new avenues for value creation, delivery, and capture (Autio et al. 2021; Bouncken and Barwinski 2021). BDA capability, as digital technology, is crucial for business success (Akter et al. 2016). Companies that use big data effectively have the ability to obtain valuable information from meaningless data, and the use of this information, which is available at any time and anywhere in the organization, makes a significant contribution to the growth and productivity of the enterprise (Chen et al. 2015).

Table 1 summarizes the selected studies investigating the relationship between BDA capabilities and firm performance from various theoretical perspectives. Pre-

Table 1 Summary of selected studies on BDA capabilities and performance outcomes

Studies	Theoretical background	BDA capabilities	Performance outcome
Chen et al. (2015)	Dynamic capability view	BDA usage	Asset efficiency and business growth
Gupta and George (2016)	Resource-based view	Tangible (data, technology, and basic resources), human (managerial and technical skills), and intangible (data-driven culture and intensity of organizational learning)	Market performance and operational performance
Garmaki et al. (2016)	Dynamic capability view	Technical infrastructure, management, personnel, and relational network capabilities	Market performance, operational performance, and financial performance
Akter et al. (2016)	Resource-based view and sociomaterialism theory	Managerial, technological, and human resource capability	Firm performance
Wamba et al. (2017)	Resource-based view and dynamic capability view	Infrastructure flexibility, managerial capability, and employee expertise capability	Financial performance
Ferraris et al. (2018)	Resource-based view	Technological and management capabilities	Firm performance
El-Kassar and Singh (2019)	Resource-based view	Big data acceptance, routinization, and assimilation	Green innovation, competitive advantage, and organizational performance
Wamba et al. (2019a)	Resource-based view	Technology quality, information quality, and talent quality	Firm performance
Wang et al. (2019)	Resource-based view and configurational theory	Data integration and interpretation capability, predictive analytics capability, technical and analytical skills of personnel	Healthcare quality
Dubey et al. (2019b)	Resource-based view and institutional theory	Tangible resources and human skills	Cost performance and operational performance
Mikalef et al. (2019b)	Complexity theory	Data, technology, technical skills, managerial skills, structural practices, relational practices, and procedural practices	Firm performance
Vitari and Raguseo (2020)	Resource-based view and contingency theory	BDA transactional value, BDA strategic value, BDA transformational value, and BDA informational value	Firm performance
Upadhyay and Kumar (2020)	Dynamic capability view and sociomaterialism theory	Infrastructure capability, talent capability, and management capability	Firm performance
Bag et al. (2020)	Dynamic capability view	Talent capability and management capability	Sustainable supply chain performance
Yasmin et al. (2020)	Dynamic capability view	Infrastructure, management, and human resource capability	Operational and market performance

Table 1 (continued)

Studies	Theoretical background	BDA capabilities	Performance outcome
Mikalef and Krogstie (2020)	Resource based view	Tangible (data, basic resources, technology), intangible (data-driven culture and organizational learning), and human (managerial and human)	Incremental and radical innovation process capabilities
Gu et al. (2021)	Resource-based view, contingency theory, and dynamic capability view	Big data analytics capability as a single dimension	Supplier development and firm performance
Chatterjee et al. (2021)	Dynamic capability view, resource-based view, and absorptive capacity theory	Adoption of business analytics and data-driven culture	Product innovation, process innovation, firm performance, and competitive advantage

vious studies, in both the IT and BDA literatures, support a positive link between analytical capabilities and firm-level outcomes (Akter et al. 2016; Bharadawaj, 2000; Kim et al. 2011; Mikalef et al. 2019b; Wang et al. 2019). Several studies in the BDA capability literature heavily depend on the DCV and posit that BDA capabilities tend to enhance firm performance by reducing operational costs (Srinivasan and Arunasalam 2013); maximizing profit with optimized prices (Schroeck et al. 2012); improving sales, market share, and profitability (Manyika et al. 2011); increasing return on investment (Barton and Court 2012); and creating new products and services, increasing operational service quality, and creating a competitive advantage or reducing market risk (Akter et al. 2016; Gunasekaran et al. 2017).

Wamba et al. (2019a) found a positive relationship between BDA quality and firm performance through the moderating effect of analytics quality and firm strategy alignment. Wang et al. (2019) noted that BDA capabilities, together with organizational resources and capabilities (evidence-based decision-making, data governance, planned dynamic capability, and improvisational capability), can improve healthcare quality. Yasmin et al. (2020) showed a high association between BDA capabilities and firm performance using an integrated multicriteria decision-making methodology. In a more recent study, Gu et al. (2021) investigated the impact of BDA capability on supplier development and business performance. They emphasized the strong moderating and mediating effects of BDA capability on the link between supplier development and firm performance.

These studies examining the relationship between BDA and firm performance suggest that BDA might provide an impetus for developing distinctive and dynamic capabilities (Mikalef et al. 2019a, b). While there is a consensus that BDA generates positive organizational outcomes, we know little about how firms can manage and capitalize on this potential to achieve greater performance. The lack of a clear articulation of the mechanism underlying the BDAMC–performance relationship, especially in the context of emerging markets, hampers our understanding of the multifaceted and dynamic nature of BDAMC. Building on this view, we examine the BDAMC-performance link through DDC. In the context of emerging markets, it is critical to scrutinize how and under which circumstances BDAMC generates greater performance. The basic argument here is that firms operating in emerging markets need sufficient analytical skills and knowledge, as well as cultural understanding, to manage BDAMC successfully.

