Technological Forecasting & Social Change 197 (2023) 122884

Contents lists available at ScienceDirect

Technological Forecasting & Social Change

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

Big data analytics capabilities: Patchwork or progress? A systematic review of the status quo and implications for future research

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ARTICLE INFO

Keywords:
Big data
Big data analytics capabilities
Dynamic capabilities
IT capabilities
IT strategy

ABSTRACT

This paper presents a systematic literature review of the research field on big data analytics capabilities (BDACs). With the emergence of big data and digital transformation, a growing number of researchers have highlighted the need for organizations to develop BDACs. Despite valuable efforts to examine determinants and contributions to performance measures, the research field on BDACs remains relatively unexplored. The review reveals a patchwork of studies lacking a theoretical and conceptual foundation and questions arise regarding the reliability and validity of predominantly survey-based empirical studies. Drawing on findings from related capability concepts, this paper suggests the use of clearer definitions and items and a greater variety of methods to facilitate further exploration of BDACs. Finally, future research areas and implications are outlined.

1. Introduction

Fueled by digitization, large volumes of digital data, often referred to as 'big data', are accessible to public administrations and private enterprises at low costs to enhance their operations. While big data analytics (BDA) are essential to convert big data into information, they are not sufficient to generate valuable knowledge, guide, and improve strategic decision-making. Scholars have stressed that, in addition to the technical and analytical expertise required for BDA, firms must cultivate and foster managerial expertise, adopt a more data-centric business approach and organizational culture, promote organizational learning, and foster organizational capabilities to derive valuable insights from big data (Gupta and George, 2016; Wamba et al., 2017; Mikalef et al., 2018).

Based on these seminal works, the number of studies on big data analytics capabilities (BDACs) in different domains, particularly general management, supply chain management, and health care, has increased significantly. As a result, scholars may have independently searched and applied prior research to study BDACs without much consolidation, leading to apparent inconsistencies in its conceptualization, dimensions, theories, and methods applied. Consequently, theoretical contributions and practical implications have been piecemeal, making it difficult to comprehend the progress in the field and providing a lack of guidance for subsequent research. Despite the existence of early literature review papers on BDACs (e.g., Mikalef et al., 2018; Arunachalam et al., 2018), a comprehensive framework for organizing the key components of BDACs is still missing. Therefore, to highlight the status quo of the concept in the extant literature and consolidate existing research, a systematic literature review is conducted comprising a comprehensive organizing framework to guide future research.

Accordingly, we propose to conduct an interpretative literature review of BDAC with three primary objectives. Firstly, we aim to synthesize extant literature regarding the fundamental building blocks of BDAC, such as antecedents, dimensions, and outcome variables. Secondly, we will discuss whether and to what extent research in this domain has advanced with respect to the evolution of definitions, theoretical assumptions, research contexts and industries, levels of analysis, and theoretical lenses adopted. To further this, we will thirdly emphasize the need to compare BDACs with prior organizational capabilities, such as IT, digitalization, and dynamic capabilities, in order to identify significant gaps, unaddressed issues, and promising future research directions.

To this end, we conducted an interpretative literature review of scientific papers published in the past 25 years that explicitly addressed BDACs. Based on Scopus and Web of Science, we initially retrieved 218 papers. After independently applying relevant exclusion criteria, 103 papers were thoroughly analyzed. Our findings suggest that, despite the surge in BDAC research, various issues related to conceptual and

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https://doi.org/10.1016/j.techfore.2023.122884
Received 10 February 2023; Received in revised form 21 September 2023; Accepted 25 September 2023
Available online 6 October 2023

theoretical foundations as well as the reliability and validity of empirical results affect the overall value of the results.

Through providing insights into the extant literature of BDACs, investigating the broad range of aspects encompassed by the concept and its main components, our review contributes to the further development of this research field. Furthermore, we contribute to the more general management and organizational literatures, highlighting similarities and differences of the BDACs approach with more common concepts of organizational capabilities. Additionally, our study adds to the burgeoning literature on digitalization and digital transformation. Lastly, we contribute to forming a forward-looking research agenda, on which researchers can build to derive theoretical and methodological approaches to address research gaps and shortcomings in an accumulative manner while adding more knowledge to the existing body of literature to advance the field.

The remainder of our paper is structured as follows. To derive the right search strategy for the literature review, a brief overview of the concepts of big data, BDA, and similar concepts to BDACs in early literature is provided in Section 2. The following section describes the review methodology, followed by a descriptive assessment of the state of development of BDACs research. Next, we will critically assess them, highlighting research gaps and propose a future research agenda in Section 5 before providing a conclusion and limitations in the final section.

2. Research context

2.1. Big data and big data analytics

Big data is frequently related to large-scale, real-time streaming, and complex data generated by various sources such as environmental sensors, GPS signals, satellites, social media, or smartphones (Wamba et al., 2015) the use of which requires sophisticated processing methods (Wang et al., 2018a; Beyer and Laney, 2012). Big Data is defined as "*data that is too large, fast, and complex to adequately manage using traditional methods or software within an acceptable time.*" (Sahut et al., 2022: 5). Hence, big data alone is unlikely to improve decision-making quality or any kind of performance (Zhang et al., 2022a; Ross et al., 2013). Whether or to what extent big data benefits a company or organization depends on their goals, their specific products and services, and methods and techniques available and applied to generate new knowledge and innovation (Gupta and George, 2016; Markus, 2015), which has been subsumed under BDA.

BDA is considered as a means to process and analyze big data with the aim of extracting insights and value (Wamba et al., 2017; Chen and Zhang, 2014; White, 2012; Russom, 2011) through the comprehensive application of advanced analytics methods, procedures, tools, and infrastructure to handle big datasets (Chatterjee et al., 2023; Jha et al., 2020). BDA is referred to as "*the activities involved in the specification, capture, storage, access and analysis of such datasets to make sense of its content and to exploit its value in decision-making*" (Zhang et al., 2022a: 2). Although big data-specific technologies continuously advance there are a significant number of organizations that are unable to reap benefits from their investments in big data and in BDA in the sense of acquiring technologies, software, and other tools (Morimura and Sakagawa, 2023; Popovič et al., 2018; Wamba et al., 2017). It has been pointed out that the productivity paradox, i.e., investments in information technology alone do not generate adequate productivity gains (Brynjolfsson and Hitt, 1998; Brynjolfsson, 1993), seems also to apply to BDA (Wamba et al., 2017; Irani, 2010; Sharif and Irani, 2006).

Research has stressed that BDA technologies are rather sophisticated, hence, organizations should shift their attention beyond pure technology to the development of firm-specific inimitable capabilities (Gupta and George, 2016). Consequently, scholars emphasized the term 'BDAC' as to get to grips with the shift to the big data era and to offer practitioners guidance regarding identifying and developing it (e.g., Horng et al., 2022; Elia et al., 2022; Mikalef et al., 2018).

2.2. Early conceptualizations of big data analytics-related capabilities

In the practitioner's literature, organizations' analytics capability was generally proposed as a new concept embracing relevant organizational resources which enable organizations to exploit big data (Kiron et al., 2014). However, previous works mainly published in the practitioner-oriented literature or conference proceedings already highlighted at least some aspects of BDACs without explicitly referring to the term.

For instance, in their book "*Competing on analytics: the new science of winning*", Davenport and Harris (2007) generally regarded analytical capabilities as the distinctive capability of firms to select the optimal price, detect quality problems, determine the lowest possible level of inventory or, to spot loyal and profitable customers in the big data environment. Although they argued that organizations should develop such capabilities to gain competitiveness in the big data environment, the term was used without an explanation and a conceptualization, and it was later developed into a full concept by Gupta and George (2016).

The concept of business intelligence capabilities suggested by Xu and Kim (2014) is related to BDAC as it proposes to combine multi-dimensional combination of sub-capabilities, pertaining to IT infrastructures, data management, analytical skills, collaborative governance, and execution (analytics-based process).

Olszak (2014) defines dynamic business intelligence capability as organizations' capability to integrate, build, and reconfigure information resources, as well as business processes, to deal with fast-changing business environments.

The concept of information processing capability of an organization refers to "… *its capacity to capture, integrate, and analyze data and information, and use the insights gained from data and information in the context of organizational decision making*" (Cao et al., 2015: 385).

Finally, Kung et al. (2015) propose to use the concept of big data competence defined as a firm's ability to obtain, store, process, and analyze large quantities of data of various types, and deliver knowledge, which enables them to extract value from big data in a timely manner.

On the one hand, these conceptualizations, which are related to BDAC, illustrate the need to precisely define and subsequently operationalize which factors and cause-effect relationships are included in each case. On the other hand, they make clear that BDAC research can, if not must, draw on a pool of constructs, but should make clear what distinguishes BDAC from similar conceptualizations. These aspects will be addressed in the literature review.

3. Review methodology

In order not to erroneously disregard relevant articles, we base our literature review on two relevant data sources, viz. Scopus and Web of Science, despite their great overlap (Khanra et al., 2020; Harzing and Alakangas, 2016). Furthermore, a protocol as proposed by Lu et al. (2018) and Jabbour et al. (2020) including clearly defining appropriate keywords, conceptual boundaries, and exclusion criteria has been adopted to ensure the robustness of the systematic review.

Mainly based on the aforementioned seminal works, a set of keywords that directly address the concept of BDAC has been derived and applied (see Appendix A). Our initial search, limited to peer-reviewed articles including BDAC-related review papers published in English, returned 199 records from Scopus and 126 records from Web of Science. After removing duplicates by manually checked all the retrieved records, a total of 218 records were obtained for three further phases of screening, i.e., titles, keywords, and sources screening, abstract screening, and full texts screening. The first screening focused on eliminating (a) those articles that only focus on technical aspects, do not emphasize management issues (b) so recently published that full texts are not accessible, (c) too short to be categorized as a research study, or (d) published in journals not listed in the SCImago Journal Ranking

(González-Pereira et al., 2010) (n = 62). Subsequently, based on the abstract screening, those articles have been excluded that had a very narrow focus on a specific business case or did not report explicit BDAC implications (n = 45). As a result of these two preliminary screening rounds 111 records were selected for an intensive full-text screening (see Fig. 1).

Finally, the authors independently read and assessed the full texts of the remaining articles, compared their findings, and finally decided on excluding another six papers because of their limited contributions to the concept of BDAC. Consequently, 103 relevant articles (indicated by an * in the reference list), i.e., 47.2 % of the initially identified articles, are included in the following assessment and discussion.

To bring additional structure to the findings regarding the status quo of BDAC research it is proposed to apply two organizing frameworks. Following literature reviews on various organizational phenomena (e.g., Schilke et al., 2018; Eriksson, 2014; Martineau and Pastoriza, 2016; McGrath and Nerkar, 2023), we categorize the studies according to whether they examine antecedents, mediators, moderators, or outcomes. Additionally, the underlying theory, if any, and the typology used are identified (see Fig. 2). Furthermore, to come up with reliable and valid results all papers are assessed for their BDAC definitions, the nature of the study (e.g., conceptual, multi case, survey), level of analysis (e.g., individual, firm, industry), theories used, and specifications such as country focus, industry, or firm size in case of empirical studies.

With regard to demonstrating knowledge gaps and new avenues for future research we follow earlier review papers (Hassan et al., 2022; Paul et al., 2021a; Paul et al., 2021b) and use the TCCM framework (i.e., theory development, contexts, characteristics, methodology) proposed by Paul and Rosado-Serrano (2019).

4. Descriptive assessments of the state of BDAC research

Due to the topicality of the technological reference point, i.e., BDA, it is not surprising that we could not identify any scientific study that explicitly addressed the BDAC concept before Gupta and George (2016) defined BDAC 2016 as "… *a firm's ability to assemble, integrate, and deploy its big data-specific resources.*" (1049).

Since then, the number of studies on BDAC and related citations has steadily increased. Most prominent journals publishing research on BDAC have been Journal of Business Research (8), Sustainability (8), Technological Forecasting and Social Change (7), and Information and Management (6). It is striking that no traditional management and organizational journals have taken up the topic, despite it is – at least – a variant of the much published and cited organizational capabilities concept. A few researchers have devoted themselves to the topic and published several times on BDAC, while the majority of authors have one publication, predominantly empirical studies, to their credit. We ran a couple of bibliometric analyses using among others VOSviewer, however, did not find interesting results except that the bulk of the identified papers origin from three primary domains, i.e., general management (e.g., Akter et al., 2016; Gupta and George, 2016; Wamba et al., 2017; Mikalef et al., 2018), supply chain management (e.g., Arunachalam et al., 2018), and health care (e.g., Wang and Hajli, 2017; Wang et al., 2018a; Wang et al., 2018b).

