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Article — Published Version

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Review of Managerial Science

Provided in Cooperation with:

Springer Nature

Suggested Citation: Korherr, Philipp; Kanbach, Dominik (2021) : Human-related capabilities in big data analytics: a taxonomy of human factors with impact on firm performance, Review of Managerial Science, ISSN 1863-6691, Springer, Berlin, Heidelberg, pp. 1-28, <https://doi.org/10.1007/s11846-021-00506-4>

This Version is available at:

<https://hdl.handle.net/10419/287235>

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Human-related capabilities in big data analytics: a taxonomy of human factors with impact on firm performance

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Received: 29 March 2021 / Accepted: 17 November 2021
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Abstract

This study intends to provide scholars and practitioners with an understanding of human resource challenges in the context of Big Data Analytics (BDA). This paper provides a holistic framework of human-related capabilities that organizations must consider when implementing BDA to facilitate decision-making. For this purpose, the authors conducted a systematic literature review adapted from Tranfield et al. (BJM 14:207–222, 2003) to identify relevant studies. The 75 publications reviewed provided the sample for an inductive, and systematic data evaluation following the well-known and accepted approach introduced by Gioia et al. (ORM 16:15–31, 2012). The comprehensive review uncovered 33 first-order concepts linked to human-related capabilities, which were distilled into 15 s-order themes and then merged into five aggregated dimensions: Personnel Capability, Management Capability, Organizational Capability, Culture and Governance Capability, and Strategy and Planning Capability. The study is, to the best of the authors' knowledge, the first to categorize all relevant human-related capabilities for successful BDA application. As such, it not only provides the scientific basis for further research, but also serves as a useful overview of the critical factors for BDA use in decision-making processes.

Keywords Big data analytics · Human capabilities · Big data · Decision-making · Data-driven management

JEL Classification M00 · M15 · M20

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1 Introduction

Since its emergence in the early 1990s (Cox and Ellsworth 1997), Big Data has grown into one of the economic cornerstones of today's value creation and its importance to decision-makers in firms is increasing steadily (Einav and Levin 2014). Although many business processes and actions are now carried out automatically, the majority of important decisions are still made by humans. It is regrettable that decisions based on the limited knowledge of one or several people are prone to error and most likely do not lead to the optimal outcome for the organization (Minciu et al. 2020). Considering these problems, the question arises of how analytical methods—more specifically Big Data Analytics (BDA)—may enable humans to make better decisions and thrive in this world of variety, uncertainty, complexity, and ambiguity (Minciu et al. 2020).

Data on its own is a meaningless set of numbers, but processing and structuring the variety and velocity of this raw asset enables value creation (Lamba and Dubey 2015). It is highly unlikely that a competitive advantage will be generated solely through the collection of an enormous amount of data (Wamba et al. 2017). Rather, it is through analyzing the data and deriving relevant insights that managerial decision making is supported (Yasmin et al. 2020), value is added, and economic failure is prevented (Amankwah-Amoah and Adomako 2019). However, the ability to do so is not developed overnight, but rather must be built over time. All personal, managerial, cultural, and organizational skills and strategies have an immense influence on employees and executives, and can therefore be identified as human-related capabilities.

Concurrent with the rise of processed data volumes and the expansion of the analytical toolkits available to organizations, academics have increasingly been researching BDA, and the number of publications in this field has risen dramatically over the last decade. While the majority of these publications focus on technological aspects of BDA, several researchers have dedicated their work to the related management capabilities. Gupta and George (2016) laid the foundation for future BDA research and focused on providing an overview of relevant resources—grouped into tangible and intangible resources as well as human skills—to create a BDA capability. In addition, there is a huge literary base investigating specific individual capabilities that are needed to enable the successful handling of BDA—for example personal soft skills (Caputo et al. 2019). This shows that scholars have begun to point out which types of BDA capabilities are necessary to facilitate the integration of enormous data sets into decision-making processes and optimize organizational performance (Shamim et al. 2020). On the one hand, BDA systems and technologies are required to adequately transform heterogeneous data sets (Mandal 2018). On the other hand, organizations have to build up human and organizational capabilities (Côrte-Real et al. 2017; Mishra et al. 2019; Upadhyay and Kumar 2020) to ensure the proper handling of all the technological aspects of BDA (Chen et al. 2012). While it is known that human aspects are of importance in the context of big data, a comprehensive overview of all relevant, human-related capabilities is still missing.

Currently, the technological progress of BDA is outpacing the corresponding social developments: Algorithms and the corresponding hardware have become increasingly sophisticated, but organizations and individuals still struggle to handle big data effectively (Scholz 2017). Several different research streams have been developed that examine how BDA affects firm performance and, correspondingly, which capabilities are needed to implement BDA effectively. While a broad variety of capabilities and related organizational characteristics have been identified by such research, there is still no comprehensive scientific framework that organizes the human-related aspects of BDA implementation (Wang et al. 2018a, b). Up until now, scholars have examined BDA capabilities, correlating individual aspects and various characteristics in several different industries (e.g. Chae and Olson 2013; Hausladen and Schosser 2020; Wang et al. 2018a, b), which has led to a highly fragmented theoretical base. The lack of a holistic taxonomy of relevant human capabilities prevents researchers and practitioners from focusing on all the relevant dimensions that must be taken into account to successfully transform an organization into a digitalized, data-driven company (Caputo et al. 2019). A fundamental understanding of factors relevant to BDA is crucial in enabling researchers to derive substantial theoretical implications as well as behavioral guidelines for practical application (Gupta and George 2016). These reflections prompted the following research question: *What are the human-related capabilities necessary for organizations to implement Big Data Analytics?* In order to answer this question, we first conducted a systematic literature review, identifying and consolidating all relevant analytic capabilities discussed in the academic literature. Following that, a qualitative coding approach was used to structure the identified features and building blocks within our sample of publications and establish a holistic taxonomy of human-related BDA capabilities.

This paper is structured as follows: In Sect. 2, we provide a rationale for our research approach. Followed by a detailed description the methodology used to conduct the literature review before describing our coding procedure, which sets the foundation for structuring the data. Next, in Sect. 4, we explain the developed taxonomy in more detail. The paper closes by putting forward its theoretical and practical contributions, limitations, and an overview of future research directions based on our framework.

2 Theoretical frame

The research approach described in the following is mirrored in the light of two elementary theoretical approaches in order to set up the necessary rationale for both, the inductive coding approach, as well as the taxonomy of human-related BDA capabilities. The Resource-Based View (RBV) is a theory that claims that firms should exploit their own resources in the best possible way to enhance the own performance and create a competitive advantage. The resource-based managerial framework is one of the most acknowledged theories within management literature (Barney 2001). The resources available for a company and the correlating capabilities, which are core elements of the RBV, have gained great interest within academic

research (Aker et al. 2016). Within Information System (IS) literature, various authors (e.g. Aral and Weill 2007; Bharadwaj 2000) relate to the general classification of resources from Grant (1991) who separated between tangible and intangible resources as well as human skills. The evolution of the resource-based theory has led to the development of many different related concepts. In 1993, Amit and Schoemaker (1993) first mentioned capabilities as conceptual cornerstone of the RBV and developed the established theory further. Many scholars linked their research to these basic theories (Teece et al. 1997), while modifying them to adequately explain why organization compete better than others in situations of unpredictable change (Eisenhardt and Martin 2000). The resulting theory—Dynamic Capabilities—has become one of the most influential theoretical frameworks for the evaluation how organizations can expand value creation through making usage of IT (Bhatt and Grover 2005; Fosso Wamba et al. 2019). Building on this status, we decided to conduct a systematic literature review and follow an inductive coding approach to identify the human resources and capabilities needed to implement BDA successfully. The above-mentioned two theories assisted the authors to illuminate and reflect the phenomenon of the role of dynamic human capabilities—the resources of an organization in the context of BDA application.

3 Methodology

In conducting a systematic literature review (SLR) of an existing body of literature, we endeavored to avoid biases and provide a reproducible method of searching and synthesizing information (Kraus et al. 2020). Figure 1 summarizes the relevant steps in our process and the number of publications considered at each stage. The resulting sample of identified publications served as the basis for our inductive analysis, which we carried out following the approach described by Gioia et al. (2012). As we aimed to provide the highest standards of evidence and qualitative rigor for both

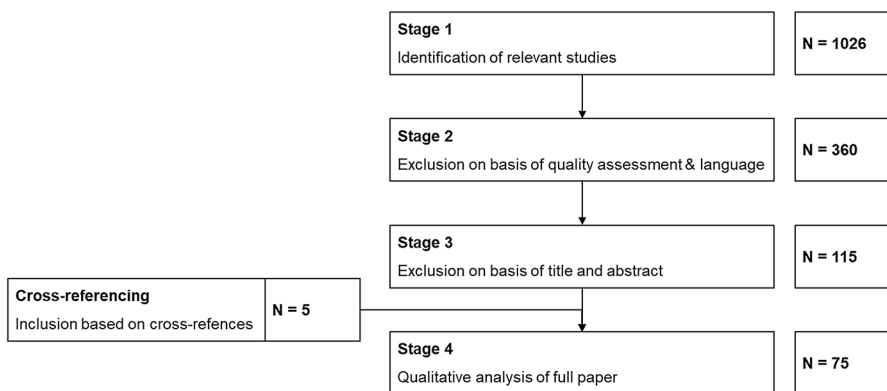


Fig. 1 Systematic literature review process with the number of papers per stage

academia and practitioners, we included only peer-reviewed papers that met high quality standards (Denyer and Tranfield 2006; Gioia et al. 2012).

3.1 Protocol development

As the first step of our SLR, we developed a review protocol as the basis for our ongoing research (Kraus et al. 2020). We developed a search strategy, defined criteria for the inclusion or exclusion of studies, designed the methodology for the data synthesis, and organized the elements into a protocol. However, we did not see this protocol as a fixed, limiting regulation, but rather as a guideline that set the direction for the entire review process (Kraus et al. 2020).

