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Big data analytics capabilities: A systematic literature review and research agenda

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Abstract:	With big data growing rapidly in importance over the past few years', academics and practitioners have been considering the means through which they can incorporate the shifts these technologies bring into their competitive strategies. To date, there has been an emphasis on the technical aspects of big data with limited attention on the organizational changes they entail and how they should be leveraged strategically. As with any novel technology, it is important to understand the mechanisms and processes through which big data can add business value to companies and have a clear picture of the different elements and their interdependencies. To this end, the present paper aims to provide a theoretical discussion leading up to a research framework that can help explain the mechanisms through which big data lead to competitive performance gains. The research framework is grounded on past empirical work on IT-business, and builds on the resource-based view (RBV) and dynamic capabilities view (DCV) of the firm. By identifying the main areas of focus for big data and explaining the mechanisms through which they should be leveraged, this paper attempts to add to literature on how big data should be examined as a source of a competitive advantage.
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Abstract

With big data growing rapidly in importance over the past few years, academics and practitioners have been considering the means through which they can incorporate the shifts these technologies bring into their competitive strategies. To date, emphasis has been on the technical aspects of big data, with limited attention paid to the organizational changes they entail and how they should be leveraged strategically. As with any novel technology, it is important to understand the mechanisms and processes through which big data can add business value to companies, and to have a clear picture of the different elements and their interdependencies. To this end, the present paper aims to provide a systematic literature review that can help to explain the mechanisms through which big data analytics (BDA) lead to competitive performance gains. The research framework is grounded on past empirical work on IT business value research, and builds on the resource-based view and dynamic capabilities view of the firm. By identifying the main areas of focus for BDA and explaining the mechanisms through which they should be leveraged, this paper attempts to add to literature on how big data should be examined as a source of competitive advantage. To this end, we identify gaps in the extant literature and propose six future research themes.

Keywords: Big Data, Dynamic Capabilities, Resource-Based View, Competitive Performance, IT Strategy

1. Introduction

The application of big data in driving organizational decision making has attracted much attention over the past few years. A growing number of firms are focusing their investments on big data analytics (BDA) with the aim of deriving important insights that can ultimately provide them with a competitive edge (Constantiou & Kallinikos, 2015). The need to leverage the full potential of the rapidly expanding data volume, velocity, and variety has seen a significant evolution of techniques and technologies for data storage, analysis, and visualization. However, there has been considerably less research attention on how organizations need to change in order to embrace these technological innovations, as well as on the business shifts they entail (McAfee et al., 2012). Despite the hype surrounding big data, the issue of examining whether, and under what conditions, big data investments produce business value, remains underexplored, severely hampering their business and strategic potential (McAfee et al., 2012). Most studies to date have primarily focused on infrastructure, intelligence, and analytics tools, while other related resources, such as human skills and knowledge, have been largely disregarded. Furthermore, orchestration of these resources, the socio-technological developments that they precipitate, as well as how they should be incorporated into strategy and operations thinking, remains an underdeveloped area of research (Gupta & George, 2016).

Over the past few years, several research commentaries have stressed the importance of delving into the whole spectrum of aspects that surround BDA (Constantiou & Kallinikos, 2015; Markus, 2015). Nevertheless, exploratory empirical literature on the topic is still quite scarce (Gupta & George, 2016; Wamba et al., 2017). Past literature reviews on the broader information systems (IS) domain have demonstrated that there are multiple aspects that should be considered when examining the business potential of IT investments (Schryen, 2013). Furthermore, the particularities of each technological development need to be thoroughly examined in order to fully capture the interdependencies that develop between them, and how they produce value at a firm level. Past literature on IT business value has predominantly used the notion of IT capabilities to refer to the broader context of technology within firms, and the overall proficiency in leveraging and mobilizing the different resources and capabilities (Bharadwaj, 2000). It is therefore important to identify and explore the domain-specific aspects that are relevant to BDA within the business context (Kamioka & Tapanainen, 2014).

While there is a growing stream of literature on the business potential of BDA, there is still limited work grounded on established theories used in the IT-business value domain (Gupta & George, 2016). The lack of empirical work in this direction significantly hinders research concerning the value of BDA, and leaves practitioners in unchartered territories when faced with implementing such initiatives in their firms. Hence, in order to derive meaningful theoretical and practical implications, as well as to identify important areas of future research, it is critical to understand how the core artifacts pertinent to BDA are shaped, and how they lead to business value (Constantiou & Kallinikos, 2015). Therefore, we employ a systematic literature review grounded in the established resource-based view (RBV) of the firm, as well as the emerging dynamic capabilities view (DCV). We select these theoretical groundings since the former provides a solid foundation upon which all relevant resources can be identified and evaluated towards their importance, while the latter enables examination of the organizational capabilities towards which these resources should be directed in order to achieve competitive performance gains (Mikalef et al., 2016). As such, the DCV exerts complementarities in relation to the RBV by providing an explanation of the rent-yielding properties of organizational capabilities that can be leveraged by means of BDA (Makadok, 2001). Our theoretical framework that guides the systematic literature review uncovers some initial findings on the value of BDA, while also providing a roadmap on several promising research streams.

The rest of the paper is structured as follows. In section 2, we describe the research methodology used to conduct the systematic literature review, and outline the main steps followed. Next, in section 3, we distinguish between the concepts of big data, BDA, and BDA capability, and present some definitions as described in literature for each. In section 4, we proceed to describe the main theoretical foundations upon which we build on and develop the proposed research framework. We then summarize existing work on the business value of BDA according to the identified themes. In section 5, we outline a series of areas that are currently under-researched and propose appropriate theoretical stances that could be utilized in their examination. In closing, section 6 presents some concluding remarks on the area of BDA and their application to the strategic domain.

2. Research methodology

Following the established method of a systematic literature review (Kitchenham, 2004; Kitchenham, 2007; Kitchenham et al., 2009), we undertook the review in distinct stages. First, we developed the review protocol. Second, we identified the inclusion and exclusion criteria for relevant publications. Third, we performed an in-depth search for studies, followed by critical appraisal, data extraction and a synthesis of past findings. The next sub-sections describe in detail the previously mentioned stages.

2.1 Protocol development

The first step of the systematic literature review was to develop a protocol for the next steps. In accordance with the guideline, procedures, and policies of the *Cochrance Handbook for Systematic Reviews of Intervention* (Higgins & Green, 2008), the protocol established the main research question that guided the selection of papers, the search strategy, inclusion and quality criteria, as well as the method of synthesis. The review process was driven by the following research question: *What are the definitional aspects, unique characteristics, challenges, organizational transformations, and business value associated with big data?* By focusing on these elements of the research question, the subject areas and relevant publications and materials were identified.

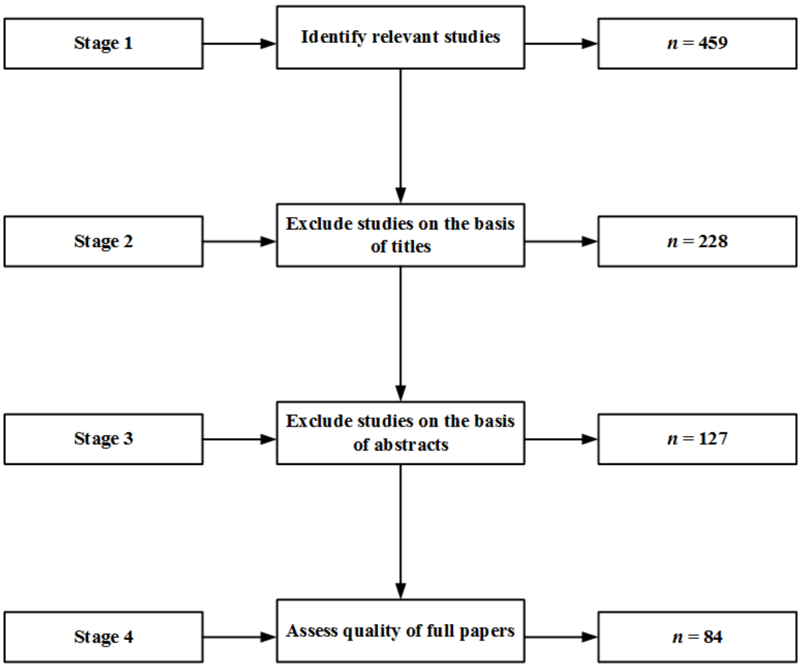

Figure 1 Stages of the study selection process

2.2 Inclusion and exclusion criteria

Due to the importance of the selection phase in determining the overall validity of the literature review, a number of inclusion and exclusion criteria were applied. Studies were eligible for inclusion if they were focused on the topic of how big data can provide business value. Publications were selected from 2010 onwards, since that is when the term gained momentum in the academic and business communities. The systematic review included research papers published in academic outlets, such as journal articles and conference proceedings, as well as reports targeted at business executives and a broader audience, such as scientific magazines. In-progress research and dissertations were excluded from this review, as were studies that were not written in English. Finally, given that our focus was on the business transformation that big data entails, along with performance outcomes, we included quantitative, qualitative, and case studies. Since the topic of interest is of an interdisciplinary nature, a diversity of epistemological approaches was opted for.