4.1. Definitions and conceptualizations of BDAC

As mentioned in reviews of other management domains, too, it is necessary that the individual studies contain a clear definition of the

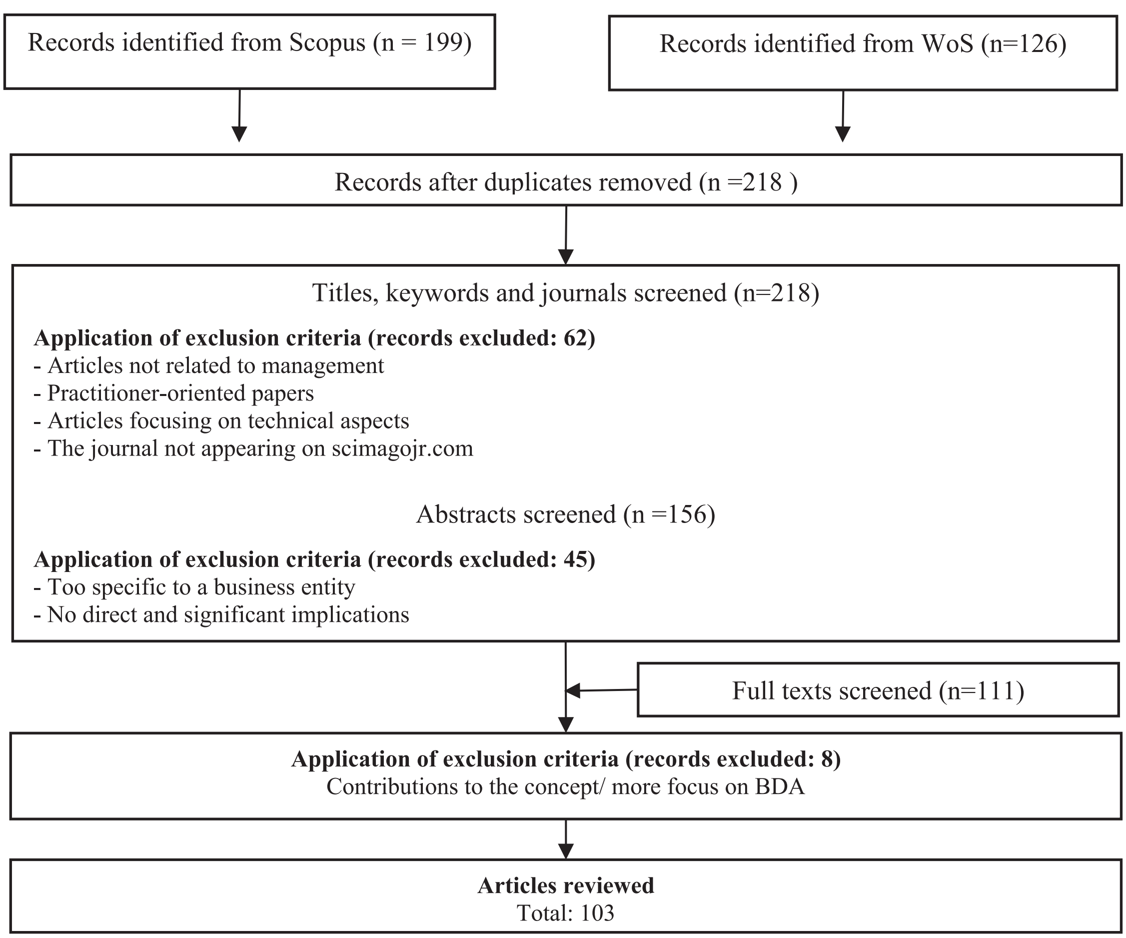

Fig. 1. The search protocol used in the study.

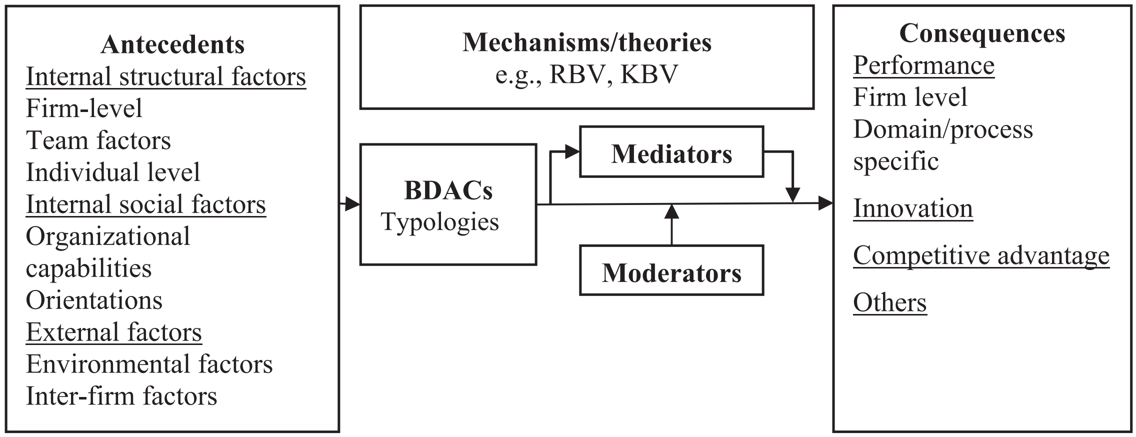

Fig. 2. Organizing framework.

phenomenon to be examined, here BDAC. It allows evaluating their contribution regarding their statements and results. Interestingly, this is only the case for 55 articles (53.4 %) of which many refer to early definitions and categorizations of BDACs provided in practitioners' papers and similar concepts (Srinivasan and Swink, 2018; Kiron et al., 2014). In particular, 15 papers refer to the definition proposed by Gupta and George (2016), while the ones proposed by Akter et al. (2016) and Wamba et al. (2017) are referenced 12 and 9 times respectively. Table 1 provides an overview of the five most frequently used definitions.

Regarding BDAC definitions, it is remarkable that a couple of studies solely emphasize the process of collecting, analyzing, and extracting insights from data. Although some of those encompass certain big data specific resources, organizational aspects such as human and management skills are widely neglected, especially in studies related to the domain of health care and supply chain management. Frequently, definitions of prior studies are not applied in the theory and method sections but mainly used as a kind of justification for the study at large.

Table 1
The most frequently used definitions of BDACs.

Author(s)	Definition/conceptualization	References
Gupta and George (2016)	BDAC is defined as "… *a firm's ability to assemble, integrate, and deploy its big data-specific resources.*" (p. 1049)	15
Akter et al. (2016)	The conceptualization of BDAC contains three dimensions (i.e., management, technology, and human) that "… *highlight[s] the importance of the complementarities between them for high level operational efficiency and effectiveness for improved performance and sustained competitive advantage.*" (p. 114)	12
Wamba et al. (2017)	BDAC is regarded as "… *the competence to provide business insights using data management, infrastructure (technology) and talent (personnel) capability to transform business into a competitive force.*" (p. 3)	9
Srinivasan and Swink (2018)	"…*organizational facility with tools, techniques, and processes that enable a firm to process, organize, visualize, and analyze data, thereby producing insights that enable data-driven operational planning, decision-making, and execution.*" (p. 1851)	5
Wang and Hajli (2017), Wang et al. (2018a)	BDAC is defined as "*the ability to acquire, store, process and analyze large amount of health data in various forms, and deliver meaningful information to users, which allows them to discover business values and insights in a timely fashion.*" (p. 4)	4
Mikalef et al. (2020b)	BDAC is defined as "*the ability of a firm to effectively deploy technology and talent to capture, store and analyze data, toward the generation of insight.*" (p. 7)	4
Mikalef et al. (2018)	BDAC 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.*" (p. 557)	3

If one additionally includes the studies that do not define BDAC at all, this already casts a clear shadow on the general comparability of the results as well as the continuous progress in this research field. Accordingly, we would like to point out that existing literature seemingly has not paid adequate attention to the different types of capabilities subsumed in the concept, thus neglecting a specific conceptualization of BDACs.

Against this background, it is not surprising that there is only a limited number of works that explicitly present the concept of BDAC with reference to extensive research on organizational capabilities or dynamic capabilities (e.g., Gold et al., 2001; Wang and Ahmed, 2007). Since its inception, research on BDACs seemingly followed an integrative approach that draws for dimensions, inputs, and measurement items studied on adjacent capabilities views, e.g., IT capability (e.g., Bhatt and Grover, 2005). However, a clear delineation to and (or) systematic elaborations of differences or specifics of BDAC are widely lacking. While a simple count reveal – not surprisingly – that in the context of general management studies predominantly refer to the resource-based view (RBV), dynamic capabilities or a combination of both (60 of 103 studies) however, in many cases this is limited to rather general statements and the uncommented reference to seminal works (e.g., Barney, 1991; Wernerfelt, 1984). In contrast, in the works published in the context of health care and supply chain management, more specific theoretical concepts are used, such as such as organizational information processing theory (OIPT), information lifecycle management or configuration theory.

While BDAC is frequently grounded in the wider context of IT capability research, recent studies seem to neglect this fact. With rare exceptions (Akter et al., 2016; Gupta and George, 2016), many scholars provide only a quite limited discussion of theories and concepts as they mainly use them for the selection of the variables and research items. For instance, application of rbv is limited basically as a mean to refer to its generic categories, i.e., tangible, intangible and human resources, whereas early on BDAC scholars like Mikalef et al. (2018) have emphasized that it requires specific capabilities beyond regular ones to develop big data specific capabilities. Similarly, other authors use the generic dimensions of the IT capability concept, i.e., managerial, personnel capabilities, and infrastructure flexibility, without a rigorous assessment of their appropriateness and connection to the specific BDAC context under investigation.

Applying for example OIPT seems to be more appropriate as it addresses information processing requirements and capabilities within an organization to transform data into information and facilitate strategic decision making (Premukar et al., 2005). More recently OIPT has been more frequently adopted by researchers (e.g., Sabharwal and Miah, 2021; Ashaari et al., 2021; Sheng et al., 2021).

4.2. Level of analysis, methods applied, and sample characteristics of BDAC research

The great majority of BDAC studies (>90 %) address research objectives and questions at the firm level such as to what extent or how various determinants that can be subsumed under BDAC influence firm-level outcomes like performance or innovation (Mikalef et al., 2019b, 2020a; Wamba et al., 2020). Interestingly, many of these studies at the firm-level use surveys and do not measure performance based on firm-level data like annual reports. Our sample contains only four studies (3.9 %) that address BDAC either at the team or project level.

Regarding the nature of studies (see Table 2) questionnaire-based studies prevail (81.6 %) while other types of papers that would be expected in such a premature research field like conceptual studies or case studies (Pathak et al., 2021; Schlegel et al., 2021; Yasmin et al., 2020; Popovič et al., 2018) seem to be underrepresented. Strikingly, the majority of survey papers develop a set of hypotheses in what is presented as new research niches often without examining whether and how their research is relevant for theory development.

While it is widely acknowledged that survey-based research offers a range of benefits, there it comes with certain disadvantages especially the reliability and validity of the data collected and the statistical findings. In the next section, we will emphasize this issue when providing an in-depth analysis of the content and context of the studies and particularly how surveys have been conducted. Further discussion on the most appropriate research approaches for future studies is provided in the 'Discussion and future research opportunities' section.

Table 3 shows the distribution with respect to the *statistical methods applied* within the 92 empirical papers. Structural Equation Modelling (SEM) dominates with 66 papers (71.7 % of all quantitative papers), of which 47 studies use Partial Least Square-based SEM and 19 papers covariance-based SEM analysis.

In order to assess the theoretical foundation and reliability we further examine and compare the number of hypotheses proposed and confirmed as well as the measurement items selected in the quantitative papers. An average of 6.76 hypotheses proposed and tested seems to be quite comparable to other organizational research fields. However, the very high percentage of statistically supported hypotheses (85.5 %) raises epistemological concerns and doubts regarding the validity of the findings. Such concerns are furthered as many studies are very vague with regard to the selection of data sources as well as response rates or data treatment.

Besides, many authors also reuse survey items from other capability concepts, i.e., IT capability and prior studies. While BDACs is considered an emerging domain, this may be an issue which can restrict research advancements in the field. Additionally, the use of SEM in survey studies tends to result in similar sample sizes, with an average of 287 and the majority having sample sizes of 250–300. This correlation highlights the preference for a sample of around 300 when utilizing SEM as a quantitative method, likely due to the need for a certain threshold to obtain significant results.