3.2 Search strategy and data sources

Our search strategy is based on a search string developed by combining various keywords (Tranfield et al. 2003). We discussed the set of keywords in the review team and selected the most appropriate search terms: *big data analytics capabilities*, *big data analytics*, *data analytics*, *business analytics*, *human capabilities*, *human dimensions*, *characteristics*, *management skills*, *dynamic capabilities*, and *resource-based view*. We formulated a search string containing the above-mentioned terms and scanned databases for the titles, abstracts, and keywords associated with the publications. We screened a wide range of electronic databases, including Business Source Ultimate, Emerald, Taylor & Francis, Elsevier, Wiley, Springer, IEEE Xplore, Nature Publishing, ACM Digital Library, Oxford, Cambridge, and Web of Science. The authors agreed to include conference proceedings in the search. Our search identified a total of 1026 papers at the initial stage.

3.3 Inclusion and exclusion criteria

In order to provide a reliable basis for further analysis and to ensure that all included papers are of high quality, we examined all papers with regard to the scientific rigor applied by their authors. We only included papers published in journals listed in either VHB-Jourqual 3 or the Scimago Journal Rank (SJR) to guarantee quality and credibility. Furthermore, peer-reviewed publications that were not written in English or German were excluded. The elimination of papers that did not meet the quality or language requirements reduced the number of eligible papers to 360. Subsequently, all remaining non-eliminated articles were reviewed with regard to their title, abstract, and keywords. Publications that were found to neither focus on the capability aspects of BDA nor have relevance to our defined research question were excluded at this step. Therefore, some high-quality articles that did not address capabilities were not included in our sample. As BDA is a timely topic, relevant studies however, can also be found in non-ranked outlets, for example conference proceedings. In order to provide a holistic literature review incorporating all germane papers, we also considered these outlets and decided to include five additional

papers that relate to the topic of BDA capabilities. Those publications were identified while reviewing identified articles and appeared highly relevant for our taxonomy and were consequently manually added to the entirety. To ensure that the added publications meet the quality standards, they were assessed by the authors and additionally challenged within the research group. In total, for the taxonomy of BDA capabilities, we selected 75 publications in total, which we consider to be a trustworthy and valuable basis.

3.4 Inductive research

In order to ensure that this research was carried out with the necessary scientific rigor, we applied the approach laid out by Gioia et al. (2012). Following an inductive approach, we aggregated 748 identified aspects of BDA capabilities into 33 first-order concepts. We then began to seek similarities and potential overlaps among the still-large number of categories (Gioia et al. 2012). By giving those categories phrasal descriptors (i.e., labels) we identified deeper structural similarities. Overall, we abstracted 15 s-order themes that adequately summarized the 33 first-order concepts. This pivotal step helped us to gain a comprehensive understanding of the potential dimensions of relevant BDA capabilities. We then distilled a comprehensive set of five different BDA capabilities found to be related to the human aspects of this otherwise highly technical field. The entire inductive coding process was conducted by both authors following a collaborative approach. At the initial stage of the process, both authors worked individually through all studies in the sample combined with a regular exchange and discussions of main aspects and findings of these studies to ensure that both have a common understanding. After completing this work, both authors started the coding process. In regular intervals, coding results were compared, and potential differences were discussed until a common agreement was reached. In order to mitigate biases any researcher bias in the coding process, a pressure-test of preliminary findings with the research group of the authors' chair was conducted. The research group confirmed our categorization for most cases while we made smaller adjustments for others.

These aggregated dimensions, in conjunction with the second-order themes and first-order concepts, provide the conceptual depth needed to fully understand the human aspects of BDA capabilities and enable further applications within the research. Figure 2 depicts the outcome of the inductive analysis just described.

4 Taxonomy of human-related big data analytics capabilities

We defined *Personnel Capability*, *Management Capability*, *Organizational Capability*, *Culture & Governance Capability*, and *Strategy & Planning Capability* as the five key capability dimensions. The Personnel and Management capabilities focus on individual skills and abilities required for successful BDA usage. The following two dimensions—Organizational Capability and Culture & Governance Capability—detail organizational and cultural factors, which are highly important structural

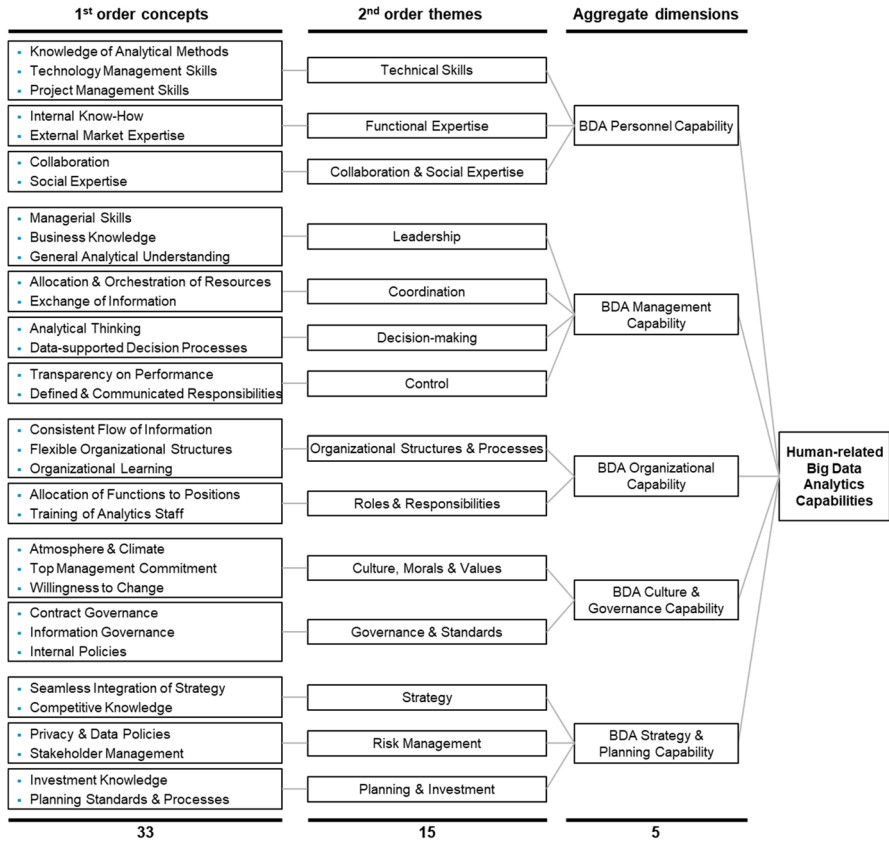


Fig. 2 Taxonomy of human-related Big Data Analytics capabilities, structured according to Gioia et al. (2012), with total counts listed below each category

preconditions for successful BDA application. Lastly, Strategy & Planning outlines necessary strategic considerations and discusses essential elements of planning and investment decisions regarding Big Data.

4.1 Personnel capability

Technical and managerial skills of employees are often summarized under the general term “human resources” (Bharadwaj 2000; Mishra et al. 2019). The taxonomy developed in this study reflects the importance of both those skill sets; however, it clearly distinguishes between the personal (technical) skills of the employees and managerial aspects of the company. Personnel Capability is a general term covering *technical skills*, *functional expertise*, and *collaboration and social expertise*. It is comprised of all the skills that employees can develop through education, further training, and seminars and capabilities that companies can acquire by hiring skilled individuals.

Technical skills relate to individual abilities and, in the context of Big Data Analytics, consist of three components: *knowledge of analytical methods*, *technology management skills*, and general *project management skills*. Firstly, knowledge of analytical methods includes feeling confident engaging in both data pre-processing and actual modeling. At the beginning of an analytical project, data gathering and pre-processing—meaning the mining of data and its validation (Song et al. 2020)—are fundamental steps. Pre-processing sets the foundation for the actual modeling, which requires different methods and analytical techniques (Shuradze and Wagner 2016). Depending on the nature of the data and the desired result, descriptive statistics, regression analysis, cluster analysis, neural networks, or time series models may be applied (Chen and Jiang 2020; Davenport et al. 2001). Throughout this process, employees must be aware of the strengths, weaknesses, and limitations of applied statistical methods, and thus of the generated modeling results, to ensure the proper deployment of any findings (De Mauro et al. 2018). Secondly, advanced analytical software enables the handling of large data volumes using the above-mentioned methods. Programming skills, such as being able to work with Java(Script) or Python, are necessary to set up analytical models (Akter et al. 2020a, b; Chen and Jiang 2020). Thirdly, firms increasingly follow a project-based approach to applied analytics, meaning that analytic experts must collaborate with other departments. Substantial project management know-how and adherence to a structured process during the full life cycle of the project are required to make this collaboration a success (Akter et al. 2020a, b).

Functional expertise concentrates on individual knowledge regarding the organizations' *internal know-how* regarding processes and structures and *external market expertise*. To apply BDA successfully, relevant employees need explicit knowledge of the organization's strategy, business model, competitive factors, and internal resource constraints (Davenport et al. 2001) in order to correctly interpret business problems and formulate appropriate solutions (Wamba et al. 2017). Familiarity with relevant organizational business functions, internal environments, and end-to-end processes is necessary to facilitate the application of BDA and comprehensive analytical methods (Kim et al. 2012; Saggi and Jain 2018; Wamba et al. 2017). Knowledge of the organization's market environment and detailed information on consumer activities, preferences, and demands indicates complete market expertise (Akter et al. 2020a, b; Erevelles et al. 2016; Kiron et al. 2014).