Under a high level of uncertainty, adopting and developing organizational processes using the managerial capabilities of BDA is vital for achieving higher firm performance (Janssen et al. 2017). BDAMC supports managers in planning, coordinating, investing, and controlling complex big data activities (Wamba et al. 2017). BDAMC creates remarkable opportunities for managers to determine the direction and content of digitalization in business (Ritter and Pedersen 2020). BDAMC sustains firm performance by making the routine activities of a firm's basic management functions more systematic and organized through the effective use of resources related to BDA. For example, BDA planning capability is used to systematize the distribution and use of big data in business processes to increase both operational and financial performance (Barton and Court 2012). Investment decision capability helps firms utilize big data sets to make profit-loss calculations to prevent financial losses (Ryan and Gates 2004); coordination capability is used to structure the cross-functional synchronization of departmental activities across firms to improve operational, supply chain, marketing, financial, and overall business performance (Davenport 2006); and controlling capability is crucial for the continuous monitoring of performance to check whether all kinds of financial and human resources are being used appropriately (Mandal 2019; Schroeck et al. 2012). Therefore, we hypothesize:

H1: BDAMC is positively related to the effect of BDA on the operational performance of a firm.
H2: BDAMC is positively related to the effect of BDA on the financial performance of a firm.

BDAMC is one of the crucial aspects of BDA capabilities and is regarded as a firm-specific management capability developed by workers in the same organization over time and used to make difficult business decisions by applying a data-driven management framework (Akter et al. 2016). BDAMC is crucial for selecting and implementing the right BDA initiatives by relying on objective information extracted from data sets (Ferraris et al. 2018). As decision-makers, managers should determine the best options for their firms depending on their analytical skills and abilities (Provost and Fawcett 2013). A DDC, meanwhile, is defined as a culture where managers make decisions based on the insights derived from data rather than following their intuitions. A DDC is also seen as a critical intangible resource to develop BDA capabilities in an organization (Gupta and George 2016; Kiron and Shockley 2011) highlight three main characteristics of a DDC: (i) analytics should be seen as a strategic asset by a firm, (ii) top management of a firm should support analytics and analytical initiatives across the organization, and (iii) decision-makers should have access to data-driven insights. As understood from the characteristics of a data-driven culture, BDAMC is expected to positively affect the spread of a DDC in a firm. Therefore, we propose the following hypothesis.

H3: BDAMC is positively related to the DDC of a firm.

2.2.2 The mediating role of DDC

Recent studies in the literature argue that BDA capabilities have indirect effects on firm performance, which are mediated by the firm's changing organizational capabilities and resources (Côrte-Real et al. 2017). However, the current studies are insufficient to provide a roadmap for how firms should utilize BDA capabilities to enhance organizational performance. Firms have little knowledge of which organizational capabilities and resources they need to strengthen to achieve high returns from big data investments (Mikalef et al. 2018).

In BDA research, culture is taken as a critical source for the success of big data investments (Gupta and George 2016) because the success of technology initiatives in a firm depends on organization-wide cultural adaption (Heinze and Heinze 2020). When transition processes to new technology are a part of the organizational culture, communication and information-sharing practices among workers and technology application processes all improve, and the management of new technology becomes easier (Bhatti and Ahsan 2016). DDC is considered to bring business-oriented cultural transformation to a firm, especially where the context is dynamic. In this vein, the DDC of a firm changes the mindset of an organization from "what we think" to "what we know" according to the context in which firms operate (McAfee et al. 2012). That is why many studies relate the failures of big data projects to the lack of a supportive organizational culture rather than a lack of technological infrastructure (Lavalle et al., 2011; Ross et al. 2013). To take full advantage of big data, it is necessary to develop a data-oriented culture and make decisions in line with the information obtained from the data.

A firm's culture consists of a complex set of beliefs, values, assumptions, and symbols. These elements provide the ways through which a firm conducts and changes strategic and operational tasks (Chatterjee et al. 2021). For instance, a DDC serves as a cultural catalyzer that enhances learning, communication, and information-sharing, as well as an engine to transform and apply new ideas and processes successfully. However, creating a DDC is not easy work for large businesses with a long history. According to a study by Davenport and Bean (2018), nearly all respondents (99%) stated that their business had been trying to make a shift to a DDC, but only one-third of the companies had realized this objective. Although this gap is highlighted every year in surveys, the success level of companies has not yet improved. Therefore, it is expected that a DDC will have a big impact on a firm's operational and financial performance by improving decision-making processes with the information obtained from big data sets inside and outside the company.

According to the DCV, organizational culture can influence both the dynamic capabilities and organizational outcomes of a firm (Gnizy et al. 2014; Shamim and Abbasi 2012). BDAMC is a dynamic analytics-based capability that helps firms plan, coordinate, control, and make investment decisions (Wamba et al. 2017) related to big data initiatives. These capabilities are valuable in supporting operational and financial performance results in an organization by reacting to changes and ensuring sustainability in performance (Mandal 2018). However, without a cultural adaptation to data-driven working habits, developing managerial BDA capabilities cannot, on its own, create a higher performance (McAfee et al. 2012; Wang et al. 2016). In big data