Table 2
Nature of studies of the reviewed articles.

Paper types	Number of articles
Survey based quantitative	84
Mixed method	7
Literature review	4
Multi case studies	4
Conceptual	1
Single case study	1
Meta analysis	0
Panel data quantitative	0
Secondary data quantitative	0
Other	2
Total	103

Table 3
Statistical methods applied in quantitative studies.

Methods	Number of studies	Examples
PLS-SEM	47	Akter et al. (2016), Mikalef et al. (2020a)
Covariance-based SEM	19	Demir et al. (2022), Singh and Singh (2019)
OLS and probit regression	10	Zhang et al. (2020), Park and Singh (2022)
Hierarchical regression	7	Sheng et al. (2021), Shamim et al. (2021)
Mediation analysis	4	Zhang et al. (2022b), Rialti et al. (2019)
Fuzzy-set QCA	2	Mikalef et al. (2019a), Wang et al. (2019)
Others	3	Uddin Murad et al. (2022), Bag et al. (2022)
Total	92	

With regard to further *sample characteristics*, we found that a majority of the survey-based papers are conducted in just one country (71 studies) whereas there are only four collecting data from two and 16 obtaining survey data from 3 or more countries. Assuming that developed economies would take the lead in BDAC it is striking that the minority of studies stems from the US (6 studies), the UK (3), France (3), or Italy (3). Survey data originates primarily from emerging and developing countries such as China (21), Pakistan (9), India (8), Jordan (5) or other developing nations (14). It is difficult to assess the information about industries and firm sizes covered precisely as the majority of the survey-based studies lack detailed statistics about the industries or firm sizes. Particularly, a limited number of the papers specify firm sizes. Especially, it is unclear as many studies indicate that data were collected from manufacturing firms of different industries and some authors do not clarify how they collected data from individuals to address the firm level. Overall, there are 46 articles in which data were collected from firms of different sizes. Especially, most of the papers investigate manufacturing companies of different industries, from which 27 papers collect the data. This fact explains why a significant number of reviewed papers are based on such developing countries, where manufacturing firms are concentrated. Accordingly, existing studies pay inadequate attention to developed economies, and those industries where big data plays a major role such as commerce, logistics and transportation. Additionally, very few studies examine whether BDAC is dependent of firm sizes and there is no comparison of the capabilities between large, medium, and small firms.

5. Discussion and future research opportunities

5.1. Framework-related components

This section provides an overview of the main components of BDAC, such as typologies, antecedents, outcome variables, moderators, and mediators. It provides an in-depth discussion on the state of development of each component and presents a general organizing framework for them. Additionally, we will identify key issues and suggest research directions by applying the aforementioned TCCM framework.

5.1.1. Typologies of BDAC

The seminal works of Akter et al. (2016), Gupta and George (2016), and Wamba et al. (2017) have provided the foundations for the dimensions and typologies of BDAC from an IT capability perspective; however, current research in this area appears to have stagnated. 31 of the papers in the sample address BDAC typologies, 26 of which specify and define the typologies predominantly based on prior studies. We also found eight other articles that only focus on investigating one or two typologies of BDAC. Overall, we found similar approaches but no consistency or convergence with regard to their dimensions. Several scholars suggested based on RBV and the IT capability three primary typologies of BDAC, which reflect three important dimensions of capabilities and resources required to capture and apply insights from big data, namely technological infrastructure, managerial capabilities, and personnel skills. The details about the typologies of BDAC and the associated papers are provided in Appendix C.

Although the typologies examined in the majority of the reviewed papers are alike but not identical, showing a high level of inconsistency in the terms used by the authors, it reflects the significant convergence in research with respect to this BDAC building block. In addition, although there exist several studies focusing on each typology of the phenomenon, authors have paid little attention to this research direction. Besides, the last research gap regarding this aspect are the theories adopted to propose the typologies as other theoretical lenses have not been widely employed for proposing BDAC dimensions. Again, it becomes apparent that authors, especially from different domains have independently proposed the typologies or deliberately developed slightly different ones to set themselves apart from other work and signal novelty, which is often requested by the peer-review system.

Implications for future research regarding BDAC typologies

Although we observe little research progress with respect to this component, there have been several emerging research directions that we suggest future studies follow. First, although the three typologies may have derived from IT capability, some authors have emphasized the central aspects and their nature in the big data context, especially identifying insightful process-oriented typologies of BDAC. We, therefore, call for further research in this avenue as these typologies are especially useful to accommodate different contexts of big data usage, where the significance of each typology can differ, or it may require more dimensions to be added. Second, we call for further studies on each existing typology and its corresponding inputs and outcomes instead of focusing on all the dimensions as their importance may vary depending on the context. Last, future research can address industry-specific BDAC dimensions emphasizing which should be further developed in each industry.

5.1.2. Antecedents of BDACs

34 of the articles (33 %) directly address antecedents of BDAC. In addition, there is limited progress and consolidation in recent publications, which shows that inadequate attention has been paid to research on this primary component. Based on early IT capability literature and the seminal works, which are mainly predicated on the RBV (e.g., Akter et al., 2016; Gupta and George, 2016; Wamba et al., 2017), a majority of the papers still refer to the three primary constituents of this view to propose pertinent inputs and the second-order constructs of the phenomenon, namely tangible, intangible and human resources. Eleven of those only refer to the three categories to test their research model without making further extensions or figuring out which the specific resources in each category could be. There are 19 papers referring to the three dimensions as the input factors in the theoretical section without further studying them empirically (see Appendix D).

Although there is not much difference in the findings in different domains, the antecedents identified may represent the different focuses on the required resources in different contexts. First of all, in the general management stream, many use the RBV and DC view to determining antecedents of BDAC, whose common ones are tangible resources like data, technology, basic resources, intangible such as data-driven culture, organizational learning, and human skills, i.e., managerial and technical ones (e.g., Behl, 2022; Mikalef et al., 2020a; Mikalef et al., 2020b; Mikalef et al., 2019b; Mikalef et al., 2018; Lozada et al., 2019; Gupta and George, 2016). Some important insights have been added to the literature on this component, albeit rather limited such as developmental culture, customer, technology, and entrepreneurial orientation (Lin and Kunnathur, 2019), management and process innovation or open innovation (Henao-García et al., 2021; Arias-Pérez et al., 2022), data availability or big data utilization and knowledge sharing of big data (Ramadan et al., 2020; Demir et al., 2022), data quality (Côrte-Real et al., 2020), intellectual capital (Chen and Chen, 2022), alliance management capability (Dubey et al., 2021). Notably, Anwar et al. (2018) further identify the specific factors of the resource categories, in which compatibility, modularity, and connectivity are found to be critical elements of the technical dimensions, whereas technological and business knowledge are the sub-dimensions of personnel capabilities, and technology management knowledge reflects the key aspect of the management category. From a KBV perspective, Upadhyay and Kumar (2020) identify internal analytics knowledge and organizational culture, whereas Shamim et al. (2020) emphasize data governance as a significant input factor of BDAC. Some key knowledge-related inputs include knowledge absorption capacity (Khan and Tao, 2022), big data knowledge management (Horng et al., 2022), technical knowledge, technology management knowledge, business knowledge, and relational knowledge (Qaffas et al., 2022).

Secondly, there are more antecedents in the health care context, which reflect important factors of big data collecting and analyzing processes in this sector such as data aggregation, data processing, data visualization, and big data architectural components (Wang and Hajli, 2017). Thirdly, with regards to supply chain management, Srimarut and Mekhum (2020) find that supply chain connectivity plays an essential role in building BDAC in this sector whereas Srinivasan and Swink (2018) identify supply chain visibility as a BDAC antecedent. In brief, existing papers have neglected research on BDAC antecedents or restated generic resources from prior works as the majority of papers published in 2020, 2021, and 2022 do not examine this factor.

Implications for future research regarding the antecedents

It is important to study the influence of various antecedents to understand the mechanisms that foster BDACs building (Popovič et al., 2018), but the progress is stagnated. Hence, we recommend that authors, firstly, should thoroughly understand existing grounded theories to derive BDA-specific resources and capabilities rather than generally employing the RBV or adapting IT capabilities antecedents. Secondly, the existing literature is mostly focused on the firm level, it is called for approaches that incorporate or address different organizational levels (Mikalef et al., 2018; Gupta and George, 2016). Regarding individual-level antecedents, it is necessary to investigate, whether previous studies which dealt with human skills (e.g., Behl, 2022; Belhadi et al., 2020; Mikalef et al., 2020b; Wang and Hajli, 2017; Gupta and George, 2016) address these skills on an individual basis (e.g. differentiating jobs) or as a general construct. It may be of interest to transfer the idea of a global mindset (e.g., Levy et al., 2007) on BDAC, i.e., the mindset of managers regarding the value of big data and BDA (Pigni et al., 2016) as proposed by Mikalef et al. (2019b) and Prescott (2014). Concerning the team level, it often requires multiple actors from various disciplines to extract values from big data (Ferraris et al., 2019; Janssen et al., 2017). Thus, interdisciplinary teams with various skill sets can foster BDAC (Mikalef et al., 2019a), which can be facilitated using BDA (Barlette and Baillette, 2022; Mikalef et al., 2019a), thus enabling firms to improve performance (Akhtar et al., 2019; Akhtar et al., 2018; Sheng et al., 2017).

At the already relatively broadly studied firm level, the logic and institutional pressures that hinder the implementation of BDA in the context of SMEs have been highlighted (Bertello et al., 2021). In this regard, the costs of deploying big data initiatives need to be considered more carefully (Mikalef et al., 2020a, 2020b). Future research regarding firm-level antecedents may also examine factors related to strategies that may be adopted to develop a sound data-driven culture within a firm (Kamble and Gunasekaran, 2020). Given the application of BDAC approaches using the still quite vague construct of absorptive capacity (Božič and Dimovski, 2019; Lam et al., 2017; Gao et al., 2017), it would be interesting to adopt acquisition, assimilation, transformation, and exploitation to identify key antecedents and/or mediators of BDAC at the organizational level. Apart from these three levels, authors have attempted to introduce several inter-organizational factors as inputs for building BDAC such as global integration and environmental determinism (Jha et al., 2020). Yet, it has been suggested to not only develop interdisciplinary collaborative teams within a firm but also to build ecosystems with partners as well as to foster BDAC (Barlette and Baillette, 2022; Mikalef et al., 2019b).

5.1.3. Mediators and moderators of BDAC

Concerning the mediators, 37 papers focus on mediating factors and 6 papers use BDAC as a mediator. The most frequently used mediators include dynamics capabilities, orientation, and agility, followed by some context-specific mediating factors. For example, it is found that dynamic capabilities mediate the impact of BDAC on outcome variables such as innovative capability (Mikalef et al., 2019b), service innovation (Xiao et al., 2020), or competitive performance (Mikalef et al., 2020b). Similarly, business intelligence infrastructures (Ilmudeen, 2021), data-driven decision-making (Ashaari et al., 2021), manufacturing agility (Awan et al., 2021), innovative capability and information quality (Bahrami and Shokouhyar, 2022), ambidexterity of big data (Aljumah et al., 2021) and sustainable marketing (Horng et al., 2022) are identified as the mediators of the link between BDAC and organizational performance. There are several other mediating factors tested such as process-oriented dynamic capabilities (Wamba et al., 2017; Contreras Pinochet et al., 2021; *Munir et al., 2023), knowledge management innovation (Ferraris et al., 2019), organizational culture (Upadhyay and Kumar, 2020; Wamba et al., 2020c), as well as analytics capability-business strategy alignment (Akter et al., 2016) on the relationship between BDAC and various outcomes. Within the supply chain context, supply chain agility is found to mediate the relationship between BDAC and competitive advantage, whereas circular economy practices and sustainable supply chain flexibility can lead to sustainable supply chain performance (Edwin Cheng et al., 2022). The details about the mediators and the mediated links are provided in Appendix E.