2.3 Data sources and search strategy

The search strategy started by forming search strings that were then combined to form keywords. In addition, during the search we employed wildcard symbols in order to reduce the number of search strings. Combinations of two sets of keywords were used, with the first term being ‘big data,’ and the second term being one of 12, which were reviewed by a panel of five experts. These search terms included: analytics capability, competitive performance, firm performance, organizational performance, dynamic capabilities, resource-based view, human skills, managerial skills, analytics ecosystems, data scientist, competencies, and resource management. Keywords were searched within the title, abstract, and keyword sections of the manuscripts. The search strategy included electronic databases such as Scopus, Business Source Complete, Emerald, Taylor & Francis, Springer, Web of Knowledge, ABI/inform Complete, IEEE Xplore, and the Association of Information Systems (AIS) library. To further complement our search, we applied the search terms in the search engine Google Scholar, as well as the AIS basket of eight journals.

The search was initiated on September 5, 2016 and ended on February 26, 2017. At stage 1, 459 papers were identified and entered into the reference manager EndNote. At stage 2, all authors went through the titles of the studies of stage 1 in order to determine their relevance to the systematic review. At this stage, studies that were clearly not about the business aspects of big data were excluded, independently of whether they were empirical. In addition, articles that were focused on big data for public administration were not included in the next stage. The number of retained articles after the abovementioned process was 228. In the third stage, all remaining articles were examined in terms of their abstracts and their focus in relation to the research question we had defined. However, some abstracts were of varying quality, some were lacking information about the content of the article, while others had an apparent disconnect with their title and did not fit our focus. At this stage, each papers' abstract was reviewed independently by each author. From the 228 abstracts assessed, 101 were omitted, leaving 127 papers to be further analyzed.

2.4 Quality assessment

Each of the 127 papers that remained after stage 3 was assessed independently by the authors in terms of several quality criteria. Studies were examined in terms of scientific *rigor*, so that appropriate research methods had been applied; *credibility*, to assess whether findings were well presented; and *relevance*, which was assessed based on whether findings were useful for companies engaging in big data projects, as well as the academic community. Taken together, these criteria provided a measure of the extent to which a publication would make a valuable contribution to the review. At this stage another 43 papers were excluded, leaving 84 papers for data extraction and synthesis. These papers were then coded according to their area of focus, allowing a categorization to be constructed. The derived categories were a result of identifying the main research areas that papers aimed to contribute towards. By categorizing papers, we were able to extract the details needed to answer each of the posed research questions.

2.5 Data extraction and synthesis of findings

In order to synthesize findings and categorize studies based on their scope, an analysis of the different research streams was performed. The first step was to identify the main concepts from each study, using the authors' original terms. The key concepts were then organized in a spreadsheet in order to enable comparison across studies and translation of findings into higher-order interpretations. An analysis was conducted based on the following areas of focus: organizational performance outcomes of big data, human skills and knowledge, tangible and intangible resources, team orchestration and project management, adoption and diffusion of big data initiatives, governance in big data projects, as well as ethical and moral issues related to big data within the business domain. For empirical studies, the the authors also recorded the type of study conducted (e.g. qualitative, quantitative, case study), the sample size, the instruments used (e.g. surveys, interviews, observations), as well as contextual factors surrounding the study (e.g. industry, country, firm size). Constant consensus meetings of all researchers established the data extraction stage and the categorization of publications. The remaining 84 papers were analyzed in detail in accordance with the coding scheme, and relevant data were extracted, analyzed, and synthesized.

3. Defining big data in the business context

Big data is becoming an emerging topic of interest in IS, computer and information sciences, management, and social sciences (Constantiou & Kallinikos, 2015). This phenomenon is largely attributed to the widespread adoption of social media, mobile devices and sensors, integrated IS, and artifacts related to the Internet of Things. The surging interest in big data is also reflected in the academic literature, which spans multiple disciplinary domains (Chen et al., 2016). While the different epistemological domains provide an alternative perspective on the notion of big data, the definitions and key concepts put forth by each differ significantly (Wamba et al., 2015). As such, the first step of the systematic literature review is to identify the key concepts and develop integrative definitions of each. Notions such as big data, BDA, and BDA capability are often used interchangeably in the literature. However, their theoretical underpinnings reflect a different perspective in how they are perceived and measured (Cao & Duan, 2014a). Therefore, it is imperative to clearly define the meaning of these concepts, and that aspects they encompass.

3.1 Big data

As a starting point, we provide an overview of how big data have been defined in past studies, as well as what attributes are integral to the concept. Several definitions of big data have been put forth to date in attempts to distinguish the phenomenon of big data from conventional data-driven or business analytics approaches (Table 1). Some scholars focus on the origin of the data, emphasizing the various channels from which they are collected, such as enterprise IS, customer transactions, machines or sensors, social media, cell phones or other networked devices, news and network content, as well as GPS signals (Chen et al., 2012; Opresnik & Taisch, 2015). The majority of scholars emphasize the "three Vs" that characterize big data: *volume*, *velocity*, and *variety* (McAfee et al., 2012; Davis, 2014; Sun et al., 2015). Volume refers to the sheer size of the dataset due to the aggregation of a large number of variables and an even larger set of observations for each variable. (George et al., 2016). In addition, many definitions highlight the growing rate at which the quantity of data increases, commonly expressed in petabytes or exabytes, used by decision makers to aid strategic decisions (Akter et al., 2016a). Velocity reflects the speed at which these data are collected, updated, and analyzed, as well as the rate at which their value becomes obsolete (Davis, 2014; George et al., 2016). The 'newness' of data that decision makers are able to collect, as well as the capacity to analyze these data-streams, is an important factor when it comes to improving business agility and enabling real-time actions and intraday decision making (White, 2011; Boyd & Crawford, 2012). Variety refers to the plurality of structured and unstructured data sources, which, amongst others, include text, audio, images, video, networks, and graphics (Constantiou & Kallinikos, 2015; George et al., 2016). While there are no universal benchmarks for defining the volume, velocity, and variety of big data, the defining limits are contingent upon size, sector, and location of the firm, and are subject to changing limits over time (Gandomi & Haider, 2015).

Author(s) and date	Definition
Russom, 2011	Big data involves the data storage, management, analysis, and visualization of very large and complex datasets.
White, 2011	Big data involves more than simply the ability to handle large volumes of data; instead, it represents a wide range of new analytical technologies and business possibilities.

