Strategic business value from big data analytics: An empirical analysis of the mediating effects of value creation mechanisms

Strategic Business Value from Big Data Analytics: An empirical analysis of the mediating effects of value creation mechanisms

Elia, G., Raguseo, E., Solazzo, G., & Pigni, F.

Information & Management

Abstract

Big data are a prominent source of value capable of generating competitive advantage and superior business performance. This paper represents the first empirical investigation of the theoretical model proposed by Grover et al. (2018) considering the mediating effects of four value creation mechanisms on the relationship between Big Data Analytics Capabilities (BDAC) and four value targets. The four value creation mechanisms investigated (the source of the value being pursued) are transparency, access, discovery, and proactive adaptation, while the four value targets (the impacts of the value creation process) are organization performance, business process improvement, customer experience and market enhancement, and product and service innovation. The proposed empirical validation of the Grover et al.'s (2018) model adopts an econometric analysis applied to data gathered through a survey involving 256 BDA experts. The results reveal that transparency mediates the relationship for all the value targets, access and proactive adaptation mediate only in case of some value targets, while discovery does not have any mediating effect. Theoretical and practical implications are discussed at the end of the paper.

Keywords: Big data analytics; Value creation mechanisms; Value targets; Mediation.

1. Introduction

The Big Data paradigm envisions scenarios characterized by a large amount of data (Volume) generated and computed at high speed (Velocity), coming from structured and unstructured sources (Variety), that incorporates possible incongruences and non-reliable information (Veracity) that do not affect the overall value that can derive from it (Elia et al., 2020). Big data are a prominent source of value to achieve competitive advantage and superior business performance (Côrte-Real et al., 2017), even if their distinctive features such as volume, variety and veracity do not always ensure separately value creation (Cappa et al., 2021). Big data applications have been proven to enhance decision-making processes (Erevelles et al., 2016) and operations in numerous domains including supply chain management (Gunasekaran et al., 2017), customer relationship management (Nam et al., 2019), or healthcare management (Wang and Hajli, 2017) in the aim to have more information on businesses and improve the firm's performance. There are many examples of real applications of Big Data in firms and organizations. Among them, eBay leverages Big Data to process structured (e.g. purchases) and unstructured (e.g. behavioral activity) data to enhance recommendation service of similar items and to detect frauds in a predictive way (Grover et al., 2018). Walmart relies on Big Data for two main purposes: to inform consumers about the products they already bought from Walmart and offered with a lower price by a competitor in the aim to send them a gift voucher and compensate the price difference; and to scan and analyze social media channels for identifying (actual or potential) customers who mention a Walmart product in the aim to offer them a special discount on such items (Grover et al., 2018). In the financial industry, Deutsche Bank, Wells Fargo and Bank of America use Big Data to analyze customer data interactions along customers digital touchpoints (e.g., web site clicks, voice recordings, transaction records, bankers' notes) to understand the overall customer experience and identify elements that may hinder or support services purchase (Grover et al., 2018). Southwest Airlines adopted a similar approach to analyze the interactions between personnel and customers to anticipate customers' needs, provide better service offerings, and train service personnel on unrecognized customer needs (Mikalef et al., 2019; Erevelles et al., 2016). Within the public sector, the New South Wales State Emergency Service (NSW-SES) used big data to improve the operations delivery. It integrated multiple structured and unstructured data sources owned by multiple agencies and actors (i.e., Bureau of Meteorology, the NSW-SES website, social media as Twitter and Facebook), and combined them with historical information to improve the effectiveness and rapidity of responses to crises and disasters (e.g., floods, storms and other natural and man-made disasters) (Fosso Wamba et al., 2015).

Also, Merck used Big Data technologies for developing vaccines faster (Henschen, 2014), Volvo to forecast which component might fail under what circumstances, and Xerox to analyze telemetric data to provide better customer service and reduce costs (Big Data Insight Group, 2012).

Procter & Gamble, a pioneer in the extensive adoption of big data, analyzed structured and unstructured data sources (e.g., customer interactions through web site and social media, supply chain operations, R&D activities) to understand consumer behavior and facilitate quick decision making (Purkayastha & Koti, 2017). Amazon leveraged its big data sources to provide its customers (both current and potential ones) with highly customized product suggestions, thus improving the relationship with them (Purkayastha & Rao, 2014) and generating about a third of sales from personalized product recommendations (Fosso Wamba et al., 2017). Finally, Ramco Cements Limited adopted Big Data to analyze the huge amount of data deriving from diverse sources and realize a system capable to list performance goals and visualize interactive graphs through which comparing actual achievement with expected goals, thus making more intelligent the business decisions (Dutta & Bose, 2015).

In the literature, big data analytics (BDA) focus on how extracting and generating useful knowledge that can lead to more effective management (Chen et al., 2012). Then, the BDA process aims at elaborating and interpreting data to develop actionable insights for competitive advantage, thus becoming a major determinant of firm performance, especially by enhancing the market-directed capabilities (Suoniemi et al., 2020).

To gain a deeper comprehension of the determinants of BDA contributions to firm performance, the concept of BDA capabilities (BDAC) has been recently introduced (Mikalef et al. 2020a). BDAC are defined as the knowledge, skills and abilities that combine technology and management issues to explore data potential (Fosso Wamba et al., 2020a) through sophisticated statistical, computational and visualization tools. BDAC make organizations capable to master both the knowledge extraction and the effects that data processing and analysis may have on decision-making through data visualization. Hence BDAC could help firms to monitor their economic and financial context

(Mikalef et al., 2020a) and market success (Upadhyay and Kumar, 2020), thus supporting strategic business value creation (Akter et al., 2020).

Although the growing literature on BDA research (Gupta and George, 2016; Akter et al., 2019; Mikalef et al., 2020a) and the developments of information technology capabilities studies (Mikalef et al., 2020b), it persists a relevant gap in our understanding of BDAC influence on organizational outcomes (Fosso Wamba et al., 2020). More specifically, little is known about: 1) the value creation mechanisms that could play a critical role in explaining the relationship between BDAC and firm performance, 2) the mechanisms by which data-based insights are transformed into actions and business value (Su et al., 2021; Mikalef et al., 2019). Few studies investigated the impact of BDAC on value creation targets by considering the mediation effect of value creation mechanism (Akter et al., 2016; Côrte-Real et al., 2017). This represents a critical hole worth study and investigation, as it may reveal those mechanisms by which an investment in BDA translates into performance (Zheng and Zhou, 2019).

Grover et al. (2018)'s theoretical study provides a comprehensive contribution for deepening our understanding of the mediating effect of BDAC. The authors proposed a holistic theoretical framework to describe the mediating effects of value creation mechanisms on the relationship between BDAC and value targets. However, without any empirical test or operationalization, which represents itself a critical area of research in the general big data field (Mikalef et al., 2019; Anwar et al., 2018). In our study, we contribute to fulfill this gap by proposing the quantitative analysis of the mediating role that the value creation mechanisms (i.e., transparency, access, discovery, proactive adaptation) exert on the relationships between BDAC and the sources of value targets (i.e., organization performance, business process improvement, customer experience and market enhancement, product and service innovation) (Grover et al., 2018). In other words, we empirically measure the mediating relationships proposed theoretically by Grover et al. (2018) attempting to answer the following research question: *"Do transparency, access, discovery and proactive* *adaptation as value creation mechanisms play a mediating role in the relationship between BDAC and value targets?".*

Our study investigates the relationship existing between BDAC and value targets discovering and qualifying the potential mediators that may affect such linkage. In particular, the value creation mechanisms represent the possible ways BDAC create results that can be turned into actions to impact value (Grover et al., 2018). We focus on transparency that concerns the openness of information and communication flows (Bertot et al., 2010), access that concerns the availability and possibility to use data (Ghasemaghaei, 2020), discovery that concerns data-driven decision making (Mikalef et al., 2019), and proactive adaptation that concerns the capacity to follow the market changes and requirements (Aslam et al., 2018). We considered the four value creation mechanisms mentioned above since related constructs where already established in literature, enabling then a better analysis of related concept and the emerging nomological network. Future research will provide further evidence by looking at the other value creation mechanisms proposed theoretically by Grover et al. (2018).

Value targets represent the possible ways through which BDA can generate value for organizations (Grover et al., 2018). In particular, BDA may impact performance through decision making and strategic positioning (Jyothibabu et al., 2010), business process improvement and efficient organization of the work (Bhatt and Troutt, 2005), customer satisfaction and market penetration (Wang et al., 2012), product and service innovation (Mikalef et al., 2018).

We tested the research question cited above by implementing a survey involving 256 BDA experts certified by the Italian Ministry of Economic Development who had significant experience in the design and implementation of BDA projects within companies and organizations.

The rest of the paper is structured as follows: next section describes the theoretical background of the study and the hypotheses searched for. Then, it is presented the methodology adopted and the results achieved. Finally, findings are discussed by highlighting both research and managerial implications. The article ends by providing conclusions and guidelines for future studies.

2. Theoretical Framework

Based on the conceptualization of BDAC provided by Gupta and George (2016), the role of a system of mechanisms such as transparency, accessibility, discovery, and proactive adaptation is studied to understand the strategic value targets generated by BDAC (i.e. organization performance, business process enhancement, innovation of products and services, customer experience and market development). These four value creation mechanisms are proposed theoretically by Grover et al. (2018), and we investigate them empirically.

For this reason, the managerial theories underpinning this research derive from the theoretical framework of the Grover et al.'s (2018) study, and help to understand "how" value is created in organizations. We refer to the Resource Based View (Mata et al., 1995), Dynamic Capability View (Teece and Pisano, 1997), and Absorptive Capacity View (Roberts et al., 2012).

Framed into the Resource Based View (RBV), BDAC allow for integrating and analyzing multiple sources of data into a single and unique bundle of conceptual elements, thus becoming specific for the organization along a significant time frame. In such a way, BDAC can be considered as heterogeneous and immovable resources (Barney, 1986, 1991; Rumelt, 1984; Wernerfelt, 1984; Mahoney and Pandian, 1992) so that competitors cannot procure them from the market and cannot compete without facing serious economic difficulties for their internal development. Hence, BDAC can be configured as resources that are inimitable (difficult to be copied by external actors), rare (difficult to be found or assembled into the market), non-substitutable (difficult to be replaced by other resources), valuable (that generate economic value) and exploitable (that create advantage in a way that competitors cannot do) (Anwar et al., 2018), which effectively deploy technology and talent to collect and process data (Mikalef et al., 2020), and generate valuable insights for supporting decision making, innovation, customer satisfaction, supply chain and market performance (Terziovski, 2010; Wu et al., 2006, Dubey et al., 2019). Nevertheless, current markets are characterized by high environmental uncertainty, volatility, complexity and ambiguity (Schoemaker et al, 2018.), with frequent changes and global scope. This calls for organizations to focus on strengthening their dynamic capabilities, i.e. their capacity to sense, seize and shape opportunities and threats, and maintain competitiveness through cultivating, developing, integrating, protecting, and reconfiguring the intangible and tangible assets of the organization (Teece, 2007). Therefore, by looking at the Dynamic Capability View (DCV) as an aggregate multidimensional construct (Barreto, 2010), BDAC allow for flexibly combining internal and external resources, technologies and learning processes to enhance the capacity to detect earlier new technological advancements that can be transformed into a competitive advantage (Pavlou et El Sawy, 2011), in the aim to extract knowledge from data and exploit market opportunities. In such a way, BDAC enable organizations to leverage their resources to respond rapidly to fast changes in dynamic markets (Eisenhardt and Martin, 2000) and incorporate external knowledge within organizations to gain competitive advantage (Helfat and Peteraf, 2009; Day, 2014). Actually, conceived as a dynamic capability, BDAC include the capacities and knowledge of dedicated persons, collaborations with both internal and external actors, knowledge exchange processes, available systems to access to multiple data sources, and proper data collection and processing methods (Janssen et al., 2017).

