Information & Management 57 (2020) 103169

Contents lists available at ScienceDirect

Information & Management

journal homepage: www.elsevier.com/locate/im

Exploring the relationship between big data analytics capability and competitive performance: The mediating roles of dynamic and operational capabilities

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ARTICLE INFO

Keywords:
Big data analytics
Dynamic capabilities
Operational capabilities
Business value
Resource-based view

ABSTRACT

A central question for information systems (IS) researchers and practitioners is if, and how, big data can help attain a competitive advantage. To address this question, this study draws on the resource-based view, dynamic capabilities view, and on recent literature on big data analytics, and examines the indirect relationship between a firm's big data analytics capability (BDAC) and competitive performance. The study extends existing research by proposing that BDACs enable firms to generate insight that can help strengthen their dynamic capabilities, which, in turn, positively impact marketing and technological capabilities. To test our proposed research model, we used survey data from 202 chief information officers and IT managers working in Norwegian firms. By means of partial least squares structural equation modeling, results show that a strong BDAC can help firms build a competitive advantage. This effect is not direct but fully mediated by dynamic capabilities, which exerts a positive and significant effect on two types of operational capabilities: marketing and technological capabilities. The findings suggest that IS researchers should look beyond direct effects of big data investments and shift their attention on how a BDAC can be leveraged to enable and support organizational capabilities.

1. Introduction

The value of big data analytics in directing organizational decision making has attracted much attention over the past few years [1]. A growing number of firms are accelerating the deployment of their big data analytics initiatives with the aim of developing critical insight that can ultimately provide them with a competitive advantage [2]. Some practitioners and researchers have associated big data with the next frontier for innovation, competition, and productivity [3], while others have even claimed that it is a revolution that will transform how we live, work, and think [4]. Following the rapid expansion of data volume, velocity, and variety, significant developments have been documented in terms of techniques and technologies for data storage, analysis, and visualization. Yet, empirical research on the competitive potential that big data analytics can offer is still at a rudimentary state with a general lack of understanding concerning the mechanisms through which such investments result in competitive performance [5,6]. This fact is rather surprising when taking into account the surge of companies venturing in the area of big data analytics [7]. In addition, there is scarce research on how organizations should proceed to embed big data analytics into the organizational fabric and little knowledge toward the strengthening of which organizational capabilities they should leverage their investments [1,8]. Most reports to date on the business value of big data have been from consultancy firms, popular press, and individual case studies, which lack theoretical insight [5]. There is, as a result, limited understanding on how firms should approach their big data initiatives and inadequate empirical support to support the claim that these investments result in any measurable business value [8].

While big data analytics has largely been regarded as a breakthrough technological development in academic and business communities [9], there is an ongoing debate about if, and under what conditions, such technologies can lead to competitive performance gains [10,11]. Arnott and Pervan [12] caution for ungrounded optimism with big data initiatives, while an increasing number of studies now delve into the tensions organizations face in realizing competitive performance gains from big data [13]. Sharma et al. [14] argue that while there is some evidence that big data analytics can create value, the

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https://doi.org/10.1016/j.im.2019.05.004
Received 8 February 2018; Received in revised form 20 May 2019; Accepted 22 May 2019
Available online 29 May 2019

claim that such investments can be a source of competitive performance gains requires a deeper analysis. Günther et al. [13] survey literature in the field and identify six areas surrounding big data and competitive performance. The authors argue that there is a need for more empirical research explicating the mechanisms through which big data analytics effects are diffused and competitive performance gains are realized. Similar issues are noted in the trade press, where Marr [15], for instance, highlights that there is still a sizeable number of companies that fail to outperform their competition from big data investments. A recent survey of Fortune 1000 companies showed that in spite of investment enthusiasm in big data, results vary significantly in terms of success [16]. These findings from research and practice highlight that the challenge for most companies in realizing performance gains from their big data investments is not related to technology. The biggest impediments are of an organizational nature and include leveraging big data analytics to support and shape strategy [17].

To address these critical gaps in the literature, we ground our study on the notion of big data analytics capability (BDAC), which is defined as the ability of a firm to effectively deploy technology and talent to capture, store, and analyze data, toward the generation of insight [5]. Following the emerging body of research on BDACs [5,6,8,18], this study argues that big data are a necessary resource but not sufficient condition to drive competitive performance gains. To orchestrate and leverage big data toward improved competitive performance, firms' need to acquire and develop a unique mixture of technological, human, financial, and intangible resources, which will be difficult for competitors to imitate. While several studies have begun to adopt such a holistic perspective of big data [5,6,19], there is still limited understanding concerning the mechanisms through which a BDAC can result in competitive performance gains. Recent studies argue that effects of BDACs on competitive performance are indirect and are mediated by changes in firm's organizational capabilities [8,13,20]. In this stream of work, the dynamic capabilities view has been posited as a relevant theoretical perspective to explain effects of BDACs, as structured adoption is seen as an enabler of the underlying processes that comprise a firm's overall dynamic capability and can subsequently facilitate better evolutionary fitness by renewing operational capabilities and resulting in competitive performance gains [10,21,22]. To derive any meaningful theoretical and practical implications, as well as to identify important areas of future research, it is critical to understand if the core artifacts pertinent to big data analytics lead to competitive performance gains and through what mechanisms these effects are achieved [2].

Consequently, this study seeks to answer two closely related research questions:

(1) *Does a BDAC result in competitive performance gains?*

and

(2) *Through what mechanism of mediating organizational capabilities are competitive performance gains attained?*

To answer these questions, we build theoretically on the resource-based view (RBV) and dynamic capabilities view of the firms that are presented in the next section. Further, we define the notion of a BDAC and illustrate how it is conceptually developed. Next, we provide an argument on how a firm's BDAC and the resulting insight result in competitive performance gains. We hypothesize that a strong BDAC has the potential to impact two distinct types of operational capabilities: marketing and technological capabilities. We theorize that the effect is indirect and is mediated through a firm's dynamic capabilities, which help sustain evolutionary fitness, by translating insight from a BDAC to renewed operational capabilities that best fit market needs. In sequence, these renewed operational capabilities are the source of a competitive advantage. To examine these associations, we develop a survey-based study and in the subsequent sections describe the data collection procedures and measures for each used concept. Next, we present the results of our empirical analysis, followed by a discussion on the theoretical and practical implication of findings, as well as some core limitations.

2. Theoretical background

2.1. Big data analytics capabilities

Past literature has shown that when assessing the business value of information systems (IS) investments, it is important to take a broader view and capture all the underlying factors that enable effective and efficient use of IT as a differentiator of firm success [23]. The notion of IT capability has been widely used when attempting to measure business value of investments, and is defined as the *"firm's ability to mobilize and deploy IT-based resources in combination or co-present with other resources and capabilities"* [23]. Studies on IT capability typically base their theoretical assumptions and operationalization's on the RBV of the firm [24,25]. Specifically, the RBV argues that a competitive advantage emerges from unique combinations of resources that are economically valuable, scarce, and difficult to imitate [26]. These resources are heterogeneously distributed across firms, and their innate traits – such as path dependency, embeddedness, and causal ambiguity – enable them to deliver a competitive advantage [26]. Similarly, the main assumption in the concept of IT capability is that while resources can be easily replicated, distinctive firm-specific capabilities cannot be readily assembled through markets, and can, thus, constitute a source of a sustained competitive advantage [27]. The IT capability literature recognizes that the ability to mobilize and deploy IT-based resources can be a source of a competitive advantage and differentiate firms for competition [28].

The literature has defined big data analytics as "a new generation of technologies and architectures, designed to economically extract value from very large volumes of a wide variety of data, by enabling high velocity capture, discovery and/or analysis" [8]. Nevertheless, this definition does not include the organizational resources that are required to leverage such technologies and data, and to ultimately realize competitive performance gains. As the objective of this study is to identify resources that will enable firms to develop BDACs, the choice of the RBV as the underlying theoretical framework is deemed as suitable. Consequently, building on the RBV and on prior studies on big data analytics, we define the notion of BDAC as the ability of a firm to effectively deploy technology and talent to capture, store and analyze data, toward the generation of insight. Consistent with prior studies that utilize the categorization of Grant [29] concerning the types of resources that are necessary to develop an IT capability [30–32], we adopt the same approach in relation to building a BDAC. Grant [29] distinguishes resources into tangible (e.g., physical and financial resources), human skills (e.g., employee's skills and knowledge), and intangible (e.g., organizational culture and organizational learning).