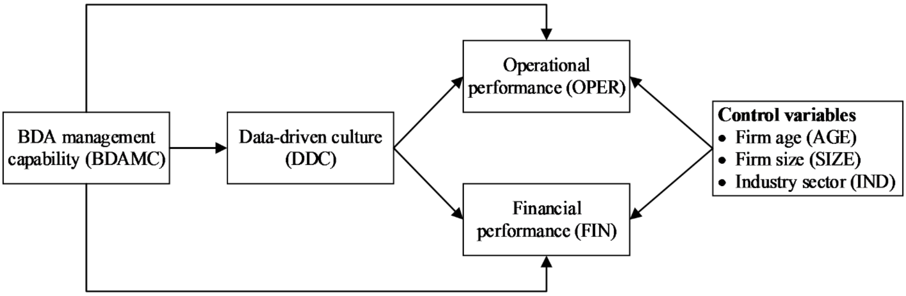

Fig. 1 Research framework

studies, it is generally argued that culture is one of the biggest challenges in managing big data (McAfee et al. 2012). To enhance the power of BDAMC in firm performance, a DDC is essential because firms use analytical culture as a competitive force to support firm performance. Firms with an organization-wide analytical culture are highly competitive in analytics. Therefore, firms with a poor analytical culture should focus on developing their analytical mindset rather than investing directly in BDA tools and infrastructure (Thirathon et al. 2017). In this direction, it will be logical to take DDC as a mediator in the relationships between BDAMC and the effect of BDA on the operational and financial performance of a firm.

H4a: DDC mediates the relationship between BDAMC and the effect of BDA on the operational performance of a firm.

H4b: DDC mediates the relationship between BDAMC and the effect of BDA on the financial performance of a firm.

Figure 1 displays the research framework along with the hypothesized relationships.

3 Research methodology

3.1 Survey context

The rationale for choosing Turkey as the survey setting is two-fold. First, Turkey is a sizeable country that exhibits comparable features with several other big emerging markets (Bouguerra et al. 2022a; Yasmin et al. 2020). Most emerging markets, including Turkey, are growing rapidly and becoming more involved in international business. Their share of worldwide foreign direct investment inflows has exceeded those of developed countries in recent years (UNCTAD, 2021). Turkey is a member of the G20 group of leading economies and the 17th largest economy globally (World Bank 2021). It positions itself as a global player for investment, linking markets across Europe, Asia, and Africa. With its rapid economic growth and as one of the primary recipients of FDI worldwide, Turkey represents a favored target for doing business and a hot spot for developing new technologies and excelling in innovation and learning capabilities (Bouguerra et al. 2022b). For instance, more than 65% of industrial firms in Turkey reported an increase in innovation activity. Also, R&D expenditure as a share of GDP more than doubled from 0.50% to 2004 to 1.09% in

2020 (OECD, 2022). Second, the management of big data and performance outcomes are expected to differ significantly across countries. Liu and Vrontis (2017) posit that emerging markets can vary in their sociocultural, economic, political, and institutional dimensions compared to developed countries, which obviously increases the need to study and explore the contexts of emerging markets and specifically delineate how firms operating in emerging markets can develop and manage new technologies successfully. Thus, studying diverse contexts such as emerging markets would further advance understanding of the development and management of new technologies where the environment is fluid and dynamic. For instance, firms operating in emerging markets face many more obstacles and challenges in the use of new technologies and the process of creating value from them (Shamim et al. 2020). Studies in this field are, however, predominantly carried out in advanced industrialized economies with stable business environments. Therefore, it is vital to investigate and understand the changes related to the management of and strategies for new technologies and their impact on firm performance in emerging markets.

3.2 Sample and data collection

In this study, a survey method is used to gather data from IT experts in Turkish firms who actively use big data in their operations.

The questionnaire-based survey method is useful for testing hypotheses, describing the population, building research models, and generalizing research statements (Lee and Shim 2007). All measurement items in the questionnaire were adapted from the extant literature. The survey development and validation consisted of several steps. In the first step, the originally designed measurement items were reviewed by four IT professionals and five academics to ensure content validity in terms of understandability, clarity, and responsiveness. In the second step, required modifications were made to the measurement items, and the same professionals and academics rechecked the revised survey. In the third step, the survey questionnaire was distributed to 40 IT professionals with analytical expertise to review and revise the items if necessary. After their feedback, minor adjustments were made to the survey. In this stage, we also used the survey responses of this group as a pilot study and pre-tested the survey items to increase reliability and validity.

The final version of the survey questionnaire was sent to 600 randomly selected firms from different sectors with extensive use of big data in business operations in Turkey. The potential respondents included business analysts, big data analysts, IT professionals, and digital officers of these firms, as well as managers and analysts in digital-born organizations (data-driven firms from sectors such as software, telecommunications, e-commerce, and energy) who have a high level of analytical knowledge and experience. Additionally, we utilized multiple responses for each firm. In total, 2,500 questionnaires were distributed (with 3 to 5 respondents in each firm). Surveys were collected via e-mail or face-to-face, according to the firms' requests. After two rounds of data collection, we received 477 responses across 132 firms, of which 432 were usable. This yielded an effective response rate of 17.28%, which is comparable to studies in similar settings (Kriauciunas et al. 2011). The key features of the respondents and responding firms are presented in Table 2. In addition, we used

Table 2 Characteristics of respondents and responding firms

Characteristics of respondents (N=432)		*Number*	*%*
Experience level	Less than 5 years	191	44.2
	5–10 years	154	35.6
	11–20 years	61	14.1
	Over 21	26	6.0
Job position	Analyst	175	40.5
	IT expert	115	26.6
	Digital officer	71	16.4
	Manager	71	16.4
Education level	Undergraduate	257	59.5
	Graduate and doctorate	175	40.5
Characteristics of firms (N=132)		***Number***	***%***
Industry sector	Banking and insurance	23	17.4
	Software and IT	20	15.2
	Health, chemical, and pharmaceutical industry	13	9.8
	Wholesale, retail, E-commerce	12	9.1
	Construction and products	10	7.6
	Transportation and tourism	9	6.8
	Automotive	8	6.1
	Oil and energy	7	5.3
	Telecommunications, media, and communications	6	4.5
	Food and drink	5	3.8
	Others	19	14.4
Geographic scope	Local	33	25.0
	Global	99	75.0
Total number of employees	Less than 50	12	9.1
	50–249	21	15.9
	250–499	10	7.6
	500–999	13	9.8
	1000 and above	76	57.6
Firm's sectoral experience	Less than 5 years	6	4.5
	5–10 years	16	12.1
	11–20 years	24	18.2
	21–40 years	36	27.3
	Over 40	50	37.9

ANOVA and t-tests to check whether there was a difference between the measurement of key constructs used in the survey and the survey respondents with respect to characteristics such as job position, experience, education level, and sector. The results, shown in Appendix A, revealed no significant variations ($p>0.1$) between the groups and their responses to the survey measures. We then used the firm-level data for model estimation.