Finally, based on the Absorptive Capacity View (ACV), organizations develop abilities to recognize, acquire, assimilate, transform and exploit knowledge from external sources (Cohen and Levinthal, 1990), and use it effectively to achieve their goals (Tseng et al., 2011). Such abilities are incorporated into a set of routines and strategic processes at organizational level that includes acquisition (capacity to identify and acquire external knowledge), assimilation (capacity to analyze, process, interpret and understand information obtained from external sources), transformation (capacity to combine newly acquired and assimilated knowledge and existing knowledge) and exploitation (capacity to apply acquired and transformed knowledge) (Zahra and George, 2002). In such a view, and considering that firm's performance is highly dependent on its effectiveness in processing and interpreting data, the absorptive capacity of a firm facilitates the exploitation of BDAC (Zeng & Glaister, 2018) to enhance agility and innovation performance (Khan et al., 2022), as well as the ability of organizations to identify and assimilate valuable external data and knowledge to pursue innovation goals and competitive actions. Thus, by leveraging their absorptive capacity, organizations can identify new data sources, acquire new knowledge and competencies, develop new solutions, and learn new capabilities to enhance the maturity stage of BDAC and gain sustainable competitive advantage (Dahiya et al., 2021).

In this view, the theory background of this article grounds on these three frameworks for their relevance towards the nature of the study that investigate multiple views of value creation such as the integration of heterogeneous elements (typical of the RBV), the flexible combination of knowledge resources and learning flows (typical of the DCV), and the identification of external knowledge to innovate (typical of the ACV).

2.1 BDA and BDA Capabilities

In the current complex business environment characterized by the leading role of data, both theory and practice have considered big data a revolution for business and management (McAfee et al., 2012), and BDA as the next frontier for innovation, competition, and productivity. Big data is a concept characterized by a significant volume of both structured and unstructured data that can be described through the 5 Vs model (i.e. volume, velocity, variety, veracity, value) (Fosso Wamba et al., 2017). It comprehends technology, economic and organization related issues (Raguseo and Vitari, 2018), and can be considered an enabler to increase the company performance (Elia et al., 2020) and consolidate the competitive advantage (Kubina et al., 2015) by improving either the efficiency or the effectiveness of activities (Suoniemi et al., 2020).

BDA is, then, the process of using advanced technologies to collect and analyze big data to uncover useful information and provide solid insights to make better decisions across business processes (Fosso Wamba et al., 2020). BDA can be further considered “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 analysis” (Mikalef et al., 2017). Recent studies focused on different perspectives of BDA, embracing issues related to decision-making process, firm's performance and competitive advantage, information processing throughout the organization's value chain, data generation within ecosystems and its usage for digital transformation and sustainable society, data privacy and ethics (Mikalef et al., 2020d).

Current evidence suggests that the deployment of BDA helps firms hook emerging opportunities and threats, generate critical insights, and adapt their operations based on competitive environmental trends (Chen et al., 2012; Mikalef et al., 2019a). By leveraging BDA, organizations gain a competitive advantage in the market by making predictions for future events (Hajli et al., 2021). Grover et al. (2018) observed that companies undertake BDA initiatives to analyze customers' purchases and predict customers' propensities, thus achieving multiple objectives such as: i) to enhance sales and increase the personalization level of future purchases; ii) to establish in real time the basic reasons of failures and imperfections, or forecast potential problems; iii) to analyze and understand online consumer reviews to improve quality and pursue innovation goals; iv) to implement fast reactions and develop anomaly detection capability; v) to adjust processes and identify operational roadblocks.

Despite BDA's proven advantages and business value when applied to problems within data-intensive domains (Mikalef et al., 2019), only few studies focus on the challenges that companies face during the implementation of big data initiatives (Gupta and George, 2016). Indeed, little is known about the organizational factors that, integrated with data sources and analytical tools and processes, determine the real success of big data projects and their contribution to firm performance. BDAC has been proposed as a viable framework to study this relationship, referring to a firm's ability to leverage big data to gain actionable insights (Mikalef et al., 2017) by combining technology, management and personnel (Fosso Wamba et al., 2020). Indeed, BDAC refers to the complex process of obtaining valuable information, such as hidden patterns, unidentified correlations, users' preferences, and market trends from the massive amount of structured and unstructured data (Hariri et al., 2019).

To date, most of the studies related to BDAC have explored only the direct relationship with company performance (Akter et al., 2016; Yasmin et al., 2020) through the prevalent prism of theoretical perspectives such as the resource-based view (Erevelles et al., 2016), the dynamic capability view (Ciampi et al., 2020), and the absorptive capacity view (Roberts et al., 2012). These studies mainly focus on the role that firms' internal and external capabilities (or a combination of them) play in disseminating and using knowledge in an effective way, thus impacting firms' value creation (Rehman et al., 2016). While many BDAC are conceptualized, both Fosso Wamba et al. (2015) and Akter et al. (2016) have suggested that they could be related to three broad categories of capabilities: management (i.e., BDA planning, investment, coordination and control), technology (i.e., connectivity, compatibility and modularity), and talent (i.e., technical, business and relational knowledge). Also Davenport et al. (2012) suggested that the BDAC effort should be on data management capability throughout the operations, human resources and talent capability, and advanced IT infrastructure capability.

McAfee and Brynjolfsson (2012) identified the key challenges of BDAC (i.e. talent management, IT infrastructure, and decision-making capability), whereas Kiron et al. (2014) focused on three core elements related to BDAC: management culture (e.g. planning, coordinating, controlling), data management infrastructure (e.g. openness, compatibility, interoperability), and skills (e.g. analytical talent, technical and business knowledge, insights dissemination).

Remarkable contributions to BDAC conceptualization can be found in Gupta and George (2016) and Mikalef et al. (2017), who defined a multidimensional three-level aggregation of big data-specific resource constructs such as tangibles (e.g., internal/external data, technology, and basic resources as time and investments), humans (e.g., managerial and technical skills, data analytics knowledge), and intangibles (e.g., data-driven culture and intensity of learning organization, governance and IT/business alignment).

Table 1 synthesizes the most relevant perspectives on BDAC, which may contribute to enrich the set of organizational capabilities that make organizations more performing and competitive.

Table 1. List of the most relevant contributions to BDAC conceptualization

Related Studies	BDAC typologies
Kim et al. (2012)	• IT Management • IT Infrastructure • IT Personnel
Fosso Wamba et al. (2015), Akter et al. (2016)	• Management (BDA planning, investment, coordination and control) • Technology (connectivity, compatibility and modularity) • Talent (technical, business and relational knowledge)
Davenport et al. (2012)	• Big data management (analytics management of core business and operational functions) • Advanced IT infrastructure (open-source platforms ensuring connectivity, compatibility and modularity) • Human resources and talent capability (data scientists or human resource capability)
McAfee and Brynjolfsson (2012)	• Decision-making • IT infrastructure • Skills and knowledge of data scientists
Kiron et al. (2014)	• Management culture (analytics planning, sharing and coordination, investment, control of analytics as a whole) • Data management infrastructure (organizational openness, compatibility analytics technology, collaborative use of data) • Skills (analytical talent, technical and business knowledge, organization effectiveness in disseminating insights)
Gupta and George (2016), Mikalef et al. (2017)	• Tangibles (data, technology and basic resources) • Human skills (technical and managerial skills) • Intangibles (data-driven culture and intensity of organizational learning)

2.2 Creating Business Value through BDAC

BDAC can be interpreted as a distinguishing organizational ability through which organizations can benefit from the strategic value embedded in big data, whose business exploitation is still scarce (Grover et al., 2018). This is confirmed by recent studies that have investigated the direct relationships existing between BDAC and value creation under multiple dimensions, including organizational performance (Côrte-Real et al., 2017; Mikalef et al., 2019), agility (Fosso Wamba et al., 2020a), competitive advantage (Fosso Wamba et al., 2017; Mikalef et al., 2020a), decision making effectiveness (Cao et al., 2015), business strategy alignment (Sheng et al., 2017), business performance (Nam et al., 2019), and strategic business value (Akter et al., 2020). A systemic view on the studies about BDAC and firm-level performance outcomes has been performed by Yasmin et al. (2020).

These studies limit their scope and analysis mainly to the direct effect of BDAC on organizational performance, without exploring the mediation effects that may intervene in this relationship. Only recently the interest of scholars moved in this direction. Table 2 synthesizes the most recent and relevant contributions by highlighting the different targets of the BDAC relationships and the mediating factors influencing such relationships.

Table 2. Contributions investigating the mediated relationship of BDAC with firm performance

Related studies	BDAC relationship on	Mediated by
Anwar et al. (2018)	Firms' performance	Competitive advantage and analytics culture
Raguseo and Vitari (2018)	Business value	Market performance and customer satisfaction
Mikalef et al. (2020a)	Incremental and radical innovation capabilities	Environmental uncertainty (dynamism, heterogeneity, hostility)
Rialti et al. (2019)	Organizational performance	Ambidexterity and agility
Fosso Wamba et al. (2020b)	Organizational outcomes (especially on the financial and market dimension)	BDA-enabled sensing capability and analytics culture
Shabbir and Gardezi (2020)	Organizational performance	Knowledge management practices
Mikalef et al. (2020b)	Competitive performance	Dynamic (sensing and seizing) and operational (marketing and technological) capabilities
Shahbaz et al. (2020)	Perceived sales performance	CRM capabilities
Ciampi et al. (2021)	Business model innovation	Entrepreneurial orientation

Interestingly, these studies assumed a narrow declination of business value as the dependent variable, thus focusing their analysis on a partial and limited perspective of the phenomenon. To overcome such limitations and face the related challenges, this article adopts a multidimensional definition of business value (Grover et al., 2018) based on the integration of content (i.e. which strategic changes should be made), process (i.e. how such changes should be made), and context (i.e. conditions through which these changes can be made). In that study, the authors investigated how organizations leverage dynamic capabilities to build and reconfigure internal and external resources to achieve superior performance in turbulent environments (Sambamurthy et al., 2003), and how such capabilities affect value creation processes (Melville et al., 2004). Their proposed framework qualifies the relationship between IT investments in BDA infrastructure and the business impact through two key processes: BDAC building and BDAC realization. The former relies on the establishment of a BDA infrastructure made by big data assets (i.e., data sources and platforms), analytics portfolios, and human talent for integrating, managing and analyzing big data. The latter concerns the value creation mechanisms of BDA that may have a positive impact on different value targets. The mechanisms include transparency and access, discovery and experimentation, prediction and optimization, customization and targeting, learning and crowdsourcing, continuous monitoring and proactive adaptation. Such mechanisms mediate the linkages between BDAC and value targets that are represented by four distinct sources: organization performance, business process improvement, customer experience and market enhancement, product and service innovation.