Building on the previously mentioned classification, prior studies have emphasized on specific aspects of big data analytics that are critical for firms. When it comes to tangible resources, data, technology, and other basic resources are noted as being fundamental to big data success. The defining characteristics of big data include volume, variety, and velocity [33]. Nevertheless, it is frequently mentioned that IT strategists and data analysts are particularly concerned with the quality and availability of the data they analyze [34]. While data itself is a core resource, it is also important for firms to possess an infrastructure capable of storing, sharing, and analyzing data. Big data call for novel technologies that are capable of handling large amounts of diverse and fast-moving data [5]. One of the main characteristics of such data is that it is in an unstructured format and requires sophisticated infrastructure investments to result in meaningful and valuable information [35]. Basic resources such as financial support are necessary, especially because big data investments are noted as taking some time to result in measurable business value [36]. Concerning human skills, literature recognizes that both technical- and managerial-oriented skills are required to derive value from big data investments [6,37]. In a highly influential article, Davenport and Patil [38] address the important role that the emerging job of the data scientist will have in the context of big data. While one of the most critical aspects of data science is the ability of data-analytic thinking, such competences are not only important for the data scientist but also throughout the organization, particularly, for employees in managerial positions [39]. Finally, concerning intangible resources, a data-driven culture and organizational learning are noted as being critical aspects of effective deployment of big data initiatives [17,40]. In firms engaging in big data projects, a data-driven culture has been noted as being a key factor in determining their overall success and continuation [41]. Nevertheless, due to the constantly evolving technological landscape associated with such technologies, it is important that a logic of continuous learning is infused in organizations that invest in big data [17].

While big data-related technologies will continue to be a central part of discussions, it is important for firms to focus on other resources that are needed to develop an inimitable BDA capability. For instance, Janssen et al. [42] argue that the quality of decisions made based on big data-generated insight depends largely on the quality of the inputs and on the quality of the process that transforms the inputs into outputs. The authors conclude that the quality of decision-making based on big data is heavily dependent on a firm's overall BDA capability, which includes the capacities and knowledge of persons involved, collaboration and knowledge exchange processes, the availability of infrastructure and data, as well as well-established collecting and processing methods. McAfee et al. [1] stress the importance of fostering a data-driven decision-making culture, where managers base their actions on insight rather than instinct. Vidgen et al. [17] argue that becoming data-driven is not merely a technical issue but requires that firms organize their business analytics departments and align their analytics capability with their business strategy. As such, the notion of BDA capability extends the view of big data to include all related organizational resources that are important in leveraging big data to their full strategic potential.

2.2. Big data and competitive performance

While empirical studies centered on the competitive performance gains of developing a BDAC are rather scarce, some research has demonstrated a positive overall association [5,18,21]. In the broader domain of IT-business value research and the emerging IT-enabled organizational capabilities perspective, there is a growing consensus that IT enables firms to attain a state of competitive advantage by strengthening intermediate organizational capabilities [43,44]. The main premise of this view is that IT capabilities, and as an extension BDAC, are central as they develop complementary effects with intermediate organizational capabilities that ultimately lead to competitive advantage. While these are just some of the early studies that suggest a positive impact of BDACs, more research is required to understand the mechanisms through which data-based insight is transformed into action [45]. The main argument that is put forward in existing research is that big data analytics can allow firms to make sense of vast amounts of data and reconfigure their strategies based on trends that are observed in their competitive environment [46]. The importance of big data analytics is evident from the increasing investments made from firms, and particularly those working in complex and fast-paced environments [47]. Managers nowadays are relying ever more on big data analytics to inform their decision-making and direct future strategic initiatives [2].

The value of investing in BDACs is clearly reflected in a recent article by Liu [48], who notes that big data analytics constitutes a major differentiator between high-performing and low-performing firms, as it enables firms to be more proactive and swift in identifying new business opportunities and gain a competitive edge. Additionally, the study reports that big data analytics have the potential to decrease customer acquisition costs by 47% and enhance revenues by approximately 8%. A report by MIT Sloan Management Review shows that companies that are leaders in the adoption of big data analytics are much more likely to produce new products and services compared to those that are laggards [49]. Nevertheless, the value that firms realize from big data investments is highly contingent upon the idiosyncratic capabilities that they develop in deriving meaningful insight [42]. Adopting a socio-materialistic perspective in conceptualizing a firms BDACs, Wamba et al. [6] find a positive impact on firm performance. Yet, the main premise that all of the aforementioned studies build on is that the generation of insight is insufficient to provide any competitive performance gains without the necessary transformation of organizational capabilities [10]. Thus, it is important to examine the effect of a firms' BDAC on different types of organizational capabilities and how they, as mediating conditions, influence competitive performance [8,13,17].

2.3. Organizational capabilities

The competitive benefits that a firm currently has managed to obtain are a result of strengths built in reaction to environmental responsiveness strategies. These strengths can be explained in terms of organizational capabilities, i.e., processes that facilitate the most efficient, effective, and competitive use of a firms' assets whether tangible or intangible [50]. In this perspective, capabilities represent the potential of a business to achieve certain objectives by means of focused deployment and represent the building blocks on which firms compete in the market. Designing and constructing desired organizational capabilities is a procedure that unfolds over time and reflects choices made in support to a firm's long-term competitive strategy. Organizational capabilities emerge through the strategic application and complex interactions of resources that a firm owns or is capable of controlling, and the most effective means of orchestrating and deploying them [51]. Following the definition of Winter [52], a capability can be described as a high-level routine (or a collection of routines), with routines comprising of purposefully learned behaviors, highly patterned, repetitious or quasi-repetitious, founded in part in tacit knowledge. Past research in the domain of strategic management has made great strides to develop and refine different types of organizational capabilities. The consensus is that capabilities operate quite differently and result in varying levels of competitive advantage and firm performance based on a number of internal and external factors [53]. Based on the idea that firms must be both stable enough to continue to deliver value in their own distinctive way and agile and adaptive enough to restructure their value proposition when circumstances demand it, there is a well-documented distinction between operational (ordinary) and dynamic capabilities.

In incomplete markets, heterogeneity among firm capabilities can serve as the basis for developing competitive advantages and rent differentials [54]. Operational capabilities are defined as those capabilities through which a firm makes its living in the short term [52]. Two key operational capabilities are marketing (i.e., capabilities needed for addressing customer needs) and technological capabilities (i.e., capabilities needed for producing products or services). Nevertheless, conditions of high environmental uncertainty, market volatility, and frequent change have raised questions regarding the rate to which operational capabilities erode and cease to provide competitive gains [53]. It is suggested that in such circumstances the focus should be shifted to strengthening capacities of change and re-adjustment of operational capabilities. The dynamic capabilities view has been put forth to answer this gap as a neo-Schumpeterian theory of the firm [55]. The dynamic capabilities view repositions the focus on the renewal of existing organizational capabilities as a means of competitive survival for the firm [52]. Correspondingly, dynamic capabilities are defined as those capabilities used to extend, modify, change, and/or create operational capabilities [52,53]. The main differentiation between

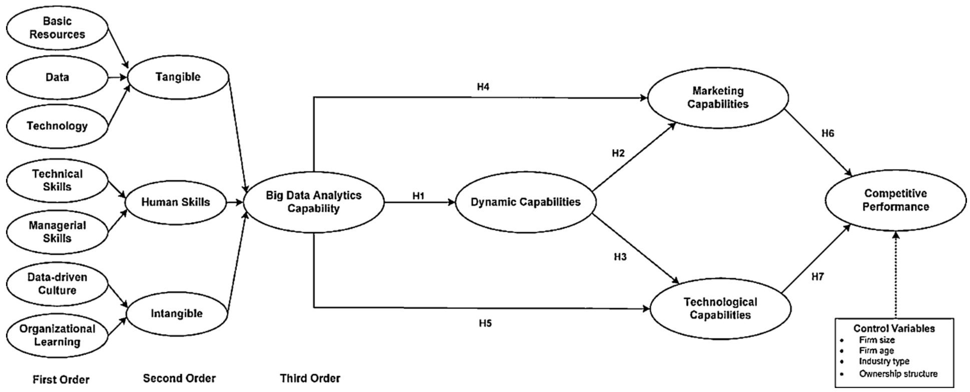

Fig. 1. Research model.

Table 1
Constructs and definitions.