Collaboration and social expertise enhance individual abilities and overarching organizational prerequisites. In many cases, the project-oriented application of BDA poses great challenges to the employees of departments that collaborate only infrequently (Ferraris et al. 2019). An effective communication skill set, meaning the application of listening, teaching, and persuading skills (Davenport et al. 2001), is critical, even though these skills are stereotypically lacking in analytics employees (Kung et al. 2015). Moreover, the willingness to share new insights and knowledge across departments ensures the success of BDA (Olszak 2014). Organizations have to ensure that smooth collaboration and exchange of information among all stakeholders is promoted (Upadhyay and Kumar 2020). A lean business structure with close interaction (McLaughlin 2017) and frequent cross-functional meetings of line

employees and analysts (Munodawafa and Johl 2019; Upadhyay and Kumar 2020) help to facilitate information exchange.

Collaboration and social expertise, functional expertise, and technical skills are all highly individual components that can be acquired or learned. Nonetheless, strategic and organizational structures set the framework in which employees collaborate and apply analytical methods on a basis of functional expertise. Furthermore, management and leadership styles affect an organization's Personnel Capability, as they influence the behavior of individuals and reflect the organization's cultural norms, values, and overarching strategy.

4.2 Management capability

Even though business realities are nowadays dominated by data, decisions in most organizations are still made based on the instincts of senior executives and managers (Kiron et al. 2014). In many companies, the opinion of the highest paid person is still considered superior to data in making trend-setting business decisions (McAfee and Brynjolfsson 2012). However, research shows that executives should start to augment their own experience with data-based insights and should try to trust data-based recommendations. Therefore, executives have to develop a general understanding of analytical methods in order to be able to comprehend why analytics-based recommendations may vary from their own experience (Ransbotham et al. 2015). Researchers agree that a critical, but underestimated factors for firm success in the era of Big Data are the capabilities of the management team, a prepared and open mindset (Olszak 2014) and first-hand experience in making analytics-based decisions in order to reduce discomfort while applying analytical methods for decision-making (Ransbotham et al. 2015). It is important to understand that firms do not succeed over others "simply because they have more or better data," but because their leadership knows how to use it (McAfee and Brynjolfsson 2012, p. 8). Research acknowledges the importance of investing into building management capabilities, saying that "The technical challenge of using big data is real, but the managerial challenge is even greater, dealing from top to bottom of the organizational hierarchy" (Yasmin et al. 2020, p. 2). *Leadership, coordination, decision-making, and control* are the individual abilities of specific people or roles and have to be developed within an organization to cope with the challenge of successfully applying BDA. These capabilities are summarized under the term Management Capability.

Leadership styles are deeply rooted in organizational settings (Gupta et al. 2019) and reflect the characteristics of the relevant executives (Pedro et al. 2019). *Managerial skills, business knowledge, and a general analytical understanding* are characteristics that should be displayed by a successful leader. First and foremost, managers are responsible for facilitating the collaboration of operational and business functions within a firm (Cragg et al. 2011) as cross-functional interaction in the context of BDA is mostly not explored yet and poses various challenges (Arunachalam et al. 2018). Having trusting and constructive working relationships in place between data managers and functional managers is also of great importance and may "lead to

the development of superior human big data skills” (Gupta and George 2016, p. 15). Apart from that, solid business knowledge, a sense for analytics, and a good understanding of upcoming data-related trends, including changes in customer behavior (Olszak 2014), are useful in developing ideas on how to use analytical methods effectively (Elbashir et al. 2013). Industry expertise about practices and competitors are further prerequisites for executives, so that they may allocate suitable resources to analytical undertakings (Ciampi et al. 2021). Lastly, executives need a general analytical understanding of BDA. The ability to understand, interpret, and properly assess data outputs is a precondition for making the correct decisions (Shamim et al. 2019).

Coordination—the *allocation and orchestration of resources* and the *exchange of information*—is a very relevant capability for executives in a BDA context (Hao et al. 2019). In a highly dynamic environment, an organization’s managers have to coordinate BDA actions (Shokouhyar et al. 2020) in line with formal and informal guidelines and procedures (Kim et al. 2012). Therefore, having knowledge of the required IT infrastructure in line with the firm’s needs is essential (Elbashir et al. 2013) in order to allocate tangible resources, form an appropriate team of analytical and functional experts, and provide clear guidance on decision-making (McLaughlin 2017). Managers must coordinate efforts (Akter et al. 2020a, b) and orchestrate tasks to minimize the burden for employees (Wamba et al. 2017). Furthermore, executives must ensure an open and direct information exchange among all involved employees as key element of the facilitation of cultural shift that is required when implementing BDA (Kiron et al. 2014). Frequent cross-functional meetings facilitate interpersonal exchange and objective functional discussion (Rialti et al. 2019), which enables the enhanced use of analytics and consequently improves executives’ decision proposals based on derived data insights. Thus, differentiate the organization from competitors (Wang and Hajli 2017).

In fact, executives should understand and use these decision templates in their daily work. Decision-making based on data recommendations versus personal opinions often requires that executives rethink their practices and adapt to a new way of working (Dubey et al. 2018). Ideally, organizations achieve a state in which managers feel comfortable with the data-based decisions they have made. Therefore, a good balance between personal assessment and analytical results is elementary (Kiron et al. 2014). Furthermore, it is important that executives display a strong aptitude for *analytical thinking* (Mikalef et al. 2020a, b) along with the ability to interpret complex analyses (Dubey et al. 2018). Appropriately structured processes, a clear allocation of decision bodies, and transparent escalation levels (McLaughlin 2017) provide additional security, help sustainably anchor *data-supported decision processes* in organizations (Upadhyay and Kumar 2020), and justify the high investment costs of BDA with the value generated through improved decisions (Shokouhyar et al. 2020; Suoniemi et al. 2020).

Within the dimension of control, all information technology-related supervisory activities are summarized. More specifically, this dimension comprises formal and informal capabilities intended to ensure the adequate use of analytical methods (Kim et al. 2012). Suitable control requires that organizations establish *transparency on performance* criteria of BDA (Akter et al. 2020a, b; Wamba et al. 2017). Constant

and diligent monitoring of BDA performance ensures proper utilization of provided resources (Akter et al. 2020a, b) and have an impact on the sustainable organizational performance (Zhang et al. 2020). In addition, clearly *defined and communicated responsibilities* and roles should enable smooth monitoring and facilitate any corrective actions (Kim et al. 2012; Wamba et al. 2017).

Management capabilities are specific skills that can be assigned to a single person or role and are developed over time. As many stakeholders are involved, managing BDA projects demands a variety of different skills from executives. The required skills include the ability to coordinate and control resources, as well as the ability to lead and guide people. For many organizations, BDA is a relatively new topic, which makes the task of leading employees through the change with a clear strategic direction in mind a particularly important one. Management skills are a highly relevant building block for a successful BDA project.

4.3 Organizational capability

Structural adaptations, strict alignment of all organizational divisions, and smooth processes are highly important for a successful analytical transformation and long-term application of BDA (Mikalef et al. 2020a, b). Establishing such organizational capabilities does not occur overnight. Structures, responsibilities, and processes develop and grow as organizational needs emerge. Agility and flexibility must always be guaranteed in order to react dynamically and ensure the long-term strategic competitive advantage of an organization (Rialti et al. 2019). Organizational Capability refers to the ability of an organization to establish *organizational structures and processes* as well as to define *roles and responsibilities* that consider strategic goals and corporate culture.

Organizational structures and processes are comprised of three major aspects a firm needs to be capable of implementing: a *consistent flow of information*, highly *flexible organizational structures*, and strong *organizational learning* ability. Frequent communication and exchange of information is a key component for successful BDA application (Kiron et al. 2014). It is highly important to define efficient modes of communication among the involved workforce (McLaughlin 2017) in order to ensure a consistent flow of information (Ferraris et al. 2019) and to avoid the creation of knowledge silos in business units (Kiron et al. 2014). BDA thrives on data and information; therefore, the more high-quality information is fed into the respective analytical models, the more accurate decision proposals can be formulated. To be successful in this regard, the organization is required to be highly flexible and able to adapt to changing markets and turbulent environments (Lin and Kunnathur 2019). Agility within the firm's structure and processes helps to reallocate internal and external resources (Vidgen et al. 2017), enhances firm performance, and aids its operation under volatile market conditions (Dubey et al. 2017). This constant adaptation also requires a certain learning ability of the organization. According to Gupta and George, "data does not tell the whole story; it is always the theory that explains" (2016, p. 16). Organizations are obliged to ensure constant development based on continual knowledge enhancement in relevant internal and

external business actions, as well as theoretical knowledge (Dubey et al. 2017). The decisive factor in this context is the ongoing alignment of existing expertise (exploitation) and new knowledge (exploration) (Bhatt and Grover 2005).

The roles and responsibilities theme refers to the *clear allocation of functions to positions* in the organizational framework and the in-depth *training of analytics staff* and the related workforce. Firstly, an important step closely connected to the structural context is the identification of key stakeholders and decision-makers in information technology (IT) and business functions, as this facilitates communication across BDA projects. Furthermore, it is important to clarify responsibilities with regard to data ownership, analysis, and cost management (Mikalef et al. 2019a). Installing steering committees that assess the value and cost of data (Mikalef et al. 2019a) is a useful step to make sure that the project proceeds in line with the strategic organizational focus (Ashrafi et al. 2019). Secondly, an in-depth understanding of BDA has to be obtained by the firm, either by hiring well-trained staff or by providing in-depth analytical training to their employees (Dubey et al. 2018). Utilizing collaboration with universities in order to leverage student and academic staff resources (Vidgen et al. 2017) is also a possible option. When it comes to firm employees, evaluating the need for training and development is recommended (Jha et al. 2020), along with an assessment of the expected impact of corresponding actions taken throughout the BDA project (McLaughlin 2017).

A well-designed organizational structure in which roles and responsibilities are allocated appropriately and processes are clearly defined helps employees to implement cultural and strategic objectives in line with the organization's intentions. Organizational capabilities form a structural framework, which connects the personal abilities and skills of individual employees and managers with organizational structures and processes.