The framework proposed by Grover et al. (2018) has the strength to provide a systemic and holistic view of the BDAC impact on firms' performance but, at the same time, it lacks validation of the relationships between BDAC, value creation mechanisms and value targets. To shed light on this issue, this research aims to investigate the mediating role that value creation mechanisms may have in the relationships between BDAC and the sources of value targets. More specifically, considering the complexity of the research due, on one side, to the multi-dimensional aspect of value targets and, on the other side, to the numerous value creation mechanisms to be considered, we decided to start preliminarily from four mechanisms such as Transparency, Access, Discovery, and Proactive adaptation since their operationalization is established in literature therefore providing a solid base for comparing it to existing conceptualizations.

Mediating effect of Transparency

Transparency represents not only the ability to allow consistent and reliable data visualization, but also provides a systemic view of the business processes and company outcomes. Transparency is a type of value creation mechanism for big data initiatives (Fosso Wamba et al., 2015) and is enabled by various applications ranging from advanced analytic insights to real-time processes.

Even though BDAC are important in explaining the impacts on firm performance, other factors, as the transparency with which data are shared in the company, can explain the different ability of firms to extract value from the BDAC developed. This could happen because transparency fosters decision-making across the organization playing a mediating effect between the development of BDAC and company value targets. Thanks to the transparency, companies can access and use data in a more efficient way. For example, by analyzing streaming data such as real-time performance data, a company can have significant effects on related value targets for example to fraud detection or preventive maintenance. Consider Amazon who benefits of both access to data and strong BDAC. Through customization they can provide a better customer experience increasing sales and the customer satisfaction. Since it is supposed that BDAC are not directly related to company outcomes, and since transparency is supposed to have a mediating effect between BDAC and the company value targets, referring to Grover et al.'s (2018) theoretical model, we hypothesize that:

H1a. Transparency mediates the relationship between BDAC and organization performance

H1b. Transparency mediates the relationship between BDAC and business process improvement

H1c. Transparency mediates the relationship between BDAC and consumer experience and market enhancement.

H1d. Transparency mediates the relationship between BDAC and product and service innovation

Mediating effect of Access

Access represents the capacity to provide descriptive data and distribute them throughout the organization, and measures the extent to which the BDA system is available over time, ensuring convenience and scalability (Nelson et al., 2005). A benefit in obtaining big data, and thus in increasing the available data volume, variety and velocity, is the enhancement of data accessibility, which allows organizations to make more informed and faster decisions (Ghasemaghaei, 2020). Using data analytic tools allows firms to improve decision-making performance (Ghasemaghaei et al., 2018), make real-time adjustments to their offerings and interact with their customers continuously (Bharadwaj and Noble, 2017), and increase economic benefits (Lam et al., 2017).

Access is also considered one of the system quality components that allows to predict business value and company performance (Ji-fan Ren et al., 2017). For example, dashboards can provide real-time access to information on a company activity systems. Based on this context and referring to Grover et al.'s (2018) theoretical model, and since it is supposed that BDAC are not directly related to company outcomes, the mediation role that access has in the relationships between BDAC and value targets leads to the following hypotheses:

H2a. Access mediates the relationship between BDAC and organization performance

H2b. Access mediates the relationship between BDAC and business process improvement

H2c. Access mediates the relationship between BDAC and consumer experience and market enhancement

H2d. Access mediates the relationship between BDAC and product and service innovation

Mediating effect of Discovery

In the BDA domain, discovery generally refers to "deeper dive" into the data to understand patterns, trends and relationships to derive pragmatic results that can yield important outcomes. Discovery examines "what happened in the past", then diagnoses "why it happened", and finally determines the root cause to understand and discern the bigger picture of "what is happening" and "why it is happening" (Delen and Zolbanin, 2018). Discovery within BDA can be a prospective value creator for business, which can allow handling big data to extract their real meaning, and develop insights to support and encourage their usage. Discovery analytics is often the most emphasized aspect of BDA, and developing its related capabilities can be crucial to reaching specific value targets. Currently, many software are available in the market to support analysts for improving company performance and making better decisions that lead organizations toward success. Furthermore, Lehrer et al. (2018) demonstrate that the retrospective and prospective characteristics of discovery analytics (in terms of predictive and prescriptive features) enable service innovations and thus contribute to creating new value propositions. For example, many banks use BDA applications though discovery to improve the quality of bank-customer interactions by identifying customer opportunities and problems.

Based on this context and referring to Grover et al.'s (2018) theoretical model, and since it is supposed that BDAC are not directly related to company outcomes, the mediation role that discovery has in the relationships between BDAC and value targets leads to the following hypotheses:

> **H3a.** Discovery mediates the relationship between BDAC and organization performance
>
> **H3b.** Discovery mediates the relationship between BDAC and business process improvement
>
> **H3c.** Discovery mediates the relationship between BDAC and consumer experience and market enhancement
>
> **H3d.** Discovery mediates the relationship between BDAC and product and service innovation

Mediating effect of Proactive adaptation

Proactive adaptation is a strategic process that leverages organizational agility to sense and identify innovation opportunities, and define proper strategies to catch them by seizing and combining assets, knowledge and relationships rapidly (Goldman et al., 1995). Agility includes the firm's capabilities related to interactions with customers to both sense and respond them in expeditious way (Hajli et al., 2020), as well as the orchestration of internal operations and utilization of the business ecosystem (Sambamurthy et al., 2003). For example, through supply chain agility, firms develop a deep knowledge of partner activities and are capable to address the market uncertainty.

Furthermore, Blome et al. (2013) consider supply chain agility as a dynamic capability through which influencing positively the company operational performance, while Aslam et al. (2018) state that supply chain agility supports firms to seize market opportunities by configuring short-term supply chain actions. Implementing BDA systems also increases the ability to adapt quickly, adjust critical issues and anticipate future problems (Grover et al., 2018). In such a way, BDAC can determine better performance by the mediating effect of proactive adaptation. Based on this context and referring to

Grover et al.'s (2018) theoretical model, and since it is supposed that BDAC are not directly related to company outcomes, the mediation role that proactive adaptation has in the relationships between BDAC and value targets leads to the following hypotheses:

H4a. Proactive adaptation mediates the relationship between BDAC and organization performance

H4b. Proactive adaptation mediates the relationship between BDAC and business process improvement

H4c. Proactive adaptation mediates the relationship between BDAC and consumer experience and market enhancement

H4d. Proactive adaptation mediates the relationship between BDAC and product and service innovation

Figure 1 summarizes the hypotheses tested in this study.

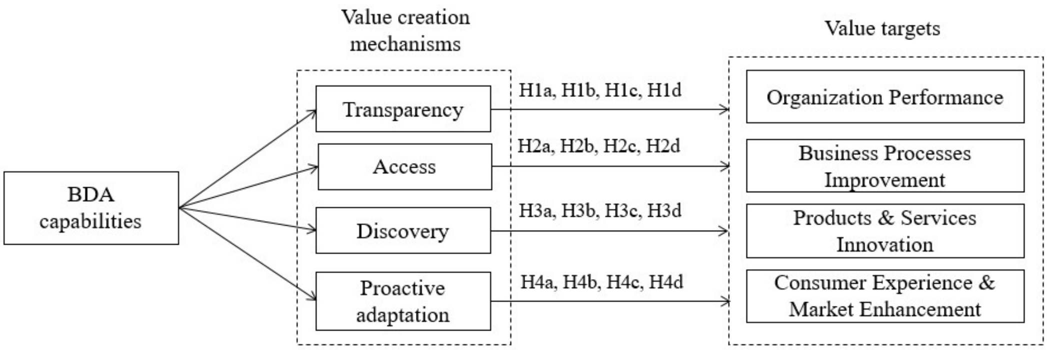

Figure 1. Research framework

From a mathematical perspective, Figure 1 can be represented as follows, by showing both the indirect effect of X on Y through $M_1 = a_1b_1$, $M_2 = a_2b_2$, $M_3 = a_3b_3$, $M_4 = a_4b_4$, and the direct effect of X on Y = c':

$$M_1 = a_0 + a_1X+e_{M1}$$

$$M_2 = b_0+a_2X+e_{M2}$$

$$M_3 = c_0+a_3X+e_{M3}$$

$$M_4 = d_0+a_4X+e_{M4}$$

$$Y=c'_0+c'X+b_1M_1+b_2M_2+ b_3M_3+ b_4M_4+e_{Y*}$$

$$Y=c_0+cX+e_Y$$

3. Methodology

3.1 Scale development

We delivered a questionnaire on September 2020 to a sample of 2,894 BDA experts certified by the Italian Ministry of Economic Development who had significant experience in the design and implementation of BDA projects within companies and organizations. We delivered the questionnaire to empirically validate the theoretical framework proposed by Grover et al. (2018).

Before sending the final questionnaire, a double validation process was performed. First, a team of five managers experienced in big data verified the comprehension and consistency of the questions included in the questionnaire. Their comments and feedback were collected and then discussed to create an updated version of the questionnaire. This new version was sent to another group of five managers with big data experience for the final validation. Finally, 256 questionnaires were gathered, specifically related to a sample of 121 companies with less than 10 employees, 60 companies with 10-50 employees, 42 companies with 51-300 employees, and 33 companies with more than 500 employees. Table 3 provides further details about the sample involved.

Table 3. Demographics

	Number of companies	**Percentage of companies**
Size		
Up to 10	121	47.27%
From 10 to 50	60	23.44%
From 51 to 500	42	16.41%
More than 500	33	12.89%
Role of respondent		
Advisor	63	24.61%
CEO	97	37.89%
Managerial role or other roles involved in BDA	96	37.50%
Total	*256*	*100.00%*

The questionnaire was composed by four sections. The first section was about the demographics of the respondent. The second included questions on the development of BDA capabilities. The other two sections were about the four value creation mechanisms analyzed in this work, and the four value targets. For all the sections, except the first, we used a seven-point Likert scale, with answers ranging from “completely disagree” (−3) to “completely agree” (+3). Tables A1, A2 and A3 provide details about the items used in the questionnaire and the study we referred to for defining the Likert scales. To define the operationalization of the variables, we started considering the original wording of the scales and then we re-adapted to our BDAC’s case the existing Likert scales already validated in literature (see Table A1, A2 and A3 for the references).

3.2 Measures

Independent variable

The independent variable included in the research framework refers to BDA capabilities (Gupta and George, 2016). It is based on seven first-order variables, which are based on a seven-point Likert scale (Table A1), and grouped in three dimensions: tangibles, human skills and intangibles (Fugure 2).

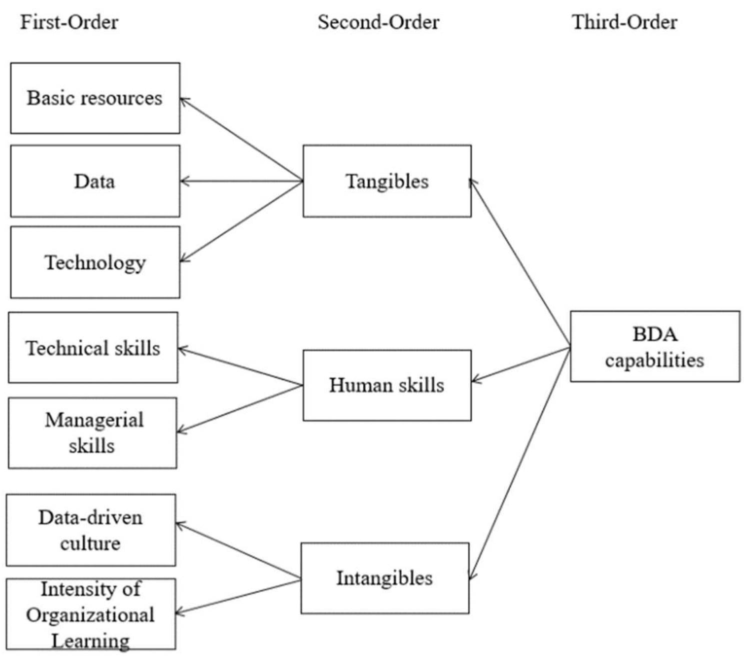

Figure 2. BDA capabilities

Mediating variables

As mediating variables, we chose the value creation mechanisms suggested by Grover et al. (2018). Every value creation mechanism was based on a seven-point Likert scale (Table A2). The first variable, transparency, refers to the ability to create value based on the ability to generate descriptive data about the firm's business processes and outcomes. Then, access, refers to the ability to take and disseminate data widely across a firm. Discovery refers to leverage BDA for achieving insights. Proactive adaptation leverages organizational agility to recognize chances for innovation and seize competitive market opportunities. Finally, agility involves a firm's capabilities to interact with customers, manage internal operations, and interrelate with external business partners.