Construct	Definition	Source(s)
Big Data Analytics Capability	Big Data Analytics Capability (BDAC) is defined as the ability of the firm to capture and analyze data toward the generation of insights, by effectively deploying its data, technology, and talent through firm-wide processes, roles and structures	Adapted from Gupta and George [5]; Kiron et al. [119]; Wamba et al. [6]
Dynamic Capabilities	Dynamic capabilities are defined as the capacity of the firm to (a) sense and shape opportunities and threats, (b) seize opportunities, and (c) maintain competitiveness through enhancing, combining, protecting, and, when necessary, reconfiguring the business enterprise's intangible and tangible assets	Teece [61]
Marketing Capabilities	Marketing capabilities are defined as the ability of the firm to serve certain customers based on the collective knowledge, skills, and resources related to market needs.	Spanos and Lioukas [120]; Wilden and Gudergan [73]
Technological Capabilities	Technological capabilities are those competencies that are required from the firm to convert inputs into outputs	Spanos and Lioukas [120]; Wilden and Gudergan [73]
Competitive Performance	Competitive performance is defined as the degree to which a firm attains its objectives in relation to its main competitors	Rai and Tang [121]

operational and dynamic capabilities is that the former allows firms to make a living in the present while the latter enables their modification in response to the shifting external environment [52]. As such, dynamic capabilities are particularly important for the competitive survival of firms in contemporary dynamic and quasi-globalized markets [56]. Dynamic capabilities are suggested to deliver rents from new combinations of capabilities and assets, and produce outcomes that are capable of shaping the marketplace, such as entrepreneurship, innovation, and semi-continuous asset orchestration and business reconfiguration [57]. Therefore, the definition of dynamic capabilities specifies that they can create value indirectly, by changing a firm's operating capabilities [58].

3. Research model

Drawing on the RBV and dynamic capabilities view of the firm, this study proposes the research model shown in Fig. 1. We propose that firms need a combination of tangible, human, and intangible resources to build a BDAC. While tangible resources cannot by themselves create a BDAC, the same applies for human and intangible resources. Therefore, BDAC are conceptualized as a higher order concept, comprising of tangible resources, human skills, and intangible resources, consistent with the classification of Grant [29], with each of these dimensions consisting of more than one subdimension as illustrated below. The classification of resources into tangible, human skills, and intangible has been long used in the IT capability literature [5,23,59,60]. To develop a strong BDAC, all three types of resources need to be invested in by the firm and contribute to the emergence of the higher order notion. The study argues that the value of a BDAC stems from its capacity to enhance a firm's dynamic capabilities. In doing so, a BDAC strengthens a firm's sensing, seizing, and transforming capabilities, which ultimately leads to stronger marketing and technological capabilities. It is through this sequence of associations that the renewal of operational capabilities is achieved, and firms are able to attain a competitive advantage.

Building on the RBV [26], the dynamic capabilities view [55,61], and the emerging literature on big data analytics [1,5,6], this study proposes an evolutionary fitness view [62], by which a BDAC enables firms to reposition themselves in the face of chancing business environments. A strong BDAC alleviates the risk of obsolesce for operational capabilities as by feeding a firm's dynamic capabilities, evolutionary fitness and renewal of operational capabilities are achieved [58]. As such, we argue that a firm's BDAC has an indirect effect on marketing and technological capabilities and effectively competitive performance, which is mediated by an enhanced effect on dynamic capabilities. The main argument made is that by fostering a BDAC, firms strengthen their ability to sense emerging opportunities and threats, seize opportunities before competitors, and transform the organizational resource base accordingly. The effect of BDAC in this process is discernible by the deployment of enhanced operational capabilities, which result in competitive performance gains (Table 1).

In today's competitive environment, firms must constantly reconfigure and update the means through which they do business to remain competitive. The ability to respond to changes is a complex process that includes sensing emerging threats and opportunities, seizing opportunities for development and survival and transforming existing modes of operation to better fit market needs (i.e., dynamic capabilities). Firms that utilize insight generated from big data analytics are in a better position to identify emerging conditions and reposition themselves accordingly [6]. The notion that insight generated through information technologies such as big data analytics can act as an enabler of dynamic capabilities has been put forth in management literature [63]. According to this view, insight generated through analytics can help expand the locus of decision making and provide a set of previously unavailable sets of decision options to the firm [10,53]. Furthermore, the processing power enabled by current big data analytics technologies allows for the transformation of raw data into actionable insight in much shorter cycle times, contributing toward improved response speed, effectiveness, and efficiency when dealing with environmental changes and seizing emerging opportunities [64]. Nevertheless, being able to transform existing modes of operation does not boil down solely on the technology itself, Janssen et al. [42] find that decision-making quality is dependent upon the level to which firms have developed their BDACs. Essentially, those firms that are better in transforming their operations are those that have established firm-wide practices regarding big data analytics and established a data-driven culture [14,17].

When looking into applications of big data analytics in the organizational context, it has been shown to enable the identification of new business opportunities through the combination of diverse data sources [65]. By coalescing data from different sources, insight can be generated that was previously unobtainable. For instance, Erevelles et al. [66] note the example of Southwest Airlines that uses big data analytics on interactions between personnel and customers to better understand customer needs. The insight from the speech analytics methods are used to sense unrecognized customer needs, develop a deeper understanding of the main requirements of their customers including claims from disrupted flights, details about reservations, food and beverage preferences, and offering personalized offers, as well as for training service personnel accordingly. The analytics solution of Southwest Airlines allows customer service representatives to understand the nuances of every recorded customer interaction. Different metrics guide service personnel to the best solution in every scenario. Furthermore, Southwest Airlines track sentiment on social media about the airline itself, its main competitors, and the airline industry as a whole. Insight from analyzing these types of data allows the airline to stay current with trends and operate efficiently. In effect, the BDAC that Southwest Airlines has managed to develop is utilized toward reconfiguring its existing means of operation. In a recent report by MIT Sloan Management Review, another interest case is discussed, that is of Nedbank, the fourth largest bank in South Africa is described [49]. Nedbank developed an impressive niche in creating value-added services for its clients. Nedbank Market Edge pulls together credit and debit card information with geolocation, demographic, and other transactional data, and enables the generation of insight into customers' behavior that would have been very difficult to identify without the tool. The analytics solution provided by Nedbank has since been used by its customers which among others include McDonalds and Burger King, as well as the bank itself, demonstrating that it can make significant business contributions to the banks credit and debit card line of business as well as for retail and business banking [67]. Although the bank tracked customer profitability by product for many years, when it decided to utilize Market Edge, it was able to identify and target customers with offers more effectively. The BDAC developed by Nedbank enabled it both to develop a new marketable solution to its clients, better capture market needs, seize the opportunity through highly detailed data, and transform its marketing approach by offering personalized discounts and other incentives to increase patronage. Similar case studies showcase that a strong BDAC can not only help firms identify threats and opportunities, but it can also reinforce seizing of opportunities as insights are backed-up with empirical evidence and transform operations through incremental or radical adaptations in existing modes of doing business [41,68]. Consequently, value from a BDAC is a result of improved decision making and repositioning in relation to external needs and opportunities [69]. Nevertheless, the quality of decision making, and as an extension a firm's ability to sense, seize, and respond, is largely dependent upon the BDAC that they are able to develop [42]. From the foregoing discussion, we hypothesize that:

H1. BDAC will have a positive effect on dynamic capabilities

Although dynamic capabilities may produce competitive performance gains on their own right, it is suggested in literature that one of their mechanisms of action is by enabling, or strengthening, existing operational capabilities [58]. As such, dynamic capabilities are defined as the capacity of the firm to sense and shape opportunities and threats, to seize opportunities, and to maintain competitiveness through enhancing, combining, protecting, and, when necessary, reconfiguring the business enterprise's intangible and tangible assets [61]. This idea has been initiated by the argument made by Eisenhardt and Martin [70], which states that dynamic capabilities are necessary but not sufficient conditions for competitive advantage. According to this perspective, competitive performance does not rely on dynamic capabilities *per se* but, rather, on the resource configurations created by dynamic capabilities. In this sense, dynamic capabilities are perceived as strategic options that allow firms to renew their existing operational capabilities when the opportunity or need arises [71]. Zahra et al. [72] supported this view proposing that dynamic capabilities impact competitive performance by facilitating changes in operational capabilities. Protogerou et al. [58] also adopt this perspective, demonstrating that dynamic capabilities create value indirectly by changing and strengthening operational capabilities. Specifically, theoretical claims and empirical findings suggest that dynamic capabilities exert a positive effect on the enhancement of marketing and technological capabilities [58,73]. The logic behind these mechanisms of action is that firms that regularly exercise their sensing processes can strengthen their market knowledge and understand both their customer needs as well as identify underserved profitable market segments [73]. In turn, enhanced sensing capacities of external developments can trigger seizing and transforming processes to better adapt to market conditions, thus resulting in improved marketing capabilities [53]. Similarly, by fostering strong dynamic capabilities, firms are also better able to detect new technological advancements earlier [74]. The ability to do so is also suggested to give an advantage in leveraging such advancements before competition, thus contributing to improved technological capabilities [75]. We can, therefore, hypothesize that:

H2. Dynamic capabilities will have a positive effect on marketing capabilities

H3. Dynamic capabilities will have a positive effect on technological capabilities

In the context of big data analytics, the generated insight has been suggested to trigger firms in realizing gaps or areas of ignorance, and taking action to adjust their marketing and technological capabilities [66]. Specifically, by developing strong BDACs, firms have been shown to be better positioned to sense emerging market opportunities and threats and to respond appropriately through renewed marketing capabilities [76]. Insight generated through a strong BDAC can enable more precise needs identification through sentiment sensing and social media monitoring for instance [46,76], allow for a better understanding of consumer behavior, interactions, and experiences with a product or service [77,78], facilitate more detailed and real-time customer segmentation by coalescing data from a variety of sources [79,80], and help to better identify noncustomer groups [46]. In turn, BDACs can support firms in seizing opportunities, as for example prioritizing target customers and segments [81], dynamically allocate resources to accommodate consumer needs [82], and support real-time process orchestration by translating strategic KPI's into operational metrics to inform decision-making and guide actions [10]. The outcome of strong BDACs can be discerned as an increased ability to transform marketing approaches, reshaping the way marketing is performed, customers are identified and approached, as well as the extent to which products and services are adapted to suit their needs.