Regarding the moderators, fewer papers examine these factors with only 25 articles and 6 others using BDAC as a moderator to test their research model. With regard to the factors impacting the link between BDAC and firm performance, Rialti et al. (2019) emphasize the extent of organizational resistance to the implementation of information systems and the need for a fit with these systems. Similarly, other moderators include organizational creativity and customers as analysts (Awan et al., 2021), the business value of big data (Aljumah et al., 2021) for firm performance, and information visibility for new product development (Dubey et al., 2021). Behl (2022) determines organizational culture and innovation moderates the impact of BDAC on firm performance and competitive advantage, whereas firm culture is found to be a moderator between BDAC and firm innovation (*Munir et al., 2023). Some other environment-related moderators include technology uncertainty (Bhatti et al., 2022b), competitive intensity (Olabode et al., 2022), flexibility orientation (Khan and Tao, 2022), event criticality, and disruption (Chen et al., 2022). In the supply chain context, it has been shown that flexible and control orientation positively and negatively moderate the BDAC–collaborative performance relationship (Dubey et al., 2019b). Furthermore, organizational flexibility is found to be a moderator of the association between BDAC and supply chain agility (Dubey et al., 2019a). Sheng et al. (2021) find the moderating role of market turbulence on the link to mass customization whereas data-driven culture has been used as a moderator of the link between BDACs and supply chain integration (Liu et al., 2022; Yu et al., 2021a). These non-exhaustive examples further illustrate the heterogeneity, inconsistency, and therefore low generalizability of previous findings of BDAC, which calls for future consolidation. We provide a detailed list of moderators and the moderated links in Appendix F.

Implications for future research regarding mediators and moderators

Since much fewer articles investigate the mediating and moderating factors to achieve favorable outcomes with BDAC. However, examining mediating and moderating mechanisms can help to improve methodological rigor (Hassan et al., 2022; Kahiya, 2018). Future research, thus, should intensify investigations of the mediating and moderating role of various factors, depending on the contexts, sectors, and outcomes.

On the one hand, it has been suggested that future studies should enhance their models by considering a broader set of mediating variables or contextual factors such as type of industries and size of the organizations (Belhadi et al., 2020). Regarding the impact of BDAC on co-innovation, Lozada et al. (2019) for instance propose a variety of mediating variables ranging from knowledge leakage and absorptive capability to information technology capabilities, knowledge management practices, or strategic orientation. Furthermore, future studies should continue to explore the mediators of BDAC and other important outcome variables such as innovation and context-specific consequences.

On the other hand, further investigations on boundary conditions should be conducted to derive better insights into the association between BDAC and its antecedents or outcome variables. For example, Wamba et al. (2017) highlight the role of organizational culture and top management commitment in building BDAC in a firm. Lastly, an interesting line of inquiry is that future studies could further examine whether environmental and industry factors such as environment dynamism, heterogeneity, and hostility (Mikalef et al., 2019b), environmental uncertainty (Mikalef et al., 2020a) to test whether BDAC is conditioned by such external elements. Overall, we suggest further exploring such moderators as the environmental and contextual factors on the link between BDAC and various outcomes as existing studies mostly investigate moderators of the link between BDAC and organizational performance.

5.1.4. Outcomes and consequences of BDACs

Outcome variables seem to have been extensively studied in the literature of BDAC, in which we identify 87 articles (84.5 %) examining the consequences of the phenomenon in various contexts. Most papers address among others the impacts of BDAC on different types of performance. In particular, generic terms such as organizational or firm performance are referred to in 17 articles, followed by operational performance (six articles). Even more vague or research-specific are the studies that state that BDAC enhances decision-making performance (Shamim et al., 2020; Awan et al., 2021; Chen et al., 2022), boosts information processing capacity, enables sales, and operations performance (Schlegel et al., 2021), improve the market, marketing, growth and financial performance (e.g., Qaffas et al., 2022; Song et al., 2022; Olabode et al., 2022; Gupta and George, 2016; Yasmin et al., 2020). Furthermore, the impact of BDAC on competitive advantage also receives much attention from scholars (Behl et al., 2022; Horng et al., 2022; Jha et al., 2020; Anwar et al., 2018).

Another research direction highlights the impact of BDAC on innovation and learning performance (Bag et al., 2020), especially various authors focus on its nuanced aspects such as innovative capabilities (Mikalef et al., 2019b, 2020a; Ramadan et al., 2020), co-innovation (Lozada et al., 2019), service innovativeness (Song et al., 2020; Xiao et al., 2020; Shamim et al., 2021), eco-innovation (Munodawafa and Johl, 2019), innovation performance (Contreras Pinochet et al., 2021; Demir et al., 2022), dual innovation (Su et al., 2022), and business model innovation (Ciampi et al., 2021). Likewise, there are various other factors related to organizational capabilities such as dynamic capabilities (Mikalef et al., 2020b, 2019b; Xiao et al., 2020; Wamba et al., 2017), innovation capabilities (Bahrami and Shokouhyar, 2022; Ramadan et al., 2020), digital platform and network capabilities (Bhatti et al., 2022a), followed by a variety of context-specific variables. The great majority of such context-specific papers test, not surprisingly, outcomes related to supply chain management such as swift trust and collaborative performance (Dubey et al., 2019b), supply chain performance (e.g., Jabbour et al., 2020; Bag et al., 2020; Zhang et al., 2020; Edwin Cheng et al., 2022; Gu et al., 2021; Dubey et al., 2019a; Nisar et al., 2022; Dubey et al., 2022), supply chain resilience, responsiveness, agility, alertness and preparedness (e.g., Bag et al., 2022; Dubey et al., 2019b; Mandal, 2019; Singh and Singh, 2019), or supply chain integration (e.g., Liu et al., 2022; Razaghi and Shokouhyar, 2021). Overall, although several authors have attempted to summarize the outcome variables of BDAC in their work (e.g., Bahrami and Shokouhyar, 2022), our study provides an exhaustive list of BDAC outcomes and consequences in Appendix G, grouping them into five categories namely competitive advantages and performance, innovation, capabilities, supply chain performance, and others.

On the one hand, while the most popular consequences in the seminal works are competitive advantage and firm performance, recent papers output many new outcome variables. Thus, the multitude of publications has made much progress with respect to this aspect, which represents a range of its non-exhaustive benefits in different contexts and organizational natures. Having said that, the output factors are produced without much consolidation with prior BDAC studies, so we find it challenging to categorize the outcome elements into our organizing framework. In addition, almost all the benefits belong to the firm-level of analysis across various industries, 16 of which are dedicated to the manufacturing sector and six papers are centered on the healthcare industry, where a wealth of big data can be generated. These statistics are consistent with our analysis of the industries and contexts of research, which reflect that this domain is still developing and there are significant research gaps to be addressed. The investigation on BDAC benefits in other sectors, for instance, is neglected although big data can make a great impact on such fields as commerce, logistics, and transportation, services, and marketing services providers as discussed earlier.

On the other hand, many of the outcome variables are mostly proposed and tested in quantitative survey-based papers, where they may be the results of dubious methods considering the fact that nearly 90 % of the hypotheses tested in the sample are supported and the findings are method-driven with the dominance of SEM methods. To support this argument, we further analyze the survey items for various constructs and questions employed in such articles. In particular, we find that many studies use subjective measurement items, in a sense that such measures are loosely associated with the literature or prior studies, and it is questionable as many questions for the measurements are subjective rather than based on facts, especially for the operationalization of performance, competitive advantage, and other output variables. For instance, there exists a tendency in many questionnaires to ask the respondents (e.g., managers) whether the organization outperforms competitors and advertising is at lower prices than competitors in the market, to name a few.

To systematically categorize the key findings from the studies, we will apply an organizing framework that has shown its usefulness and practicability for many organizational phenomena such as employee loyalty (Hornung and Nippa, 2014), or dynamic capabilities (Schilke et al., 2018). It distinguishes antecedents – of BDAC – from approaches that offer typologies of BDAC and from outcomes or consequences of possessing or lacking BDAC. Fig. 3 provides an illustrative overview of the various aspects and findings regarding antecedents, typologies, mediators, moderators, and outcomes outlined in the sections above.

Implications for future research regarding BDAC outcomes

Despite much progress with respect to the outcome variables, these factors are not consolidated with prior BDAC papers as recent papers continuously suggest additional research into the benefits of BDAC with greater nuance and fine-grained categories of performance, capabilities, and innovation. In spite of the plentiful evidence on the outcomes, we propose that future studies should continue to rest on such consequences, especially in the association between BDACs and other organizational capabilities. Considering the context-dependent nature of BDACs, non-performance outcomes and domain-specific benefits are expected to be carved out in future studies, taking firm sizes into account as suggested by Bertello et al. (2021).

In addition, there is a need to further explore the values and benefits of BDACs at different levels and to objectively operationalize

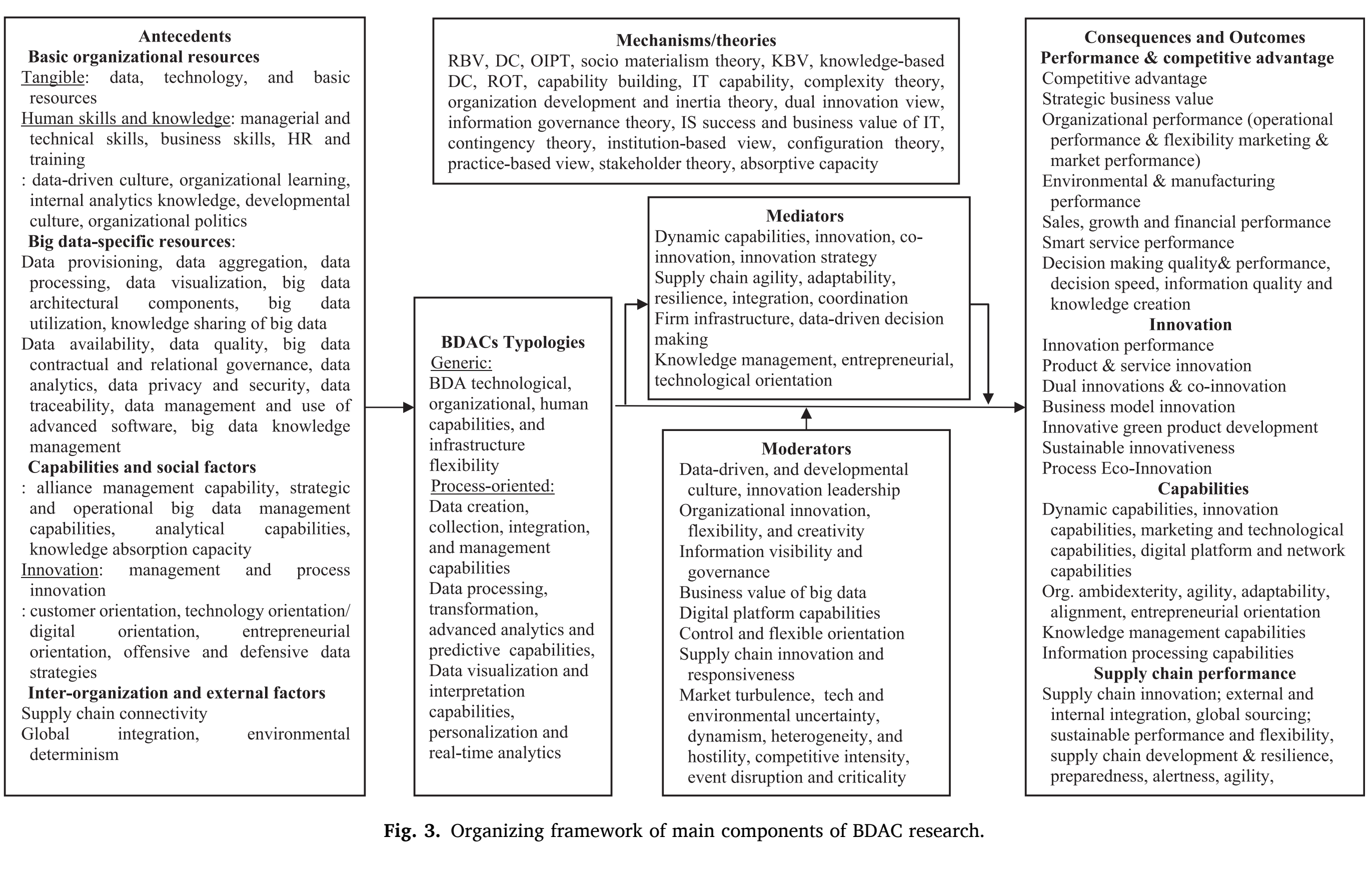

Fig. 3. Organizing framework of main components of BDAC research.

performance and outcome measures to develop clear metrics and to allow for inter-organizational comparison at least within certain industries as it is suggested to investigate industry-specific outcome variables. Authors should give careful consideration to the operationalization of relevant constructs, given the critical issues regarding the measure items and hypothesis testing as previously specified. Last but not least, and often forgotten when focusing on one specific organizational phenomenon, future research should expand beyond a BDAC-centric perspective, as further internal and external factors need to be taken into account to grasp the impact of BDACs on improving performance indicators (Mikalef et al., 2020a).