Dependent variables

The dependent variables are referred to in the research framework as value targets. In line with Grover et al. (2018), we identified four different targets of BDA value creation: organizational performance (e.g. quality of decision-making); business process improvement (e.g. increased efficiency of business processes); product and service innovation (e.g. new characteristics of products and services offered); customer experience and market enhancement (e.g. enhanced customer satisfaction and retention). They are operationalized on a seven-point Likert scale (Table A3).

4. Results

4.1 Psychometric properties of the measures

Before the regressions, we performed a confirmatory factor analysis to evaluate the psychometric properties of the variables. We verified the convergent validity by computing the t-statistic of each factor loading. They were all statistically significant, and all the t-values were higher than the cutoff point of 1.980. Also, the constructs were all satisfactory with the Kaiser-Meyer-Olkin measure with a value of 0.813, and with the Bartlett's test with a chi-square value of 637.65 (p-value = 0.001). Also acceptable levels of reliability and average variance extracted (AVE) were achieved since they were higher than the acceptable threshold values (Bagozzi and Yi, 1988), thus highlighting the convergent validity in the measurement model. We also checked for common method bias and found it was not a serious problem since the Harman's single-factor test indicated a value of 41.94% of the total variance lower than the recommended threshold of 50%. We also checked the non-response bias issue. Wagner and Kemmerling (2010) found a way to assess the non-response bias as the comparison of responses from early versus late respondents. We verified in this direction the non-response bias and we observed that there were not any differences between the comparison of early versus late respondents in terms of means of the variables.

Table 4. Psychometric table of measurements

Construct	Sub construct	Acronym	AVE	CR	CA	Factor loading
BDA capabilities	Data – Tangibles	D1	0.657	0.851	0.739	0.731
		D2				0.863
		D3				0.832
	Technology – Tangibles	T1	0.715	0.883	0.799	0.828
		T4				0.838
		T5				0.871
	Basic Resources – Tangibles	BR1	0.590	0.742	0.866	0.941
		BR2				0.941
	Technical Skills – Human skills	TS1	0.757	0.939	0.915	0.825
		TS2				0.718
		TS3				0.938
		TS4				0.943
		TS5				0.904
	Managerial Skills – Human skills	MS1	0.808	0.967	0.948	0.882
		MS2				0.909
		MS3				0.919
		MS4				0.901
		MS5				0.881
		MS6				0.839
	Data-driven Culture – Intangibles	DDC1	0.748	0.922	0.888	0.752
		DDC2				0.890
		DDC3				0.919
		DDC4				0.888
	Intensity of Organizational Learning – Intangibles	IOL1	0.839	0.954	0.908	0.909
		IOL2				0.939
		IOL3				0.927
		IOL4				0.887
		IOL5				
Value creation mechanism	Transparency	TR1	0.768	0.943	0.925	0.870
		TR2				0.864
		TR3				0.895
		TR4				0.874
		TR5				0.877
Value creation mechanism	Accessibility	AC1	0.834	0.938	0.900	0.909
		AC2				0.941
		AC3				0.889
Value creation mechanism	Discovery	DS1	0.681	0.865	0.760	0.857
		DS2				0.752
		DS3				0.862
Value creation mechanism	Proactive adaptation	PA1	0.827	0.950	0.928	0.918
		PA2				0.924
		PA3				0.921
		PA4				0.872
Value target	Organization Performance	OP1	0.709	0.945	0.930	0.832
		OP2				0.869

		OP3				0.817
		OP4				0.829
		OP5				0.831
		OP6				0.866
		OP7				0.851
Value target	Business Processes Improvement	BPI1	0.738	0.962	0.954	0.909
		BPI2				0.887
		BPI3				0.904
		BPI4				0.868
		BPI5				0.913
		BPI6				0.879
		BPI7				0.787
		BPI8				0.822
		BPI9				0.744
Value target	Products and Services Innovation	PSI1	0.694	0.941	0.904	0.816
		PSI2				0.834
		PSI3				0.826
		PSI4				0.837
		PSI5				0.853
		PSI6				0.777
Value target	Consumer Experience and Market Enhancement	CE1	0.740	0.919	0.877	0.731
		CE2				0.910
		CE3				0.894
		CE4				0.894

Note: all the factor loading are significant with a p-value less than 0.001.

Table 4 shows the discriminant validity of Likert based variables and it was supported since each variable shared more variance with its own measurement items than with the other variables (Fornell and Larcker, 1981), whereas Table 5 presents the correlation existing among the variables.

Table 5. Correlation matrix (square roots of the average variance extracted in diagonal)

No.	Variable	1	2	3	4	5	6	7	8	9
1	BDA capabilities	0.803								
2	Transparency	0.624	0.876							
3	Accessibility	0.557	0.485	0.913						
4	Discovery	0.629	0.627	0.510	0.825					
5	Proactive Adaptation	0.459	0.505	0.289	0.377	0.909				
6	Organization Performance	0.615	0.538	0.488	0.453	0.360	0.842			
7	Business Processes Improvement	0.616	0.621	0.496	0.527	0.450	0.708	0.859		
8	Products and Services Innovation	0.586	0.580	0.456	0.499	0.453	0.646	0.667	0.833	
9	Consumer Experience and Market Enhancement	0.538	0.537	0.430	0.421	0.382	0.712	0.628	0.656	0.860

4.2 Regression results

We used the PROCESS macro for SPSS to assess the structural model. In this study, the mediation process of transparency, access, discovery and proactive adaptation on the relationship between BDAC and value targets was analyzed. Bootstrapping was applied to test the significance of the four indirect effects, with 5,000 bootstrap samples, and a 95% confidence level for all the intervals. Table

6 illustrates the results on the outcome variables, whereas Table 7 shows the results of the direct and indirect effects.

Overall, Table 6 indicates that the direct effect of BDAC on the four value targets is always statistically significant, and specifically, it is equal to 0.077 for organization performance, 0.108 for business process improvement, 0.095 for products and services innovation, and 0.101 for consumer experience and market enhancement. Moreover, the overall effect of the model (i.e., 0.119 for organization performance, 0.138 for business process improvement, 0.128 for products and services innovation, and 0.110 for customer experience and market enhancement) is higher than the single direct effect of BDAC on the four value targets, thus showing the importance of the mediating variables.

Mediating effect of transparency

Table 6 highlights that transparency always has a mediating effect on the relationship between BDAC and the four value targets. The bootstrapping range between the lower LLCI and the upper ULCI confidence level of transparency, pertaining to the indirect effect of the BDAC for the four value targets, does not include in all four cases 0. This confirms the mediating effect of transparency as a value creation mechanism.

Furthermore, when considering Table 7, it appears that BDAC have a positive and significant effect on the four value creation mechanisms. Additionally, when the outcome variables are the four value targets and the four value creation mechanisms are the independent variables, transparency in all four cases has a significant and positive effect. This provides additional evidence of the mediating effect of transparency as value creation mechanism. Thus, based on such results, it is possible to conclude that Hypotheses H1a, H1b, H1c and H1d have been verified.

Mediating effects of access

Table 6 highlights that access has a mediating effect on the relationship between BDAC and organization performance and business process improvement. The bootstrapping range between the lower LLCI and the upper ULCI confidence level of access, pertaining to the indirect effect of BDA capabilities on the two value targets previously mentioned, does not include 0 in either of the two cases. This confirms the mediating effect of transparency on organizational performance and business process improvement. In case the other two value targets are considered (products and services innovation, and customer experience and market enhancement), access does not play a mediating effect since the range between the lower LLCI and the upper ULCI contains 0.

Furthermore, in Table 7, when the outcome variables are the four value targets, and the four value creation mechanisms are the independent variables, access has a significant and positive effect only for organizational performance and business process improvement. This provides further evidence of the mediating effect of access on these two value creation mechanisms. Thus, based on these results, it is possible to conclude that Hypotheses H2a and H2b are supported, while H2c and H2d are not.

Mediating effect of discovery

Table 6 shows that discovery never has a mediating effect on the relationship between BDAC and the four value targets. The bootstrapping range between the lower LLCI and the upper ULCI confidence level of transparency, pertaining to the indirect effect of the BDAC on the four value targets, in all four cases includes 0. This confirms the absence of a mediating effect of discovery as value creation mechanism.

Furthermore, in Table 7, where the outcome variables are the four value targets and the four value creation mechanisms are the independent variables, discovery in all four cases does not have a significant and positive effect. This provides additional evidence of the absence of a mediating effect of the discovery value creation mechanism. Thus, based on such results, it is possible to conclude that Hypotheses H3a, H3b, H3c and H3d have not been verified.

Mediating effect of proactive adaptation

Table 6 shows that proactive adaptation has a mediating effect on the relationship between BDAC and product and service innovation. The bootstrapping range between the lower LLCI and the upper ULCI confidence level of proactive adaptation, pertaining to the indirect effect of BDA capabilities on the one value target previously mentioned, does not include 0. This confirms the mediating effect of proactive adaptation on product and service innovation. If the other three value targets are considered, proactive adaptation does not have a mediating effect, since the range between the lower LLCI and the upper ULCI contains 0.

Furthermore, in Table 7, when the outcome variables are the four value targets and the four value creation mechanisms are the independent variables, proactive adaptation has a significant and positive effect on product and service innovation. This provides additional evidence of the mediating effect of proactive adaptation on the value creation mechanism considered. Thus, based on these results, it is possible to conclude that Hypothesis H4c is supported, while H4a, H4b and H4d are not. In summary, Table 8 provides a summary of these regression findings.