Nevertheless, being able to do so requires more than just the data and the technology to analyze it. Janssen et al. [42] argue that it is important for decision-makers to have the skills to interpret outcomes of big data analytics and take actions upon them. Sharma et al. [14] underscore the importance of fostering appropriate decision-making structures, essentially enabling a data-driven culture to diffuse throughout the firm. The point of culture and organizational learning is also highlighted by Erevelles et al. [66], who note that it is critical to develop the necessary structures and processes around big data analytics that will enable the firm to generate and utilize innovative ideas. This underscores the importance of both human capital and organizational capital resources in extracting hidden insights from big data that can help revamp a firm's marketing capability. An example of such an effect of a firm utilizing its BDAC to enhance its marketing capabilities is Tipp24 AG, a service that places bets on European lotteries and makes predictions. Tipp24 AG has managed to harness the power of big data analytics to developed personalized marketing offers, utilizing data that include transactions, customer characteristics and preferences, as well as other data that come from interactions with their systems every day. Leveraging this data, Tipp24 AG developed predictive models that could produce analytics much faster, reducing the time needed by 90%. The speed of these analyses combined with the massive amount and variety of data that is inserted into the models enabled the company to revolutionize their marketing capabilities. Tipp24 AG now customizes and targets each advertisement it sends to customers, with these messages being produced automatically. From the foregoing arguments, we can hypothesize that:

H4. BDAC will have a positive indirect effect on marketing capabilities, which will be mediated by a positive effect on dynamic capabilities.

Firms that develop strong BDACs are not limited in enhancing their marketing capabilities, as several cases demonstrate that they can also have positive effects on technological capabilities. Technologically competent firms are able to develop systems and processes that allow them to engage in shared problem solving, implement and develop prototype products and services, and absorb technological knowledge from outside firm boundaries [58]. Firms that invest in developing their BDACs are shown to be better positioned in identifying inefficiencies in their internal and external operations [83]. When it comes to internal sensing, big data analytics can enable firms to identify inefficiencies in processes [84], detect deviations from quality controls, and best practices such as anomaly detection [85], and proactively locate cases of high risk and fault occurrence [77,86]. With regards to external process sensing, BDACs can contribute toward identifying bottlenecks or other potential hazards in supply chains [87], detect market disturbances and monitor the financial environment [88,89], and help predict prices and availability of key resources for production [90,91]. Such capabilities can, in turn, enable firms to seize emerging opportunities or avoid threats through real-time process orchestration [87], dynamic resource allocation, and financial risk assessment [92,93]. The capabilities that are enabled through a strong BDAC can facilitate technological capability transformation by allowing temporal process reconfiguration and adjusting operational inefficiencies [47]. Applications of BDACs toward renewal of technological capabilities can be found in a range of industries including healthcare [94,95], manufacturing [96,97], bank and financial institutions [98], energy and communication infrastructure providers [99], as well as in the oil and gas sector amongst others [100].

The example of smart energy systems serves to demonstrate the impact that BDACs can have in improving technological capabilities of firms. Zhou et al. [99] highlight the convergence of the internet and the various intelligent devices spread throughout energy systems. In such smart grids, the main source of data comes from the advanced metering infrastructure, which deploys a large number of smart meters and other measuring terminals at the end-user side. These smart meters enable the collection of massive amounts of data, and in combination with data from other smart devices on the grid, such as sensors and thermostats used throughout the whole process of power generation, transmission, distribution, substation and consumption, as well as weather and mobile data, allow energy power generation forecasting, system fault identification, and user energy consumption forecasting, thus supporting the decision-makings of different participants in energy systems. As a result, a large number of companies are now developing BDACs to harness the power of data and radicalize their technological capabilities by introducing data-driven smart energy management [101]. Realizing technological capability improvements in the energy industry however requires more than the physical infrastructure and the data itself. Literature consistently highlights that realizing technological capability improvements in any industry, including energy and infrastructure, requires employees with the appropriate technical and business skill-set [102], as well as a data-driven culture and an orientation toward organizational learning [103]. A prominent case study that underscores the potential of BDACs toward improving a firm's technological capabilities is that of Intel, the semiconductor manufacturer. Intel had to test every chip that came off its production line through a quality check, which meant running roughly 19.000 tests on each individual chip [104]. Using its BDAC, Intel managed to change the manufacturing process, significantly reducing the number of tests required for quality assurance. Intel analyzed historical data collected during manufacturing and was able to identify when a specific step in one of its manufacturing processes deviated from normal tolerances, leading to defects in the produced chips. This data-intensive process has enabled Intel to detect failures in its manufacturing line and revamp its production process by reducing tests on chips that are produced under normal manufacturing tolerances. These examples clearly show that a strong BDAC can help firms extract insights from data originating from a number of sources and facilitate making decisions and initiating competitive actions based on newly gained intelligence.

H5. BDAC will have a positive indirect effect on technological capabilities, which will be mediated by a positive effect on dynamic capabilities

Effective operational capabilities are necessary for achieving and sustaining a competitive advantage [105]. Prior literature in the management and IT domain clearly shows that strong operational capabilities contribute positively to attain and sustain competitive performance [53]. The positive effect that operational capabilities have on competitive performance has been documented in multiple ways, such as by increasing revenue [106], reducing costs associated with developing and delivering products [107], as well as improving the quality of a firm's existing processes and products [108]. Specifically, each type of operational capability contributes to competitive performance in different ways. Marketing capabilities allow firms to better understand their customers current and future needs, as well as to effectively reposition themselves in light of competitor's actions [58]. On the other hand, strong technological capabilities enable the firm to transform inputs into outputs in an effective and efficient way. By having this ability, firms are in a better position to achieve and sustain a state of competitive advantage as they are more capable of meeting an increased variety and change frequency of market expectations, while at the same time being able to limit excessive costs, time-to-produce, and organizational disruptions [73]. Firms that are not effective in renewing their technological capabilities may find that their product and service offerings fail to create commercial success [109]. Equally, a weak marketing capability may negatively impact competitive performance by hindering a firm's understanding of customer needs, as well as limiting it in reaching a broad consumer base and creating customer satisfaction and loyalty [110]. In other words, we argue that the more a firm is equipped with capabilities of producing product and service offerings that are in alignment with customer needs and expectations, and the better it is translating these into value positions, the greater its competitive success will be. Thus, we hypothesize the following:

H6. Marketing capabilities have a positive effect on competitive performance

H7. Operational capabilities have a positive effect on competitive performance

4. Empirical study

4.1. Survey, administration, and data

This study adopted the questionnaire-based survey method as it enables generalizability of outcomes, allows for easy replication, and facilitates the simultaneous investigation of a large number of factors [111]. Additionally, survey-based research is a well-documented way of accurately capturing the general tendency and identifying associations between variables in a sample. Suggestions by Straub et al. [112] emphasize the importance of survey-based research in exploratory settings and predictive theory to be able to generalize results. The constructs and corresponding survey items used in this questionnaire are based on previously published latent variables with psychometric properties that support their validity. All constructs and respective items were operationalized on a 7-point Likert scale, a well-accepted practice in large-scale empirical research where no standard measures exist for quantifying notions such as resources and capabilities [113]. A pretest was conducted in a small-cycle study, with 23 firms to examine the statistical properties of the measures. The pretesting procedure enabled us to assess the face and content validity of items and to ensure that key respondents would be in place to comprehend they survey as intended. After the completion of the survey during the pretest phase, respondents were contacted by phone and asked about the quality of the questions and asked to provide suggestions to improve clarity of the instrument.