	These new systems handle a wide variety of data, from sensor data to Web and social media data, improved analytical capabilities, operational business intelligence that improves business agility by enabling automated real-time actions and intraday decision making, faster hardware and cloud computing including on-demand software-as-a service. Supporting big data involves combining these technologies to enable new solutions that can bring significant benefits to the business.
Beyer & Laney, 2012	Big data: high-volume, high-velocity, and/or high-variety information assets that require new forms of processing to enable enhanced decision making, insight discovery, and process optimization.
McAfee et al., 2012	Big data, like analytics before it, seeks to glean intelligence from data and translate that into business advantage. However, there are three key differences: Velocity, variety, volume.
Grantz & Reinsel, 2012	Big data focuses on three main characteristics: the data itself, the analytics of the data, and presentation of the results of the analytics that allow the creation of business value in terms of new products or services.
Boyd & Crawford, 2012	Big data: a cultural, technological, and scholarly phenomenon that rests on the interplay of (1) Technology: maximizing computation power and algorithmic accuracy to gather, analyze, link, and compare large datasets. (2) Analysis: drawing on large datasets to identify patterns in order to make economic, social, technical, and legal claims. (3) Mythology: the widespread belief that large datasets offer a higher form of intelligence and knowledge that can generate insights that were previously impossible, with the aura of truth, objectivity, and accuracy.
Schroeck et al., 2012	Big data is a combination of volume, variety, velocity and veracity that creates an opportunity for organizations to gain competitive advantage in today's digitized marketplace.
Bharadwaj et al., 2013	Big data refers to datasets with sizes beyond the ability of common software tools to capture, curate, manage, and process the data within a specified elapsed time.
Kamioka & Tapainen, 2014	Big data is large-scale data with various sources and structures that cannot be processed by conventional methods and that is intended for organizational or societal problem solving.
Bekmamedova & Shanks, 2014	Big data involves the data storage, management, analysis, and visualization of very large and complex datasets. It focuses on new data-management techniques that supersede traditional relational systems, and are better suited to the management of large volumes of social media data.
Davis, 2014	Big data consists of expansive collections of data (large volumes) that are updated quickly and frequently (high velocity) and that exhibit a huge range of different formats and content (wide variety).
Sun et al., 2015	Big data: the data-sets from heterogeneous and autonomous resources, with diversity in dimensions, complex and dynamic relationships, by size that is beyond the capacity of conventional processes or tools to effectively capture, store, manage, analyze, and exploit them.
Opresnik & Taisch, 2015	Big data typically refers to the following types of data: (1) traditional enterprise data, (2) machine-generated/sensor data (e.g. weblogs, smart meters, manufacturing sensors, equipment logs), and (3) social data.
Constantiou & Kallinikos, 2015	Big data often represents miscellaneous records of the whereabouts of large and shifting online crowds. It is frequently agnostic, in the sense of being produced for generic purposes or purposes different from those sought by big data crunching. It is based on varying formats and modes of communication (e.g. text, image, and sound), raising severe problems of semiotic translation and meaning compatibility. Big data is commonly deployed to refer to large data volumes generated and made available on the Internet and the current digital media ecosystems.
Akter et al., 2016a	Big data is defined in terms of five 'Vs:' volume, velocity, variety, veracity, and value. 'Volume' refers to the quantities of big data, which are increasing exponentially. 'Velocity' is the speed of data collection, processing and analyzing in the real time. 'Variety' refers to the different types of data collected in big data environments. 'Veracity' represents the reliability of data sources. Finally, 'value' represents the transactional, strategic, and informational benefits of big data.

Abbasi et al., 2016	Big data differs from 'regular' data along four dimensions, or '4 Vs'—volume, velocity, variety, and veracity.

Table 1 Sample definitions of big data

Adding to the existing body of definitions, several scholars have included different aspects of big data in their conceptualizations (Table 2). For instance, a commonly acknowledged aspect of big data is its veracity (Akter et al., 2016; Abbasi et al., 2016). Veracity refers to the degree to which big data is trusted, authentic, and protected from unauthorized access and modification (Demchenko et al., 2013). Analyzing high-quality and reliable data is imperative in enabling management to make cognizant decisions and derive business value (Akter et al., 2016b). Hence, big data used for business decisions should be authenticated and have passed through strict quality-compliance procedures before being analyzed (Dong & Strivastana, 2013; Gandomi & Haider, 2015). This vast amount of data is argued to be an important enabler of creating value for organizations (Gandomi & Haider, 2015). Oracle introduced value as a defining aspect of big data. According to Oracle's (2012) definition, big data are frequently characterized by low value density, meaning that the value of the processed data is proportionately low compared to its volume. Seddon and Currie (2017) included two additional dimensions in the definition of big data: variability and visualization. Variability refers to the dynamic opportunities that are available by interpreting big data, while visualization has to do with the representation of data in meaningful ways through artificial intelligence methods that generate models (Seddon & Currie, 2017).

Attribute	**Definition**
Volume	Volume represents the sheer size of the dataset due to the aggregation of a large number of variables and an even larger set of observations for each variable. (George et al., 2016)
Velocity	Velocity reflects the speed at which data are collected and analyzed, whether in real time or near real time from sensors, sales transactions, social media posts, and sentiment data for breaking news and social trends. (George et al., 2016)
Variety	Variety in big data comes from the plurality of structured and unstructured data sources such as text, videos, networks, and graphics among others. (George et al., 2016)
Veracity	Veracity ensures that the data used are trusted, authentic, and protected from unauthorized access and modification. (Demchenko et al., 2013)
Value	Value represents the extent to which big data generates economically worthy insights and/or benefits through extraction and transformation. (Wamba et al., 2015)
Variability	Variability concerns how insight from media constantly changes as the same information is interpreted in a different way, or new feeds from other sources help to shape a different outcome. (Seddon & Currie, 2017)
Visualization	Visualization can be described as interpreting the patterns and trends that are present in the data. (Seddon & Currie, 2017)
3Vs: Volume, Velocity, Variety (Chen & Zhang, 2014)	
4Vs: Volume, Velocity, Variety, Veracity (Zikopoulos & Eaton, 2011; Shroeck et al., 2012; Abbasi et al., 2016)	
5Vs: Volume, Velocity, Variety, Veracity, Value (Oracle, 2012; Sharda et al., 2013)	
7Vs: Volume, Velocity, Variety, Veracity, Value Variability, Visualization (Seddon & Currie, 2017)	

Table 2 Defining characteristics of big data

3.2 Big data analytics

Some definitions of big data focus solely on the data and their defining characteristics (Davis, 2014; Akter et. al., 2016; Abbasi et al., 2016); others extend and include the analytical procedures, tools, and techniques that are employed (Russom, 2011; Bharadwaj et al., 2013); while some even go on to describe the type of impact that the analysis and presentation of big data can yield in terms of business value (White, 2011; Beyer & Laney, 2012; Schroeck et. al., 2012; De Mauro et al., 2015). This point is made very clear by the definition provided by Gantz and Reinsel (2012), who state that BDA revolve around three main characteristics: the data itself, the analytics applied to the data, and the presentation of results in a way that allows the creation of business value. In this definition, the process of analyzing the data is outlined without linking it to any tangible or intangible business outcome. George et al. (2016) posit that big data refers to large and varied data that can be collected and managed, whereas data science develops models that capture, visualize, and analyze the underlying patterns in the data. To make this distinction more apparent, some scholars use the term BDA to emphasize the process and tools used in order to extract insights from big data. In essence, BDA encompasses not only the entity upon which analysis in performed—i.e. the data—but also elements of tools, infrastructure, and means of visualizing and presenting insight. This distinction is quite eloquently put in the definitions of Kwon et al. (2014), and Lamba and Dubey (2015). Nevertheless, while the definitions of BDA encompass a wider spectrum of elements critical to the success of big data, they do not include the organizational resources that are required to transform big data into actionable insight. Becoming a data-driven organization is a complex and multifaceted task, and necessitates attention at multiple levels from managers. To address the transition to a data-driven era and provide practitioners with guidelines on how to deploy their big data initiatives, scholars have begun utilizing the term 'BDA capability' to reference a company's proficiency in leveraging big data to gain strategic and operational insight.

Authors and date	**Definition**
Loebbecke & Picot, 2015	Big data analytics: a means to analyze and interpret any kind of digital information. Technical and analytical advancements in BDA, which—in large part—determine the functional scope of today's digital products and services, are crucial for the development of sophisticated artificial intelligence, cognitive computing capabilities, and business intelligence.
Kwon et al., 2014	Big data analytics: technologies (e.g. database and data mining tools) and techniques (e.g. analytical methods) that a company can employ to analyze large-scale, complex data for various applications intended to augment firm performance in various dimensions.
Ghasemaghaei et al., 2015	Big data analytics, defined as tools and processes often applied to large and disperse datasets for obtaining meaningful insights, has received much attention in IS research given its capacity to improve organizational performance.
Lamba & Dubey, 2015	Big data analytics is defined as the application of multiple analytic methods that address the diversity of big data to provide actionable descriptive, predictive, and prescriptive results.
Müller et al., 2016	Big data analytics: the statistical modeling of large, diverse, and dynamic datasets of user-generated content and digital traces.