Table 6. Results of the direct and indirect effects

Effect	**Effect**	**SE**	**LLCI**	**ULCI**	**t**	**P**
Direct effect of X on Y						
Direct effect of BDA capabilities on organization performance	0.077	0.024	0.034	0.128	4.671	0.000
Direct effect of BDA capabilities on business processes improvement	0.108	0.029	0.050	0.165	3.690	0.000
Direct effect of BDA capabilities on products and services innovation	0.095	0.028	0.040	0.150	3.400	0.001
Direct effect of BDA capabilities on consumer experience and market enhancement	0.101	0.031	0.039	0.163	3.204	0.002
Indirect effect of X on Y						
Indirect effect of BDA capabilities on organization performance	**Effect**	**Boot SE**	**Boot LLCI**	**Boot ULCI**		
Total	0.119	0.025	0.068	0.169		
Transparency	0.043	0.020	0.003	0.081		
Access	0.032	0.015	0.005	0.062		
Discovery	-0.005	0.017	-0.035	0.032		
Proactive adaptation	0.007	0.014	-0.020	0.033		
Indirect effect of BDA capabilities on business processes improvement	**Effect**	**Boot SE**	**Boot LLCI**	**Boot ULCI**		
Total	0.138	0.028	0.082	0.193		
Transparency	0.060	0.023	0.013	0.105		
Access	0.034	0.019	0.001	0.075		
Discovery	0.018	0.023	-0.027	0.066		
Proactive adaptation	0.025	0.014	-0.003	0.054		
Indirect effect of BDA capabilities on products and services innovation	**Effect**	**Boot SE**	**Boot LLCI**	**Boot ULCI**		

Total	0.128	0.022	0.085	0.171		
Transparency	0.068	0.022	0.020	0.110		
Access	0.025	0.018	-0.008	0.063		
Discovery	0.006	0.022	-0.037	0.053		
Proactive adaptation	0.029	0.013	0.004	0.056		
Indirect effect of BDA capabilities on customer experience and market enhancement	**Effect**	**Boot SE**	**Boot LLCI**	**Boot ULCI**		
Total	0.110	0.028	0.053	0.165		
Transparency	0.069	0.023	0.022	0.112		
Access	0.025	0.020	-0.012	0.068		
Discovery	0.001	0.025	-0.047	0.052		
Proactive adaptation	0.016	0.015	-0.013	0.048		

Note: SE = standard error; LLCI and ULCI = lower and upper level for confidence level; t = t-statistic; p = p-value; ***p-value < 0.1%; ** p < 1%; * p < 5%; †< 10%.

Table 7. Results on the outcome variables

Outcome (Y)	Organization performance						Business processes improvement						Products and Services Innovation						Consumer Experience and Market Enhancement					
Variables	**Coeff.**	**SE**	**T**	**p**	**LLCI**	**ULCI**	**Coeff.**	**SE**	**T**	**p**	**LLCI**	**ULCI**	**Coeff.**	**SE**	**t**	**p**	**LLCI**	**ULCI**	**Coeff.**	**SE**	**t**	**p**	**LLCI**	**ULCI**
Outcome: Transparency																								
Constant	0.939**	0.307	3.057	0.002	0.333	1.544	0.988**	0.308	3.211	0.001	0.382	1.595	0.948**	0.310	3.063	0.002	0.338	1.558	0.938**	0.308	3.041	0.003	0.330	1.546
BDA capabilities	0.264***	0.022	12.083	0.000	0.221	0.307	0.261***	0.022	11.975	0.000	0.218	0.305	0.264***	0.022	12.013	0.000	0.220	0.307	0.264***	0.022	12.088	0.000	0.221	0.307
R squared	40.89%						40.35%						40.61%						40.92%					
F	145.989						143.408						144.307						146.126					
Outcome: Access																								
Constant	1.016**	0.334	3.038	0.003	0.357	1.675	1.056**	0.335	3.165	0.002	0.399	1.719	1.068**	0.331	3.226	0.001	0.415	1.721	1.027**	0.334	3.076	0.002	0.369	1.685
BDA capabilities	0.237***	0.024	9.979	0.000	0.190	0.284	0.234***	0.024	9.864	0.000	0.187	0.281	0.235***	0.023	10.019	0.000	0.189	0.281	0.236***	0.024	9.998	0.000	0.190	0.283
R squared	32.07%						31.46%						32.24%						32.15%					
F	99.598						97.303						100.374						99.963					
Outcome: Discovery																								
Constant	1.168***	0.276	4.233	0.000	0.624	1.712	1.205***	0.275	4.375	0.000	0.662	1.747	1.182***	0.279	4.239	0.000	0.632	1.732	1.203***	0.278	4.333	0.000	0.655	1.750
BDA capabilities	0.239***	0.020	12.179	0.000	0.200	0.278	0.237***	0.019	12.138	0.000	0.199	0.276	0.237***	0.020	12.013	0.000	0.198	0.276	0.236***	0.020	12.021	0.000	0.198	0.275
R squared	41.28%						41.00%						40.62%						40.65%					
F	148.336						147.323						144.314						144.513					
Outcome: Proactive adaptation																								
Constant	2.727***	0.329	8.276	0.000	2.077	3.376	2.814***	0.335	8.400	0.000	2.153	3.474	2.833***	0.334	8.472	0.000	2.174	3.493	2.831***	0.333	8.495	0.000	2.174	3.487
BDA capabilities	0.191***	0.023	8.136	0.000	0.144	0.237	0.183***	0.024	7.688	0.000	0.136	0.230	0.182***	0.024	7.660	0.000	0.135	0.228	0.181***	0.024	7.691	0.000	0.135	0.228
R squared	23.88%						21.80%						21.76%						21.89%					
F	66.197						59.112						58.671						59.146					
Outcome (Y)																								
Constant	1.989***	0.281	7.066	0.000	1.434	2.544	0.450	0.328	1.373	0.171	-0.196	1.096	0.659*	0.315	2.091	0.038	0.038	1.281	1.171**	0.354	3.305	0.001	0.473	1.870
BDA capabilities	0.119***	0.025	4.671	0.000	0.068	0.169	0.108**	0.029	3.699	0.001	0.050	0.165	0.095**	0.028	3.400	0.001	0.040	0.150	0.101**	0.031	3.204	0.002	0.039	0.163
Transparency	0.161**	0.062	2.593	0.010	0.039	0.285	0.230**	0.072	3.214	0.001	0.089	0.372	0.259**	0.069	3.761	0.001	0.123	0.395	0.259**	0.078	3.329	0.001	0.105	0.412
Access	0.133*	0.052	2.550	0.011	0.030	0.237	0.146*	0.061	2.405	0.017	0.026	0.265	$0.105^{\dagger}$	0.059	1.778	0.077	-0.011	0.222	0.103	0.066	1.565	0.119	-0.027	0.234
Discovery	-0.019	0.069	-0.276	0.782	-0.155	0.117	0.078	0.080	0.978	0.329	-0.079	0.235	0.024	0.076	0.318	0.751	-0.126	0.175	0.006	0.087	0.064	0.949	-0.166	0.177
Proactive adaptation	0.039	0.054	0.712	0.477	-0.069	0.146	0.139*	0.062	2.249	0.026	0.017	0.261	0.160**	0.059	2.694	0.008	0.043	0.277	0.088	0.067	1.314	0.190	-0.044	0.220
R squared	42.18%						48.88%						47.06%						37.53%					
F	30.203						39.776						36.797						24.873					

Note: SE = standard error; LLCI and ULCI = lower and upper level for confidence level; t = t-statistic; p = p-value; ***p-value < 0.1%; ** p < 1%; * p < 5%; †< 10%.

Table 8. Summary of the main findings

Hp	Mediation effect	Supported/Not supported
	Transparency	
H1a	BDA capabilities → Transparency → Organizational performance	Supported
H1b	BDA capabilities → Transparency → Business processes improvement	Supported
H1c	BDA capabilities → Transparency → Products and service innovation	Supported
H1d	BDA capabilities → Transparency → Consumer experience and market enhancement	Supported
	Access	
H2a	BDA capabilities → Access → Organizational performance	Supported
H2b	BDA capabilities → Access → Business processes improvement	Supported
H2c	BDA capabilities → Access → Products and service innovation	Not supported
H2d	BDA capabilities → Access → Consumer experience and market enhancement	Not supported
	Discovery	
H3a	BDA capabilities → Discovery → Organizational performance	Not supported
H3b	BDA capabilities → Discovery → Business processes improvement	Not supported
H3c	BDA capabilities → Discovery → Products and service innovation	Not supported
H3d	BDA capabilities → Discovery → Consumer experience and market enhancement	Not supported
	Proactive adaptation	
H4a	BDA capabilities → Proactive adaptation → Organizational performance	Not supported
H4b	BDA capabilities → Proactive adaptation → Business processes improvement	Not supported
H4c	BDA capabilities → Proactive adaptation → Products and service innovation	Supported
H4d	BDA capabilities → Proactive adaptation → Consumer experience and market enhancement	Not supported

5. Discussions and conclusion

The study provides a holistic view of the multiple nature of the mediators that may affect the relationship between BDAC and the dimensions of value targets that encompass organizational performance, process improvement, product innovation, and customer experience.

We surveyed 256 BDA experts certified by the Italian Ministry of Economic Development who had significant experience in the design and implementation of BDA projects within companies and organizations. In our sample, we observed that BDA is more popular in manufacturing and service industries, but that firms still fail to extract and appropriate value from their BDA investments.

We demonstrate that BDAC have a positive effect on the achievement of strategic business value in terms of organizational performance, business process improvement, product and service innovation, customer experience and market development (Table 7). This result confirms the findings of previous studies that investigated the impact of BDA capability development on strategic business value (e.g., Mikalef et al., 2019).

Interestingly, the original test we performed of the theorized mediating effects (Grover et al., 2018) were confirmed empirically only for some cases (Table 8). Transparency was a key mediating factor for all the value targets investigated. Information transparency supports the sharing of data and information among companies and enables the appropriate mechanisms for extracting value from the capabilities developed by leveraging big data. Transparency is effective since it is “an outcome of communication behaviors within an organization that reflects the degree to which employees have access to the information requisite for their responsibilities” (Street and Meister, 2004). Transparency, also, make individuals more aware about how their role fit into the strategic direction of the company, enhancing their level of engagement and trust towards the management (Vogelgesang and Lester, 2009) in achieving better business performance. This result indirectly confirms that BDA creates value mainly through its impact on decision-making processes, since transparency makes individuals more responsible for their actions and decisions (Parris et al., 2016; Halter et al., 2009), thus affecting multiple dimensions of value (Ghasemaghaei, 2018).

Transparency within organizations is also achieved by describing the business processes in terms of actors involved, activities performed, resources consumed, and data produced (Lehnert et al., 2017; Vergidis et al., 2008), which create an analytic basis to design possible initiatives to improve single processes (Dumas et al., 2013). Transparency can also guide managers in identifying and allocating more efficiently R&D investment opportunities that bring to innovative outputs (Zhong, 2018).

Finally, transparency of information that an organization reveals about its internal processes and performances usually provide a credible signal of brand integrity that enhances customer attractiveness (Cambier and Poncin, 2020), and support the personalization of online customer experience (Lambillotte et al., 2022).

Surprisingly, *discovery,* arguably the most advertised aspect of BDA, was found to not play a significant role in explaining the mechanisms through which BDA leads to value creation. While we did not gather information concerning the maturity of the firm in handling BDA, the overall picture emerging from the data points suggests that BDA investments are directed at supporting current processes and practices. This could be probably due to the characteristics of discovery, which requires time-consuming, competency-intensive and cost-significant efforts to process big data to obtain valuable outputs (Safhi et al., 2019), requiring to implement purposefully frameworks and tools for the effective organization, processing, and analysis of huge datasets (Rodríguez-Mazahua et al., 2016). Furthermore, as discovery mainly refers to a certain mindset where data are at the base of the decision-making process, it requires a specific organizational maturity or mindset (Pigni et al., 2016) before effectively mediate the relationship between BDAC and business value. Actually, the discovery of valuable data and information that can be valorized from both strategic and operational point of view relies on the capability of organizations to address three key challenges characterizing the big data domain, such as data complexity, computational complexity, and system complexity (Jin et al., 2015). More specifically, data complexity is related to the complexity of types, structures and patterns of data that make difficult their perception, representation, and interpretation; computational complexity concerns the multi-sources, huge volume, and fast-changing nature of data that make difficult their processing and elaboration; finally, system complexity is linked to hardware and software architectures and processing frameworks for energy-optimized computing.