4.4 Culture and governance capability

All employees, regardless of their position, act according to their own values and moral concepts, norms, and unwritten external expectations. These implicit rail guards form the cultural guidelines for all corporate activities (Shamim et al. 2020). Many companies struggle with the successful application of BDA “because of a mismatch between the organization's existing culture and capabilities and the emerging tactics to exploit analytics successfully” (Barton and Court 2012, p. 82). It is becoming increasingly evident that regulatory systems constitute fundamental guidelines for an organization's strategic direction and employees' values, orientation, and norms (Kiron et al. 2014; Mikalef et al. 2018a, b; Vidgen et al. 2017). These policies and standards are summarized within the organization's governance. Culture and Governance Capability subsumes the organizational abilities to formulate the *culture, morals, and values* related to all BDA entities involving *governance and standards* and policies to enable effective handling of BDA.

Corporate culture in the context of BDA is comprised of the firm's *atmosphere and climate, top management commitment, and willingness to change*. Values, norms, tacit behaviors, and artifacts have to be derived from the corporate strategy,

vision, and mission so that they effectively and implicitly influence the actions of employees and create an atmosphere trusting of data (Olszak 2014). A data-driven work atmosphere is enhanced by the willingness of executives to actually follow data-driven decision templates rather than their instincts (Dubey et al. 2018; Kiron et al. 2014; Pedro et al. 2019) and to revise prior decisions if data analysis overrides them (Mikalef, Boura, et al., 2018). Moreover, a strong commitment to data-driven decision-making by upper management characterizes a data-driven culture (Chen et al. 2015; Gong and Janssen 2020). Top-level support of initiatives and analytical activities within the company strengthens the acceptance among and involvement of employees (Cao et al. 2019; Chen et al. 2015). Persuasive executives who consider data an asset (Dubey et al. 2018) and see the integration of BDA into the overall corporate strategy as imperative have a positive impact on successful BDA implementation (Kiron et al. 2014). If the upper managerial buy-in is lacking, analytical methods may become a political issue and, consequently, BDA projects will not take off (Arunachalam et al. 2018). Finally, organizational willingness to change is a critical aspect of corporate culture, as an ambiguous environment requires firms to continuously improve analytical processes and methods (Ngo et al. 2020) and break down existing organizational and mental barriers (Bharadwaj 2000). For firms to thrive, best practice approaches across organizational units must support a flexible and agile mindset among employees (Olszak 2014; Popovič et al. 2018). Key element here, is to understand that data is a highly valuable resource and information is a substantial component (Galbraith 2014).

Contract governance, information governance, and internal policies are needed to set regulatory guidelines for all the above-mentioned aspects of BDA. First, stakeholder management and dedicated communication are essential when it comes to the sourcing and deployment of external data (McLaughlin 2017). Therefore, contractual governance is important to ensure a steady stream of highly relevant, top-quality data (Shamim et al. 2020). Agreements and contracts with Big Data providers have to define clear responsibilities and procedures to ensure this high quality (Janssen et al. 2017). Second, information governance regulates the handling of any type of information and enhances the relevant capabilities of organizations with regard to “the creation, capture, valuation, storage, usage, control, access, archival, and the deletion of information and related resources over its life cycle” (Mikalef et al. 2020a, b, p. 3). Third, internal policies (Bhatt and Grover 2005), ethics (Ngo et al. 2020), processes, and frameworks (Munodawafa and Johl 2019), as well as internal communication and knowledge exchange (Shabbir and Gardezi 2020), are deciding relational governance factors in building trust among organizational entities (Janssen et al. 2017).

BDA requires an organization to undergo transformational changes in many areas. Values, norms, and organizational culture are deeply affected by this turnaround. Especially with regard to data exploitation, established systems of values and standards must be altered (Zuboff 2015). Having clear governance and organizational standards in place facilitates the successful management of this cultural shift.

4.5 Strategy and planning capability

The transformation required to become a data-driven company is a multi-layered and complex project, which must be guided appropriately by the management (Mikalef et al. 2018a, b). Hence, the strategy and planning behind such an undertaking are of great importance. Many executives perceive the formulation of a distinct BDA strategy as the pivotal point in this transformational journey (Vidgen et al. 2017). Strategy & Planning defines a company's ability to adapt its general strategic orientation in response to external and internal developments and to align its corporate resources and capacities with the overall management *strategy* regarding *risk management* and data policies. *Planning and investment* decisions require that several entities work together to achieve greater performance while operating in line with their individual visions, missions, cultures, and governance. Therefore, we separate this capability from the skills and abilities of individuals.

Formulating a distinct strategy, aligning actions, and allocating resources accordingly facilitates the successful management of an analytics project (Davenport et al. 2001). These measures have to be in line with the overall vision and the IT-specific vision of the organization (Coleman et al. 2016; McLaughlin 2017). The ability to integrate BDA projects into the overall corporate context in close alignment with the firm's strategy encourages employees to actually make use of innovative opportunities (Ferraris et al. 2019; Lin and Kunnathur 2019). Another highly relevant aspect of BDA strategy is knowledge of any competitor's strategic actions (Elbashir et al. 2013) and the firm's competitiveness in this context (Munodawafa and Johl 2019). This knowledge permits the firm to act promptly in response to changes.

Risk management strategies involving *privacy and data policies* as well as *stakeholder management* are increasingly relevant to BDA. The application of analytical methods always comes with certain security concerns and the need for data protection (Aker et al. 2020a, b). Since BDA deploys both internal and external data, organizations must also comply with any general legal conditions. Internal policies like user authorizations and access restrictions and external terms such as third-party or non-disclosure agreements have to be considered (Pedro et al. 2019). Apart from that, dealing with different stakeholders—either internal data analysts or external organizations who deliver or buy data—poses risks that must be managed appropriately. Communication and training as well as clearly defined risk profiles and constant monitoring support employees in the appropriate handling of data, keeping the risk to the organization to a minimum while simultaneously reaping the benefits of BDA (Obitade 2019).

BDA projects require appropriate planning and thoughtful investments. Investment decisions must be made based on a structured decision-making process (Kim et al. 2012). Several factors must be taken into account, such as the effects on employees, enhancements of end-users' decision-making abilities, and the cost of effort for end-user training (Aker et al. 2020a, b). Appropriate timing, strategy,

and *investment knowledge* are fundamental to ensuring the conversion of IT investments into business value (Elbashir et al. 2013; Mandal 2019). BDA projects have to reach a certain level of maturity in order to achieve their full potential and justify the investment (Mikalef et al. 2019b). Another major precondition for successful BDA implementation is having pre-defined *planning standards and processes* with appropriate organizational planning structures (Akter, et al. 2020a, b; Ferraris et al. 2019). These actions integrate organizational principles, the company vision, and strategic orientation to achieve sustainable success (McLaughlin 2017). Firms are ideally agile enough to quickly react to changing environmental conditions with the reallocation of invested resources while minimizing negative external effects (Munodawafa and Johl 2019; Wamba et al. 2017).

Throughout the process of implementing BDA, multiple new factors will influence the organization. Careful development of an adapted strategy that considers market expertise and the firm's competitive environment helps organizations master the task of successful BDA implementation. Furthermore, navigating through such a great challenge requires detailed planning and careful consideration of investment decisions. In this context, risk management becomes very important: Policies and legal regulations constitute critical rail guards during the transformative process of becoming a data-driven company.

5 Conclusion, limitations, and directions for future research

5.1 Conclusion

By reviewing the most influential publications, we were able to classify all relevant aspects of human-related BDA capabilities. Starting from a base of 748 identified aspects, we inductively identified 33 first-order concepts, which were subsequently aggregated into 15 unique human-related second-order themes. These categories, such as Technical Skills, Leadership, Roles & Responsibilities, Governance & Standards or Planning & Investment to mention some examples, formed the basis for our five key capabilities: Personnel Capability, Management Capability, Organizational Capability, Culture & Governance Capability, and Strategy & Planning Capability.

Summarizing our research results, it can be concluded that the successful application of BDA in organizations poses great challenges, which must be addressed above all by management and decision-makers. Due to the rapid developments in the field of BDA, especially on the technological level, human-related capabilities have to evolve accordingly in order to meet the demands of the market. Given the dynamic nature of the phenomenon, the roles of employees in companies will change, and so will their respective areas of activity (Richins et al. 2017). There is likewise a risk that these transformational changes will affect human-related capabilities needed in the context of BDA (Angrave et al. 2016). However, academic discussions on this

development help to gain a clearer understanding of the topic and to provide support for executives, entrepreneurs, as well as employees to accept these new situations and to react accordingly. With our taxonomy we want to help giving this highly dynamic phenomenon a tangible form for academics, and practitioners, to provide guidance for navigating through further developments in the field of applied BDA.

With this taxonomy, we make a compelling contribution for researchers and scholars. The study outcome reflects the latest state of the literature and provides an in-depth analysis of the fundamental aspects of BDA implementation, which until now have been mostly discussed superficially, if at all. Our taxonomy sheds light on important factors that influence the successful application of BDA in an organizational context. Our work was inspired by two well-established theories—RBV and Dynamic Capabilities—that emphasize the important role own organizational (human) resources play in the creation of a competitive advantage (Barney 1991). The ability to reconfigure, adapt and expand organizational capabilities enables organizations to deploy and protect their intangible assets to remain competitive (Teece 2007). The fast emergence of BDA in the organizational context is a considerable change that organizations have to respond to by mobilizing their human resources. Hence, the two theories provide strong support for the human-capabilities framework we have developed. Our five-dimensional taxonomy claims that several human resource related challenges are associated with the organizational usage of BDA. It is supposed to serve as basic tool for both researchers and practitioners to make use of and build on, once the use of BDA becomes more widespread. The taxonomy is highly flexible, easy to understand, and can be adapted and updated easily, therefore providing an ideal basis for further research in this emerging field. We presented the taxonomy as useful in the context of BDA projects; however, it is applicable to various other data-related research activities. The developed framework exploits state-of-the-art literature as we not only incorporate high-quality, peer-reviewed publications, but also cite carefully selected recently published studies in non-ranked journals, as BDA is still a relatively new topic within academia. By building on this fundamental knowledge base of published manuscripts and most-recent articles from various conferences, our paper helps to gain a deeper understanding of HR practices within the context of Big Data Analytics. Although other scientific classifications exist, to our knowledge our work provides the only holistic taxonomy in the context of human-related BDA capabilities and therefore provides a significant and valuable contribution to research.