The non-response bias was tested by comparing early and late responses, in line with Armstrong and Overton's (1977) recommendations. The test results indicated no significant variation in the responses between early and late respondents ($p>0.1$) for the following measures used in the survey: BDAMC (t-value = -0.66, $p=0.51$), DDC (t-value = −0.37, $p = 0.71$), operational performance (t-value = − 1.35, $p = 0.18$), and financial performance (t-value = −0.27, $p = 0.78$). Therefore, non-response bias did not appear to be present in our study.

3.3 Measurement of variables

This study used perceptual measures to evaluate each variable. The variables for our study were drawn from prior research and were measured on 5-point Likert scales (1 = "strongly disagree" to 5 = "strongly agree").

Independent variable. The construct for BDAMC was adapted from Wamba et al. (2017) and composed of 17 items, including four sub-dimensions: planning capability (PLCAP), investment decision capability (IDCAP), coordination capability (COCAP), and control capability (COCAP).

Mediating variable. The mediating variable of DDC was drawn from Gupta and George (2016) and included five items.

Dependent variable. The effect of BDA on firm performance was used as the dependent variable and denoted by two dimensions: operational performance (OPER) and financial performance (FIN). Both OPER and FIN were adapted from earlier studies (Aydiner et al. 2019a, b; Bayraktar et al. 2009; Gunday et al. 2011) and were measured by seven and four items, respectively. It should be noted that we did not measure both dimensions of firm performance (i.e., operational and financial) absolutely. Instead, they were measured as the effect of BDA on the respective performance items. While we acknowledge that there may be some methodological implications of measuring firm performance perceptually through this method, several studies have measured firm performance via the effects or adoption of BDA (e.g., Aydiner et al. 2019a, 2019b; Ramanathan et al. 2017; Wamba et al. 2017). Although it would be promising to make use of the objective measures of firm performance, it should also be borne in mind that gaining access to such measures that involve both operational and financial dimensions of firm performance is the main obstacle. We also feel that relying on the perceptual evaluation of multiple respondents at different levels from each firm as key informants is an excellent way to obtain a more accurate evaluation of the effect of BDA on firm performance and also to minimize bias, as they typically have good knowledge of various related domains.

Control variables. Three control variables were used: firm age (AGE), firm size (SIZE), and industry (IND). AGE was measured by the number of years the firm has been in business. AGE is vital because older firms may have more resources and opportunities for developing BDAMC to increase firm performance. It should, however, also be noted that older firms, compared to younger firms, are envisaged to be less effective in creating innovation value due to their internal organizational rigidities and less flexible organizational structures (Bouncken et al. 2021b).

SIZE was measured by the total number of employees. SIZE, in particular, is selected because large firms can have more resources for developing BDAMC than small and medium-sized enterprises (SMEs).

IND was broadly classified into two industry clusters, including the manufacturing and service industries.

Table 3 Descriptive statistics and discriminant validity of constructs*

	Mean	SD	VIF	1	2	3	4	5	6	7
1. BDAMC	4.111	0.428	2.486	*0.876*						
2. DDC	4.167	0.443	2.665	0.741	*0.780*					
3. OPER	4.168	0.451	2.493	0.647	0.678	*0.731*				
4. FIN	4.267	0.601	1.846	0.513	0.517	0.634	*0.909*			
5. AGE	3.818	1.197	1.295	-0.016	-0.003	-0.036	0.162	1.000		
6. SIZE	3.909	1.454	1.302	0.051	0.054	0.028	0.058	0.416	1.000	
7. IND	1.492	0.502	1.119	-0.045	0.036	-0.014	-0.025	-0.178	-0.298	1.000

Note: *Square roots of average variances extracted (AVEs) are given on diagonal as italicized

Appendix B summarizes the measurement items used in this study, along with their sources.

3.4 Common method bias

According to Podsakoff et al. (2003), self-reported survey data have the potential for common method bias (CMB). Therefore, we performed multiple statistical analyses to evaluate the severity of CMB. First, we applied Harman's one-factor test. According to this method, the rate of the total variance explained should not be more than 50% in one factor (Podsakoff et al. 2003). In our study, it was determined that a single factor explained 39% of the total variance, indicating that CMB was not a significant concern. Second, in line with the suggestion of Kock and Lynn (2012), we checked the variance inflation factors (VIFs) of the latent variables. To avoid CMB, all latent variables must have a VIF value of less than 3.3 (Kock 2017, p 280). In our study, the full collinearity VIFs of the latent variables were less than 3.3 (see Table 3), indicating that CMB was not a significant concern. Finally, we checked the correlation values between latent variables. According to Bagozzi et al. (1991), correlation values should be less than 0.90 to avoid CMB. In Table 3, all correlation values were less than 0.90, demonstrating that CMB was not a severe concern in our study.