To test the research model, an electronic survey was sent to the 500 largest firms in Norway. We collected data from Norway, one of the most competitive nations in terms of international private industry, ranking at 11th place according to the 2017–2018 Global Competitiveness Report of the Global Economic Forum [114]. Norway has very high levels of information and communication technology adoption, and a very dynamic business sector that places it in a good place to capitalize on the opportunities of the digital transformation. The names and titles of senior IS executives in Norway's 500 largest firms were obtained from several sources, such as corporate directories, personal contacts, and professional forums. Respondents were initially contacted by phone to inform them about the purpose of the study, as well as data anonymity and confidentiality issues. After the phone contact, an email invitation to participate in the study was sent to respondents followed by two email reminders, each spaced apart by a three-week interval. After this period, respondents were re-contacted by phone to ask about any additional comments they had on the survey, and those that had not replied were asked about difficulties they had in completing the questionnaire. The data collection process lasted for approximately six months (February 2017 – July 2017), and on average, completion time of the survey was 15 min. The final sample comprises 213 responses, 202 of which were complete and retained for further analysis. This response rate is higher than respective studies using key informants but can be justified by the personal communication by phone with each of the potential respondents and that in some cases more than one individuals were recommended from each company as being in place of complete the questionnaire [115]. Furthermore, a personalized report for each respondent was provided, benchmarking their company to country averages obtained from the survey.

The responses received came from companies of a diverse industry background (Table 2). The largest proportion came from the banking and financial services sector (13.8%), followed by consumer goods (10.8%), oil and gas (10.4%), industrials (9.4%), while a large proportion came from a variety of other sectors (37.1%). The vast majority were large firms, accounting for 64.8% of the sample. The survey was predominantly targeted to senior managers in the IS department, as they likely to be the most knowledgeable about strategic issues relating to IT use in the firm. However, to ensure a collective response, the respondents were instructed to consult other employees within their firms for information that they were not knowledgeable about.

Table 2
Descriptive statistics of the sample and respondents.

Factors	Sample (N = 202)	Proportion (%)
Industry		
Bank and Financials	28	13.8%
Consumer Goods	22	10.8%
Oil and Gas	21	10.4%
Industrials (Construction & Industrial goods)	19	9.4%
ICT and Telecommunications	11	5.4%
Technology	9	4.4%
Media	9	4.4%
Transport	8	3.9%
Other (Shipping, Basic Materials, Consumer Services etc.)	75	37.1%
Firm size (Number of employees)		
1 – 9	1	0.5%
10 – 49	34	16.8%
50 – 249	36	17.8%
250+	131	64.8%
Total Big Data Analytics Experience		
<1 year	42	20.7%
1 – 2 years	49	24.2%
2 – 3 years	53	26.2%
3 – 4 years	36	17.8%
4+ years	22	10.8%
Age of Company		
<1 year	0	0.0%
1 – 4 years	5	2.4%
5 – 9 years	16	7.9%
10 – 49 years	92	45.5%
50+ years	89	44.0%
Respondent's position		
CEO/President	15	7.4%
CIO	73	36.1%
Head of Digital Strategy	42	20.8%
Senior Vice President	33	16.3%
Director	21	10.4%
Manager	18	8.9%

As all data were collected from a single respondent, there is a possibility that typical bias exists. To examine if there is a risk of method bias in our sample, we followed the guidelines of Podsakoff et al. [116] and performed a series of statistical analyses to assess the severity of common method bias. First, we conducted a Harmon one-factor tests on the four main variables of our study: BDA, dynamic, marketing, and technological capabilities. The results did not yield a unifactor solution, and the maximum variance explained by any one factor was 35.2%, an indication of an absence of common method bias. Second, we also tests for goodness-of-fit, following the guidelines of Tenenhaus et al. [117] for PLS path modeling. The results showed that the model has an adequate goodness-of-fit as it exceeds the threshold of 0.36 as suggested by Wetzels et al. [118]. The outcomes of these analyses suggest that our research model and its operationalization are not contaminated by common method biases. In addition, to determine if there was any nonresponse bias in our sample, the profile of the respondents was compared with those on the mailing list we collected for each company, such as size and industry of operation. The chi-square analysis revealed no systematic response bias. In addition to nonresponse, we also examine late-response bias by comparing early (first two weeks) and late responses (last two weeks) through chi-square tests for firm size, industry, expenditure, and firm experience with big data. The outcomes showed that there were no statistically significant differences.

4.2. Measurements

The scales for the various constructs were adopted from prior literature and have therefore been previously tested in empirical studies. Appendix A provides a summary of the scales used, their descriptive statistics, and the supporting literature.

BDAC was defined in accordance with the study of Gupta and George [5] as a firm's capability to assemble, integrate, and deploy its big data-based resources. This definition clearly distinguishes and separates the process of orchestrating big data-related resources from any performance outcomes [8]. As such, BDAC is conceptualized and developed as a third-order formative construct. The three underlying pillars that comprise a BDAC are big data-related tangible, human skills, and intangible resource constructs, which, in turn, are formulated as second-order formative constructs, comprising of seven first-order constructs. Specifically, the tangible big data-related components of a BDAC include basic resources (e.g., financial), technology (e.g., software and hardware), and data [6], which are represented as formative first-order constructs. Human skills are developed as a Type II second-order construct (first-order reflective and second-order formative) consisting of two dimensions. These are technical skills that are concerned with the ability to handle the technological components and analytical requirements of big data, and managerial skills that are mostly revolved around recognizing the value of big data and understanding where to apply insight efforts [76]. Finally, intangible resources were conceptualized and developed as a Type II second-order construct (first-order reflective and second-order formative), with the underlying dimensions being a data-driven culture and organizational learning. A data-driven culture describes the level to which organizational members make decisions based on insight derived from data analysis [1]. Organizational learning on the other hand refers to the concentrated efforts of firm members to exploit existing knowledge and continuously explore new knowledge to keep up with unpredictable market conditions [122]. The development of the BDAC construct and the dimensions and subdimensions that comprise it are depicted in Table 3.

Dynamic Capabilities (DC) refer to a firm's capacity to (a) sense and shape opportunities and threats, (b) seize opportunities, and (c) maintain competitiveness through enhancing, combining, protecting, and, when necessary, reconfiguring the business enterprise's intangible and tangible assets [61]. Consequently, and following contemporary empirical studies, they are developed as a Type II second-order construct (first-order reflective and second-order formative), with sensing, seizing, and transforming being the underlying dimensions [123]. Items for each dimension were adopted from prior empirical research that measures the specific notions of dynamic capabilities [58]. We asked respondents to evaluate their effectiveness in each of the three dimensions/capabilities through a total of nine items on a 7-point Likert scale.

Marketing Capabilities (MC) represent a firms outward-based competencies [120]. They refer to the capacity of the firm to link with and serve particular customer groups [124]. The questions used to measure marketing capabilities were based on Spanos and Lioukas [120] scale and include items such as building privileged relationships with customers and suppliers, market knowledge, control over distribution channels, and strong "installed" customer base. We asked respondents to evaluate their effectiveness in marketing capabilities through a total of four items on a 7-point Likert scale.

Technological Capabilities (TC) reflect the organizational capacity to employ technologies to convert inputs into outputs [125]. The items used to measure firms' technological capabilities include efficient production department, technological capabilities and infrastructure, and economies of scale and technical experience. The measurement of technological capabilities was based on the scale of Spanos and Lioukas [120] and has been empirically confirmed to be reliable in multiple other studies [73]. Respondents were asked to evaluate their effectiveness in several aspects pertaining to technological capabilities through a total of three items on a 7-point Likert scale.

Competitive Performance (CP) is developed conceptually as the degree to which a firm performs better than its key competitors [121]. Respondents were asked to evaluate the relative performance of their firm in terms of profitability, market share, growth, innovativeness, cost leadership, and delivery cycle time [121,126]. Following the argument that competitive performance can be measured by subjective data, we measured the construct as a formative latent variable comprising of seven indicators [120]. Respondents were asked to assess the degree to which they believed that their firm performed better than their main competitors on a 7-point Likert scale (1 – Totally disagree; 7 – Totally agree).

Control Variables. Firm size was measured as an ordinal value in accordance with the recommendations of the European Commission (2003/361/EC) into micro (0–9 employees), small (10–49 employees), medium (50–249 employees), and large (more than 250 employees). Firm age was measured as the age since the inception of the firm. Industry subtypes were controlled as they can capture different conditions of the environment that influence the firms' responsiveness in deploying marketing and technological capabilities and were operationalized as dummy variables. Finally, we measured ownership structure as a binary control variable, differentiating between private and publicly controlled firms.

5. Analysis

To assess the hierarchical research model's validity and reliability, we applied partial least squares-based structural equation modeling (PLS-SEM) analysis. Specifically, the software package SmartPLS 3 was used to conduct all analyses [127]. PLS-SEM is considered as an appropriate methodology for this study as it permits the simultaneous estimation of multiple relationships between one or more independent variables, and one or more dependent variables [128]. PLS-SEM is a soft modeling technique and is variance-based, with the advantage for allowing (i) flexibility with respect to the assumptions on multivariate normality, (ii) usage of both reflective and formative constructs, (iii) the ability to analyze complex models using smaller samples, (iv) the more robust estimation of formative constructs, and (v) the potential use as a predictive tool for theory building [129]. PLS-SEM is widely used in analyzing data for the estimation of complex relationships between constructs in many subject areas including in business and

Table 3
Big Data Analytics Capability (BDAC) and sub-dimension development.