As BDA is a tremendously important emerging area in business, our publication also poses a valuable contribution for practitioners. The defined five capabilities function as a structuring agent for all those who plan to implement BDA in their organizations or those who already use analytical methods and want to expand their basic knowledge. Organizations operate in a turbulent, dynamic environment with a variety of data, uncertain external conditions, and ever-changing consumer behaviors. Our taxonomy encapsulates this volatile, dynamic

environment in a systematized, fixed framework that still offers the necessary flexibility. The 15 s-order themes comprise all relevant human-related aspects of BDA, without overlap, though great attention is paid to emphasizing the correlations and entanglements between the different aspects. Along with the RBV and Dynamic Capabilities theory, the provided categorization gives practitioners a valuable, applicable structure to conduct a comprehensive assessment of the status quo of their own organization. As this work provides the details needed to drill down the five different dimensions to 15 s-order themes, a detailed analysis of the company's capabilities is possible. In order to successfully apply BDA within an organization, managers and decision makers have to understand the competitive advantage they can gain when they consider all relevant aspects proposed in the framework. This work contributes to theory and practice alike, to expand the knowledge base and facilitate the successful utilization of BDA.

5.2 Limitations and future research directions

Despite having carefully planned and executed our search strategy, there always remains the risk of unintentionally neglecting a source. Nonetheless, given the precautionary measures that have been taken, such as the inclusion of all well-accepted databases, the development of a research protocol, the careful planning of the search string (Kraus et al. 2020), and including latest and most relevant not-peer reviewed literature, we are confident that our sample of literature is comprehensive. Any reduction in sample size was driven solely by our strict quality criteria described and documented in the research protocol. A further potential limitation might be the bias of the researchers themselves, as it is possible that a different research team would have arrived at a different taxonomy. However, as we have followed both a systematic literature review methodology (Tranfield et al. 2003) and a well-accepted inductive approach for assessing and structuring the obtained information (Gioia et al. 2012), we have exerted considerable mitigative efforts to avoid any bias through the application of scientific rigor. A last limiting factor is that our study was carried out without a focus on any specific industry. As a result, the developed taxonomy is intended for general use across industries, which we consider a valuable contribution. However, one might argue that certain industries require an individual framework created under consideration of industry specifications. Doing so may result in a taxonomy with a focus on different capabilities. Nevertheless, we acted according to our ambition, which was to create a scheme applicable across industries and company sizes. Given the fact that the majority of papers included in our sample conducted their research across various industries and company sizes, we conclude that our five-dimensional taxonomy meets the prerequisites for a holistic and overarching structure. However, determining if the presented taxonomy is valid for various analytical fields—not only for BDA is a potential new field of research. Hence, one avenue for further research could be to test the taxonomy within one or several cases and fields of application to test the validity of the model, as well as the

composition of the various first-order concepts and aggregated second order themes. Here various empirical approaches for the data collection should be applied—e.g. interviews, surveys, observations or a case study methodology. Moreover, we certainly recommend using both qualitative and quantitative methods to evaluate which BDA capabilities are most decisive for companies in various industries. Especially start-up companies or very small organizations may differ in regard to the capabilities they need to apply BDA successfully. This question is of great interest, as data analytics is becoming increasingly important for young and small firms. An avenue for further research could therefore be to elaborate on these capabilities to provide founders with a reliable basis. Furthermore, two topics require more scientific attention as they are not fully understood yet. The first focus area is leadership: While the role of leadership in BDA implementation has been widely covered in literature, there is currently no in-depth understanding of how leadership can ensure that analytical methods are continuously deployed on a long-term basis. Second, up to now no comprehensive framework for BDA governance, which would be of particular relevance for globally operating firms with complex structures, has been developed. Considering the findings of this study and the abovementioned potential future research directions, it is clear that BDA necessitates a comprehensive management and cultural revolution for which organizations must be thoroughly prepared and may need guidance to successfully compete in a competitive market environment. Furthermore, the entanglement of all mentioned aspects in the taxonomy presents a challenge for all organizations as they have to keep an eye on every aspect to manage the change successfully.

Appendix

See Table 1.

Table 1 Reviewed manuscripts sorted by authors

#	Manuscript title	Authors	Citation
1	Reshaping competitive advantages with analytics capabilities in service systems	Akter, S., Gunasekaran, A., Wamba, S. F., Babu, M. M., & Hani, U	Akter et al. (2020a, b)
2	Building dynamic service analytics capabilities for the digital marketplace	Akter, S., Motamarri, S., Hani, U., Shams, R., Fernando, M., Mohiuddin Babu, M., & Ning Shen, K	Akter et al. (2020a, b)
3	How to improve firm performance using big data analytics capability and business strategy alignment?	Akter, S., Wamba, S. F., Gunasekaran, A., Dubey, R., & Childe, S. J	Akter et al. (2016)
4	Big data analytics and business failures in data-Rich environments: An organizing framework	Amankwah-Amoah, J., & Adomako, S	Amankwah-Amoah and Adomako (2019)

Table 1 (continued)

#	Manuscript title	Authors	Citation
5	IT assets, organizational capabilities, and firm performance: How resource allocations and organizational differences explain performance variation	Aral, S., & Weill, P	Aral and Weill (2007)
6	Understanding big data analytics capabilities in supply chain management: Unravelling the issues, challenges and implications for practice	Arunachalam, D., Kumar, N., & Kawalek, J. P	Arunachalam et al. (2018)
7	The role of business analytics capabilities in bolstering firms' agility and performance	Ashrafi, A., Zare Ravasan, A., Trkman, P., & Afshari, S	Ashrafi et al. (2019)
8	Making Advanced Analytics Work For You: A practical guide to capitalizing on big data	Barton, D., & Court, D	Barton and Court (2012)
9	A resource-based perspective on information technology capability and firm performance: An empirical investigation	Bharadwaj, A. S	Bharadwaj (2000)
10	Types of information technology capabilities and their role in competitive advantage: An empirical study	Bhatt, G. D., & Grover, V	Bhatt and Grover (2005)
11	A dynamic capability view of marketing analytics: Evidence from UK firms	Cao, G., Duan, Y., & El Banna, A	Cao et al. (2019)
12	Innovating through digital revolution: The role of soft skills and Big Data in increasing firm performance	Caputo, F., Cillo, V., Candelò, E., & Liu, Y	Caputo et al. (2019)
13	Business analytics for supply chain: A dynamic-capabilities framework	Chae, B. K., & Olson, D. L	Chae and Olson (2013)
14	Important Skills for Data Scientists in China: Two Delphi Studies	Chen, C., & Jiang, H	Chen and Jiang (2020)
15	How the use of big data analytics affects value creation in supply chain management	Chen, D. Q., Preston, D. S., & Swink, M	Chen et al. (2015)
16	Business intelligence and analytics: From big data to big impact	Chen, H., Chiang, R. H. L., & Storey, V. C	Chen et al. (2012)
17	Exploring the impact of big data analytics capabilities on business model innovation: The mediating role of entrepreneurial orientation	Ciampi, F., Demi, S., Magrini, A., Marzi, G., & Papa, A	Ciampi et al. (2021)
18	How Can SMEs Benefit from Big Data? Challenges and a Path Forward	Coleman, S., Göb, R., Manco, G., Pievatolo, A., Tort-Martorell, X., & Reis, M. S	Coleman et al. (2016)
19	Assessing business value of Big Data Analytics in European firms	Côrte-Real, N., Oliveira, T., & Ruivo, P	Côrte-Real et al. (2017)
20	Organizational information systems competences in small and medium-sized enterprises	Cragg, P., Caldeira, M., & Ward, J	Cragg et al. (2011)
21	Data to knowledge to results: Building an analytic capability	Davenport, T. H., Harris, J. G., De Long, D. W., & Jacobson, A. L	Davenport et al. (2001)

Table 1 (continued)

#	Manuscript title	Authors	Citation
22	Human resources for Big Data professions: A systematic classification of job roles and required skill sets	De Mauro, A., Greco, M., Grimaldi, M., & Ritala, P	De Mauro et al. (2018)
23	Examining the role of big data and predictive analytics on collaborative performance in context to sustainable consumption and production behaviour	Dubey, R., Gunasekaran, A., Childe, S. J., Luo, Z., Wamba, S. F., Roubaud, D., & Foropon, C	Dubey et al. (2018)
24	Can big data and predictive analytics improve social and environmental sustainability?	Dubey, R., Gunasekaran, A., Childe, S. J., Papadopoulos, T., Luo, Z., Wamba, S. F., & Roubaud, D	Dubey et al. (2017)
25	Enhancing the business value of business intelligence: The role of shared knowledge and assimilation	Elbashir, M. Z., Collier, P. A., Sutton, S. G., Davern, M. J., & Leech, S. A	Elbashir et al. (2013)
26	Big Data consumer analytics and the transformation of marketing	Erevelles, S., Fukawa, N., & Swayne, L	Erevelles et al. (2016)
27	Big data analytics capabilities and knowledge management: impact on firm performance	Ferraris, A., Mazzoleni, A., Devalle, A., & Couturier, J	Ferraris et al. (2019)
28	Organizational Design Challenges Resulting From Big Data	Galbraith, J. R	Galbraith (2014)
29	Roles and capabilities of enterprise architecture in big data analytics technology adoption and implementation	Gong, Y., & Janssen, M	Gong and Janssen (2020)
30	Toward the development of a big data analytics capability	Gupta, M., & George, J. F	Gupta and George (2016)
31	Achieving superior organizational performance via big data predictive analytics: A dynamic capability view	Gupta, S., Drave, V. A., Dwivedi, Y. K., Baabdullah, A. M., & Ismagilova, E	Gupta et al. (2019)
32	Big Data, Big Data Analytics Capability, and Sustainable Innovation Performance	Hao, S., Zhang, H., & Song, M	Hao et al. (2019)
33	Towards a maturity model for big data analytics in airline network planning	Hausladen, I., & Schosser, M	Hausladen and Schosser (2020)
34	Factors influencing big data decision-making quality	Janssen, M., van der Voort, H., Wahyudi, A	Janssen et al. (2017)
35	A note on big data analytics capability development in supply chain	Jha, A. K., Agi, M. A. N., & Ngai, E. W. T	Jha et al. (2020)
36	Investigating the value of sociomaterialism in conceptualizing it capability of a firm	Kim, G., Shin, B., & Kwon, O	Kim et al. (2012)
37	The Analytics Mandate	Kiron, D., Prentice, P. K., & Ferguson, R. B	Kiron et al. (2014)
38	Managing Big data for firm performance: A configurational approach	Kung, L., Kung, H. J., Jones-Farmer, A., & Wang, Y	Kung et al. (2015)