4 Data analyses and results

To test our research model, we adopted the PLS-SEM method (Kock 2010, 2018) using WarpPLS 6.0. The PLS-SEM is a variance-based approach, and in recent years, it has been widely used for path-analytical models (Kock 2019b). When compared to the traditional covariance-based SEM approach, PLS-SEM is less stringent in assumptions allowing (i) flexibility in multivariate normality, (ii) analysis of complex models with smaller sample sizes, and (iii) the usage of both formative and reflective constructs (Hair et al. 2017; Kock 2018). In addition, PLS-SEM is more suitable than covariance-based SEM in explaining complex relationships by avoiding two critical problems: inadmissible solutions and factor indeterminacy (Dubey et al. 2019a; Peng and Lai 2012). PLS-SEM is more useful for predictive purposes and allows researchers to check the predictive validity of the exogenous variables (Peng and Lai 2012). These advantages can explain the increasing use of PLS-SEM for complex models in

Table 4 Item loadings

Construct	Items	Loading*
Big data analytics management capability (BDAMC)	Planning capability (PLCAP)	0.890
	Investment decision capability (IDCAP)	0.812
	Coordination capability (COCAP)	0.868
	Control capability (CNCAP)	0.928
Operational performance (OPER)	OPER1	0.720
	OPER2	0.742
	OPER3	0.801
	OPER4	0.797
	OPER5	0.554
	OPER6	0.671
	OPER7	0.801
Financial performance (FIN)	FIN1	0.894
	FIN2	0.923
	FIN3	0.908
	FIN4	0.910
Data-driven culture (DDC)	DDC1	0.771
	DDC2	0.742
	DDC3	0.821
	DDC4	0.801
	DDC5	0.761

Note: *All item loadings are significant at $p<0.01$

business and management studies in the era of big data (El-Kassar and Singh 2019; Mandal 2018; Ratzmann et al. 2016; Wamba et al. 2015). In our study, PLS-SEM was the most suitable tool to examine the predictive power of BDAMC. We followed Peng and Lai's (2012) two-stage guidelines in model estimation: first, testing the measurement model and then testing the hypotheses with the structural model.

4.1 Measurement model

Our research model, as shown in Fig. 1, included both first-order reflective constructs and a second-order formative construct. For the second-order formative construct BDAMC, factor loadings of second-order dimensions were recorded as new variables in the null model. These new variables were used as latent variables (Isal et al. 2016; Kock and Lynn 2012; Wetzels et al. 2009). Thus, modeling could be conducted between sub-dimensions without collinearity problems (Kock 2010, 2019a). Appendix C presents the factor loadings, validity, and reliability values of the four underlying dimensions of BDAMC.

In Table 4, the factor loadings of the first-order constructs and second-order latent variables are presented. All loadings are above the lower limit of 0.50 (Bagozzi and Yi 1988; Wetzels et al. 2009) and significant ($p<0.01$), attesting to the model validity (Hair et al. 2011).

Table 5 illustrates that, at the construct level, Cronbach's alpha (CA) and composite reliability (CR) values were well above the threshold criterion of 0.70 (Nunnally 1978), exhibiting a satisfactory level of construct reliability. For convergent validity, we examined AVE (average variance extracted) values. Each construct had an AVE

Table 5 Reliability of constructs

Construct	Composite reliability	Cronbach's alpha	AVE
BDAMC	0.929	0.898	0.767
DDC	0.886	0.838	0.608
OPER	0.888	0.852	0.535
FIN	0.950	0.930	0.826

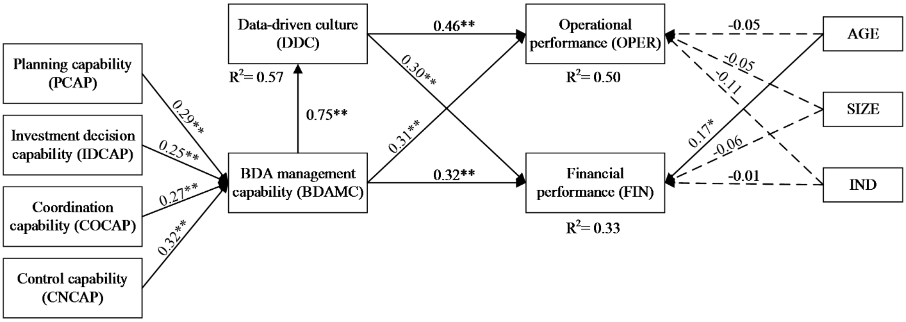

Fig. 2 Results of PLS-SEM analysis
Note: $*p<0.05$, $**p<0.01$

Table 6 Structural estimates

Hypothesis	Effect of	Effect on	β	Total effect	Indirect effect	t-value	Result
H1	BDAMC	OPER	0.31*	0.65	---	3.77	Supported
H2	BDAMC	FIN	0.32*	0.54	---	3.91	Supported
H3	BDAMC	DDC	0.75*	0.75	---	10.36	Supported
H4a	BDAMC x DDC	OPER	---	---	0.34*	5.85	Supported (Partial mediation)
H4b	BDAMC x DDC	FIN	---	---	0.23*	3.66	Supported (Partial mediation)

Note: $*p<0.01$

value above the lower limit of 0.50, confirming the convergent validity of the study's constructs.

To assess discriminant validity, we examined the square root of the AVE value for each construct to confirm that it was greater than its highest correlation with any other construct (Fornell and Larcker 1981). In Table 3, the values in the diagonal are the square roots of the AVE values, which are greater than the correlations between variables, attesting to the discriminant validity of the study's constructs. Because the VIF values were less than 5, it can also be assumed that there was no collinearity problem in the model (Hair et al. 2016; Kock 2018).