Third-order	Type	Second-order (sub-dimensions)	Type	First-order (sub-dimensions)	Type
BDA Capability	Formative	Tangible Resources	Formative	Data	Formative
				Technology	Formative
				Basic Resources	Formative
		Human Skills	Formative	Managerial	Reflective
				Technical	Reflective
		Intangible Resources	Formative	Data-Driven Culture	Reflective
				Organizational Learning	Reflective

management research [130,131]. In addition, PLS-SEM enables the analysis of indirect and total effects, making it possible to not only simultaneously assess the relationships between multi-item constructs but also to reduce the overall error associated with the model [132]. In terms of sample size requirements, the 202 responses received exceed both the requirements of: (1) ten times the largest number of formative indicators used to measure one construct, and (2) ten times the largest number of structural paths directed at a particular latent construct in the structural model [128]. Finally, as the proposed research model builds more on exploratory theory building, rather than theory testing, PLS-SEM is a better alternative than covariance-based SEM.

5.1. Measurement model

As the model contains both reflective and formative constructs, we used different assessment criteria to evaluate each. For first-order reflective latent constructs, we conducted reliability, convergent validity, and discriminant validity tests. Reliability was assessed at the construct and item level. At the construct level, we examined Composite Reliability (CR) and Cronbach Alpha (CA) values, and established that their values were above the threshold of 0.70 [133]. Indicator reliability was assessed by examining if construct-to-item loadings were above the threshold of 0.70 (Appendix B). To assess convergent validity, we examined if AVE values were above the lower limit of 0.50, with the lowest observed value being 0.57, which greatly exceeds this threshold. Discriminant validity was established through three means. The first looked at each constructs AVE square root to verify that it is greater than its highest correlation with any other construct (Fornell–Larcker criterion). The second tested if each indicators outer loading was greater that its cross-loadings with other constructs [134]. Recently, Henseler et al. [135] argued that a new criterion called the Heterotrait–Monotrait ratio (HTMT) is a better assessment indicator of discriminant validity. The HTMT ratio is calculated based on the average of the correlations of indicators across constructs measuring different aspects of the model, relative to the average of the correlations of indicators within the same construct. Values below 0.85 are an indication of sufficient discriminant validity; hence, the obtained results confirm discriminant validity (Appendix C). The abovementioned results (Table 4) suggest that first-order reflective measures are valid to work with and support the appropriateness of all items as good indicators for their respective constructs.

For formative indicators, we first examined the weights and significance of their association with their respective construct. Although all of the indicators' weights for data and basic resources were statistically significant, one of the three indicators weights (BR2) of the technology construct was found to be nonsignificant. According to Cenfetelli and Bassellier [136], formative constructs are likely to have some indicators with nonsignificant weights. Their suggestion is that a nonsignificant indicator should be kept, providing that the researchers can justify its importance. Since the technology construct is proposed as an aggregate of three items, where each captures a different big data-related technology, we believe that it is critical to include the indicator in the model as it makes a distinct contribution. A similar approach is followed by Gupta and George [5] in their operationalization of BDAC. Next, to evaluate the validity of the items of formative constructs, we followed MacKenzie et al. [137] and Schmiedel et al. [138] guidelines using Edwards [139] adequacy coefficient (R^2a). To do so, we summed the squared correlations between formative items and their respective formative construct and then divided the sum by the number of indicators. All R^2_a value exceeded the threshold of 0.50 (Table 5), suggesting that the majority of variance in the indicators is shared with the overarching construct and that the indicators are valid representations of the construct. Similarly, for the higher order constructs, we first examined the weights of the formative lower order constructs on their higher order constructs. All weights were significant, and the results of

Table 5
Higher-order construct validation.

Construct	Measures	Weight	Significance	VIF	R^2_a
Data	D1	0.532	$p<0.001$	1.164	0.78
	D2	0.327	$p<0.01$	1.631	
	D3	0.570	$p<0.001$	1.608	
Basic Resources	BR1	0.688	$p<0.001$	2.137	0.73
	BR2	0.415	*n.s.*	2.260	
Technology	T1	0.299	$p<0.01$	2.011	0.74
	T2	0.485	$p<0.001$	1.552	
	T3	0.427	$p<0.01$	2.032	
Tangible	Data	0.438	$p<0.001$	1.780	0.81
	Basic Resources	0.348	$p<0.001$	1.384	
	Technology	0.505	$p<0.001$	1.797	
Human	Managerial Skills	0.657	$p<0.001$	2.146	0.91
	Technical Skills	0.465	$p<0.001$	2.146	
Intangible	Data-Driven Culture	0.667	$p<0.001$	1.249	0.90
	Organizational Learning	0.544	$p<0.001$	1.219	
BDAC	Tangible	0.407	$p<0.001$	3.041	0.92
	Human	0.464	$p<0.001$	3.012	
	Intangible	0.307	$p<0.001$	1.669	
Dynamic Capabilities	Sensing	0.377	$p<0.001$	1.694	0.91
	Seizing	0.408	$p<0.001$	1.792	
	Transforming	0.432	$p<0.001$	1.847	

Table 4
Assessment of reliability, convergent, and discriminant validity of reflective constructs.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
(1) Data	**n/a**												
(2) Basic Resources	0.288	**n/a**											
(3) Technology	0.571	0.243	**n/a**										
(4) Managerial Skills	0.561	0.427	0.370	**0.875**									
(5) Technical Skills	0.470	0.487	0.307	0.576	**0.947**								
(6) Data-driven Culture	0.269	0.322	0.222	0.307	0.343	**0.811**							
(7) Organizational Learning	0.529	0.365	0.384	0.513	0.376	0.356	**0.885**						
(8) Sensing Capability	0.333	0.376	0.296	0.286	0.225	0.384	0.346	**0.802**					
(9) Seizing Capability	0.377	0.315	0.255	0.438	0.310	0.278	0.421	0.485	**0.880**				
(10) Transforming Capability	0.329	0.371	0.213	0.442	0.402	0.351	0.358	0.543	0.503	**0.907**			
(11) Marketing Capability	0.194	0.366	0.120	0.233	0.241	0.311	0.181	0.583	0.271	0.341	**0.756**		
(12) Technological Capability	0.351	0.433	0.351	0.339	0.348	0.394	0.361	0.504	0.526	0.428	0.502	**0.830**	
(13) Competitive Performance	0.262	0.351	0.322	0.255	0.292	0.350	0.382	0.506	0.465	0.525	0.513	0.576	**0.789**
Mean	4.62	4.16	4.21	4.39	4.24	4.45	4.71	4.88	4.58	4.51	5.31	5.02	4.14
Standard Deviation	1.80	1.72	2.01	1.64	1.71	1.53	1.41	1.45	1.38	1.37	1.29	1.28	1.52
AVE	n/a	n/a	n/a	0.766	0.897	0.658	0.784	0.644	0.774	0.822	0.572	0.690	0.623
Cronbach's Alpha	n/a	n/a	n/a	0.847	0.885	0.741	0.724	0.720	0.852	0.891	0.711	0.773	0.738
Composite Reliability	n/a	n/a	n/a	0.908	0.946	0.853	0.879	0.844	0.911	0.933	0.799	0.869	0.806

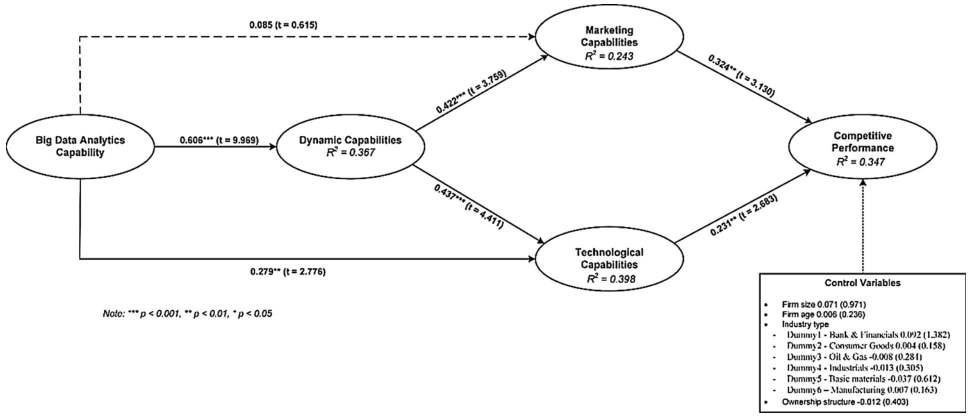

Fig. 2. Estimated relationships of structural model.

the Edward adequacy coefficient for each were again greater than the limit of 0.50 [139]. A mixture of the repeated indicator approach and a use latent variables scores in a three-stage approach was applied, in coherence with the guidelines of [140]. In the first stage, the repeated indicator approach was used to obtain latent variable scores for the first-order constructs, which in the second stage served as manifest variables in the measurement model of the second-order constructs. This was then repeated for the higher order construct based on latent variables scores of the second-order constructs. Next, we examined the extent to which the indicators of formative constructs presented multicollinearity. Variance inflation factor (VIF) values below 10 suggest low multicollinearity; however, a more restrictive cut-off of 3.3 is used for formative constructs [141]. All values were below the threshold of 3.3, indicating an absence of mutlicollinearity.