Table 1 (continued)

#	Manuscript title	Authors	Citation
39	Analysis of requirements for Big Data Adoption to maximize IT Business Value	Lamba, H. S., & Dubey, S. K	Lamba and Dubey (2015)
40	Strategic orientations, developmental culture, and big data capabili	Lin, C., & Kunnathur, A	Lin and Kunnathur (2019)
41	Exploring the influence of big data analytics management capabilities on sustainable tourism supply chain performance: the moderating role of technology orientation	Mandal, S	Mandal (2018)
42	The influence of big data analytics management capabilities on supply chain preparedness, alertness and agility: An empirical investigation	Mandal, S	Mandal (2019)
43	Big data: The management revolution	McAfee, A., & Brynjolfs-son, E	McAfee and Brynjolfs-son (2012)
44	Dynamic capabilities: taking an emerging technology perspective	McLaughlin, S. A	McLaughlin (2017)
45	Big Data Analytics Capabilities and Innovation: The Mediating Role of Dynamic Capabilities and Moderating Effect of the Environment	Mikalef, P., Boura, M., Lekakos, G., & Krogstie, J	Mikalef et al. (2019a)
46	Big data analytics and firm performance: Findings from a mixed-method approach	Mikalef, P., Boura, M., Lekakos, G., & Krogstie, J	Mikalef et al. (2019b)
47	The role of information governance in big data analytics driven innovation	Mikalef, P., Boura, M., Lekakos, G., & Krogstie, J	Mikalef et al. (2020a, b)
48	Complementarities between information governance and big data analytics capabilities on innovation	Mikalef, P., Boura, M., Lekakos, G., & Krogstie, J	Mikalef and Boura et al. (2018a, b)
49	Exploring the relationship between big data analytics capability and competitive performance: The mediating roles of dynamic and operational capabilities	Mikalef, P., Krogstie, J., Pappas, I. O., & Pavlou, P	Mikalef et al. (2020a, b)
50	Organizational capabilities that enable big data and predictive analytics diffusion and organizational performance: A resource-based perspective	Mishra, D., Luo, Z., Hazen, B., Hassini, E., & Foropon, C	Mishra et al. (2019)
51	Big data analytics capabilities and eco-innovation: A study of energy companies	Munodawafa, R. T., & Johl, S. K	Munodawafa and Johl (2019)
52	Factor-based big data and predictive analytics capability assessment tool for the construction industry	Ngo, J., Hwang, B. G., & Zhang, C	Ngo et al. (2020)
53	Big data analytics: a link between knowledge management capabilities and superior cyber protection	Obitade, P. O	Obitade (2019)

Table 1 (continued)

#	Manuscript title	Authors	Citation
54	Towards an understanding business intelligence. A dynamic capability-based framework for Business Intelligence	Olszak, C. M	Olszak (2014)
55	Capabilities and Readiness for Big Data Analytics	Pedro, J., Brown, I., & Hart, M	Pedro et al. (2019)
56	The impact of big data analytics on firms' high value business performance	Popovič, A., Hackney, R., Tassabehji, R., & Castelli, M	Popovič et al. (2018)
57	Minding the analytics gap	Ransbotham, S., Kiron, D., & Prentice, P. K	Ransbotham et al. (2015)
58	Big data analytics capabilities and performance: Evidence from a moderated multi-mediation model	Rialti, R., Zollo, L., Ferraris, A., & Alon, I	Rialti et al. (2019)
59	A survey towards an integration of big data analytics to big insights for value-creation	Saggi, M. K., & Jain, S	Saggi and Jain (2018)
60	Application of big data analytics and organizational performance: the mediating role of knowledge management practices	Shabbir, M. Q., & Gardezi, S. B. W	Shabbir and Gardezi (2020)
61	Big Data in Organizations and the Role of Human Resource Management	Scholz, T. M	Scholz (2017)
62	Big data analytics capability and decision making performance in emerging market firms: The role of contractual and relational governance mechanisms	Shamim, S., Zeng, J., Khan, Z., & Zia, N. U	Shamim et al. (2020)
63	Connecting big data management capabilities with employee ambidexterity in Chinese multinational enterprises through the mediation of big data value creation at the employee level	Shamim, S., Zeng, J., Shafi Choksy, U., & Shariq, S. M	Shamim et al. (2019)
64	Impact of big data analytics capabilities on supply chain sustainability	Shokouhyar, S., Seddigh, M. R., & Panahifar, F	Shokouhyar et al. (2020)
65	Towards a conceptualization of data analytics capabilities	Shuradze, G., & Wagner, H. T	Shuradze and Wagner (2016)
66	Creating sustainable innovativeness through big data and big data analytics capability: From the perspective of the information processing theory	Song, M., Zhang, H., & Heng, J	Song et al. (2020)
67	Big data and firm performance: The roles of market-directed capabilities and business strategy	Suoniemi, S., Meyer-Waarden, L., Munzel, A., Zablah, A. R., & Straub, D	Suoniemi et al. (2020)
68	The intermediating role of organizational culture and internal analytical knowledge between the capability of big data analytics and a firm's performance	Upadhyay, P., & Kumar, A	Upadhyay and Kumar (2020)

Table 1 (continued)

#	Manuscript title	Authors	Citation
69	Management challenges in creating value from business analytics	Vidgen, R., Shaw, S., & Grant, D. B	Vidgen et al. (2017)
70	Big data analytics and firm performance: Effects of dynamic capabilities	Wamba, F. S., Gunasekaran, A., Akter, S., Ren, S. J. fan, Dubey, R., & Childe, S. J	Wamba et al. (2017)
71	Exploring the path to big data analytics success in healthcare	Wang, Y., & Hajli, N	Wang and Hajli (2017)
72	Big data analytics: Understanding its capabilities and potential benefits for healthcare organizations	Wang, Y., Kung, L. A., & Byrd, T. A	Wang et al. (2018a, b)
73	An integrated big data analytics-enabled transformation model: Application to health care	Wang, Y., Kung, L. A., Wang, W. Y. C., & Cegielski, C. G	Wang, et al. (2018a, b)
74	Big data analytics capabilities and firm performance: An integrated MCDM approach	Yasmin, M., Tatoglu, E., Kilic, H. S., Zaim, S., & Delen, D	Yasmin et al. (2020)
75	Achieving the success of sustainability development projects through big data analytics and artificial intelligence capability	Zhang, H., Song, M., & He, H	Zhang et al. (2020)

Author contributions PK is the corresponding author who conducted the structured review and wrote the manuscript. DK supervised the review process, provided methodological guidance, and revised the manuscript.

Funding Open Access funding enabled and organized by Projekt DEAL. None.

Declarations

Conflict of interest The authors have no conflicts of interest to declare.

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References

Akter S, Wamba SF, Gunasekaran A, Dubey R, Childe SJ (2016) How to improve firm performance using big data analytics capability and business strategy alignment? *Int J Prod Econ* 182:113–131. <https://doi.org/10.1016/j.ijpe.2016.08.018>