However, this is an interesting outcome, which seems to relate more to the contingency of current BDA investments than to the actual role of discovery. Further investigation is therefore advisable to better understand the role of discovery in affecting value.

The results also highlight that easy *access* to data and the ability to disseminate them across the firm allow organizational performance and an improvement in business processes, but contrary to what we expected, they do not allow to explain how BDAC creates value in terms of product and service innovation, customer experience and market development. This further corroborates the idea that current BDA initiatives are targeted primarily to support decision-making processes more than product innovation (Mikalef et al., 2020a), and operational performance more than market performance (Yasmin et al., 2020).

Finally, the role of *proactive adaptation* was empirically confirmed in the case of products and service innovation. In companies that develop BDAC, the process that leverages organizational agility to identify rapidly new market opportunities by assembling physical assets, knowledge, and relationships affects the innovation strategy of firms. Therefore, when aiming to achieve higher levels of product and service innovation firms may focus on leveraging their strategic agility for extracting value from big data, thus contributing to fulfill the so-called innovation gap - the measure of the mismatching between what the organization offers and what the market requires (Ruiz-Moreno et al., 2016). As for the other value targets, the role of proactive adaptation was not fully supported, probably because the stimulus to adapt to the changing environment may originate alternatively from within (Teece, 2007) and outside (Eisenhardt and Martin, 2000) the organization, thus balancing a resource-driven and opportunity-driven approach to the value creation function (Mishra, 2017).

These results echo findings dating back to the early conceptualization of IT capabilities (e.g., Pavlou and El Sawy, 2011), indicating that BDAC manifests similar behavior and uses. It then becomes even more important that BDAC studies highlight and focus on the idiosyncrasies of big data value creation when effects and outcomes are expected to differ from the accumulated body of evidence.

5.1 Theoretical implications

More specifically, for the first time we empirically test the mediating effects of the value creation mechanism between BDAC and value targets as theorized in Grover et al.'s (2018).

We found that exploiting big data successfully to realize its business value needs relevant investments not only in terms of data infrastructure and technologies, but also in the ability to appropriate the returns from these investments. Through the empirical analysis, indeed, we demonstrated that businesses need to develop those mechanisms facilitating the alignment of business with the strategy. Such alignment involves processes, governance, and corporate culture to leverage data for competitiveness (Grover et al., 2018). While our results corroborate the overall findings or previous study, we originally demonstrated a different effectiveness of values creation mechanisms in the relationship between BDAC and value targets. In particular, we found the existence of different effects according to the different value creation mechanisms and value targets. The results reveal that transparency mediates the relationship for all the value targets, access mediates only organizational performance and business process improvement, proactive adaptation mediate only products and service innovation, while discovery does not have any mediating effect. These findings have profound implications for BDA and BDAC studies. For the first time, we have an empirical measure of the different role played by value creation mechanisms opening the field to further studies aiming at identifying new mechanism and studying their influence on the relationship between BDAC and value targets, and understand both internal and external organizational conditions (e.g., maturity, readiness) that may affect such relationship.

5.2 Practical implications

Our study found counter-intuitive results that refute some of the most industry-emphasized aspects of BDA. Factors such as easy access to data and discovery are found irrelevant in mediating the relationship between BDA and value creation. While the result was unexpected and therefore found us with little contextual data to further explore it, we suppose that both organizational maturity and readiness factors, as suggested in previous studies (e.g., Raguseo et al., 2021), may play a significant role.

Furthermore, this study demonstrates how to best leverage BDA to achieve business value enabling managers to designing and implement ad-hoc organizational practices tailored to the context and characteristics of their organizations, to achieve the targeted value dimension. For example, by promoting practices that leverage transparency rather than discovery, organizations may have more chances to achieve value targets that may more easily generate a measurable returns on BDA investment.

Transparency emerged as the most significant value mechanism to affect value targets (Table 7), suggesting managers to focus their attention for maximizing DBA returns on solutions impacting the decision making processes capable, in particular, to provide consistent and reliable data visualization, and a systemic view of the business processes and company outcomes.

A further managerial implication concerns the strategic importance for organizations to invest in BDAC to support and enhance their level of competitiveness. Knowledge, skills and abilities that combine technology and management capabilities enabling the exploitation and exploration of the value potential embedded into data represent the key pillars upon which organizations can design a valuable strategy that leveraging data to support decisions allows to build their competitive advantage.

Moreover, looking at a specific value target (e.g., organizational performance), organizations can leverage the supporting mediating factors resulting from the analysis (specifically transparency and access) to design proper initiatives and practices to achieve their objectives.

5.3 Limitations and future research

As many explorative studies, also this research has some limitations that constitute remarkable opportunities for future research. While we adopted a cross-sectional design with the measures collected at the same point in time, a longitudinal study could spread the findings and capture the dynamics of the mediation. Similarly, future studies could investigate more deeply and through interviews the reasons for the observed difference in the mediating effects. In particular, whereas transparency fully mediates the relationships between BDAC and the four value targets, and contrarily discovery does not mediate the same relationships, the remaining value creation mechanisms (i.e., access and proactive adaptation) have a fluctuating dynamic. This represents an aspect that should be further investigated, eventually exploring how organizational maturity or readiness affect mediation. Another limitation concerns the fact that people who responded to this study are based in one country (Italy) and in large part from firms with less than 500 employees. These two factors combined, may potentially limit the generalizability of the results to other countries. For this reason, future research could be oriented to enlarge the data sample to other countries, firm sizes, and possibly to perform cross-country analyses.

An early suggestion lies in the implied different maturity of BDA initiatives that, still in their early phases, remain focused on current processes and activities. Very few firms, then, would manifest an effective mediation of discovery. Moreover, future research could evaluate the existence of other mechanisms in explaining the value creation opportunities from big data as well as the existence of complementary effects, including the investigation of enabling versus automating impact on organizational capabilities (Mikalef et al., 2020d), and the combination of BDA with other technologies to jointly create business value (Dong and Yang, 2020). Interestingly, our research suggests that observed value creation mechanisms are parallel with what was already known concerning IT capabilities, and that more work should be put into their complementary theorization as distinct and idiosyncratic objects of analysis. A further area of investigation refers to the relationships between the adoption of BDA and the information governance, conceived as the set of competencies and practices to manage the entire life cycle of information, especially for what concerns the innovation outcomes in continuously changing and uncertain contexts (Mikalef et al., 2020c). Finally, it could be also interesting to investigate the mediation effect of the same value creation mechanisms for each of the three dimensions of BDAC, i.e., tangible resources (e.g., data and technology), human skills (e.g., managerial and technical abilities), and intangible resources (data-driven culture and organizational learning) (Su et al., 2021; Mikalef et al., 2018, 2019; Gupta and George, 2016). This would allow to better qualify the influence the different components of BDAC have on the mediation relationship between BDAC and each value target.

References

Akter, S., Bandara, R., Hani, U., Fosso Wamba, S., Foropon, C. and Papadopoulos, T. (2019) Analytics-based decision-making for service systems: A qualitative study and agenda for future research. *International Journal of Information Management*, 48, 85–95.

Akter, S., Fosso Wamba, S., Gunasekaran, A., Dubey, R. and Childe, S.J. (2016) How to improve firm performance using big data analytics capability and business strategy alignment?. *International Journal of Production Economics*, 182, 113-131.

Akter, S., Michael, K., Uddin, M. R., McCarthy, G. and Rahman, M. (2020) Transforming business using digital innovations: the application of A.I., blockchain, cloud and data analytics. *Annals of Operations Research*, 1-33.

Anwar, M., Khan, S. Z. and Shah, S. Z. A. (2018) Big data capabilities and firm's performance: a mediating role of competitive advantage. *Journal of Information and Knowledge Management*, 17(4), 1850045.

Aslam, H., Blome, C., Roscoe, S. and Azhar, T. (2018) Dynamic supply chain capabilities: How market sensing, supply chain agility and adaptability affect supply chain ambidexterity. *International Journal of Operations and Production Management*, 38(12), 226-2285.

Bagozzi, R. P. and Yi, Y. (1988) On the Evaluation of Structural Equation Models. *Journal of the Academy of Marketing Science*, 16, 74–94.

Barney, J. B. (1986). Organizational culture: can it be a source of sustained competitive advantage?. *Academy of Management Review*, 11(3), 656-665.

Barney, J. B. (1991). Firm resources and sustained competitive advantage. *Journal of Management*, 17(1), 99-120.

Barreto, I. (2010). Dynamic capabilities: A review of past research and an agenda for the future. Journal of management, 36(1), 256-280.

Bharadwaj, N. and Noble, C. (2017) Finding innovation in data rich environments. *Journal of Product Innovation Management*, 34 (5), 560-4.

Big Data Insight Group (2012). What businesses can learn from big data and high performance analytics in the manufacturing industry. Available online (www.nimbusninety.com/applied-insight-big-data)

Blome, C., Schoenherr, T. and Rexhausen, D. (2013) Antecedents and enablers of supply chain agility and its effect on performance: a dynamic capabilities perspective. *International Journal of Production Research*, 51(4), 1295-1318.

Cambier, F. and Poncin, I. (2020). Inferring brand integrity from marketing communications: The effects of brand transparency signals in a consumer empowerment context. *Journal of Business Research*, 109, 260-270.

Cao, G., Duan, Y. and Li, G. (2015). Linking business analytics to decision making effectiveness: A path model analysis. *IEEE Transactions on Engineering Management*, 62(3), 384-395.

Cappa, F., Oriani, R., Peruffo, E. and McCarthy, I. (2021) Big data for creating and capturing value in the digitalized environment: unpacking the effects of volume, variety, and veracity on firm performance. *Journal of Product Innovation Management*, 38(1), 49-67.

Chen, H., Chiang, R.H. and Storey, V. C. (2012) Business intelligence and analytics: from big data to big impact. *MIS Quarterly*, 36(4), 1165-1188.

Ciampi, F., Demi, S., Magrini, A., Marzi, G. and Papa, A. (2020) Exploring the impact of big data analytics capabilities on business model innovation: The mediating role of entrepreneurial orientation. *Journal of Business Research*, 123, 1-13

Cohen, W. M. and Levinthal, D. A. (1990). Absorptive capacity: A new perspective on learning and innovation. *Administrative Science Quarterly*, 128-152.

Côrte-Real, N., Oliveira, T. and Ruivo, P. (2017) Assessing business value of Big Data Analytics in European firms. *Journal of Business Research*, 70, 379–390.

Dahiya, R., Le, S., Ring, J. K. and Watson, K. (2021). Big data analytics and competitive advantage: the strategic role of firm-specific knowledge. *Journal of Strategy and Management*, 15(2), 175-193.

Danneels, E. (2002) The dynamics of product innovation and firm competences. *Strategic Management Journal*, 23(12), 1095-1121

Davenport, T. H., Barth, P. and Bean, R. (2012) How 'big data' is different. *MIT Sloan Management Review*, 54(1), 21-24.

Day, G. S. (2014). An outside-in approach to resource-based theories. *Journal of the Academy of Marketing Science*, 42(1), 27–28

Delen, D. and Zolbanin, H. M. (2018) The analytics paradigm in business research. *Journal of Business Research*, 90, 186-195.