5.2. Additional TCCM analysis

In addition to the implications for future research provided in the framework-related components (characteristics of BDACs), we will dive deeper into the existing tensions and gaps to provide recommendations and reorientation for future research with regards to the remaining categories of the TCCM framework (i.e., theories, contexts, and methodologies).

5.2.1. Definitions and conceptualizations

As many papers do not provide a definition of BDACs, we call for closer attention to this aspect, especially focusing on the incorporation of other resources and capabilities and even environmental factors in addition to pure technological aspects. Furthermore, as a majority of existing definitions predicates on those by Gupta and George (2016), Akter et al. (2016), Wamba et al. (2017), and later definitions are based on one another, we believe that it is not of great importance to gain consolidation as the dimensions and components may vary depending on the contexts. Nevertheless, it is critical to explicitly provide a precise definition with clear elaborations on the rationale for the reference so as to reduce ambiguity. Besides, research on specific typologies, i.e., BDA management and technological capabilities are gaining popularity, which requires concrete definitions in future papers.

Furthermore, there is inadequate focus on the proper conceptualization as most of the studies ignore this task and insufficiently examine the dimensions of BDACs from a theoretical perspective, and mainly use those dimensions for picking the survey items. Besides, no researcher made the attempt to investigate what differentiates BDACs from other organizational capabilities and derive deeper insights into the characteristics of BDACs. We, therefore, suggest the need for further comparing and even testing the link between BDACs and prior capabilities concepts to carve out BDACs specifics, and come up with appropriate antecedents, novel constructs, and item measures. It is also important to re-theorize BDACs, conducting an in-depth investigation to provide a holistic conceptualization to push the field forward.

5.2.2. Theory development

While RBV and DC are – not surprisingly – the dominant theories applied in publications on BDACs as we have shown in Section 4, these views are not rigorously employed in the literature. More importantly, as it requires capabilities beyond basic resources to develop BDAC, employing generic RBV categories hinders insightful explorations of the input and conditional factors for building BDACs, which, as a result, limits the theoretical development. Also, there are recent calls for advancing the concept of BDACs by using other theoretical lenses such as KBV (Côrte-Real et al., 2020; Dubey et al., 2019a) as this theory can be adopted to discover the mechanisms through which specialized sets of tacit and explicit knowledge can be coordinated and aggregated to convert it into commercial outcomes. Besides, absorptive capacity is a prime basis in the process of turning data insights into useful knowledge (Božič and Dimovski, 2019) and could thus be employed to further conceptualize BDACs. Lastly, OIPT has recently been used to determine capabilities and requirements for handling big data and information (Ashaari et al., 2021; Schlegel et al., 2021), which appears to be an appropriate theoretical lens. Hence, we suggest adopting and integrating this theory to foster research development. Given the flexibility of BDACs in incorporating various insights from different theoretical streams, i.e., technical and management, we believe that scholars should not limit their theoretical integration only to the suggested trajectories as it is interesting to approach this concept from various perspectives and theoretical backgrounds as to enrich and advance BDAC research.

5.2.3. Research contexts

Due to its nascent nature, yet, maybe as an indication of its independence from cultural influences, most papers do not cover many geographical locations, and a majority of those obtain data from developing countries. Many authors suggest the need to conduct further research covering more nations to validate their results, especially those at the heart of the BDA revolution and developed economies where big data infrastructure and technologies are at maturity, such as the US, Europe, and China (Jha et al., 2020; Lozada et al., 2019; Wamba et al., 2017). In addition, as much research is on the manufacturing sector, it is important to cover more industries and sectors where big data is abundant such as transportation and services. Overall, future research should be conducted on different industries, geographic areas, and cultures to enrich cross-national comparative research or to obtain further implications (e.g., Bag et al., 2020; Song et al., 2020; Ferraris et al., 2019; Bertello et al., 2021; Wamba et al., 2020; Wamba et al., 2020c; Jeble et al., 2018). It is especially interesting to investigate the dependency of BDAC on firm sizes, which can be achieved by comparing the insights obtained from firm sizes, and examining which sub-BDACs, relevant resources, and conditions should be prioritized in each case. Finally, there is a call for further research on industry-specific BDACs, and future studies may address to what extent BDACs are industry-specific and how they can be developed and utilized to produce and capture value (e.g., Mikalef et al., 2019a; Singh and Singh, 2019; Wamba et al., 2020c; Kamble and Gunasekaran, 2020; Ramadan et al., 2020).

5.2.4. Methodology

Concerning studies applying quantitative research methods, there is a clear dominance – similar to other fields – of using cross-sectional data. Furthermore, we identify mostly generic limitations especially related to the survey items, sample size, and operationalization of the variables. Some papers lack questions for item measures, and many other papers simply reuse construct measurements from such papers as Akter et al. (2016) or Gupta and George (2016) without an appropriate justification or further extension. The reuse of survey items directly taken from previous studies shows that there is an inadequate theoretical examination with respect to the studied factors and their constructs. As BDAC is an emerging field with many typical characteristics, this approach is questionable as not many big data-specific aspects are added. Consequently, future works should reconstruct such measurements and re-operationalize such variables as the performance outcomes and competitive advantage in the context of BDACs.

Many quantitative studies also seem to be method-oriented, which reflects the authors' desired results rather than their attempts to search for interesting insights. These concerns reflect that the responses are well predictable, and that explains why 90 % of the hypotheses are confirmed, thus influencing the reliability of the findings as well as their contributions to literature. We further argue that authors tend to focus on proving their methods and the collected data valid even with complex models in lieu of investigating the sub-groups like those of similar industries and firm sizes. Besides, many surveys were carried out on respondents in an entity, yet the authors did not clarify how data were combined. Accordingly, we call for the need to properly select the respondents, sample, and its size in future research, investigating or even comparing the findings across different sectors and firm natures.

Overall, considering the nascent nature of BDAC research and its complexity, more longitudinal studies and well-designed surveys are called for to better observe the dynamics of relevant factors as suggested in some key studies in the sample (Wamba et al., 2020c; Wang et al., 2020; Wamba et al., 2017). Many authors in this domain also propose to use panel data to examine the stability of findings across time and also to potentially investigate a time-lag effect (Ferraris et al., 2019; Dubey et al., 2019a). Besides, it is suggested that future work could include the evaluation of unobserved heterogeneity in the data analysis strategy (Akter et al., 2016).

More importantly, it is surprising that survey studies significantly dominate in such a young field whereas secondary data, explorative studies, and replications do not exist and multiple case studies or interviews with experts are very limited. There is no paper employing multiple case studies to make a comparison between high-performing firms and unsuccessful ones to identify relevant capabilities. These methodological shortcomings, in our opinion, should be rigorously addressed in future papers. Our experience tells us that these are largely consistent with those discussed regarding other organizational phenomena. They range from more replication studies (Wamba et al., 2017), calls for using multiple data sources of data to enhance the validity of results (Wang et al., 2020), single and multiple case studies (Dubey et al., 2019a; Rialti et al., 2019) to mixed methods approaches (Munodawafa and Johl, 2019). Finally, it is obvious to apply advanced methods and techniques associated with BDA like supervised and unsupervised machine learning where appropriate to discover hidden patterns or increase the predictive power of findings (Kamble and Gunasekaran, 2020).

5.3. Reflections on the differences between BDACs and related concepts of capability

In this section, we provide a brief comparison between BDACs and three other widely-referenced capabilities: Information Technology (IT), digitalization, and dynamic capabilities. We examine influential studies that outline the key components of these concepts.

Firstly, the literature of IT capability is the backbone, on which BDAC conceptualization and constructs operationalization are built with similar inputs based on the RBV, including IT infrastructure, human resources, and IT-enabled intangibles (Bharadwaj, 2000), and similar typologies like IT management, personnel and infrastructure capability based on socio-materialism theory (Kim et al., 2012). Likewise, the main outcomes associated with this capability are firm performance (Bharadwaj, 2000; Kim et al., 2012), or competitive advantage (Bhatt and Grover, 2005). Notwithstanding their similarities, some early works postulate that the IT capability leverages organizational-level resources like information, communication, and connectivity technologies to enhance the "day-to-day running of the firm," whereas BDAC requires extensive roles of advanced technologies, skills, and responsibilities from highly specialized professionals to handle big data (Gupta and George, 2016; Akter et al., 2016). Thus, there exists a range of antecedents related to big data-specific resources and capabilities, more theories adopted, and many more outcomes in BDAC literature, which make BDAC different from the earlier concept.

Secondly, drawing on a literature review paper by Annarelli et al. (2021), digitalization capabilities are of a different stream of literature, which leverages firm digital and basic resources to produce outcomes like value co-creation, innovation, and competitive advantage. Nevertheless, the focus of digital capabilities is on digital networks, and it is viewed as a high-order capability and a representative of dynamic capabilities, whose dimensions include sensing opportunities and threats, seizing capabilities, and reconfiguring firms' digital resources and routines. Thirdly, it is noticeable that dynamic capabilities have been employed to study BDACs, which have been used as a mediator and outcome variable in some reviewed articles. Through the framework provided by Schilke et al. (2018), DC is viewed as a generic theory to study other phenomena, in which the antecedents, moderators, and outcome variables are more generic and context-independent than those of BDAC. Besides, BDAC may gain less convergence and consensus on various aspects in comparison with dynamic capabilities. In general, there are significant overlaps between the IT capability and BDACs with respect to the conceptualization, which calls for an in-depth focus on BDAC aspects to reduce the influence of the IT capability view on future BDAC research. Regarding digitalization and dynamic capabilities, although there is much deviation in these research domains, it is encouraged to incorporate these views to derive insightful, nuanced, and novel findings from BDAC research.

5.4. Contributions to research

Our study responds to the calls in existing literature to provide an organizing framework to deal with the great complexity of the important phenomenon of BDACs. Due to its emerging nature, we also employed the TCCM framework to cover the most significant aspects surrounding this concept. From our perspective, this paper contributes significantly to the field of management research in four key ways. Firstly, it offers a thorough examination of the existing literature in this area, sheds light on the current state of BDACs research, and presents a well-structured framework for organizing this knowledge encapsulating its antecedents, dimensions, typologies, moderators, and mediators. This framework aids in better understanding the intricacies of BDACs, making it an essential reference point for researchers and practitioners. Secondly, based on the TCCM framework, the work identifies various research gaps in existing literature and recommends promising avenues for future research and outlines a research agenda aimed at advancing the field of BDAC accordingly. Next, though not exhaustive, we highlight significant connections to prominent organizational and management concepts and theories and those from other domains. These interdisciplinary connections offer fertile ground for scholars from adjacent fields to explore BDACs. By capitalizing on existing knowledge, scholars can contribute to enriching future conceptualizations of BDACs, fostering interdisciplinary collaboration, and broadening the scope of research in this dynamic area. Lastly, to comprehend the discourse surrounding the term BDACs, to categorize them into a structured framework, and to identify future research avenues, this paper employed various protocols and frameworks that have been recommended in the field. Our method can be adopted in future research to offer an insightful approach to similar concepts in a holistic manner.

6. Conclusion

This research aimed to enhance the understanding of the conceptualization of BDACs and to provide an up-to-date assessment of the current state of research in this domain by using an interpretative literature review approach. Our review of the scholarly literatures on BDACs identified and evaluated a number of insightful publications from various domains and authors, which have increased significantly in the past three years. Our in-depth analyses have identified a range of concepts and elements that offer a pool of ideas for future research. However, we have also identified vagueness, inconsistencies, and gaps that require further research initiatives.

We acknowledge the limitations of our work, such as the potential exclusion of relevant articles and/or books or book chapters from our sample and suggest that future research should employ different approaches to validate and evaluate the framework and the factors included. Furthermore, the process of synthesizing the conceptualization and conducting the analyses was conducted using a qualitative approach, which does not completely rule out other explanations. We have attempted to provide recommendations and integrate various suggestions made in prior studies, but it is worth noting that some shortcomings and suggested avenues for further research still remain.