Table 3 Sample definitions of big data analytics

3.3 Big data analytics capability

Despite the limited published research on big data, some studies have focused on the challenges that companies face during the implementation of big data projects (Gupta & George, 2016; Vidgen et al., 2017). Particularly within the IS domain, researchers recognize that the success of big data projects is not only a result of the data and the analytical tools and processes, but includes a broader range of aspects (Garmarki et al., 2016). To address this issue, the notion of BDA capability has been proposed, which is broadly defined as the ability of a firm to provide insights using data management, infrastructure, and talent to transform business into a competitive force (Kiron et al., 2014; Akter et al., 2016a). Research in this area focuses on strategy-driven BDA capabilities, and the mechanisms through which competitive performance gains are realized (LaValle et al., 2011). Some definitions of BDA capabilities focus on the processes that must be put in place in order to leverage big data (Cao & Duan, 2014b; Olszak, 2014), while others emphasize the investment of necessary resources and their alignment with strategy (Xu & Kim, 2014). In essence, the notion of BDA capability extends the view of big data to include all related organizational resources that are important in leveraging big data to their full strategic potential.

Author(s) and date	Definition
Davenport & Harris, 2007	BDA capability is defined as the distinctive capability of firms in setting the optimal price, detecting quality problems, deciding the lowest possible level of inventory, or identifying loyal and profitable customers in big data environments.
Cao & Duan, 2014a	Information processing capabilities: an organization’s capacity to capture, integrate, and analyze big data, and utilize insights derived from that big data to make informed decisions that generate real business value.
Xu & Kim, 2014	Business intelligence capabilities: a combination of a set of sub-capabilities. Derived from IT capabilities, we define business intelligence capabilities from the perspectives of infrastructures, skills, execution, and relationship.
Olszak, 2014	Dynamic business intelligence capability is the ability of an organization to integrate, build, and reconfigure the information resources, as well as business processes, to address rapidly changing environments.
Kung et al., 2015	Big data competence: a firm’s ability to acquire, store, process, and analyze large amounts of data in various forms, and deliver information to users that allows organizations to extract value from big data in a timely fashion.
	Big data resources are defined as a combination of complementary IT resources relevant to the utilization of big data to enhance firm performance.
Garmaki et al., 2016	The BDA capability entails a firm’s ability to mobilize and deploy BDA resources effectively, utilize BDA resources, and align BDA planning with firm strategy to gain competitive advantage and enhance firm performance.
Shuradze & Wagner, 2016	A data analytics capability can be defined as an organization’s ability to mobilize and deploy data analytics-related resources in combination with marketing resources and capabilities, which constitutes an innovative IT capability that can improve firm performance.
Gupta & George, 2016	BDA capability is defined as a firm’s ability to assemble, integrate, and deploy its big data-specific resources.

Table 4 Sample definitions of big data analytics capability

To date, there is limited empirical research building on the notion of BDA capability. Most studies are based on anecdotal evidence, particularly in relation to the impact of a firm’s BDA capability on performance (Agarwal & Dhar, 2014; Akter et al., 2016a). Furthermore, there are diverging views about what constitutes BDA capability, since different theoretical lenses are often employed. In this regard, the purpose of the following section is to provide a theoretically driven synthesis of past studies concerning the aspects that are important in order to develop BDA capability. Thus, we seek to distinguish between the notion of developing a BDA capability and leveraging the competence of a firm to enable or strengthen certain organizational capabilities by means of BDA. We then discuss how the former is a prerequisite for the latter, yet the existence of a BDA capability does not automatically mean that the leveraged competence is actualized.

4. Toward the development of a big data analytics capability

4.1 Resource based theory

Developing and sustaining competitive advantage is the cornerstone of strategic management literature, which draws on a number of interwoven yet distinct elements and notions (Wernerfelt, 1984; Amit & Schoemaker, 1993). Resource-based theory (RBT) has been widely acknowledged as one of the most prominent and powerful theories to explain how firms achieve and sustain competitive advantage as a result of the resources they own or have under their control (Barney, 2001). According to the underlying philosophy of RBT, an organization is perceived as a bundle of valuable tangible and intangible resources, which can be combined to generate competitive advantage (Peteraf, 1993). The original RBT defines resources as rare, inimitable, and nonsubstitutable firm-specific assets that enable a firm to implement a value-creating strategy to generate rents (Barney, 1991). This concept was later split to distinguish between resource-picking and capability-building, two distinct facets that are central to RBT. Resource-picking encompasses activities of identifying and purchasing or controlling resources that are perceived as being of strategic value, while capability-building is concerned with the orchestration and management of these resources into strategically useful assets (Makadok, 2001).

Amit and Schoemaker (1993) define resources as tradable and nonspecific firm assets, and capabilities as nontradable firm-specific abilities to integrate, deploy, and utilize other resources within the firm. Makadok (2001) further elaborates on the distinction between resource-picking and capability-building in his seminal work. According to the author, resource-picking is an important aspect since it not only helps the firm acquire good resources, but is also important for the economic impact of the firm by avoiding potentially poor or unworthy resources. Capability-building, on the other hand, is concerned with activities that relate to deploying these resources in combination with other organizational processes for the creation of intermediate goods, which can potentially provide enhanced productivity and strategic flexibility. Thus, resources represent the input of the production process while a capability is the capacity to deploy these resources in the most strategically fit way. A firm’s resources and capabilities are commonly referred to as assets (Amit & Schoemaker, 1993).

Resources and capabilities are the core components of RBT, and have received a great deal of attention in past empirical studies (Akter et al., 2016b). A characteristic of resources is that they cannot generate any business value by themselves, but require action to be leveraged strategically. This is indicated by Grant’s (1991) description of resources as nouns, because they can lie dormant like an idle plant or unused knowledge until they are needed, and can be identified independently of their use (Wu et al., 2010). Hence, a resource is something that a firm has access to, rather than something it can do (Größler & Grübner, 2006). Several types of resources have been suggested in the extant literature; nevertheless, one of the most adhered-to classifications is that of Grant (1991). According to this categorization, resources can be divided into tangible (e.g. financial and physical resources), human skills (e.g. employees’ knowledge and skills), and intangible (e.g. organizational culture and organizational learning) types (Grant, 1991). This classification has been predominantly followed in the IS capability literature (Bharadwaj, 2000; Aral & Weill, 2007; Ravichandran & Lertwongsatien, 2005).

Capabilities are described as high-level routines (or a collection of routines), with routines consisting of learned behaviors that are highly patterned, repetitious or quasi-repetitious, and founded in part in tacit knowledge (Winter, 2003). Organizational capabilities can be purposely built by focusing on the complex interactions between a firm’s resources and competencies, and are therefore more complex and difficult to imitate than just core resources (Grant, 1996). According to Teece et al. (1997), capabilities cannot easily be bought; they must be built. A basic premise of RBT is that the capability-building process can only take place following acquisition of a resource; therefore, developing capabilities is dependent on, and confined under, the types of resources a firm decides to accumulate. The conversion of resources into potentially strategic assets via the development of firm-specific capabilities has been the subject of considerable scholarly attention (Sirmon et al., 2011). The resource orchestration perspective attempts to explain the role of managers in terms of how resources are transformed into capabilities, and what necessary actions are required to effectively structure, bundle, and leverage them. This process-oriented view, which emphasizes the conversion of resources into capabilities, is seldom addressed and is largely affected by the heterogeneity of firms’ contexts (Barney et al., 2011).