Dong, J.Q. and Yang, C.-H. (2020) Business value of big data analytics: A systems-theoretic approach and empirical test. *Information and Management*, 57(1), 103124

Dubey, R., Gunasekaran, A., Childe, S. J., Blome, C. and Papadopoulos, T. (2019). Big data and predictive analytics and manufacturing performance: integrating institutional theory, resource-based view and big data culture. *British Journal of Management*, 30(2), 341-361

Dumas, M., La Rosa, M., Mendling, J. and Reijers, H.A. (2013) *Fundamentals of Business Process Management*. Springer Berlin Heidelberg, Berlin, Heidelberg

Dutta, D. and Bose, I. (2015). Managing a big data project: the case of Ramco Cements Limited. *International Journal of Production Economics*, 165, 293-306.

Eisenhardt, K. M. and Martin, J. A. (2000). Dynamic capabilities: what are they?. *Strategic Management Journal*, 21(10-11), 1105-1121.

Elia, G., Polimeno, G., Solazzo, G. and Passiante, G. (2020) A multi-dimension framework for value creation through big data. *Industrial Marketing Management*, 90, 617-632.

Erevelles, S., Fukawa, N. and Swayne, L. (2016) Big Data consumer analytics and the transformation of marketing. *Journal of Business Research*, 69(2), 897-904.

Fornell, C. and Larcker, D. F. (1981) Evaluating Structural Equation Models with Unobservable Variables and Measurement Error. *Journal of Marketing Research*, 18(1), 39-50.

Fosso Wamba, S., Akter, S., Edwards, A., Chopin, G. and Gnanzou, D. (2015) How ‘big data’ can make big impact: findings from a systematic review and a longitudinal case study. *International Journal of Production Economics*, 165, 234-246.

Fosso Wamba, S., Dubey, R., Gunasekaran, A. and Akter, S. (2020a) The performance effects of big data analytics and supply chain ambidexterity: The moderating effect of environmental dynamism. *International Journal of Production Economics*, 222, 107498.

Fosso Wamba, S., Gunasekaran, A., Akter, S., Ren, S.J., Dubey, R. and Childe, S.J. (2017) Big data analytics and firm performance: Effects of dynamic capabilities. *Journal of Business Research*, 70, 356–365.

Fosso Wamba, S., Queiroz, M. M., Wu, L. and Sivarajah, U. (2020) Big data analytics-enabled sensing capability and organizational outcomes: assessing the mediating effects of business analytics culture. *Annals of Operations Research*, 1-20.

Ghasemaghaei, M. (2020) The role of positive and negative valence factors on the impact of bigness of data on big data analytics usage. *International Journal of Information Management*, 50, 395-404.

Ghasemaghaei, M., Ebrahimi, S. and Hassanein, K. (2018) Data analytics competency for improving firm decision making performance. *The Journal of Strategic Information Systems*, 27(1), 101-113.

Goldman, S. L., Nagel, R. N. and Preiss, K. (1995) *Agile Competitors and Virtual Organizations: Strategies for Enriching the Customer*. New York: Van Nostrand Reinhold.

Grover, V., Chiang, R. H., Liang, T. P. and Zhang, D. (2018) Creating strategic business value from big data analytics: A research framework. *Journal of Management Information Systems*, 35(2), 388-423.

Gunasekaran, A., Papadopoulos, T., Dubey, R., Wamba, S. F., Childe, S. J., Hazen, B. and Akter, S. (2017) Big Data and predictive analytics for supply chain and organizational performance. *Journal of Business Research*, 70, 308-317.

Gupta, M. and George, J. F. (2016) Toward the development of a big data analytics capability. *Information and Management*, 53(8), 1049–1064.

Hajli, N., Shirazi, F., Tajvidi, M. and Huda, N. (2021) Towards an understanding of privacy management architecture in big data: an experimental research. *British Journal of Management*, 32(2), 548-565.

Hajli, N., Tajvidi, M., Gbadamosi, A. and Nadeem, W. (2020) Understanding market agility for new product success with big data analytics. *Industrial Marketing Management*, 86, 135-143.

Halter, M.V., de Arruda, M.C.C. and Halter, R.B. (2009) Transparency to reduce corruption?. *Journal of Business Ethics*, 84(3), 373-385.

Hariri, R.H., Fredericks, E.M. and Bowers, K.M. (2019) Uncertainty in big data analytics: survey, opportunities, and challenges. *Journal of Big Data*, 6(1).

Helfat, C. E. and Peteraf, M. A. (2009). Understanding dynamic capabilities: Progress along a developmental path. *Strategic Organization*, 7(1), 91–102

Henschen, D., 2014. Merck optimizes manufacturing with big data analytics. Information Week. Available online (www.informationweek.com/strategic-cio/executive-insights-and-innovation/merck-optimizes-manufacturing-with-big-data-analytics/d/d-id/1127901)

Janssen, M., van der Voort, H. and Wahyudi, A. (2017). Factors influencing big data decision-making quality. *Journal of Business Research*, 70, 338-345.

Ji-fan Ren, S., Fosso Wamba, S., Akter, S., Dubey, R. and Childe, S. J. (2017) Modelling quality dynamics, business value and firm performance in a big data analytics environment. *International Journal of Production Research*, 55(17), 5011-5026.

Jin, X., Wah, B. W., Cheng, X. and Wang, Y. (2015). Significance and challenges of big data research. *Big Data Research*, 2(2), 59-64.

Khan, A., Tao, M. and Li, C. (2022). Knowledge absorption capacity's efficacy to enhance innovation performance through big data analytics and digital platform capability. *Journal of Innovation & Knowledge*, 7(3), 100201.

Kiron, D., Prentice, P.K. and Ferguson, R.B. (2014) The analytics mandate. *MIT Sloan Management Review*, 55(4), 1.

Kubina, M., Varmus, M. and Kubinova, I. (2015) Use of big data for competitive advantage of company. *Procedia Economics and Finance*, 26, 561-565.

Lam, S.K., Sleep, S., Hennig-Thurau, T., Sridhar, S. and Saboo, A.R. (2017) Leveraging frontline employees' small data and firm-level big data in frontline management: An absorptive capacity perspective. *Journal of Service Research*, 20(1), 12-28.

Lambillotte, L., Bart, Y. and Poncin, I. (2022) Personalized Online Customer Experience: The Effect of Information Transparency: An Abstract. In *Proceedings of the Academy of Marketing Science Annual Conference*. Springer, Cham.

Lehnert, M., Linhart, A. and Roeglinger, M. (2017) Exploring the intersection of business process improvement and BPM capability development: A research agenda. *Business Process Management Journal*, 23(2), 275-292.

Lehrer, C., Wieneke, A., Vom Brocke, J., Jung, R. and Seidel, S. (2018) How big data analytics enables service innovation: materiality, affordance, and the individualization of service. *Journal of Management Information Systems*, 35(2), 424-460

Mahoney, J. T. and Pandian, J. R. (1992) The resource-based view within the conversation of strategic management. *Strategic Management Journal*, 13(5), 363-380.

Mata, F.J., Fuerst, W.L. and Barney, J.B. (1995) Information technology and sustained competitive advantage: A resource-based analysis. *MIS Quarterly*, 19(4), 487–505

McAfee, A., Brynjolfsson, E., Davenport, T.H., Patil, D.J. and Barton, D. (2012) Big data: the management revolution. *Harvard Business Review*, 90(10), 60-68.

Melville, N., Kraemer, K. and Gurbaxani, V. (2004) Review: Information technology and organizational performance: An integrative model of IT business value. *MIS Quarterly*, 28(2), 283-322.

Mendling, J., Baesens, B., Bernstein, A. and Fellmann, M. (2017) Challenges of smart business process management: An introduction to the special issue. *Decision Support Systems*, 100, 1-5.

Mikalef, P., Boura, M., Lekakos, G. and Krogstie, J. (2019) Big data analytics and firm performance: Findings from a mixed-method approach. *Journal of Business Research*, 98, 261-276.

Mikalef, P., Boura, M., Lekakos, G. and Krogstie, J. (2020a) Big data analytics capabilities and innovation: The mediating role of dynamic capabilities and moderating effect of the environment. *British Journal of Management*, 30(2), 272-298.

Mikalef, P., Boura, M., Lekakos, G. and Krogstie, J. (2020c) The role of information governance in big data analytics driven innovation. *Information and Management*, 57(7), 103361

Mikalef, P., Framnes, V., Danielsen, F., Krogstie, J. and Olsen, D.H. (2017) Big data analytics capability: antecedents and business value. In *Proceedings of the 21st Pacific Asia Conference on Information Systems (PACIS)*.

Mikalef, P., Krogstie, J., Pappas, I.O. and Pavlou, P. (2020b) Exploring the relationship between big data analytics capability and competitive performance: The mediating roles of dynamic and operational capabilities. *Information and Management*, 57(2), 103169.

Mikalef, P., Pappas, I.O., Krogstie, J. and Pavlou, P.A. (2020d) Big data and business analytics: A research agenda for realizing business value. *Information and Management*, 57 (1), 103237

Mishra, C. S. (2017) Entrepreneurial orientation. In *Creating and Sustaining Competitive Advantage* (pp. 91-145). Palgrave Macmillan, Cham.

Nam, D., Lee, J. and Lee, H. (2019) Business analytics use in CRM: A Nomological net from IT competence to CRM performance. *International Journal of Information Management*, 45, 233-245.

Nelson, R.R., Todd, P.A. and Wixom, B.H. (2005) Antecedents of information and system quality: an empirical examination within the context of data warehousing. *Journal of Management Information Systems*, 21, 199-235.

Parasuraman, A., Zeithaml, V. and Berry, L. (2005) ES-QUAL a multiple-item scale for assessing electronic service quality. *Journal of Service Research*, 7, 213-233.

Parris, D., Dapko, J., Arnold, W. and Arnold, D. (2016) Exploring transparency: A new framework for responsible business management. *Management Decision*, 54(1), 222-247.

Pavlou, P.A. and El Sawy, O.A. (2011) Understanding the elusive black box of dynamic capabilities. *Decision Sciences*, 42(1), 239-273.

Pigni, F., Piccoli, G., and Watson, R. (2016). Digital data streams: Creating value from the real-time flow of big data. *California Management Review*, *58*(3), 5-25.

Purkayastha, D. and Koti, V. B. (2017). Big Data Strategy of Procter & Gamble: Turning Big Data into Big Value. IBS Center for Management Research.

Purkayastha, D. and Rao, A. S. (2014). Amazon's Big Data Strategy. IBS Center for Management Research.

Raguseo, E. and Vitari, C. (2018) Investments in big data analytics and firm performance: An empirical investigation of direct and mediating effects. *International Journal of Production Research*, 1-16.

Raguseo, E., Pigni, F., and Vitari, C. (2021). Streams of digital data and competitive advantage: The mediation effects of process efficiency and product effectiveness. *Information & Management*, *58*(4), 103451.

Roberts, N., Galluch, P.S., Dinger, M. and Grover, V. (2012) Absorptive capacity and information systems research: Review, synthesis, and directions for future research. *MIS Quarterly*, 36(2), 625–648.

Ruiz-Moreno, A., Haro-Domínguez, C., Tamayo-Torres, I. and Ortega-Egea, T. (2016) Quality management and administrative innovation as firms' capacity to adapt to their environment. *Total Quality Management & Business Excellence*, 27(1-2), 48-63.

Rumelt, R. P. (1984). Towards a strategic theory of the firm. *Competitive Strategic Management*, 26(3), 556-570.