4.2 Hypothesis testing and structural model assessment

Figure 2 shows the results of the PLS-SEM analysis, and Table 6 presents a summary of the direct and indirect effects. Bootstrapping analysis with 5,000 resamples was

Table 7 Predictive performance of the model

Construct	R-square	Q^2	f^2	
			BDAMC	**DDC**
OPER	0.50	0.53	0.20	0.31
FIN	0.33	0.38	0.17	0.16
DDC	0.57	0.56	0.57	---

performed to achieve the significance of the estimates. As shown in both Table 6; Fig. 2, BDAMC has a significant and direct impact on operational performance ($\beta = 0.31$, $p < 0.01$), financial performance ($\beta = 0.32$, $p < 0.01$), and DDC ($\beta = 0.75$, $p < 0.01$), providing support for H1, H2, and H3, respectively. A firm's DDC has a significant impact on operational performance ($\beta = 0.447$, $p < 0.01$) and financial performance ($\beta = 0.32$, $p < 0.01$). DDC is found to have a significant mediating effect on both operational performance ($\beta = 0.34$, $p < 0.01$) and financial performance ($\beta = 0.23$, $p < 0.01$), providing support for H4a and H4b. The total effects of BDAMC on operational and financial performance are 0.65 and 0.54, while the indirect effects are 0.34 and 0.23, respectively. In other words, 53% of the total effect on operational performance and 41.5% of the total effect on financial performance are indirect effects mediated by DDC.

None of the control variables except AGE were found to have a significant effect ($p > 0.05$) on either operational or financial performance. The significant effect of AGE on financial performance ($p < 0.05$) suggests that mature firms have relatively superior financial performance than younger firms for developing BDAMC to increase the firm's financial performance. While older firms may seem more cumbersome and are less effective in generating innovation value than younger firms in general (Bouncken et al. 2021b), their formalization provides the necessary direction and helps them cope with the uncertainty and complexity of their digital innovation initiatives (Pesch et al. 2021). In this way, older firms can improve the performance of their technological initiatives by having structures that will make them more agile and flexible.

Because PLS-SEM has no universal goodness-of-fit statistics, the quality of the research model is based on its ability to predict endogenous structures (Hair et al. 2019). In our study, the endogenous variables were operational performance, financial performance, and DDC. Table 7 shows the predictive power of the structural model by examining the coefficient of determination (R^2), cross-validated redundancy (Q^2), and the effect size of the predictor variables (f^2).

R^2 is a measure of the predictive accuracy of the model (Hair et al. 2019; Shmueli and Koppius 2011). The model explains 49.7% of variance for operational performance ($R^2 = 0.50$), 33.1% for financial performance ($R^2 = 0.33$), and 56.5% for DDC ($R^2 = 0.57$). These R^2 values indicate moderate to high predictive power (Henseler et al. 2009).

The Q^2 coefficient indicates how well the independent variable can predict the dependent variable in a model, and the Q^2 value must be greater than zero (Kock 2018; Peng and Lai 2012; Wamba et al. 2019b). The Q^2 coefficient measurement is based on a blindfolding procedure that ignores some parts of the data matrix, estimates the model parameters, and predicts the neglected part using estimates (Kock 2018; Peng and Lai 2012). The Q^2 values of operational performance, financial performance, and DDC are 0.53, 0.38, and 0.56, respectively, confirming that our model possesses adequate predictive relevance.

We also examined Cohen's f^2 value of the BDAMC and DDC. Cohen's f^2 value indicates the effect size of the predictor variables (Hair et al. 2019). The effect size of BDAMC on operational performance, financial performance, and DDC is 0.20, 0.17, and 0.57, respectively, while the effect size of DDC on operational performance and financial performance is 0.31 and 0.16, respectively. Thus, the effect size of BDAMC and DDC on endogenous variables is greater than the threshold value of zero.

4.3 Model fit and quality indices

Model fit and quality indices are used to examine whether the model fits the original data (Kock 2018). In our study, we used five indices: the average path coefficient (APC), average R-squared (ARS), average block VIF (AVIF), average full collinearity VIF (AFVIF), and Tenenhaus goodness-of-fit (GoF). Appendix D presents a summary of the model fit and quality indices.

For an acceptable model, the *p* values of APC and ARS must be lower than 0.05. The values of 0.23 for APC and 0.48 for ARS are within the acceptable range, with *p* values lower than 0.001 (Kock 2010). AVIF and AFVIF values must be equal to or smaller than 5 (Kock 2018). The values of 1.63 for AVIF and 1.89 for AFVIF are within the acceptable range. Tenenhaus GoF provides information about the explanatory power of the structural model, and the acceptable value of GoF must be greater than or equal to 0.36 (Tenenhaus et al. 2005). The Tenenhaus GoF in our study is 0.63, which indicates that the explanatory power of the model is large, and the model is highly acceptable. Calculated model fit statistics reveal that the proposed research model fits well with our data.

5 Discussion and implications

Given the paucity of empirical evidence on the importance of data-oriented culture and strategies in the success of BDA investments (McAfee et al. 2012), this study has made a serious attempt to investigate the direct effect of BDAMC on operational and financial performance and DDC, as well as the mediating role of DDC on the links between BDAMC–operational performance and BDAMC–financial performance. We scrutinized this in the context of emerging markets, which has received limited scholarly attention from the point of view of business analytics. The results provided support for all hypothesized causal links in the research model.