- Akter S, Gunasekaran A, Wamba SF, Babu MM, Hani U (2020a) Reshaping competitive advantages with analytics capabilities in service systems. *Technol Forecast Soc Chang* 159(June):120180. <https://doi.org/10.1016/j.techfore.2020.120180>
- Akter S, Motamarri S, Hani U, Shams R, Fernando M, Mohiuddin Babu M, Ning Shen K (2020b) Building dynamic service analytics capabilities for the digital marketplace. *J Bus Res* 118:177–188. <https://doi.org/10.1016/j.jbusres.2020.06.016>
- Amankwah-Amoah J, Adomako S (2019) Big data analytics and business failures in data-Rich environments: An organizing framework. *Comput Ind* 105:204–212. <https://doi.org/10.1016/j.compind.2018.12.015>
- Amit R, Schoemaker PJH (1993) Strategic assets and organizational rent. *Strateg Manag J* 14(1):33–46. <https://doi.org/10.1002/smj.4250140105>
- Angrave D, Charwood A, Kirkpatrick I, Lawrence M, Stuart M (2016) HR and analytics: why HR is set to fail the big data challenge. *Hum Resour Manag J* 26(1):1–11. <https://doi.org/10.1111/1748-8583.12090>
- Aral S, Weill P (2007) IT assets, organizational capabilities, and firm performance: how resource allocations and organizational differences explain performance variation. *Organ Sci* 18(5):763–780. <https://doi.org/10.1287/orsc.1070.0306>
- Arunachalam D, Kumar N, Kawalek JP (2018) Understanding big data analytics capabilities in supply chain management: Unravelling the issues, challenges and implications for practice. *Transp Res Part e Logistics Transp Rev* 114:416–436. <https://doi.org/10.1016/j.tre.2017.04.001>
- Ashrafi A, Zare Ravasan A, Trkman P, Afshari S (2019) The role of business analytics capabilities in bolstering firms' agility and performance. *Int J Inf Manag* 47:1–15. <https://doi.org/10.1016/j.ijinfomgt.2018.12.005>
- Barney J (1991) Firm resources and sustained competitive advantage. *J Manag* 17(1):99–120. <https://doi.org/10.1177/014920639101700108>
- Barney JB (2001) Resource-based theories of competitive advantage: a ten-year retrospective on the resource-based view. *J Manag* 27(6):643–650. [https://doi.org/10.1016/S0149-2063\(01\)00115-5](https://doi.org/10.1016/S0149-2063(01)00115-5)
- Barton D, Court D (2012) Making advanced analytics work for you: a practical guide to capitalizing on big data. *Harvard Bus Rev* 90(10):78–83
- Bharadwaj AS (2000) A resource-based perspective on information technology capability and firm performance: An empirical investigation. *MIS Quarter Manag Inf Syst* 24(1):169–193. <https://doi.org/10.2307/3250983>
- Bhatt GD, Grover V (2005) Types of information technology capabilities and their role in competitive advantage: An empirical study. *J Manag Inf Syst* 22(2):253–277. <https://doi.org/10.1080/07421222.2005.11045844>
- Cao G, Duan Y, El Banna A (2019) A dynamic capability view of marketing analytics: evidence from UK firms. *Ind Mark Manag* 76:72–83. <https://doi.org/10.1016/j.indmarman.2018.08.002>
- Caputo F, Cillo V, Candelò E, Liu Y (2019) Innovating through digital revolution: the role of soft skills and Big Data in increasing firm performance. *Manag Decis* 57(8):2032–2051. <https://doi.org/10.1108/MD-07-2018-0833>
- Chae BK, Olson DL (2013) Business analytics for supply chain: a dynamic-capabilities framework. *Int J Inf Technol Decis Mak* 12(1):9–26. <https://doi.org/10.1142/S02196222013500016>
- Chen C, Jiang H (2020) Important skills for data scientists in china: two Delphi studies. *J Comput Inf Syst* 60(3):287–296. <https://doi.org/10.1080/08874417.2018.1472047>
- Chen H, Chiang RHL, Storey VC (2012) Business intelligence and analytics: from big data to big impact. *MIS Quarter Manag Inf Syst* 36(4):1165–1188. <https://doi.org/10.2307/41703503>
- Chen DQ, Preston DS, Swink M (2015) How the use of big data analytics affects value creation in supply chain management. *J Manag Inf Syst* 32(4):4–39. <https://doi.org/10.1080/07421222.2015.1138364>
- Ciampi F, Demi S, Magrini A, Marzi G, Papa A (2021) Exploring the impact of big data analytics capabilities on business model innovation: the mediating role of entrepreneurial orientation. *J Bus Res* 123:1–13. <https://doi.org/10.1016/j.jbusres.2020.09.023>
- Coleman S, Göb R, Manco G, Pievatolo A, Tort-Martorell X, Reis MS (2016) How can SMEs benefit from big data? Challenges and a path forward. *Qual Reliab Eng Int* 32(6):2151–2164. <https://doi.org/10.1002/qre.2008>
- Côrte-Real N, Oliveira T, Ruivo P (2017) Assessing business value of big data analytics in European firms. *J Bus Res* 70:379–390. <https://doi.org/10.1016/j.jbusres.2016.08.011>
- Cox M, Ellsworth D (1997) Application-controlled demand paging for out-of-core visualization. *Proc IEEE Vis Conf*. <https://doi.org/10.1109/visual.1997.663888>

- Cragg P, Caldeira M, Ward J (2011) Organizational information systems competences in small and medium-sized enterprises. *Inf Manag* 48(8):353–363. <https://doi.org/10.1016/j.im.2011.08.003>
- Davenport TH, Harris JG, De Long DW, Jacobson AL (2001) Data to knowledge to results: Building an analytic capability. *Calif Manag Rev* 2:117–138. <https://doi.org/10.2307/41166078>
- De Mauro A, Greco M, Grimaldi M, Ritala P (2018) Human resources for Big Data professions: a systematic classification of job roles and required skill sets. *Inf Process Manag* 54(5):807–817. <https://doi.org/10.1016/j.ipm.2017.05.004>
- Denyer D, Tranfield D (2006) Using qualitative research synthesis to build an actionable knowledge base. *Manag Decis* 44(2):213–227. <https://doi.org/10.1108/00251740610650201>
- Dubey R, Gunasekaran A, Childe SJ, Papadopoulos T, Luo Z, Wamba SF, Roubaud D (2017) Can big data and predictive analytics improve social and environmental sustainability? *Technol Forecast Soc Chang* 144:534–545. <https://doi.org/10.1016/j.techfore.2017.06.020>
- Dubey R, Gunasekaran A, Childe SJ, Luo Z, Wamba SF, Roubaud D, Foropon C (2018) Examining the role of big data and predictive analytics on collaborative performance in context to sustainable consumption and production behaviour. *J Clean Prod* 196:1508–1521. <https://doi.org/10.1016/j.jclepro.2018.06.097>
- Einav L, Levin J (2014) Economics in the age of big data. *Science*. <https://doi.org/10.1126/science.1243089>
- Eisenhardt KM, Martin JA (2000) Dynamic capabilities: What are they? *Strateg Manag J* 21(10–11):1105–1121
- Elbashir MZ, Collier PA, Sutton SG, Davern MJ, Leech SA (2013) Enhancing the business value of business intelligence: The role of shared knowledge and assimilation. *J Inf Syst* 27(2):87–105. <https://doi.org/10.2308/isyss-50563>
- Erevelles S, Fukawa N, Swayne L (2016) Big Data consumer analytics and the transformation of marketing. *J Bus Res* 69(2):897–904. <https://doi.org/10.1016/j.jbusres.2015.07.001>
- Ferraris A, Mazzoleni A, Devalle A, Couturier J (2019) Big data analytics capabilities and knowledge management: impact on firm performance. *Manag Decis* 57(8):1923–1936. <https://doi.org/10.1108/MD-07-2018-0825>
- Fosso Wamba S, Gunasekaran A, Akter S, Ren SJF, Dubey R, Childe SJ (2019) Big data analytics and firm performance: effects of dynamic capabilities. *J Bus Res* 57(1):356–365. <https://doi.org/10.1016/j.jbusres.2016.08.009>
- Galbraith JR (2014) Organizational design challenges resulting from big data. *J Organ Des* 3(1):2. <https://doi.org/10.7146/jod.8856>
- Gioia DA, Corley KG, Hamilton AL (2012) Seeking qualitative rigor in inductive research: notes on the gioia methodology. *Organ Res Methods* 16(1):15–31. <https://doi.org/10.1177/1094428112452151>
- Gong Y, Janssen M (2020) Roles and capabilities of enterprise architecture in big data analytics technology adoption and implementation. *J Theor Appl Electron Commer Res* 16(1):37–51. <https://doi.org/10.4067/S0718-18762021000100104>
- Grant RM (1991) The resource-based theory of competitive advantage: implications for strategy formulation. *Calif Manag Rev* 33(3):114–135. <https://doi.org/10.2307/41166664>
- Gupta M, George JF (2016) Toward the development of a big data analytics capability. *Inf Manag* 53(8):1049–1064. <https://doi.org/10.1016/j.im.2016.07.004>
- Gupta S, Drave VA, Dwivedi YK, Baabdullah AM, Ismagilova E (2019) Achieving superior organizational performance via big data predictive analytics: a dynamic capability view. *Ind Mark Manag*. <https://doi.org/10.1016/j.indmarman.2019.11.009>
- Hao S, Zhang H, Song M (2019) Big data, big data analytics capability, and sustainable innovation performance. *Sustainability* 11(24):1–15. <https://doi.org/10.3390/su11247145>
- Hausladen I, Schosser M (2020) Towards a maturity model for big data analytics in airline network planning. *J Air Transp Manag* 82(November2018):101721. <https://doi.org/10.1016/j.jairtraman.2019.101721>
- Janssen M, van der Voort H, Wahyudi A (2017) Factors influencing big data decision-making quality. *J Bus Res* 70:338–345. <https://doi.org/10.1016/j.jbusres.2016.08.007>
- Jha AK, Agi MAN, Ngai EWT (2020) A note on big data analytics capability development in supply chain. *Decision Support Syst*. <https://doi.org/10.1016/j.dss.2020.113382>
- Kim G, Shin B, Kwon O (2012) Investigating the value of sociomaterialism in conceptualizing it capability of a firm. *J Manag Inf Syst* 29(3):327–362. <https://doi.org/10.2753/MIS0742-122290310>