Safhi, H. M., Frikh, B. and Ouhbi, B. (2019) Assessing reliability of big data knowledge discovery process. *Procedia Computer Science*, 148, 30-36.

Sambamurthy, V., Bharadwaj, A. and Grover, V. (2003) Shaping agility through digital options: Reconceptualizing the role of information technology in firms. *MIS Quarterly*, 27(2), 237-263.

Schoemaker, P. J., Heaton, S. and Teece, D. (2018). Innovation, dynamic capabilities, and leadership. *California Management Review*, 61(1), 15-42.

Sheng, J., Amankwah-Amoah, J. and Wang, X. (2017) A multidisciplinary perspective of big data in management research. *International Journal of Production Economics*, 191, 97-112.

Street, C. T. and Meister, D. B. (2004) Small business growth and internal transparency: The role of information systems. *MIS Quarterly*, 473-506.

Su, X., Zeng, W., Zheng, M., Jiang, X., Lin, W. and Xu, A. (2021) Big data analytics capabilities and organizational performance: The mediating effect of dual innovations. *European Journal of Innovation Management*. (In press).

Suoniemi, S., Meyer-Waarden, L., Munzel, A., Zablah, A.R., Straub, D. (2020) Big data and firm performance: The roles of market-directed capabilities and business strategy. *Information and Management*, 57(7), 103365.

Teece, D. J. (2007). Explicating dynamic capabilities: the nature and microfoundations of (sustainable) enterprise performance. *Strategic Management Journal*, 28(13), 1319-1350.

Teece, D.J. and Pisano, G. (1997) Dynamic capabilities and strategic management. *Strategic Management Journal*, 18(7), 509–533.

Terziovski, M. (2010) Innovation practice and its performance implications in small and medium enterprises (SMEs) in the manufacturing sector: a resource-based view. *Strategic Management Journal*, 31(8), 892-902.

Tseng, C.Y., Pai, D.C. and Hung C.H. (2011). Knowledge absorptive capacity and innovation performance in KIBS. *Journal of Knowledge Management*, 15(6), 971-983.

Upadhyay, P. and Kumar, A. (2020) The intermediating role of organizational culture and internal analytical knowledge between the capability of big data analytics and a firm's performance. *International Journal of Information Management*, 52, 102100.

Vergidis, K., Tiwari, A. and Majeed, B. (2008) Business process analysis and optimization: beyond reengineering. *IEEE Transactions on Systems, Management, and Cybernetics, Part C: Applications and Reviews*, 38(1), 69-82.

Vogelgesang, G.R. and Lester, P.B. (2009) Transparency: How leaders can get results by laying it on the line. *Organizational Dynamics*, 38(4), 252-260

Wagner, S.M. and Kemmerling, R. (2010) Handling nonresponse in logistics research. *Journal of Business Logistics*, 31(2), 357-381.

Wang, Y. and Hajli, N. (2017) Exploring the path to big data analytics success in healthcare. *Journal of Business Research*, 70, 287-299.

Wernerfelt, B. (1984). A resource-based view of the firm. *Strategic Management Journal*, 5(2), 171-180.

Wu, F., Yeniyurt, S., Kim, D. and Cavusgil, S.T. (2006) The impact of information technology on supply chain capabilities and firm performance: A resource-based view. *Industrial Marketing Management*, 35(4), 493-504

Yasmin, M., Tatoglu, E., Kilic, H.S., Zaim, S. and Delen, D. (2020) Big data analytics capabilities and firm performance: An integrated MCDM approach. *Journal of Business Research*, 114, 1-15.

Zahra, S. A. and George, G. (2002). Absorptive capacity: A review, reconceptualization, and extension. *Academy of Management Review*, 27(2), 185-203.

Zeng, J. and Glaister, K.W. (2018). Value creation from big data: Looking inside the black box. *Strategic Organization*, 16(2), 105-140.

Zheng, L. and Zhou, H. (2019) Firm's big data capability: a literature review and prospects. *Science and Technology Progress and Policy*, 36(15), 153-16.

Zhong, R.I. (2018) Transparency and firm innovation. *Journal of Accounting and Economics*, 66(1), 67-93.

Appendix

Table A1. Items for BDA Capabilities (Gupta and George, 2016)

First-order Constructs of BDA Capacity	Acronym	Items	Reference
Data	D1	We have access to very large, unstructured, or fast-moving data for analysis.	Gupta and George, 2016
	D2	We integrate data from multiple internal sources into a data warehouse or mart for easy access.	Gupta and George, 2016
	D3	We integrate external and internal data to facilitate high-value analysis of our business environment.	Gupta and George, 2016
Technology	T1	We have explored or adopted parallel computing approaches (e.g., Hadoop) to big data processing.	Gupta and George, 2016
	T2	We have explored or adopted different data visualization tools.	Gupta and George, 2016
	T3	We have explored or adopted cloud-based services for processing data and performing analytics.	Gupta and George, 2016
	T4	We have explored or adopted open-source software for big data analytics.	Gupta and George, 2016
	T5	We have explored or adopted new forms of databases such as Not Only SQL (NoSQL) for storing data.	Gupta and George, 2016
Basic Resources	BR1	Our big data analytics projects are adequately funded.	Gupta and George, 2016
	BR2	Our big data analytics projects are given enough time to achieve their objectives.	Gupta and George, 2016
Technical Skills	TS1	We provide big data analytics training to our own employees.	Gupta and George, 2016
	TS2	We hire new employees who already have big data analytics skills.	Gupta and George, 2016
	TS3	Our big data analytics staff has the right skills to accomplish their jobs successfully.	Gupta and George, 2016
	TS4	Our big data analytics staff has suitable education to fulfill their jobs.	Gupta and George, 2016
	TS5	Our big data analytics staff holds suitable work experience to accomplish their jobs successfully.	Gupta and George, 2016
Managerial Skills	MS1	Our big data analytics managers understand and appreciate the business needs of other functional managers, suppliers, and customers.	Gupta and George, 2016
	MS2	Our big data analytics managers are able to work with functional managers, suppliers, and customers to determine opportunities that big data might bring to our business.	Gupta and George, 2016
	MS3	Our big data analytics managers are able to coordinate big data-related activities in ways that support other functional managers, suppliers, and customers.	Gupta and George, 2016
	MS4	Our big data analytics managers are able to anticipate the future business needs of functional managers, suppliers, and customers.	Gupta and George, 2016
	MS5	Our big data analytics managers have a good sense of where to apply big data.	Gupta and George, 2016
	MS6	Our big data analytics managers are able to understand and evaluate the output extracted from big data.	Gupta and George, 2016
Data-driven Culture	DDC1	We consider data a tangible asset.	Gupta and George, 2016
	DDC2	We base our decisions on data rather than on instinct.	Gupta and George, 2016
	DDC3	We continuously assess and improve the business rules in response to insights extracted from data.	Gupta and George, 2016
	DDC4	We continuously coach our employees to make decisions based on data.	Gupta and George, 2016

Intensity of Organizational Learning	IOL1	We are able to search for new and relevant knowledge.	Gupta and George, 2016
	IOL2	We are able to acquire new and relevant knowledge.	Gupta and George, 2016
	IOL3	We are able to assimilate relevant knowledge.	Gupta and George, 2016
	IOL4	We are able to apply relevant knowledge.	Gupta and George, 2016
	IOL5	We have made concerted efforts for the exploitation of existing competencies and exploration of new knowledge.	Gupta and George, 2016

Table A2. Items for value creation mechanisms

Value creation mechanism	Acronym	Items	Reference
Transparency	TR1	The BDA provides information on the organization rules and regulations.	Adapted from Bertot et al., 2010
	TR2	The BDA promotes monitoring of the organization financial expenditures.	Adapted from Bertot et al., 2010
	TR3	The BDA disseminates information on the organization performance.	Adapted from Bertot et al., 2010
	TR4	The BDA promotes openness of the organization processes, like hiring and promotion.	Adapted from Bertot et al., 2010
	TR5	Overall, the BDA system has enhanced transparency in my organization.	Adapted from Bertot et al., 2010
Accessibility	AC1	Data used in data analytics is easily available.	Ghasemaghaei, 2020
	AC2	Data used in data analytics is easy to find.	Ghasemaghaei, 2020
	AC3	Data used in data analytics is where you expect to find it.	Ghasemaghaei, 2020
Discovery	DS1	The firm bases decisions on data rather than on instinct.	Mikalef et al., 2019
	DS2	The firm overrides its intuition when data contradict its viewpoints.	Mikalef et al., 2019
	DS3	The firm continuously coaches its employees to make decisions based on data.	Mikalef et al., 2019
Proactive adaptation	PA1	Adapt services and/or products to new customer requirements quickly.	Aslam et al., 2018
	PA2	React to new market developments quickly.	Aslam et al., 2018
	PA3	React to significant increases and decreases in demand quickly.	Aslam et al., 2018
	PA4	Adjust product portfolio as per market requirement.	Aslam et al., 2018

Table A3. Items for value targets

Value target	Acronym	Items	Reference
Organization Performance	OP1	The organization is successful.	Jyothibabu et al., 2010
	OP2	The organization meets its performance targets.	Jyothibabu et al., 2010
	OP3	Individuals are happy working in the organization.	Jyothibabu et al., 2010
	OP4	The organization meets its customer needs.	Jyothibabu et al., 2010
	OP5	The organization's future performance is secure.	Jyothibabu et al., 2010
	OP6	The organization has a strategy that positions it well for the future.	Jyothibabu et al., 2010
	OP7	There is continuous improvement in the organization.	Jyothibabu et al., 2010
Business Processes Improvement	BPI1	Work processes are checked continuously to prevent defects in products/services.	Bhatt and Troutt, 2005
	BPI2	Work processes are controlled to ensure their correctness.	Bhatt and Troutt, 2005
	BPI3	Emphasis is on eliminating the root causes of work processes in the business.	Bhatt and Troutt, 2005
	BPI4	Work processes in the business are designed to be defect-free to eliminate unexpected human errors.	Bhatt and Troutt, 2005
	BPI5	Work processes are evaluated continually for improvement.	Bhatt and Troutt, 2005
	BPI6	Process improvement standards are raised periodically.	Bhatt and Troutt, 2005
	BPI7	Redesign in work processes are implemented after through testing.	Bhatt and Troutt, 2005
	BPI8	New work processes that are introduced are easier to work with than earlier ones.	Bhatt and Troutt, 2005
	BPI9	Work processes support multiple tasks simultaneously.	Bhatt and Troutt, 2005
Products and Services Innovation	PSI1	Incremental innovations that reinforce its prevailing product/service lines.	Mikalef et al., 2018
	PSI2	Incremental innovations that reinforce its existing expertise in prevailing products/services.	Mikalef et al., 2018
	PSI3	Incremental innovations that reinforce how the company currently competes.	Mikalef et al., 2018
	PSI4	Radical innovations that make its prevailing product/service lines obsolete.	Mikalef et al., 2018
	PSI5	Radical innovations that fundamentally change its prevailing products/services.	Mikalef et al., 2018
	PSI6	Radical innovations that make its expertise in prevailing products/services obsolete.	Mikalef et al., 2018
Consumer Experience and Market Enhancement	CE1	We have entered new markets more quickly than our competitors.	Wang et al., 2012
	CE2	We have introduced new products or services to the market faster than our competitors.	Wang et al., 2012
	CE3	Our success rate of new products or services has been higher than our competitors.	Wang et al., 2012
	CE4	Our market share has exceeded that of our competitors.	Wang et al., 2012