The analysis of the structural model indicated that BDAMC is a significant predictor of operational performance, financial performance, and DDC. In addition, the study's findings confirmed that DDC is both a significant predictor and mediator for both operational and financial performance. Thus, our study provides crucial empirical evidence that firms should consider BDAMC and DDC as critical antecedents to increase the effect of BDA on operational and financial performance.

5.1 Theoretical implications

This study provides several theoretical contributions to extant BDA literature. First, in theoretical model structuring, we applied a DCV, which is interpreted to be a firm's ability to integrate, build, and reconfigure organizational capabilities to collect necessary data for responding to changing market conditions in highly dynamic business environments, such as emerging markets (Teece et al. 1997). DCV can serve as the internal process through which firms transform data and deploy digital resources to match market demand and develop a competitive advantage (Eisenhardt and Martin 2000). The premise of DCV is the firm's ability to develop distinct capabilities that match a specific context (Helfat and Peteraf 2015; Salvato and Vassolo, 2017); in the context of emerging markets, we apply DCV to address how firms in emerging markets complement their capabilities to manage BDA efficiently and yield greater outcomes. In this setting, firms are more challenged to organize and structure data due to a lack of skills and undeveloped supporting institutions (Shamim et al. 2020), which may require various non-technical capabilities to support an efficient, timely decision-making process. To overcome this, we integrated DDC as an underlying mechanism for BDAMC to attain high performance. The combination of different capabilities –that is, management capabilities of BDA and DDC– yielded high operational and financial performance in the context of emerging markets. Second, while most big data researchers have contributed to the literature by describing big data as a technical capability, our study handled big data from a managerial perspective by extending the literature on the BDA–firm performance relationship. Third, the use of DDC as a mediator is likely to be the most distinctive theoretical contribution to the literature: this study is the first to empirically examine the mediating role of DDC on the relationships linking BDAMC and the effect of BDA on the operational and financial performance of a firm. Despite the importance of mediation testing, most BDA studies using PLS-SEM do not test mediation effects. However, understanding mediation effects is crucial for developing BDA research to correctly explain the influence of third variables in direct relationships between two variables (Wang et al. 2016). Thus, we empirically corroborated the importance of DDC as a mediator, which is seen as critical for taking full advantage of big data (Davenport and Bean 2018; Lavalle et al., 2011). The core argument here is that DDC is an important intangible resource for better management of BDAMC as it helps firms to make information processing consistent, and facilitates the implementation of new ideas and processes for the successful interpretation, coordination, and communication of information across the organization, especially in dynamic and uncertain environments. Finally, our empirical findings regarding the BDA–firm performance relationship are compatible with the studies conducted in developed country contexts (Akter et al. 2016; Chen et al. 2015; El-Kassar and Singh 2019; Janssen et al. 2017; Wamba et al. 2017). It has been shown that, in an emerging country context, firm-level operational and financial performance can be enhanced with the use of BDAMC and organization-wide DDC creation initiatives in firms.

5.2 Managerial implications

Along with the above theoretical implications, our study also offers significant practical implications. First, beyond the technical nature of big data capability, we inform managers that they need to examine and develop a non-technical aspect of BDA to increase performance. By unpacking the underlying mechanisms (i.e., DDC) that shape the relationship between BDAMC and the two dimensions of firm performance (i.e., operational and financial performance) in the emerging market of Turkey, we stress that DDC, as a non-technical aspect of BDA, leads to stronger performance. Thus, managers need to go beyond the perception that data analytics is an exercise or experiment and focus on the fundamental objective in terms of collecting, analyzing, and deploying data to make better decisions. So, creating a DDC across the firm is vital to sustain competitiveness and improve performance.

BDAMC and a DDC can also help managers systematize and organize their routine and daily management activities with a data-oriented management framework. BDAMC can be improved as the quality of planning, investment decision-making, coordination, and control capabilities increase. In this way, managers can make evidence-based decisions with the insights obtained from data sets. This study also shows that fostering BDAMC alone is not sufficient to increase firm-level operational and financial performance. A DDC is vital for organizations to respond to changes and ensure sustainability in performance because a DDC prevents inertia in a firm by enabling evidence-based information to be transformed into action. While data-generated insight is one leg of the performance increase in BDA initiatives, the other is the data-oriented mindset and working habits, which are essential for enhancing the responsiveness of an organization.

Managers should also combine and complement different distinct and dynamic capabilities to succeed in managing BDA. We found that firms operating in an emerging market need to develop intermediary mechanisms (e.g., DDC) to better manage BDAMC and improve the effect of BDA on financial and operational performance. This implies that firms in emerging markets might have different perspectives with respect to their need to develop BDAMC, as they are more in need of managerial capabilities to nurture their growth easily. At the same time, they may not be technologically savvy enough to access, identify, and absorb such capabilities.

5.3 Limitations and future research directions

Although our research model is based on theory and tested with reliable survey data, our study has some limitations. First, future studies can examine the effects of BDA personnel expertise and infrastructure flexibility capabilities on firm performance under different mediator or moderator variables such as business strategy alignment (Akter et al. 2016), dynamic organizational capabilities (Wamba et al. 2017), or knowledge management (Ferraris et al. 2019). Second, our findings should be treated as exploratory, as they are based on a relatively limited number of companies from only a single emerging country, Turkey. Further research can indeed be undertaken with a larger sample set by extending the geographical boundaries, which will definitely enable comparisons between developed and emerging countries concerning the relationship between BDAMC and the effect of BDA on firm performance. Third, our study relied on the perceptions of survey respondents to measure firm performance. Researchers can use objective performance measures to avoid biases and measurement errors. Finally, our research model was tested with cross-sectional data. Future studies can retest our research model with panel data to increase the generalizability and examine the stability of the findings.