One notable limitation of this study pertains to the ethical considerations associated with big data-an aspect that has not been extensively addressed due to a lack of focus within existing big data literature. In the contemporary landscape, organizations utilize data for their own goals and as a bargaining tool with other entities, raising significant concerns in both academia and industry about the ethical use of personal data (Méndez-Suárez et al., 2023). It is worth noting that the scholarly community has dedicated considerable effort to formulating ethical guidelines for AI in recent years. For instance, scholars have underscored the importance of adhering to ethical principles when utilizing data for AI and machine learning models, encompassing aspects such as transparency, justice, fairness, non-maleficence, responsibility, and privacy (Jobin et al., 2019), or accountability, privacy protection, anti-discrimination, safety, or explainability (Hagendorff, 2020). Although these ethical guidelines have garnered more attention in the field of AI research, the training of AI models cannot be separated from big data. Therefore, our recommendations for both research and practical application revolve around compliance with ethical principles in the utilization of big data to avoid AI ethical failures (Méndez-Suárez et al., 2023), in which legal and ethical frameworks, such as the European General Data Protection Regulation (GDPR) (2016), or the ethics guidelines of the Association for Computing Machinery (ACM) (Gotterbarn et al., 2018), should be considered for implementation when organizations aim to employ personal data, regardless of the underlying business objectives.[1]

Overall, we are impressed by the efforts made by the various scholars and the promising research opportunities that they have suggested to further develop this field, reflecting the progressive research tendency of BDACs within a very short period of time.

Author statement

This is to certify that all authors have seen and approved the final version of the manuscript being submitted. We warrant that the article is our original work, hasn't received prior publication and isn't under consideration for publication elsewhere.

Data availability

No data was used for the research described in the article.

Appendix A. Identification of documents on Scopus and Web of Science

Database	Query boolean operators	N. records
Scopus	TITLE-ABS-KEY ("BDAC*" OR "BDA capabilit*"OR"Big Data Analytics Capabilit*"OR"big data predictive capabilit*"OR"big data capabilit*" OR "business intelligence capabilit*") AND (EXCLUDE (PUBYEAR, 2022)) AND (LIMIT-TO (DOCTYPE, "ar") OR LIMIT-TO (DOCTYPE , "re")) AND (LIMIT-TO (SUBJAREA , "COMP") OR LIMIT-TO (SUBJAREA , "BUSI") OR LIMIT-TO (SUBJAREA , "DECI") OR LIMIT-TO (SUBJAREA , "SOCI")) AND (LIMIT-TO (LANGUAGE , "English"))	199
Web of Science	("BDAC*" OR "BDA capabilit*" OR "big data analytics capabilit*" OR "BD predictive capabilit*" OR "big data capabilit*" OR "business intelligence capabilit*") (All Fields) and Articles or Review Articles or Early Access (Document Types) and Management or Business or Computer Science Information Systems or Computer Science Interdisciplinary Applications or Economics or Multidisciplinary Sciences or Computer Science Artificial Intelligence or Behavioral Sciences or Business Finance (Web of Science Categories)	126

Appendix B. Various definitions/conceptualizations of BDACs in the literature

Author(s)	Definition/conceptualization	Theories/views	Context	Prior studies
Gupta and George (2016)	BDAC is defined as "… *a firm's ability to assemble, integrate, and deploy its big data-specific resources.*" (p. 1049)	Resource-based view, IT capability		Ravichandran and Lertwongsatien (2005), Lu and Ramamurthy (2011), Kim et al. (2012), Wang et al. (2012)
Akter et al. (2016)	The conceptualization of BDAC contains three dimensions (i.e., management, technology, and human) that "… *highlight[s] the importance of the complementarities between them for high level operational efficiency and effectiveness for improved performance and sustained competitive advantage.*" (p. 114)	Entanglement view of socio-materialism, resource-based view, IT capability		Kiron et al. (2014), Davenport et al. (2012), McAfee and Brynjolfsson (2012), Wixom et al. (2013), Barton and Court (2012), Wamba et al. (2015), Ransbotham et al. (2015)
Wang and Hajli (2017), Wang et al. (2018a)	BDAC is defined as "*the ability to acquire, store, process and analyze large amount of health data in various forms, and deliver meaningful information to users, which allows them to discover business values and insights in a timely fashion.*" (p. 4)	Information lifecycle management view	Health care	Cosic et al. (2012), Hurwitz et al. (2013), LaValle et al. (2011), Simon (2013), Trkman et al. (2010), Wixom et al. (2013)
Wamba et al. (2017)	BDAC is regarded as "… *the competence to provide business insights using data management, infrastructure (technology) and talent (personnel) capability to transform business into a competitive force.*" (p. 3)	Resource-based view, IT capability, entanglement view		Kiron et al. (2014), Kim et al. (2012), Kim et al. (2011) (constructs and definitions of BDAC and dimensions)
Srinivasan and Swink (2018)	"…*organizational facility with tools, techniques, and processes that enable a firm to process, organize, visualize, and analyze data, thereby producing insights that enable data-driven operational planning, decision-making, and execution.*" (p. 1851)	Organizational information processing theory	Supply chain management	George et al. (2014)

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[1] We would like to express our gratitude to one of our reviewers for their valuable suggestion to enhance the discussion of the ethical aspect related to the utilization of big data in this paragraph.

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Author(s)	Definition/conceptualization	Theories/views	Context	Prior studies
Arunachalam et al. (2018)	BDAC in the supply chain context is referred to as "*the ability of organizations to collect and organize supply chain data from heterogeneous systems distributed across organizational boundaries, analyze it either batch-wise or real-time or near real-time and visualize it intuitively to create proactive supply chain system and support decision making.*" (p. 4)		Supply chain management	Hurwitz et al. (2013), Wang et al. (2018a), Hofmann (2017), Richey et al. (2016) (BDAC is defined based on these studies)
Mikalef et al. (2018)	BDAC 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.*" (p. 557)	Resource-based view, dynamic capabilities view		Akter et al. (2016), Kiron et al. (2014)
Dubey et al. (2019a)	"*BDAC is an organizational facility with tools, techniques, and processes that enable the organization to process, visualize, and analyze data, thereby producing insights that enable data-driven operational planning, decision making and execution.*" (p. 2095)	Dynamic capabilities view, contingency theory	Supply chain management	Srinivasan and Swink (2018)
Lin and Kunnathur (2019)	"*Big Data Capability as a firm's capability of identifying sources, where large volumes of various kinds of data flow out at high speed, and collecting, storing, and analyzing such Big Data for the purpose of accomplishing the firm's strategic as well as operational goals.*" (p. 51)	Dynamic capabilities view		Pigni et al. (2016), Chen et al. (2015)
Lozada et al. (2019)	"*… BDA capability refers to a company's management ability, that is, the continuous use and deployment of big data resources with the strategic goal of creating value and developing a competitive advantage for the firm.*" (p. 2)			Wamba et al. (2017), Garmaki et al. (2016), Gupta and George (2016), Kiron et al. (2014)
Mandal (2019)	BDA capabilities are conceptualized as "*a third-order formative construct of BDA management capability, BDA personnel expertise capability and BDA infrastructure flexibility capability*" (p. 298). "*BDA management capabilities comprise of essential first-order capabilities of planning, investment decision making, coordination and control.*" (p. 298).	Resource-based view, dynamic capabilities view	Supply chain management	Wamba et al. (2017)
Mikalef et al. (2019b)	BDAC is "*defined as the ability of a firm to capture and analyse data towards the generation of insights by effectively orchestrating and deploying its data, technology and talent.*" (p. 273)	Resource-based view, dynamic capabilities view		Gupta and George (2016), Mikalef et al. (2018), Wamba et al. (2017)
Rialti et al. (2019)	"*Organizational BDA capabilities are an ensemble of capabilities that include infrastructure flexibility, management capabilities and personnel capabilities.*" (p. 1)	Dynamic capabilities view		Wamba et al. (2017), Gunasekaran et al. (2018), Mikalef and Pateli (2017) Definition based on Wamba et al. (2017), measures of constructs based on the 3 papers.
Wang et al. (2019)	"*Big data analytics capability is defined as the ability to acquire, store, process and analyse large amounts of health data in various forms, and deliver meaningful information to users, which allows them to discover business values and insights in a timely fashion.*" (p. 368)	Configuration theory	Health care	Wang and Hajli (2017)
Belhadi et al. (2020)	"*BDA capability is defined as the ability of the organizations in developing competency to generate business insights based on organizational (i.e., BDA management), physical (i.e., IT infrastructure), and human (e.g., analytics skill or knowledge) capabilities for increased business performance*" (p. 2)	Resource-based view, dynamic capabilities view	Manufacturing firms	Mikalef et al. (2020b), Akter et al. (2016)
Côrte-Real et al. (2020)	BDACs refer to "*the extent to which BDA has been used to provide business insights into primary activities (e.g., production, distribution, and customer service).*" (p. 6)	Resource-based view, dynamic capabilities view, knowledge management		Chen et al. (2015)
Mikalef et al. (2020a)	BDAC is "*the ability of a firm to capture and analyze data toward the generation of insights by effectively orchestrating and deploying its data, technology, and talent.*" (p. 2)	Resource-based view, information governance theory		Akter et al. (2016), Gupta and George (2016), Wamba et al. (2017), Kiron et al. (2014)
Mikalef et al. (2020b)	BDAC is defined as "*the ability of a firm to effectively deploy technology and talent to capture, store and analyze data, toward the generation of insight.*" (p. 7)	Resource-based view, dynamic capabilities view, IT capability		Gupta and George (2016), Mikalef et al. (2018)
Ramadan et al. (2020)	"*Big data analytics capabilities refer to the firm's ability to recognize and analyze different data sources to provide valuable insights.*" (p. 2)		Manufacturing firms	Hu et al. (2018)
Shamim et al. (2020)	BDAC is referred to as "*a holistic approach of analysing and processing big data for value creation.*" (p. 4)	Knowledge based dynamic capabilities view, social capital theory		Wamba et al. (2017), Akhtar et al. (2019),
Song et al. (2020)	BDAC is defined "*as the capability of firms to combine, integrate, and deploy specific big data resources.*" (p. 5)	Information processing theory		Gupta and George (2016)