- Kiron D, Prentice PK, Ferguson RB (2014) The analytics mandate. *MIT Sloan Manag Rev* 55(4):1
- Kraus S, Breier M, Dasí-Rodríguez S (2020) The art of crafting a systematic literature review in entrepreneurship research. *Int Entrepreneurship Manag J* 16(3):1023–1042. <https://doi.org/10.1007/s11365-020-00635-4>
- Kung L, Kung HJ, Jones-Farmer A, Wang Y (2015) Managing big data for firm performance: a configurational approach. In: 2015 Americas conference on information systems, AMCIS 2015, 1–9
- Lamba, H. S., & Dubey, S. K. (2015). Analysis of requirements for Big Data Adoption to maximize IT Business Value. In: 2015 4th international conference on reliability, infocom technologies and optimization: trends and future directions, ICRITO 2015. <https://doi.org/10.1109/ICRITO.2015.7359268>
- Lin C, Kunnathur A (2019) Strategic orientations, developmental culture, and big data capability. *J Bus Res* 105:49–60. <https://doi.org/10.1016/j.jbusres.2019.07.016>
- Mandal S (2018) Exploring the influence of big data analytics management capabilities on sustainable tourism supply chain performance: the moderating role of technology orientation. *J Travel Tour Mark* 35(8):1104–1118. <https://doi.org/10.1080/10548408.2018.1476302>
- Mandal S (2019) The influence of big data analytics management capabilities on supply chain preparedness, alertness and agility: an empirical investigation. *Inf Technol People* 32(2):297–318. <https://doi.org/10.1108/IITP-11-2017-0386>
- McAfee A, Brynjolfsson E (2012) Big data: The management revolution. *Harv Bus Rev* 90(10):4
- McLaughlin SA (2017) Dynamic capabilities: taking an emerging technology perspective. *Int J Manuf Technol Manag* 31(1/2/3):62. <https://doi.org/10.1504/ijmtm.2017.10002924>
- Mikalef P, Pappas IO, Krogstie J, Giannakos M (2018b) Big data analytics capabilities: a systematic literature review and research agenda. *IseB* 16(3):547–578. <https://doi.org/10.1007/s10257-017-0362-y>
- Mikalef P, Boura M, Lekakos G, Krogstie J (2019a) Big data analytics capabilities and innovation: the mediating role of dynamic capabilities and moderating effect of the environment. *Br J Manag* 30(2):272–298. <https://doi.org/10.1111/1467-8551.12343>
- Mikalef P, Boura M, Lekakos G, Krogstie J (2019b) Big data analytics and firm performance: findings from a mixed-method approach. *J Bus Res* 98:261–276. <https://doi.org/10.1016/j.jbusres.2019.01.044>
- Mikalef P, Boura M, Lekakos G, Krogstie J (2020a) The role of information governance in big data analytics driven innovation. *Inf Manag* 57(7):103361. <https://doi.org/10.1016/j.im.2020.103361>
- Mikalef P, Krogstie J, Pappas IO, Pavlou P (2020b) Exploring the relationship between big data analytics capability and competitive performance: the mediating roles of dynamic and operational capabilities. *Inf Manag* 57(2):103169. <https://doi.org/10.1016/j.im.2019.05.004>
- Mikalef P, Boura M, Lekakos G, Krogstie J (2018) Complementarities between information governance and big data analytics capabilities on innovation. In: 26th European Conference on Information Systems: Beyond Digitization - Facets of Socio-Technical Change, ECIS 2018, June.
- Minciu M, Berar FA, Dobrea RC (2020) New decision systems in the VUCA world. *Manag Mark* 15(2):236–254. <https://doi.org/10.2478/mmcks-2020-0015>
- Mishra D, Luo Z, Hazen B, Hassini E, Foroqon C (2019) Organizational capabilities that enable big data and predictive analytics diffusion and organizational performance: a resource-based perspective. *Manag Decis* 57(8):1734–1755. <https://doi.org/10.1108/MD-03-2018-0324>
- Munodawafa RT, Johl SK (2019) Big data analytics capabilities and eco-innovation: A study of energy companies. *Sustainability*. <https://doi.org/10.3390/su11154254>
- Ngo J, Hwang BG, Zhang C (2020) Factor-based big data and predictive analytics capability assessment tool for the construction industry. *Autom Constr*. <https://doi.org/10.1016/j.autcon.2019.103042>
- Obitade PO (2019) Big data analytics: a link between knowledge management capabilities and superior cyber protection. *J Big Data*. <https://doi.org/10.1186/s40537-019-0229-9>
- Olszak CM (2014) Towards an understanding business intelligence: a dynamic capability-based framework for business intelligence. In: 2014 Federated conference on computer science and information systems, 2: 1103–1110. <https://doi.org/10.15439/2014F68>
- Pedro J, Brown I, Hart M (2019) Capabilities and readiness for big data analytics. *Proc Comput Sci* 164:3–10. <https://doi.org/10.1016/j.procs.2019.12.147>
- Popovič A, Hackney R, Tassabehji R, Castelli M (2018) The impact of big data analytics on firms' high value business performance. *Inf Syst Front* 20(2):209–222. <https://doi.org/10.1007/s10796-016-9720-4>
- Ransbotham S, Kiron D, Prentice PK (2015) Minding the analytics gap. *MIT Sloan Manag Rev* 56(3):63–68

- Rialti R, Zollo L, Ferraris A, Alon I (2019) Big data analytics capabilities and performance: evidence from a moderated multi-mediation model. *Technol Forecast Soc Chang* 149(October):119781. <https://doi.org/10.1016/j.techfore.2019.119781>
- Richins G, Stapleton A, Stratopoulos TC, Wong C (2017) Big data analytics: opportunity or threat for the accounting profession? *J Inf Syst* 31(3):63–79. <https://doi.org/10.2308/isyss-51805>
- Saggi MK, Jain S (2018) A survey towards an integration of big data analytics to big insights for value-creation. *Inf Process Manag* 54(5):758–790. <https://doi.org/10.1016/j.ipm.2018.01.010>
- Scholz TM (2017) Big data in organizations and the role of human resource management. *Big Data Org Role Human Resource Manag*. <https://doi.org/10.3726/b10907>
- Shabbir MQ, Gardezi SBW (2020) Application of big data analytics and organizational performance: the mediating role of knowledge management practices. *J Big Data*. <https://doi.org/10.1186/s40537-020-00317-6>
- Shamim S, Zeng J, Shafi Choksy U, Shariq SM (2019) Connecting big data management capabilities with employee ambidexterity in Chinese multinational enterprises through the mediation of big data value creation at the employee level. *Int Bus Rev* 29(6):101604. <https://doi.org/10.1016/j.ibusrev.2019.101604>
- Shamim S, Zeng J, Khan Z, Zia NU (2020) Big data analytics capability and decision making performance in emerging market firms: The role of contractual and relational governance mechanisms. *Technol Forecast Soc Chang* 161(September):120315. <https://doi.org/10.1016/j.techfore.2020.120315>
- Shokouhyar S, Seddigh MR, Panahifar F (2020) Impact of big data analytics capabilities on supply chain sustainability. *World J Sci Technol Sustain Dev* 17(1):33–57. <https://doi.org/10.1108/wjstsd-06-2019-0031>
- Shuradze G, Wagner HT (2016) Towards a conceptualization of data analytics capabilities. *Proc Ann Hawaii Int Conf Syst Sci*. <https://doi.org/10.1109/HICSS.2016.626>
- Song M, Zhang H, Heng J (2020) Creating sustainable innovativeness through big data and big data analytics capability: from the perspective of the information processing theory. *Sustainability*. <https://doi.org/10.3390/su12051984>
- Suoniemi S, Meyer-Waarden L, Munzel A, Zablah AR, Straub D (2020) Big data and firm performance: The roles of market-directed capabilities and business strategy. *Inf Manag* 57(7):103365. <https://doi.org/10.1016/j.im.2020.103365>
- Teece DJ (2007) Explicating dynamic capabilities: The nature and microfoundations of (sustainable) enterprise performance. *Strateg Manag J* 28(13):1319–1350. <https://doi.org/10.1002/smj.640>
- Teece DJ, Pisano G, Shuen A (1997) Dynamic capabilities and strategic management. *Strateg Manag J* 18(7):509–533. [https://doi.org/10.1002/\(SICI\)1097-0266\(199708\)18:7%3c509::AID-SMJ882%3e3.0.CO;2-Z](https://doi.org/10.1002/(SICI)1097-0266(199708)18:7%3c509::AID-SMJ882%3e3.0.CO;2-Z)
- Tranfield D, Denyer D, Smart P (2003) Towards a methodology for developing evidence-informed management knowledge by means of systematic review. *British J Manag* 14(3):207–222. <https://doi.org/10.1111/1467-8551.00375>
- Upadhyay P, 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. *Int J Inf Manag* 52(November2019):102100. <https://doi.org/10.1016/j.ijinfomgt.2020.102100>
- Vidgen R, Shaw S, Grant DB (2017) Management challenges in creating value from business analytics. *Eur J Oper Res* 261(2):626–639. <https://doi.org/10.1016/j.ejor.2017.02.023>
- Wamba SF, Gunasekaran A, Akter S, Ren SJF, Dubey R, Childe SJ (2017) Big data analytics and firm performance: effects of dynamic capabilities. *J Bus Res* 70(1):356–365. <https://doi.org/10.1016/j.jbusres.2016.08.009>
- Wang Y, Hajli N (2017) Exploring the path to big data analytics success in healthcare. *J Bus Res* 70:287–299. <https://doi.org/10.1016/j.jbusres.2016.08.002>
- Wang Y, Kung LA, Byrd TA (2018a) Big data analytics: Understanding its capabilities and potential benefits for healthcare organizations. *Technol Forecast Soc Chang* 126:3–13. <https://doi.org/10.1016/j.techfore.2015.12.019>
- Wang Y, Kung LA, Wang WYC, Cegielski CG (2018b) An integrated big data analytics-enabled transformation model: application to health care. *Inf Manag* 55(1):64–79. <https://doi.org/10.1016/j.im.2017.04.001>
- Yasmin M, Tatoglu E, Kilic HS, Zaim S, Delen D (2020) Big data analytics capabilities and firm performance: an integrated MCDM approach. *J Bus Res* 114(March):1–15. <https://doi.org/10.1016/j.jbusres.2020.03.028>

- Zhang H, Song M, He H (2020) Achieving the success of sustainability development projects through big data analytics and artificial intelligence capability. *Sustainability* 12(3):949. <https://doi.org/10.3390/su12030949>
- Zuboff S (2015) Big other: surveillance capitalism and the prospects of an information civilization. *J Inf Technol* 30(1):75–89. <https://doi.org/10.1057/jit.2015.5>

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