In terms of the form that capabilities can take, previous research in the area of strategic management has made great strides in developing and refining the different types of capabilities. It is generally agreed that capabilities operate quite differently from one another, and result in varying levels of competitive advantage and firm performance based on a number of internal and external factors (Hoopes & Madsen, 2008). Grounded in the idea that firms must be both stable enough to continue to deliver value in their own distinctive way, and agile and adaptive enough to restructure their value proposition when circumstances demand it, there is a well-documented distinction between operational (ordinary) and dynamic capabilities (Drnevich & Kriauciunas, 2011). Nevertheless, the resources owned or controlled by the firm are imperative in determining what types of capabilities a firm can develop, and of what value they will be (Wu, 2007).

RBT has been extensively applied to the IT context under the notion of IT capabilities (Bharadwaj, 2000). IT literature recognizes that competence in leveraging IT-based resources in combination with other organizational resources is a source of competitive and advantage (Pavlou & El Sawy, 2006). Past empirical studies have employed the notion of IT capabilities to demonstrate its direct (Bhat & Grover, 2005) or indirect impact on performance outcomes (Wang et al., 2012). The main premise adopted in these studies is that in order to develop a robust IT capability, it is necessary for a firm to have invested in all the necessary resources (Wade & Hulland, 2004). In the context of big data, it is important to identify the different types of resources, since the level of their infusion in various business functions can be a source of competitive differentiation (Davenport, 2006). A conceptual framework of RBT posits that in order for a resource or capability to be a source of competitive advantage, it must fulfill the criteria of value, rarity, inimitability, and nonsubstitutability (i.e. so-called VRIN attributes) (Barney, 1991). When these resources and their related activity systems have complementarities, they are more prone to lead to competitive advantage (Eisenhardt & Martin, 2000).

4.2 The dynamic capabilities view of the firm

Over the past decade, the DCV of the firm has emerged as one of the most influential theoretical perspectives in the study of strategic management (Schilke, 2014). Extending the resource-based view of the firm, which posits that a firm may achieve sustained competitive advantage based on the bundles of resources and capabilities it has under its control, DCV attempts to explain how a firm maintains a competitive advantage in changing environments (Priem & Butler, 2001). This shift has been ignited by commentaries from many researchers that RBT does not adequately explain why certain firms attain a competitive advantage in situations of rapid and unpredictable change where resources and capabilities are subject to erosion (Eisenhardt & Martin, 2000). Originating from the Schumpeterian logic of creative destruction, dynamic capabilities enable firms to integrate, build, and reconfigure their resources and capabilities in the face of changing conditions (Teece et al., 1997). In essence, dynamic capabilities reformulate the way a firm operates and competes in the market—a process referred to as evolutionary fitness (Helfat & Peteraf, 2009). Several alternative conceptualizations of dynamic capabilities have subsequently been presented. Some follow an approach closer to the resource-based view, which stresses the importance of strategic management (Teece & Pisano, 1994), while others approximate the logic of evolutionary economics, which enunciates the role of routines, path dependencies, and organizational learning (Barreto, 2010).

Despite considerable variation in defining dynamic capabilities, a growing consensus in the literature describes them as a set of identifiable and specific routines that have often been the subject of extensive empirical research in their own right (Eisenhardt & Martin, 2000). This approach seems to be gaining momentum in empirical studies, since it is feasible to identify and prescribe a set of operating routines that jointly constitute firm-level dynamic capabilities (Zollo & Winter, 2002; Pavlou & El Sawy, 2011). These routines are commonly recognized as learned, highly patterned, and repetitious, directed towards independent corporate actions (Winter, 2003). Consequently, to better understand dynamic capabilities it is feasible to emphasize the set of routines that underpin them, commonly referred to as capabilities. In the context of IS literature, several studies have examined how IT infused in organizational capabilities can help firms renew or reconfigure their existing mode of operating (El Sawy & Pavlou, 2006; Wang et al., 2012; Mikalef et al., 2016; Mikalef & Pateli, 2017). This perspective follows the logic proposed by Henderson and Venkatraman (1993), who stressed that alignment as a dynamic capability is not an ad-hoc event, but rather a process of continuous adaption and change. As such, they argued that 'no single IT application—however sophisticated and state of the art it may be could deliver a sustained competitive advantage.' Rather, what is important is to infuse IT investments into the organizational fabric (Kohli & Grover, 2008; Kim et al., 2011).

Concept	Definition	Author(s) and date
Asset	Anything tangible or intangible the firm can use in its processes for creating, producing, and/or offering its products (goods or services) to a market.	Wade & Hulland, 2004
Resource	Stocks of available factors that the organization owns or controls.	Amit & Schoemaker, 1993
Capability	A firm's capacity to deploy resources, usually in combination, using organizational processes, to effect a desired end. They are information-based, tangible, or intangible processes that are firm-specific and are developed over time through complex interactions among the firm's resources.	Amit & Schoemaker, 1993
Operational capability	Generally involves performing an activity, such as manufacturing a particular product, using a collection of routines to execute and coordinate the variety of tasks required to perform the activity.	Helfat & Peteraf, 2003
Dynamic capability	Can be disaggregated into the capacity (a) to sense and shape opportunities and threats, (b) to seize opportunities, and (c) to maintain competitiveness through enhancing, combining, protecting, and, when necessary, reconfiguring the business enterprise's intangible and tangible assets.	Teece, 2007
Competitive advantage	An enterprise has a competitive advantage if it is able to create more economic value than the marginal (breakeven) competitor in its product market.	Petaraf & Barney, 2003
Sustained competitive advantage	When a firm has a competitive advantage and other firms are unable to duplicate the benefits of this strategy.	Barney, 1991
VRIN	VRIN resources are valuable, rare, inimitable, and nonsubstitutable. VRIN-ness implies that resources are heterogeneously distributed among firms. Valuable, rare resources may be sources of competitive advantage, but unless they are also inimitable and nonsubstitutable, that competitive advantage will not be sustained	(Barney, 1991; Peteraf & Barney, 2003)
IT resources	Commodity-like assets that are widely available and can be purchased from the factor market.	Cragg et al., 2011
IT capability	The ability to mobilize and deploy IT-based resources in combination, or copresent, with other resources and capabilities.	Bharadwaj, 2000

Table 5 Key definitions

4.3 Resources of a big data analytics capability

While the published research on BDA capability is limited, some studies have focused on the resources necessary to develop such capability. Although resources are of very limited value without the underlying ability to orchestrate and leverage them, they are fundamental building blocks in the formation of a firm's overall BDA capability. It is therefore important to recognize the core resources and examine the most important debate concerning each of these as described by empirical research. By doing so, it is possible to provide a synthesis of findings that can guide practical support in big data deployments, and also identify underexplored areas of research that warrant further examination. The majority of studies to date have discussed the resources and processes that need to be used to leverage big data strategically, but have not offered much insight into how firms can develop a strong BDA capability (Gupta & George, 2016). Building on the foundations of RBT, and work in the field of IT management that employs the theory, we present the main resources that allow firms to develop a BDA capability. These are divided into three main categories: tangible resources (e.g. infrastructure, IS, and data), intangible resources (e.g. data-driven culture, governance, social IT/business alignment), and human skills and knowledge (e.g. data analytics knowledge, and managerial skills).

4.3.1 Tangible resources

In the context of developing a BDA capability, perhaps the core resource is the data itself. As previously mentioned, the defining characteristics of big data is their volume, variety, and velocity (Chen & Zhang, 2014). However, it is frequently mentioned that IT strategists and data analysts are particularly concerned with the quality of the data they analyze (Brinkhues et al., 2014). Although traditionally firms analyzed enterprise-specific structured data, the diversity and breadth of data sources that contemporary firms leverage render the aspect of quality highly important (Ren et al., 2016). Data quality is regarded as a critical resource, and is defined in terms of completeness, accuracy, format, timeliness, reliability, and perceived value (Brinkhues et al., 2014; Ren et al., 2016). In a heavily data-oriented economy, data resources that present the previously mentioned characteristics have been argued to be necessary for a firm to build competitive advantage (Kiron et al., 2014). Wamba and colleagues (2015) stress the importance of having availability and integrating data from various sources, which traditionally may be siloed due to existing IT architectures. The issue of availability of data is also mentioned by Mikalef et al. (2017), who find that it is common for companies to purchase data in order to complement their analytics and gain more insights into their customers and operations. A similar phenomenon is also noted in a recent report of *MIT Sloan Management Review* (Ransbotham & Kiron, 2017), in which it is highlighted that firms that share data and form alliances based on such resources tend to be more innovative. This aspect signifies the importance that the variety and diversity of data sources have in order to derive any meaningful insights and direct strategic initiatives.