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Author(s)	Definition/conceptualization	Theories/views	Context	Prior studies
Upadhyay and Kumar (2020)	"*BDAC is broadly defined as the competence to provide business insights using data management, infrastructure (technology), and talent (personal) capabilities to transform the business into a competitive force.*" (p. 2)	Resource-based view, dynamic capabilities view, socio-materialism theory		Wamba et al. (2017), Gupta and George (2016), Kiron et al. (2013) Kim et al. (2011), Kim et al. (2012) for measurement of constructs
Wamba et al. (2020)	BDAC is defined as "*a firm's ability to assemble, integrate, and deploy its big data-specific resource.*" (p. 10)	IT capability, resource-based view		Gupta and George (2016)
Xiao et al. (2020)	"*BDAC refers to the ability to provide business insights in the big data environment by using big data analytics personnel, big data analytics technical, and big data analytics management capabilities.*" (p. 18780)	Dynamic capabilities view	Service sector	Akter et al. (2016)
Yasmin et al. (2020)	BDACs are referred to "*as a balanced combination of requisite human resource, big-data skills, advanced technologies supported by large datasets to generate analytical reports and actionable insights utilized, produced, and processed by mathematical, statistical techniques, and machine learning tools for enhanced performance.*" (p. 2)	Resource-based view, dynamic capabilities view		Akhtar et al. (2019), Akter et al. (2016), Wang et al. (2019)
Zhang et al. (2020)	BDAC refers to "*a firm's ability to assemble, integrate, and deploy its big data-specific resources.*" (p. 3)	Source-position-performance theoretical framework	Sustainability development projects	Gupta and George (2016), Akter et al. (2016), Ferraris et al. (2019), Wamba et al. (2017)
Ashaari et al. (2021)	"*BDAC is termed as an organization's capacity to efficiently and strategically arrange, assemble, and apply BDA resources so that effective decision-making can be made to enhance overall organization's performance.*" (p. 1)	Resource-based view, organizational information processing theory	Higher education institutions	Mikalef et al. (2020b), Shamim et al. (2020), Janssen et al. (2017), Cao et al. (2015),
Awan et al. (2021)	BDACs refer to a "*holistic process that involves the collection, analysis, use and interpretation of data for various functional divisions to gain actionable insights, create business value and establish competitive advantage.*" (p. 86)	Resource-based view, dynamic capabilities view, institution-based view	Manufacturing sector	Akter et al. (2016)
Bertello et al. (2021)	BDAC is defined "*as the ability to acquire, store, process, and analyze large amounts of data in various forms and deliver meaningful information to users, allowing them to discover business values and insights in a timely fashion.*" (p.1040)	Resource-based view		Wang et al. (2018a)
Ciampi et al. (2021)	BDAC "*refer to the company's abilities to leverage on technology and talent to exploit BD towards the generation of the insights that are necessary to overperform rivals.*" (p. 2)	Knowledge-based view, IT capability		Mikalef et al. (2017), Wamba et al. (2017), Gupta and George (2016)
Contreras Pinochet et al. (2021)	BDAC is recognized as "*the competence to provide business insights using the capacity of data management, infrastructure (technology) and talent (personnel) to transform a business into a competitive force.*" (p. 1410)	Process-oriented dynamic capabilities, business value		Gupta and George (2016)
Gu et al. (2021)	BDAC in supply chain management is described as "*the ability of organizations to collect and organize supply chain data from heterogeneous systems distributed across organizational boundaries, analyze it either batch-wise, or real-time, or near real-time, and visualize it intuitively to create proactive supply chain system and support decision making,*" (p. 155)	Resource-based view, dynamic capabilities view, contingency theory	Supply chain management	Arunachalam et al. (2018)
Henao-García et al. (2021)	"*BDAC is defined as the ability of a firm to capture and analyze data for the generation of insights by effectively orchestrating and deploying its data, technology, and talent.*" (p. 28)	Resource-based view, dynamic capabilities view		Mikalef et al. (2018)
Schlegel et al. (2021)	BDAC is defined "*as a firm's ability to assemble, integrate and deploy its big data-based resources.*" (p. 609)	Organizational information processing theory		Gupta and George (2016), Akter et al. (2016)
Sheng et al. (2021)	BDA capability refers to "*an enterprise's ability to realize data-driven operation plan and decision-making through processing, organizing and analyzing data.*" (p. 2618)	Organizational information processing theory	Supply chain management	Dubey et al. (2019b), Gupta and George (2016)
Sun and Liu (2021)	"*BDA capabilities comprise a firm's techniques, processes and talents that enable the organization to process, visualize and analyze big data, thereby producing insights that enable data-driven operational planning, decision-making and execution.*" (p. 1163)			Kiron et al. (2014), Akter et al. (2016), Dubey et al. (2019a) for definition; Akter et al. (2016), Ferraris et al. (2019) for measures
Sabharwal and Miah (2021)	BDAC is defined as "*the combined ability to store, process, and analyze large amounts of data to provide meaningful information to users.*" (p. 9)	Organization development theory		Gupta and George (2016), Wang et al. (2019), Mikalef et al. (2020b), Shuradze and Wagner (2016)
Yu et al. (2021a)	BDAC is defined as an "*organizational facility with tools, techniques, and processes that enable a firm to process, organize, visualize, and analyse data thereby*	Organizational information processing theory	Supply chain management	Srinivasan and Swink (2018)

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Author(s)	Definition/conceptualization	Theories/views	Context	Prior studies
	producing insights that enable data-driven operational planning, decision-making, and execution." (p. 2)			
Yu et al. (2021b)	BDAC refers to "*organizational facility with tools, techniques, and processes that enable a firm to process, organize, visualize, and analyse data, thereby producing insights that enable data-driven operational planning, decision-making, and execution.*" (p. 4)	Organizational information processing theory	Health care	Srinivasan and Swink (2018)
Yu et al. (2022)	BDAC is defined as "*the ability to acquire, store, process, and analyse large amount of health data in various forms, and deliver meaningful information to users that allows them to discover business values and insights in a timely fashion.*" (p. 3)	Resource orchestration theory	Health care	Wang et al. (2018a)
Zhang and Lv (2021)	BDACs are proposed with three dimensions of tangible resources, human resources and intangible resources, which are analyzed "*from three dimensions of management capabilities, infrastructure capabilities and human capabilities.*" (p. 50525)	Resource-based view, IT capabilities	Smart cities, public sectors	Gupta and George (2016)
Behl et al. (2022)	"*Big data analytics capabilities (BDAC) are broadly defined as the competence to provide business insights using data management, infrastructure (technology) and talent (personnel) capability to transform business into a competitive force.*" (p. 380)	Organizational information processing theory, institutional theory	Micro, small and medium enterprises	Akter et al. (2016)
Elia et al. (2022)	"*BDAC are defined as the knowledge, skills, and abilities that combine technology and management issues to explore data potential through sophisticated statistical, computational, and visualization tools.*" (p. 2)	Resource-based view, dynamic capability view, and absorptive capacity view		Wamba et al. (2020b)
Liu et al. (2022)	"*BDAC refers to an organizational ability that enable firms to capture, consolidate, and analyze data thus generating new insights to implement data-driven programming, decision-making, and operation.*" (p. 2561)	Organizational information processing theories	Supply chain management	Gupta and George (2016), Srinivasan and Swink (2018)
Uddin Murad et al. (2022)	"*BDACs are an organizational ability with the necessary tools and techniques to process big data to produce internal associations, patterns, and insights.*" (p. 3)			Srinivasan and Swink (2018)
Jaouadi (2022)	"*The term big data analytics capability is the extent wherein firm has distinctive capability to identify quality problems, competency to set optimal pricing, trace profitable customers and manage lowest inventory using big data tools.*" (p. 2)			Akter et al. (2016)
Horng et al. (2022)	"*Big data analytics capabilities refer to obtaining knowledge from internal or external partners and gaining market insight through big data tools.*" (p. 24)	Knowledge-based dynamic capability view		Germann et al. (2013)
Ciasullo et al. (2022)	"*BDA capability refers to a company's management ability, that is, the ongoing deployment of big data resources at the strategic aims to create value and develop a competitive advantage for the firm.*" (p. 205)			Wamba et al. (2017)
Zhu et al. (2022)	"*…the ability of an organization to integrate, build, and reconfigure the information resources, as well as business processes, to address rapidly changing environments.*" (p. 5)	Dynamic capabilities view	Supply chain management	Lee and Kang (2015)
Arias-Pérez et al. (2022)	"*BDAC is defined as the ability of a firm to capture and analyze big data toward the generation of insights by effectively orchestrating and deploying its data, technology and talent.*" (p. 2)	Knowledge-based view		Henao-García et al. (2021)
Olabode et al. (2022)	"*the ability of a firm to effectively deploy technology and talent to capture, store and analyze data, toward the generation of insight.*" (p. 1219)	Knowledge-based view and contingency theory		Mikalef et al. (2020b)
Bhatti et al. (2022a)	"*a holistic process that involves the collection, analysis, use, and interpretation of data for various functional divisions to gain actionable insights, create business value, and establish competitive advantage*" (p. 4)	Resource-based view, dynamic capability view	Supply chain management	Wamba et al. (2020b)
Bhatti et al. (2022b)	"*a holistic process that involves the collection, analysis, use, and interpretation of data for various functional divisions with a view to gaining actionable insights, creating business value, and establishing competitive advantage.*" (p. 5)	Resource-based view, dynamic capability view	Supply chain management	Wamba et al. (2020b)
Song et al. (2022)	"*BDAC is defined as the ability to develop business insight by using data management, technical foundations and talents.*" (p. 1168)			Kiron et al. (2014)

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Author(s)	Definition/conceptualization	Theories/views	Context	Prior studies
*Munir et al. (2023)	"*it can be defined as the organization's capacity to provide insight into the use of data management, infrastructure and human capabilities to increase the competitiveness of the business.*" (p. 5)	Resource-based view, process-oriented dynamic capability view, socio-materiality theory		Kiron et al. (2014), Akter et al. (2016)
Cetindamar et al. (2022)	"*the ability of an organization to integrate, build, and reconfigure the information resources, as well as business processes, to address rapidly changing environments.*" (p. 4)		Supply chain management	Olszak (2014)

Appendix C. Typologies of BDACs proposed and studied in existing literature

Documents	Typologies of BDACs
Cetindamar et al. (2022)	BDA human, non-human and infrastructure capabilities
Qaffas et al. (2022)	Big data analytics management capability
Park and Singh (2022)	Infrastructure, human capital, knowledge management capability
Chatterjee et al. (2022)	Personalization and real-time analytics
Liu et al. (2022)	Big data technical capability and big data managerial capability
Demir et al. (2022)	Big data collection, processing, analysis and processing, transformation capability
Ashaari et al. (2021)	BDA technological, organizational, and people capabilities
AlNuaimi et al. (2021)	Technological and human capabilities
Shamim et al. (2021)	BDA management capabilities
Nisar et al. (2022), Muhammad et al. (2021)	BDA management capabilities, technical capabilities, and talent capabilities
Uddin Murad et al. (2022), Razaghi and Shokouhyar (2021), Rialti et al. (2020), *Edwin Cheng et al. (2022), Rialti et al. (2019)	BDA infrastructure flexibility, BDA management capabilities, BDA personnel expertise capability
Bag et al. (2021)	Data creation capabilities, data integration and management capabilities, advanced analytics capabilities, data visualization capabilities, and a data driven culture
Zhang and Lv (2021)	Big data system capabilities, big data human capabilities, and big data management capabilities.
Bag et al. (2020)	BDA management and talent capability
Yasmin et al. (2020)	Infrastructure, human resource, management capabilities
Belhadi et al. (2020)	Organizational (i.e., BDA management), physical (i.e., IT infrastructure), and human (e.g., analytics skill or knowledge) capabilities
Wamba et al. (2020), Wamba et al. (2017)	BDA management, infrastructure and personnel capability
Xiao et al. (2020)	BDA technology capabilities and BDA personnel capabilities
Ferraris et al. (2019), Song et al. (2022)	BDA technology and BDA management
Munodawafa and Johl (2019)	IT capability, personnel expertise capability, and management capability
Wang et al. (2019)	Data integration capability, analytical capability, data interpretation capability, predictive analytics, analytical personnel's technical and business skills
Mandal (2019)	Only focus on BDA management capabilities, which further refers to BDA planning, BDA investment decision making, BDA coordination, BDA control
Popovič et al. (2018)	Data provisioning, analytical capabilities and people skills

Appendix D. Antecedents of BDACs identified from the literature

Documents	Antecedents
Zhu et al. (2022)	Sustainable supply chain management practices
Horng et al. (2022)	Offensive and defensive data strategies, big data knowledge management
Khan and Tao (2022)	Knowledge absorption capacity
Behl (2022)	Managerial and technical skills
Demir et al. (2022)	Big data utilization, knowledge sharing of big data
Elia et al. (2022), Lozada et al. (2019), Mikalef et al. (2018), Mikalef et al. (2019b), Gupta and George (2016)	Tangible resources, human skills, intangible resources
AlNuaimi et al. (2021)	Managerial experience and employee skills (BDA human capabilities); data availability and technological infrastructures (BDA technology capabilities); e-procurements
Shamim et al. (2021)	Strategic and operational big data management capabilities
Henao-García et al. (2021)	Tangibles, intangibles, human resources, management innovation
Yu et al. (2022)	Data driven culture, digital technology orientation and their interaction
Dubey et al. (2021)	Alliance management capability
Chen and Chen (2022)	Intellectual capital
Shamim et al. (2020)	Big data contractual governance, big data relational governance
Jha et al. (2020)	Data management, advanced software, human resource and training, organizational politics, global integration, environmental determinism
Ramadan et al. (2020)	Data availability
Yasmin et al. (2020)	Management, human resources and infrastructure capability
Upadhyay and Kumar (2020)	Internal analytics knowledge, organizational culture
Srimarut and Mekhum (2020)	Supply chain connectivity
Côrte-Real et al. (2020)	Data quality
Lin and Kunnathur (2019)	Developmental culture, customer orientation, technology orientation, entrepreneurial orientation
Ferraris et al. (2019)	BDA technological and management

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Documents	Antecedents
Singh and Singh (2019)	Institutional response to supply chain disruption, IT infrastructure
Mikalef et al. (2019a)	Data, process, technology, organization, people, context
Anwar et al. (2018)	Technical capabilities: compatibility, modularity, connectivity; Personnel capabilities: technical knowledge, business knowledge, technical management knowledge
Popovič et al. (2018)	Data provisioning, analytical capabilities, people skills
Wang et al. (2018b)	Traceability, analytical capability, decision support capability, predictive capability
Srinivasan and Swink (2018)	Supply chain visibility
Wamba et al. (2017)	BDA infrastructure flexibility, management capabilities, personnel expertise capabilities
Wang and Hajli (2017)	Data aggregation, data processing, data visualization, big data architectural components
Akter et al. (2016)	BDA management capability, technology, and talent capability