5.2. Structural model

The structural model from the PLS analysis is summarized in Fig. 2, where the explained variance of endogenous variables (R^2) and the standardized path coefficients (β) are presented. The structural model is verified by examining coefficient of determination (R^2) values, predictive relevance (Stone-Geisser Q^2), and the effect size of path coefficients. The significance of estimates (t-statistics) is obtained by performing a bootstrap analysis with 5000 resamples. As depicted in Fig. 2, six of the seven direct hypotheses were empirically supported. A firms' BDAC is found to have impact on dynamic capabilities ($\beta = 0.606$, $t = 10.546$, $p < 0.001$) and on a firm's technological capabilities ($\beta = 0.279$, $t = 2.971$, $p < 0.01$). Contrary, no such significant effect was found on the impact of BDAC on marketing capabilities ($\beta = 0.085$, $t = 0.615$, $p > 0.05$). Additionally, dynamic capabilities are positively associated with both technological capabilities ($\beta = 0.422$, $t = 5.051$, $p < 0.001$) and marketing capabilities ($\beta = 0.437$, $t = 5.051$, $p < 0.001$). As hypothesized, marketing capabilities exert a positive and significant effect on competitive performance ($\beta = 0.324$, $t = 3.130$, $p < 0.01$), as do technological capabilities ($\beta = 0.231$, $t = 2.683$, $p < 0.01$). The structural model explains 36.8% of variance for dynamic capabilities ($R^2 = 0.368$), 39.8% for technological capabilities ($R^2 = 0.398$), 24.3% for marketing capabilities ($R^2 = 0.243$), and 34.7% for competitive performance ($R^2 = 0.347$). These coefficients of determination represent moderate to substantial predictive power [142]. In addition to examining the R^2, the model is evaluated by looking at the effect size f^2. The effect size f^2 allows us to assess an exogenous constructs contribution to an endogenous latent variable R^2, and as all direct values are above the thresholds of either 0.15 or 0.35, we can conclude that they have moderate to high effect sizes. Consistent with IS studies, we also examined the influence of control variables on competitive performance; however, their relationship with the dependent variable was found to be nonsignificant in all cases.

To validate our results, we tested the model with objective performance data collected from several sources such as Morningstar Inc., PROFF.no, and Purehelp.no. We ran four models with ROA (%), ROE (%), ROIC (%), and net margin (%) as indicators of firm performance. All performance variables were for the last two quarters of 2017. The outcomes of these models were largely consistent with our original analysis. The relationships between BDAC, dynamic, and operational capabilities retained their effect which continued to be positive and significant. Specifically, dynamic capabilities continued to exert a highly positive and significant effect on both marketing and technological capabilities, while BDAC positively fed a firm's dynamic capabilities. The four models account for approximately 12 percent of the variance for performance (13.1% for ROA, 12.2% for ROE, 11.7% for ROIC, and 10.9% for net margin). The effects of marketing and technological capabilities remain significant for the first three models, while for the last, only marketing capabilities continue to have a significant effect. Overall, we found that for the four proposed models, the nomological network fits the data quite well as there is consistency of results which reinforces the validity of findings (Table 6).

5.3. Test for mediation

To examine if the impact of big data analytic capability on marketing and technological capabilities is direct or is mediated by

Table 6
Summary of hypotheses and results.

Structural path	Effect	t-value [a]	Ratio to Total Effect (%)	Bias corrected 95% confidence interval	Conclusion
BDAC → MC	0.085	0.615	24.3	[0.114 – 0.474]	(Full mediation)
BDAC → MC via DC	0.265	3.205***	75.7	[0.087 – 0.422]	H4 Supported
Total indirect effect	0.350		100.0		
BDAC → TC	0.279	2.776**	52.1	[0.342 – 0.647]	(Partial mediation)
BDAC → TC via DC	0.256	3.783***	47.9	[0.112 – 0.390]	H5 Supported
Total indirect effect	0.535		100.0		

[a] * significant at p < 0.05; ** significant at p < 0.01; *** significant at p < 0.001 (two-tailed test).

dynamic capabilities, a bootstrapping approach is employed, a nonparametric resampling procedure that imposes no assumptions on normality of sampling distribution [142,143]. Based on the guidelines of [142], we first confirm that the mediated paths (BDAC→DC→MC and BDAC→DC→TC) are significant. By then, including the direct paths (BDAC→MC and BDAC→TC) in the model, we find that the former is nonsignificant ($\beta = 0.085$, $t = 0.615$, $p > 0.05$), an indication of full mediation, while the later retains its significance ($\beta = 0.279$, $t = 2.776$, $p < 0.01$). In Table 5, we present the outcomes of the mediation analysis, associated with hypotheses H4 and H5. To test for the mediation hypotheses, we used the parameter estimates from the bootstrapping procedure in PLS, based on a resampling of 5000 subsamples, and calculated the standard error of each mediation effect. We then calculated the t-statistic for each mediation path by dividing the effect of the indirect path (i.e., the product of each indirect path), by the standard error of mediation effects. This approach of assessing the significance of indirect paths provides the advantage of not imposing any distributional assumptions of the indirect effects. In addition, it allows for the calculation of the entire indirect effect simultaneously in the presence of multiple mediating effects rather than isolating part of the structural model. As the direct effect of BDAC on MC is found to be nonsignificant and the mediating path is found to be significant, we can conclude that dynamic capabilities fully mediate the effect of BDAC on marketing capabilities. On the other hand, as the direct effect of BDAC on TC is still significant and the mediating path is also significant, we demonstrate that dynamic capabilities partially mediate the effect of BDAC on technological capabilities. These results lend support to our theoretical claim that a firm's BDAC can explain substantial variance in both marketing and technological capabilities through the renewing effect of dynamic capabilities. Nevertheless, strengthened operational capabilities can also be explained by other means other than as effects of BDACs, such as introduction of new production infrastructure and machinery, which may bear little influence from big data analytics practices.

5.4. Predictive validity

In addition to examining the R^2, the model is assessed by examining the Q^2 predictive relevance of exogenous variables [144]. This indicator measures how well-observed values are reproduced by the model and its parameter estimates, verifying as such the model`s predictive validity through sample re-use [145]. The technique is a synthesis of cross-validation and function fitting and examines each constructs predictive relevance by omitting selected inner model relationships and computing changes in the criterion estimates (q^2) [146]. Values of the Q^2 predictive relevance that are greater than 0 imply that the structural model has predictive relevance, whereas values below 0 are an indication of insufficient predictive relevance [142]. From the outcomes of the analysis we find that dynamic capabilities ($Q^2 = 0.166$), marketing capabilities ($Q^2 = 0.159$), technological capabilities ($Q^2 = 0.251$), and competitive performance ($Q^2 = 0.171$) have satisfactory predictive relevance. Being an exogenous construct, BDAC does not have a Q^2 predictive relevance score. In addition, q^2 value ranges from moderate to high revealing (above 0.15 and 0.35 respectively) an adequate effect size of predictive relevance.

To examine model fit, a test of composite-based standardized root mean square residual (SRMR) was performed. The SRMR value is obtained through the difference between the observed correlation and the model implied correlation matrix. The current SRMR yields a value of 0.071, which is below the threshold of 0.08, thus confirming the overall fit of the PLS path model [147]. To further establish the predictive validity of the model, this study employs cross-validation with holdout samples [146]. Following the process described by Carrión et al. [148], the sample is randomly divided into a training sample (n = 121) and a holdout sample (n = 81). The training sample is initially used to calculate the path weights and coefficients. Then, the holdout sample observations are normalized and construct scores are created using the training sample estimations. The next step involves normalizing the construct scores of the holdout sample and then using them to create prediction scores. The results confirm the predictive validity of the model as the R^2 for the holdout is close to that of the training sample for all the dependent variables of the model. Even though model fit assessment criteria are not a prerequisite in PLS analyses, researchers have called for the development of evaluation criteria that can better support the prediction-oriented nature of PLS-SEM [149].