While data itself is a core resource, it is also important for firms to possess an infrastructure capable of storing, sharing, and analyzing data. Big data call for novel technologies that are able to handle large amounts of diverse and fast-moving data (Gupta & George, 2016). One of the main characteristics of such data is that it is in an unstructured format and requires sophisticated infrastructure investments in order to derive meaningful and valuable information (Ren et al., 2016). Some scholars examine the big data infrastructure of firms in terms of the investments made in specific technologies (Kamioka & Tapanainen, 2014), while others focus on features of the technology itself (Akter et al., 2016a; Wamba et al., 2016; Gupta & George, 2016; Garmaki et al., 2016). In particular, scalability and connectivity are cited as important, since the data accumulated and processes used fluctuate continuously. Nevertheless, it is noted by many executives that infrastructure is not a major issue for most firms, since the technology itself has extended beyond the requirements of analytics (Mikalef et al., 2017).

With big data, novel software and IS have emerged that facilitate distributed storage on nonrelational databases (e.g. Hadoop, Apache Cassandra, MongoDB, Monet, and Hazelcat), parallel processing of massive unstructured datasets, and visualization and decision aiding (Gupta & George, 2016). These technologies extend traditional ones that were built to process data in batches, enabling the processing of continuous flows of information in real time (Wamba et al., 2015). Despite these differences, the systems and software employed to analyze big data follow the same principle as that of business intelligence (Lim et al., 2013). In essence, the value of big data analysis and visualization tools is that they transform raw data and provide business managers and analysts with appropriate information to improve decision making (Wixom et al., 2011). Currently, there are multiple software tools capable of facilitating requirements from very diverse data sources, so trying to predict which ones will prevail is risky and relatively insubstantial (Vidgen et al., 2017).

Resource Type	Characteristics	Authors and date
Tangible		
– Data	*Accuracy* *Timeliness* *Reliability* *Security* *Confidentiality* *Completeness* *Currency* *Volume* *Variety* *Velocity* *Integration*	Brinkhues et al., 2014; Chae et al., 2014; Erevelles et al., 2016; Gupta & George, 2016; Kamioka & Tapanainen, 2014; Olszak, 2014; Ren et al., 2016; Wamba et al., 2015; Philips-Wren et al., 2015; Vidgen et al., 2017
– Infrastructure	*Connectivity* *Compatibility* *Modularity* *Agility* *Large-scale, unstructured databases* *Cloud services* *Reliability* *Adaptability* *Integration* *Accessibility* *Response*	Brinkhues et al., 2014; Akter et al., 2016a; Erevelles et al., 2016; Garmaki et al., 2016; Gupta & George, 2016; Kamioka & Tapanainen, 2014; Olszak, 2014; Ren et al., 2016
– Software and IS	*Integrated analytics systems* *Security and risk-management service* *Data-management service* *Open software* *Reporting and visualization systems*	Bekmamedova & Shanks, 2014; Erevelles et al., 2016; Garmaki et al., 2016; Gupta & George, 2016; Olszak, 2014

Table 6 Tangible resources

4.3.2 Intangible resources

Keeping up to date in terms of knowledge and skills, and effectively coordinating activities, resources, and tasks, is highly dependent on the capacity to forge networks internally and externally of the firm (Ravichandran & Lertwongsatien, 2005). Intangible resources therefore reflect ties, structures, and roles established to manage the different types of resources. Governance is one of the most frequent terms used to encapsulate all the activities and decision-appropriation mechanisms related to IT resources (Sambamurthy & Zmud, 1999). Recognizing the growing importance of managing large volumes of information, Tallon et al. (2013) proposed a framework specifically for uncovering the structures and practices used to govern information artifacts. Their framework distinguishes governance practices into three types: structural (assigning responsibilities, directing, and planning), procedural (shaping user behaviors through value analysis, cost control, and resource allocation), and relational (business–IT partnerships, idea exchange, and conflict resolution). Espinosa and Armour (2016) define BDA governance as the approach that analytic-based organizations use to define, prioritize, and track analytic initiatives, as well as to manage different types and categories of data related to analytics. As such, BDA governance represents the rules and controls that participants must comply with when performing relative tasks. The emphasis on big data and information governance is largely attributed to the strategic importance that it holds in contemporary enterprises. Similarly, numerous researchers note the importance of establishing governance schemes for big data (Cao & Duan, 2014b; Garmaki et al., 2016), while others recognize it as one of the main reasons why firms fail to leverage their data effectively (Posavec &Krajnović , 2016). A recurring finding that concerns the effectiveness of governance, however, is that it must follow a top-down approach, requiring commitment to data-driven decisions from top management (Vigden et al., 2017).

An additional intangible resource that is particularly important in driving the adoption of big data and the development of firm-wide BDA capability is a data-driven culture (Cao & Duan, 2014a). The notion of a data-driven culture is adopted from organizational culture, which is a highly complex concept to understand and describe (Gupta & George, 2016). In firms engaging in big data projects, a data-driven culture has been noted as an important factor in determining their overall success and continuation (LaValle et al., 2011). The main argument for the importance of a data-driven culture is that although many companies implement big data projects, the vast majority rely not on the information extracted from data analysis, but rather on managerial experience or intuition (Provost & Fawcett, 2013). This requires that organizational members, including top-level executives, middle-level managers, and even lower-level employees, make decisions based on information extracted from data (Gupta & George, 2016). Aspects that contribute towards a data-driven culture include prioritizing BDA investments, top management support in formulating decisions based on BDA, and a fact-based operating culture (Lamba & Dubey, 2015; Olszak, 2014; Kamioka & Tapanainen, 2014). It is then critical that the importance of data-driven decision making is imprinted in the organization through specific practices (Mikalef et al., 2017). In fact, it is frequently cited that organizations that are successful with BDA are those that have managed to instill the importance of data-driven insights to a breadth of departments. This alleviates siloed units and enables a greater depth and richness of data to be analyzed, while also allowing for dispersed organizational units to work collaboratively towards analytics-generated insights (Mikalef et al., 2017).

Resource Type	Characteristics	Authors and date
Intangible		
– Governance	*Control* *Coordination and monitoring* *Business–IT alignment* *Decision-rights appropriation* *Big data solution assessment and validation* *Business vision and planning* *Policy and rule structures*	Olszak, 2014; Garmaki et al., 2016; Akter et al., 2016a; Cao & Duan, 2014b; Erevelles et al., 2016; Tallon et al., 2013; Espinosa & Armour, 2016; Philips-Wren et al., 2015; Mikalef et al., 2017; Vidgen et al., 2017
– Data-driven culture	*Prioritizing BA investments* *Top management support* *Fact-based and learning culture*	Davenport et al., 2001; Davenport 2013; Kiron et al., 2014 Kiron & Shockley, 2011; Gupta & George, 2016; Lamba & Dubey, 2015; Olszak, 2014; Kamioka & Tapanainen, 2014; Mikalef et al., 2017

Table 7 Intangible resources

4.3.3 Human skills and knowledge

The capacity to utilize big data technologies and tools such as those mentioned above, and to make strategic decisions based on outcomes, is highly dependent on the skills and knowledge of the human resources. These can be further divided into technical knowledge (e.g. database management, data retrieval, programming knowledge such as MapReduce, and cloud service management), business knowledge (e.g. decision making heavily routed within the firm, strategic foresight for big data deployments, and application of insights extracted), relational knowledge (e.g. communication and collaboration skills between employees of different backgrounds), and business analytics knowledge (e.g. mathematical modeling, simulation and scenario development, and interactive data visualization). In a highly influential article, Davenport and Patil (2012) address the important role that the emerging job of the data scientist will have in the context of big data. While one of the most critical aspects of data science is the ability to think analytically about data, such skill is not only important for the data scientist, but for employees throughout the organization (Prescott, 2014). In effect, the data scientist is capable of understanding business problems and utilizing relevant data sources to generate insights based on models and visualization tools.