Appendix E. Mediating factors in BDACs research

Documents	Mediators	Link
Behl et al. (2022)	Supply chain coordination and swift trust	BDACs and supply chain risk
*Munir et al. (2023)	Process-oriented dynamic capabilities	BDACs and organizational innovation performance
Qaffas et al. (2022)	Business intelligence infrastructure	BDACs and financial/marketing performance
Song et al. (2022)	Infrastructure and value attribute of business model	BDACs and growth/financial performance
Park and Singh (2022)	Upstream supply chain management IT infrastructure, downstream supply chain inventory management IT utilization	BDACs and automated supply chain disruption risk alert tool
Bhatti et al. (2022b)	Supply chain agility and adaptability	BDACs and supply chain innovation
Nisar et al. (2022)	Innovative green product development and supply chain risk management	BDACs and innovation & learning performance
Al-Khatib and Valeri (2022)	BDACs as a mediator	Service innovation and competitive advantage
Dubey et al. (2022)	Humanitarian supply chain agility and resilience	BDACs and humanitarian supply chain performance
Bhatti et al. (2022a)	Digital platform and network capabilities	BDACs and supply chain innovation, BDACs and firm performance
Al-Khatib (2023)	Green incremental and radical supply chain innovation	BDACs and green supply chain performance
Olabode et al. (2022)	Disruptive business models	BDACs and market performance
Arias-Pérez et al. (2022)	BDACs as a mediator	Open innovation and firm performance
Al-Darras and Tanova (2022)	Entrepreneurial orientation	BDACs and organizational agility
Ciasullo et al. (2022)	Co-innovation	BDACs and organizational resilience
Horng et al. (2022)	Sustainability marketing	BDACs and competitive advantage, company performance (profitability, sales volume, intangible market assets)
Khan and Tao (2022)	BDAC as a mediator	Knowledge absorption capacity and firm's agility
Zhang et al. (2022a); *Zhang et al. (2022b)	Exploitative innovation strategy, combined ambidextrous innovation strategy	BDACs and sustainable competitive advantage
Chatterjee et al. (2022)	Customer interactivity and retention capability	BDACs and strategic sales performance
Al-Khatib (2022b)	Green incremental and radical innovation	BDACs and competitive advantage
Liu et al. (2022)	Green internal integration	BDACs and green supplier/customer integration
Elia et al. (2022)	Transparency, access, proactive adaptation	Transparency on BDACs and organizational performance, business process improvement, product and service innovation, consumer experience and market enhancement; access on BDACs and organizational performance, business process improvement; proactive adaptation on BDACs and product and service innovation
Ilmudeen (2021)	Business intelligence infrastructures	BDACs and operational performance, BDACs and marketing performance
Ashaari et al. (2021)	Data-driven decision making	BDACs and higher education institutes performance
Sheng et al. (2021)	Supply chain agility	BDACs and mass customization capability
Contreras Pinochet et al. (2021)	Process-oriented dynamic capabilities	BDACs and product innovation performance
AlNuaimi et al. (2021)	BDACs as a mediator	E-procurement and environmental performance
Gu et al. (2021)	BDACs as a mediator	Supplier development and firm performance
Yu et al. (2021b)	Suppliers and customers integrations	BDACs and operational flexibility
Ciampi et al. (2021)	Entrepreneurial Orientation	BDACs and business model innovation
Awan et al. (2021)	Manufacturing agility	BDACs and manufacturing performance
Bahrami and Shokouhyar (2022)	Innovative capability and information quality (1), supply chain resilience (2)	(1) on BDACs and supply chain resilience, (2) on BDACs and firm performance
Aljumah et al. (2021)	Ambidexterity of big data	BDACs and organizational performance
Edwin Cheng et al. (2022)	Circular economy practices and sustainable supply chain flexibility	BDACs and sustainable supply chain performance
Belhadi et al. (2020)	Green manufacturing practices, Lean Six Sigma efforts and their integration	BDACs and environmental performance
Mikalef et al. (2020b)	Dynamic capabilities	BDACs and marketing/technological capabilities
Wamba et al. (2020)	BDA dependent organization agility	BDACs and strategic business value/firm performance
Srimarut and Mekhum (2020)	BDACs as a mediator	Supply chain connectivity - agility, adaptability, alignment
Ferraris et al. (2019)	Knowledge management orientation	BDACs and firm performance
Dubey et al. (2019a)	Supply chain agility	BDACs and competitive advantage
Mikalef et al. (2019b)	Dynamic capabilities	BDACs and incremental/radical innovation
Anwar et al. (2018)	Competitive advantage	BDACs and firm performance
Wamba et al. (2017)	Process-oriented dynamic capabilities	BDACs and firm performance

Appendix F. Moderating factors in BDACs research

Documents	Moderators	Link
*Munir et al. (2023)	Organizational culture	BDACs and organizational innovation performance
Bhatti et al. (2022b)	Technology uncertainty	BDACs and supply chain innovation
Olabode et al. (2022)	Competitive intensity	Disruptive business models and market performance
Khan and Tao (2022)	Flexibility orientation	Knowledge absorption capacity and BDAC
Al-Khatib and Shuhaiber (2022)	BDACs as a moderator	Green human/structural/relational capital and green supply chain performance
Chen et al. (2022)	Event criticality and disruption	BDACs and decision speed/decision quality
Al-Khatib (2022a)	Green innovation	BDACs and green supply chain performance
Liu et al. (2022)	Data driven decision culture	BDACs and green internal integration
Behl (2022)	Organizing culture and innovation	BDACs and competitive advantage, BDACs and firm performance
Sheng et al. (2021)	Market turbulence	BDACs and supply chain agility
Gu et al. (2021)	BDACs as a moderator	Supplier development and firm performance
Yu et al. (2021a)	Data driven culture	BDACs and internal supply chain finance integration
Dubey et al. (2021)	Information visibility	BDACs and new product development
Awan et al. (2021)	Organizational creativity, customers as analysts	BDACs and manufacturing agility
Bag et al. (2022)	Innovation leadership	BDACs and healthcare supply chain innovation/ responsiveness
Aljumah et al. (2021)	Business value of big data	BDACs and organizational performance
Shamim et al. (2020)	Data driven culture	BDACs and decision making performance
Wang et al. (2020)	BDACs as a moderator	Corporate social responsibility and green supply chain management
Mikalef et al. (2020a)	Information governance, environmental uncertainty	BDACs and incremental/radical innovative capability
Sun and Liu (2021)	BDACs as a moderator	Business model novelty/efficiency design and new product development performance
Xiao et al. (2020)	Digital platform capabilities	BDACs and dynamic capabilities
Hao et al. (2019)	BDACs as a moderator	Big data and sustainability of innovation and organizational development
Rialti et al. (2019)	Organization information management system fit, and organizational resistance to information management	BDACs-ambidexterity, BDACs-agility, BDACs-organizational performance
Lin and Kunnathur (2019)	Developmental culture	Technological, customer, entrepreneurial orientation and BDACs
Dubey et al. (2019a), Srinivasan and Swink (2018)	Organization flexibility	BDACs and supply chain agility, BDACs and competitive advantage
Mikalef et al. (2019b)	Environment dynamism, heterogeneity, and hostility	BDACs and dynamic capabilities
Dubey et al. (2019b)	Control orientation and flexible orientation	BDACs and collaborative performance

Appendix G. Outcome variables of BDACs in the literature

Outcomes	References
Competitive advantage, sustainable competitive advantage	Behl et al. (2022), Horng et al. (2022), Zhang et al. (2022b), Al-Khatib (2022b), Behl (2022), Jha et al. (2020), Côrte-Real et al. (2020), Dubey et al. (2019a), Anwar et al. (2018), Ramadan et al. (2020)
Business value/strategic business value	Contreras Pinochet et al. (2021), Wamba et al. (2020)
Organizational performance (general)	Bhatti et al. (2022a), Horng et al. (2022), Elia et al. (2022), Ashaari et al. (2021), Gu et al. (2021), Bahrami and Shokouhyar (2022), Razaghi and Shokouhyar (2021), Aljumah et al. (2021), Su et al. (2022), Upadhyay and Kumar (2020), Wamba et al. (2020), Rialti et al. (2019), Ferraris et al. (2019), Mikalef et al. (2019a), Anwar et al. (2018), Wamba et al. (2017), Akter et al. (2016)
Operational performance and operational flexibility, strategic sales performance	Zhu et al. (2022), Chatterjee et al. (2022), Ilmudeen (2021), Yu et al. (2022), Yasmin et al. (2020), Srinivasan and Swink (2018), Gupta and George (2016), Yu et al. (2021b)
Market performance, marketing performance, growth and financial performance	Qaffas et al. (2022), Song et al. (2022), Olabode et al. (2022), Ilmudeen (2021), Yasmin et al. (2020), Gupta and George (2016)
Decision making quality and performance, decision speed and quality	Awan et al. (2021), Shamim et al. (2020), Chen et al. (2022)
Manufacturing performance, smart service performance, environmental performance	Zhu et al. (2022), Awan et al. (2021), Popovič et al. (2018), Zhang and Lv (2021), AlNuaimi et al. (2021), Belhadi et al. (2020)
Explorative and exploitative, incremental and radical innovation, innovation performance, innovative organizational performance, innovation and learning performance	Rialti et al. (2020), Mikalef et al. (2020a), Mikalef et al. (2019b), Muhammad et al. (2021), Demir et al. (2022), Khan and Tao (2022), Nisar et al. (2022), *Munir et al. (2023)
Product innovation performance, service innovation, business model innovation,	Contreras Pinochet et al. (2021), Shamim et al. (2021), Ciampi et al. (2021), Elia et al. (2022)
Dual innovations, co-innovation, process Eco-innovation	Su et al. (2022), Lozada et al. (2019), Munodawafa and Johl (2019)
Sustainable innovativeness, innovative green product development	Song et al. (2020), Hao et al. (2019), Bag et al. (2020)
Dynamic capabilities	Mikalef et al. (2020b), Xiao et al. (2020), Mikalef et al. (2019b), Wamba et al. (2017)
Innovation capabilities	Bahrami and Shokouhyar (2022), Ramadan et al. (2020)
Marketing capabilities and technological capabilities, digital platform and network capabilities	Bhatti et al. (2022a), Mikalef et al. (2020b)
Knowledge management capabilities and information processing capabilities	Rialti et al. (2020), Schlegel et al. (2021)
(Firm's) agility, adaptability, alignment, ambidexterity, entrepreneurial orientation, organizational resilience	Srimarut and Mekhum (2020), Wamba et al. (2020), Rialti et al. (2019), Popovič et al. (2018), Aljumah et al. (2021), Rialti et al. (2019), Ciampi et al. (2021), Khan and Tao (2022), Ciasullo et al. (2022), Al-Darras and Tanova (2022)

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Outcomes	References
Supply chain innovation and resilience, supply chain innovativeness	Bhatti et al. (2022b), Bhatti et al. (2022a), Jaouadi (2022), Bag et al. (2022), Singh and Singh (2019)
External and internal integration, internal finance integration, global sourcing, green supplier and customer integration	Razaghi and Shokouhyar (2021), Yu et al. (2021a), Chen and Chen (2022), Liu et al. (2022)
Sustainable supply chain performance and flexibility, supply chain development, green supply chain performance, humanitarian supply chain performance	Edwin Cheng et al. (2022), Gu et al. (2021), Al-Khatib (2022a), Al-Khatib (2023), Dubey et al. (2022), Nisar et al. (2022)
Swift trust and collaborative performance, strategic and tactical reverse logistics decisions	Dubey et al. (2019b), Bag et al. (2021)
Supply chain preparedness, alertness, agility, adaptability, responsiveness, automated supply chain disruption risk alert tool	Park and Singh (2022), Bhatti et al. (2022b), Bag et al. (2022), Dubey et al. (2019a), Mandal (2019)
Circular economy practices, green manufacturing practices/Lean Six Sigma efforts	Awan et al. (2021), Edwin Cheng et al. (2022), Belhadi et al. (2020)
Sustainable design and commercialization, mass customization, and internationalization	Zhang et al. (2020), Sheng et al. (2021), Bertello et al. (2021)
Information quality, knowledge creation	Bahrami and Shokouhyar (2022), Shamim et al. (2021), Awan et al. (2021)
Organization, employee, new product development	Dubey et al. (2021), Bag et al. (2020), Hao et al. (2019),
Business processes improvement, consumer experience and market enhancement	Elia et al. (2022)
Quality of (health) care services and potential benefits	Wang et al. (2019), Wang et al. (2018a), Wang and Hajli (2017)

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