6. Discussion

While the hype around big data is continuously growing, the mechanisms and conditions under which it results in business value remain largely unexplored in empirical research. The overall value of big data investments has also come into question in some articles as it is noted that only a small percentage of companies have been capable of realizing the true potential of their big data investments [150]. This finding seems surprising when considering the numerous articles of business publications that talk about the transformative power of big data analytics. Gupta and George) [5] argue that this phenomenon can be largely attributed to the fact that most of literature on big data has been drafted by consultants, which generally lacks in theoretical and large-scale empirical validity.

6.1. Implications for research

This study aims to address this issue and understand if, and through what mechanisms, big data can result in any measurable business value. To this end, we build on the notion of a BDAC as a necessary capacity that firms must cultivate to derive any substantial outcomes from their investments. We ground this notion on the well-established RBV and emphasize that BDA is not solely a technical capability but requires several other nontechnical resources to create a BDAC. Furthermore, the value of a BDAC, and big data in general, have mostly been anecdotal to date, with the exception of some early studies on its business value [5,6]. We addressed this shortcoming in literature by yielding empirical support for the theoretical framework of BDAC. Using survey data from 202 Norwegian executive-level technology managers, this study empirically explored the relationship between firms' BDAC and two types of operational capabilities: marketing and technological. This study makes an important contribution to big data literature by presenting how BDAC positively affects a firm's dynamic capabilities, which, in turn, strengthen both marketing and technological capabilities, two core pillars of competitive performance.

This assertion, theoretically, distinguishes BDAC from IT capabilities by highlighting that the value lies primarily in gaining new insight and generating intelligence and evidence to support transformation or adaptation of the firm's operations. Our empirical findings support this assumption, particularly in the positive and significant effect that BDAC has on a firm's dynamic capabilities. In effect, the value of a strong BDAC can be associated with the move toward a digital business strategy noted in the special issue editorial of Bharadwaj et al. [69]. Firms that foster the development of a strong BDAC utilize it in driving strategy and informing decisions made by top executives. In other words, a BDAC does not operate as a subordinate of business strategy but helps shape strategies in a fusion between technology and business. The insight, which is generated through big data analytics, works not only to inform sensing of opportunities and threats but also as an anchor point on which decisions can be made. Strong big data-generated insight reinforces managers decisions so that they can more confidently seize and transform operations according to market demands. This finding is in coherence with the qualitative study of Janssen et al. [42], who argue that the quality of decisions made by top managers, and the extent to which they rely on big data-generated insight, largely depends on the maturity of the firms overall BDAC.

Although there is a rich theoretical discussion and anecdotal evidence on the regenerating role that a BDAC has on firm's operations, to date, there have been very few large-scale empirical examinations to verify this claim. What is less understood is the mediating role of dynamic capabilities on the relationship between a firm's BDAC and operational capabilities. Our study tested the mediating effect of dynamic capabilities, which helps explain how value from BDAC is delivered to the firm. Specifically, we show that it is essential for firms to examine all complementary dimensions related to big data, including non-technical ones, and that their synergistic effect is what drives renewal of operational capabilities. The findings add to literature on how information technology can enable the development of dynamic capabilities, and specifically, on the importance of BDAC in repositioning the firm in the competitive landscape. The impact that a BDAC has on marketing capabilities is shown to be fully mediated by dynamic capabilities, hinting that big data fundamentally change the way firms approach and manage their customers. On the other hand, the partial mediation of dynamic capabilities on the relationship between BDAC and technological capabilities indicates that they are used for both incremental and radical changes.

Finally, our analysis demonstrates the nomological network of associations through which a BDAC results in competitive performance gains. While previous research has assumed a direct effect of a BDAC on firm performance [5], our results show that the effect on performance is indirect and contingent upon how dynamic capabilities are exercised on operational capabilities. This finding raises several important implications for practice and research. Specifically, understanding the speed and the ways in which managers use big data-generated insight could help explain the derived business value from such investments. While the development of a strong BDAC may be prerequisite in realizing any substantial returns, the effect that it has on competitive performance should be examined under the prism of actions it leads to. In this respect, it is important to understand the level to which insight is utilized, particularly when compared to instincts of top managers, which may overrule the suggestions obtained from big data analytics.

6.2. Implications for practice

The outcomes of this study also present several interesting implications for practice. First, this study shows that big data analytics is much more than just investments in technology, collection of vast amounts of data, and allowing the IT department to experiment with analytics. Important elements of gaining business value out of big data investments include recruiting people with good technical and managerial understanding of big data, fostering a culture of organizational learning, and embedding big data decision making into the fabric of the organization. It is the combined effect of these resources and effective orchestration that will help a firm develop a BDAC. This of course requires a multitude of processes to be put into action, which necessitates top management commitment and a clear plan for firm-wide big data analytics adoption. A number of studies have already began to emphasize on the importance of all these factors and provided managers with guidelines on how to develop and mature their BDACs [17].

By clearly outlining the main resources that are needed to develop a BDAC, this study can help managers develop an assessment tool of their organizations' strengths and weaknesses. The main pillars can help expose areas that have been underdeveloped or insufficiently funded. Particularly resources on the intangible part, such as intensity of organizational learning, and data-driven culture, can provide managers with an understanding of the importance of these aspects and help them form strategies to strengthen them throughout the firm. Given that many companies are still at an inaugurating stage in their big data projects, it is important to have a good overview of all the areas that should be invested in to derive value, as well as to calculate expected costs and gains. In addition, while some resources such as technical, data, and even human skills can be quite easily and quickly acquired from the market, others, and especially a data-driven culture, would need planning and a well-documented process to form. Therefore, an additional theoretical implication concerns the calculation of the time and complexity that some resources require to develop, which managers should think about well before they expect any measurable outcomes from their big data investments.

Finally, the results of our study show that even by fostering a strong BDAC, business value is not directly achieved. In other words, while firms may be producing solid data-driven knowledge as a result of their BDACs, action is required to capitalize upon it. Data-driven insight is only a component of a firm's ability to sense, seize, and reconfigure, and doing so successfully means that the organization must be designed so as to be able to respond to changes that insight indicate. This requires flexibility in operations, fast re-deployment of organizational capabilities, and dissolution of any form of inertia that can hinder insight to be transformed into action. Managers need to realize that big data-generated insight is only one component of gaining value from big data investments, and the other is responsiveness.

6.3. Limitations and future research

Despite the contributions of the present study, it is constrained by a number of limitations that future research should seek to address. First, as noted already, self-reported data are used to test most of our research hypotheses. Although considerable efforts were undertaken to confirm data quality, the potential of biases cannot be excluded. The perceptual nature of the data, in conjunction with the use of a single key informant, could suggest that there is bias, and that factual data do not coincide with respondents' perceptions. We have attempted to remedy this by instructing respondents to consult other employees in their organizations that might be better equipped to answer certain questions. Although this study relies on top management respondents as key informants, sampling multiple respondents within a single firm would be useful to check for interrater validity and to improve internal validity. Second, although we examine the value of BDACs on competitive performance, through the mediated effect of dynamic capabilities on operational capabilities, we do not factor in contextual and environmental conditions. It is highly likely that the value of directing big data initiatives may be more beneficial in some cases than in others. This is an area that future research should seek to address, and it is of increased practical value, particularly considering the costs of deploying big data initiatives. The main argument that a BDAC is necessary but not a sufficient condition to lead to competitive performance gains remains subject to several internal and external factors, which hopefully will be addressed in subsequent research studies. Finally, although the theoretical grounding of the research dictates the directions of effects, it is important that future research confirms these, removing the possibility that effects are a result of reserved causality.

7. Conclusion

This study was largely motivated by the great interest of scholars and practitioners on the phenomenon of big data. While there has been extended discussion on the side of practitioners on the value and core elements relating to big data adoption, academics have been lagging in examining organizational aspects of big data projects, and empirically verifying if, and under what conditions, these investments pay off. As a result, much of what has been written about big data focuses on specific aspects, or individual cases of big data success, but not much is known about the full range of resources that are required to develop a BDAC, and the overall business value it can produce. This study is built on the RBV and dynamic capabilities view, as well as on recent big data analytics research. The empirical results highlight the importance of investing on all complementary big data resources (i.e., tangible, human, and intangible), that jointly help develop a BDAC. By doing so, firms manage to develop evolutionary fitness as insight generated through BDAC supports a firm's dynamic capabilities, which, in turn, result in strengthened operational capabilities. The effect of this renewal is discernible through an indirect effect on two core operational capabilities: marketing and technological. Concluding, this study demonstrates that a) big data are more than just the data itself, b) developing a capability requires a number of complementary resources to be taken into account, c) insight is only one component from a strong BDAC, to other is action and reconfiguration, and d) capturing performance gains of BDAC require identifying the mechanisms and main enablers/hindrances that influence value.

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