Recognizing the importance of the data scientist in contemporary firms, some studies have even proposed methods to redesign IS curriculums (Jacobi et al., 2014). This lack of personnel with the appropriate skills is also noted in numerous studies, and constitutes a major constraint in realizing the full potential of these technologies (Tambe, 2014). A report by McKinsey Global Institute concludes that by 2018 there will be a shortage of talent necessary for organizations to take advantage of big data, with an estimate of 140,000–190,000 positions for which no trained personnel will be available (Domingue et al., 2014). While it is still vague and unclear what the critical skills that a data scientist must have are, some definitions help to clarify this. According to Mohanty et al. (2013), data scientists are practitioners of the analytics models solving business problems. They incorporate advanced analytical approaches using sophisticated analytics and data visualization tools to discover patterns in data. The core attributes of the data scientist have been distilled to having entrepreneurial and business domain knowledge, computer science skills, effective communication skills, ability to create valuable and actionable insights, inquisitiveness and curiosity, and knowledge of statistics and modeling (Chatfield et al., 2014).

Nevertheless, while the center of attention has been placed on the data scientist primarily due to the novelty of the role, other skills and knowledge sets are necessary in employees of firms engaging in BDA. Of particular relevance are technical skills such as those of the big data engineers, who are able to acquire store, cleanse, and code data from multiple sources and of various formats (Mikalef et al., 2017). Similarly, big data architects accommodate such technical knowledge by being responsible for developing blueprint plans of the data sources, as well as the appropriate technologies to leverage their potential. Due to the fusion of business and IT departments in BDA firms, the importance of a liaison person has emerged; that is, a person capable of bridging the siloed departments and making them work collaboratively (Akter et al., 2016a). The necessary skills for such employees include a good understanding of what each department/unit is doing, as well as an ability to communicate with each and build fused teams (Mikalef et al., 2017). Finally, having a good understanding of the goals and directions of the firm, as well as knowing how to measure and improve critical key performance indicators (KPIs), is of paramount importance since, in most cases, BDA are grounded on an existing problem. Therefore, an ability to identify this problem and improve by means of big data-generated insight is an important aspect of the knowledge that business executives and data analysts should have (Gupta & George, 2016).

Resource Type	**Characteristics**	**Authors and date**
Human skills & knowledge		
– Technical knowledge	*Programming* *Technical infrastructure management* *MapReduce* *Unstructured data management* *Data collection/integration*	Akter et al., 2016a; Elbashir et al., 2013; Garmaki et al., 2016; Gupta & George, 2016; Kamioka & Tapanainen, 2014; Olszak, 2014; Mikalef et al., 2017
– Business knowledge	*Business strategy* *KPIs* *Business processes*	Akter et al., 2016a; Erevelles et al., 2016; Elbashir et al., 2013; Gupta

	Change management	& George, 2016; Olszak, 2014; Garmaki et al., 2016; Olszak, 2014
– Relational knowledge	*Communication skills* *Team building*	Akter et al., 2016a; Garmaki et al., 2016; Mikalef et al., 2017
– Business analytics	*Statistical analysis* *Forecasting* *Query and analysis* *Predictive modeling* *Optimization* *Model management* *Simulation & scenario development* *Business reporting /KPIs/dashboards* *Web analytics* *Social media analytics* *Interactive data visualization* *Text, audio, video analytics* *Data and text mining*	Davenport et al., 2001; LaValle et al., 2011; Chen et al., 2012; Cao & Duan, 2014b; Chae et al., 2014; Erevelles et al., 2016; Galbraith, 2014; Garmaki et al., 2016; Lamba & Dubey, 2015; Olszak, 2014; Vidgen et al., 2017

Table 8 Human resources

4.4 Areas of big data analytics

Apart from the core resources that are required to develop a BDA capability, several studies have examined the areas in which big data initiatives can be leveraged, as well as overall firm performance gains (Akter & Wamba, 2016). The main premise is that although a BDA capability comprises mostly similar aspects that need to be taken into account independently of context, the way in which this capability is applied has considerable diversity. For instance, several studies note that companies that belong in the media and news industry apply their BDA capabilities towards personalizing content toward their customers and delivering tailored-made news and suggestions, while in the oil and gas industry there are several applications geared towards risk assessment and maintenance (Mikalef et al., 2017). Furthermore, considerable heterogeneity of BDA applications has been observed within industries, which can potentially lead to differentiated business value outcomes (Akter et al., 2016a). To this end, several recent studies attempt to examine the influence of BDA capabilities on enabling various forms of organizational capabilities (Xu et al., 2016; Pappas et al., 2016; Wamba et al., 2017).

These studies show that a BDA capability can be directed towards strengthening both operational (Chae et al., 2014) and dynamic (Erevelles et al., 2016) capabilities of a firm. Wamba et al. (2015) demonstrate that the types of value creation for big data initiatives can be divided into creating transparency (Meredith et al., 2012; Bärenfänger et al., 2014), enabling experimentation to discover needs and improve performance (Brinkhues et al., 2014; Bärenfänger et al., 2014), segmenting populations (Kowalczyk & Buxmann, 2014), enhancing or replacing human decision making (Meredith et al., 2012; Cao et al., 2015; Brinkhues et al., 2014; Bärenfänger et al., 2014), and innovating new business models, products, and services (Jelinek & Bergey, 2013). Hence, it is important when considering the potential of BDA capabilities to take into account their area of application. Utilizing BDA to improve process efficiency is most likely to have significantly less impact on a firm's competitive position compared to utilizing them to detect new customer segments or come up with new business models. Nevertheless, even if BDA capabilities are leveraged in core strategic areas, their value is likely to be dependent and contingent upon multiple factors, which will be further elaborated in the subsequent section.

5. Discussion

Despite the hype that surrounds big data, the business potential and mechanisms through which it results in competitive performance gains have remained largely underexplored to date in empirical studies. By conducting a systematic literature review and documenting what is known to date, it is possible to identify prominent themes of research that are of high relevance. We do so by defining six thematic areas of research, as depicted in the research framework in Figure 2, and provide some suggestions on how scholars could approach these problems.