6 Appendix A. Group comparisons

Variables	Industry sector		Experience level		Job position		Education level	
	F-value	*p*	F-value	*p*	F-value	*p*	t-value	*p*
BDA	1.569	0.155	0.239	0.788	0.218	0.884	0.235	0.814
DDC	0.662	0.680	0.230	0.794	0.374	0.772	1.292	0.197
OPER	0.647	0.692	0.390	0.677	1.569	0.196	-0.059	0.953
FIN	1.209	0.300	0.718	0.488	1.838	0.139	-0.074	0.941

7 Appendix B. Survey measures

Construct	Items	Source(s)
BDA management capability (BDAMC)	*Please indicate to what extent you agree with the following statements regarding the effects of BDA on your managerial activities using 5- point scales (1 = "strongly disagree" to 5 = "strongly agree").*	Wamba et al. (2017)
Planning capability (PLCAP)	1. Our firm examines innovative opportunities for the strategic use of data analytics. 2. Our firm enforces adequate plans for the utilization of data analytics. 3. Our firm performs data analytics planning processes in systematic ways. 4. Our firm adjusts data analytics plans to better adapt to changing conditions.	
Investment decision capability (IDCAP)	Regarding data analytics investments 1. Our firm estimates the effect they will have on the productivity of the employees' work. 2. Our firm projects how much these options will help end-users make quicker decisions. 3. Our firm estimates whether they will consolidate or eliminate jobs. 4. Our firm estimates the cost of training that end users will need. 5. Our firm estimates the time managers will need to spend overseeing the change.	

Construct	Items	Source(s)
Coordination capability (COCAP)	1. In our firm, data analysts and line people meet regularly to discuss important issues. 2. In our firm, data analysts and line people from various departments regularly attend cross-functional meetings. 3. In our firm, data analysts and line people coordinate their efforts harmoniously. 4. In our firm, information is widely shared between data analysts and line people so that those who make decisions or perform jobs have access to all available know-how.	
Control capability (CNCAP)	1. In our firm, the responsibility for analytics development is clear. 2. Our firm is confident that analytics project proposals are properly appraised. 3. Our firm constantly monitors the performance of the analytics function. 4. Our firm's analytics department is clear about its performance criteria.	
Data-driven culture (DDC)	*Please indicate to what extent you agree with the following statements regarding the effects of BDA on your organizational culture using 5- point scales (1 = "strongly disagree" to 5 = "strongly agree").* 1. In our firm, we consider data as a tangible asset. 2. In our firm, we base our decisions on data rather than on instinct. 3. In our firm, we override our own intuition when data contradict our viewpoints. 4. In our firm, we assess and improve business rules in response to insights extracted from data. 5. In our firm, we are encouraged to make decisions based on data.	Gupta and George (2016)
Firm performance	*Please indicate to what extent you agree with the following statements regarding the effects of BDA on your firm performance using 5- point scales (1 = "strongly disagree" to 5 = "strongly agree").*	Aydiner et al. (2019a), Bayraktar et al. (2009)
Operational performance (OPER)	1. Reduces lead-time in production. 2. Increases forecasting accuracy. 3. Improves resource planning. 4. Increases operational efficiency. 5. Reduces the inventory level. 6. Increases cost-saving. 7. Allows making more accurate costing.	Aydiner et al. (2019a, b)
Financial performance (FIN)	1. Improves return on assets (profit/total assets). 2. Improves return on sales (profit/total sales). 3. Improves return on investments (profit/total investments). 4. Increases overall profitability.	Gunday et al. (2011)

8 Appendix C. Loadings of first-order indicator variables

BDAMC	Items	Item loading*	SE	VIF	CA	SCR	AVE	β
Planning capability	PLCAP1	0.799	0.072	1.887	0.849	0.898	0.689	0.290
	PLCAP2	0.856	0.071	2.264				
	PLCAP3	0.839	0.071	2.168				
	PLCAP4	0.824	0.072	1.990				
Investment decision capability	IDCAP1	0.771	0.073	2.002	0.864	0.902	0.649	0.249
	IDCAP2	0.822	0.072	2.273				
	IDCAP3	0.832	0.071	2.140				
	IDCAP4	0.831	0.072	2.253				
	IDCAP5	0.770	0.073	1.822				
Coordination capability	COCAP1	0.869	0.071	2.299	0.861	0.907	0.709	0.275
	COCAP2	0.885	0.071	2.715				
	COCAP3	0.860	0.071	2.508				
	COCAP4	0.747	0.073	1.592				
Control capability	CNCAP1	0.785	0.072	1.879	0.836	0.891	0.671	0.315
	CNCAP2	0.838	0.071	2.059				
	CNCAP3	0.786	0.072	1.969				
	CNCAP4	0.864	0.071	2.364				

Note: *All item loadings are significant at $p<0.01$

9 Appendix D. Model fit and quality indices

Model fit and quality index	Analysis results	Acceptance criteria	Reference
Average path coefficient (APC)	0.23, $p<0.01$	$p<0.05$	Rosenthal and Rosnow (1991); Kock (2010)
Average R-squared (ARS)	0.480 $p<0.01$	$p<0.05$	Kock (2010); Jabbour et al. (2016)
Average block VIF (AVIF)	1.63	Acceptable if<=5	Kock (2010, 2018)
Average full collinearity VIF (AFVIF)	1.89	Acceptable if<=5	Kock and Lynn (2012); Kock (2018)
Tenenhaus GoF (GoF)	0.63	Greater than 0.36	Tenenhaus et al. (2005)

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