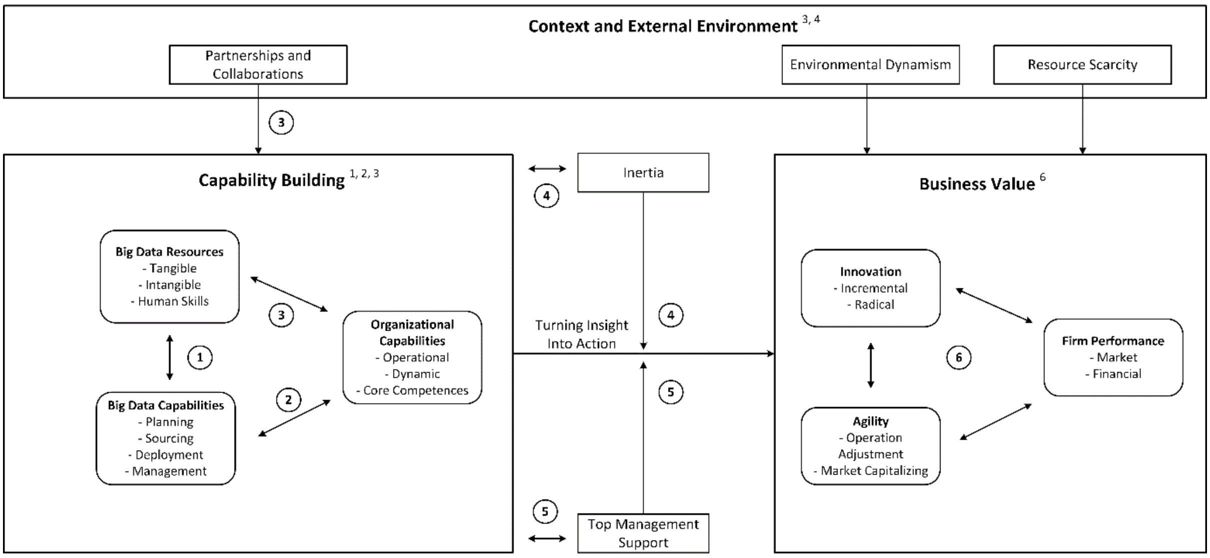

Figure 2 Big data analytics research framework

Theme 1: Resource orchestration of big data analytics

While considerable effort has been made to define the building blocks of a firm's BDA capability, little is known so far about the processes and structures necessary to orchestrate these resources into a firm-wide capability. In other words, literature has been very detailed on the resource-picking aspect of BDA, but less so on the activities that need to be put into place to develop the capability. Prior literature on IT–business value has shown that competence in orchestrating and managing such resources is a prerequisite to developing the capacity so as to leverage these resources strategically (Cragg et al., 2011; Wang et al., 2012). According to the framework of resource orchestration, structuring resources towards the building of a capability consists of acquiring, accumulating, and divesting resources (Sirmon et al., 2010). Therefore, it is important for researchers to examine the capability-building process, since it is likely that firms with similar resources will exert highly varied levels of BDA capabilities. Similarly, firms with same levels of BDA capabilities may develop them in dissimilar ways, since their value may be contingent upon several internal and external factors (Mikalef et al., 2015).

Theme 2: Decoupling big data analytics capability from big data-enabled capabilities

Although it is clear that a BDA capability refers to a firm's proficiency in orchestrating and managing its big data-related resources, it is important to differentiate between the firm's capacity to utilize its BDA capability towards insight generation of organizational-level capabilities. As such, a firm can have developed a strong BDA capability but only utilize it towards a specific type of operational capability (e.g. marketing). Therefore, the assumption that a BDA capability will enhance several organizational capabilities simultaneously is misleading. It is highly likely that industry and other contextual factors influence firms' decisions to leverage their BDA capabilities in order to gain insight in relation to different organizational capabilities. Again, the means by which they choose to leverage their BDA capabilities could differ significantly and could possibly result in variation in terms of performance gains. Consequently, it is critical to gain a deeper understanding of the specifics of each capability, since the high-level abstractions noted in strategic management literature may conceal the reality of how the capability is leveraged by means of BDA (Mikalef & Pateli, 2016).

Theme 3: Bounded rationality of big data analytics

One of the assumptions of BDA, which is not discussed very frequently, has to do with the limitations of insights that can be derived from big data itself. While BDA may enable a more data-driven decision-making approach, the types of insights that can be derived are bounded by the amount, variety, and quality of available data. Consequently, a frequently observed phenomenon is that firms try to access a diverse set of data from open sources. In some cases, it is even noted that firms are forming strategic alliances in which the exchanged resources are datasets and customer information (Ransbotham & Kiron, 2017). Hence, one of the conditions that should be taken into account when examining the strategic potential of big data is the availability of data. In a similar vein, the different forms of collaborative agreements with regards to data exchange and their resulting business value are posited to be an area of increased interest. It is highly probable that the boundaries of the insight that firms can develop, and, subsequently, the types of competitive actions that they launch, are restricted by the availability of data.

Theme 4: Turning big data analytics insights into action

To realize the value of BDA, it is necessary not only to put them into action in the generation of data-driven information for specific organizational capabilities, but also to take action to harness the insights. While some studies assume that leveraging BDA capabilities is sufficient to provide business value, it is important to examine the mechanisms of inertia that act in inhibiting their value. In a recent literature review, Besson and Rowe (2012) indicate that when it comes to organizational transformation there are five main types of inertia that hinder the value of IS. These include negative psychology inertia, socio-cognitive inertia, socio-technical inertia, economic inertia, and political inertia. The aspects of inertia can work at multiple stages within the development of a BDA capability, and also after they have resulted in insights. Nevertheless, turning BDA into action, and subsequently business value, may also be dependent upon the external environment. In highly dynamic and turbulent environments, the value of insight may be diminished by scarce resources or competitors launching competitive actions in short cycles. Hence, it is important to examine the confluence of the competitive environment when considering the business value of BDA-derived insight.

Theme 5: Trust of top managers in big data analytics insights

One specific form of distrust in the value and accuracy of BDA can be detected on the top management level. While managers may be positive about investing in BDA capabilities, when it comes to decision making they may feel that their intuition is more accurate than the analysis performed on big datasets. This phenomenon has been studied under the prism of dual process theory in the organizational context (Hodgkinson & Healey, 2011). The main premise is that managers' emotional and cognitive responses may override the insights of BDA, thereby reducing their potential value. This dichotomy between reflexive systems inherent in top managers, such as implicit stereotyping and automatic categorization, and reflective systems, such as those present in BDA that allow logical reasoning and planning, are argued to be important when measuring the impact of such investments.

Theme 6: Business value measurement

The issue of determining the right measurement indices by which to assess the value of IT is prevalent throughout IS research (Schryen, 2013). Similarly, the hype surrounding BDA may cause managers and academics to overestimate the potential business value of BDA, or develop biased performance metrics to benchmark BDA effectiveness. It is therefore important to construct specific performance measures depending on a number of contextual factors, as well as on the area in which BDA are deployed. Furthermore, it is critical to identify metrics that take into account the competitive landscape, since in highly uncertain and dynamic markets the value of BDA may be reduced due to competitors following similar strategies or scarce resources inhibiting response formation. As such, we highly encourage researchers to examine a multitude of not only objective, but also subjective, value measures.

6. Conclusion

An ever-increasing number of companies are attempting to use big data and business analytics in order to analyze available data and aid decision making. For these companies, it is important to leverage the full potential that big data and business analytics can offer with the aim of gaining competitive advantage. Nevertheless, since big data and business analytics are a relatively new technological and business paradigm, there is little research on how to effectively manage them and leverage them. While early studies have shown the benefits of using big data in different contexts, there is a lack of theoretically driven research on how to utilize these solutions in order to gain a competitive advantage. This work identifies the need to examine BDA through a holistic lens. We thereby focus on summarizing what we already know and pinpoint themes on which we still have limited empirical understanding.

To this end, this study proposes a research framework that is based on prior literature in the area of IT–business value, as well as on concepts from strategic management and management IS literature. The framework provides a reference for the broader implementation of big data in the business context. While the elements present in the research framework are on a high level and can be interpreted as quite abstract, they are purposefully described in such a manner that they can be adapted depending on the company at hand. This poses a novel perspective on big data literature, since the vast majority focuses on tools, technical methods (e.g. data mining, textual analysis, and sentiment analysis), network analytics, and infrastructure. Hence, the proposed framework contributes to big data and business strategy literature by covering the aforementioned gap. It is more important for managers and decision makers to learn how to implement big data and business analytics in their competitive strategies than to simply perform raw data analysis on large datasets without a clear direction of where this contributes to the overall business strategy.

Furthermore, this study argues that the main source of competitive edge, especially in highly dynamic and turbulent environments, will stem from companies being able to reinforce their organizational capabilities through targeted use of big data and business analytics. This of course does not lessen the importance of big data resources and capabilities, since their availability and VRIN characteristics can determine the strength of the associated insights that augment organizational capabilities (Bowman & Ambrosini, 2003; Meyer-Waarden, 2016). The concepts used in the proposed framework may help managers to better understand, plan, and organize the process of implementing BDA within a business strategy. In addition, the framework can be used as a roadmap for gradually maturing the BDA capability of a firm and deriving increased value from such initiatives.

This paper offers a theoretical framework on how to increase business value and competitive performance through targeted application of big data. Future studies should empirically test and evaluate this framework using surveys, interviews, observation, focus groups with experts (e.g. managers, decision makers) and with customers, as well as case studies from the industry. In addition, both qualitative and quantitative methods of data collection should be employed. For each different type of data, more than one method of analysis should be used (e.g. structural equation modeling, qualitative comparative analysis). The main argument of this systematic literature review is that the value of big data does not solely rely on the technologies used to enable them, but is apparent through a large nexus of associations that are eventually infused with organizational capabilities. Strengthening these capabilities by virtue of big data is what will lead to competitive performance gains, and is contingent upon multiple internal and external factors.

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