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The role of the social and technical factors in creating business value from big data analytics: A meta-analysis

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ABSTRACT

Big data analytics (BDA) has recently gained importance as an emerging technology for handling big data. The use of advanced techniques with differing levels of intelligence, such as descriptive, predictive, prescriptive, and autonomous analytics, is expected to create value for firms. By viewing BDA as a sociotechnical system, we conduct a meta-analysis of 107 individual studies to integrate prior evidence on the role of the technical and social factors of BDA in creating BDA business value. The findings underline the predominant role of the social components in enhancing firm performance, such as the BDA system's human factors and a nurturing organizational structure, in contrast to the minor role of the technological factors. However, both the technical and social factors are found to be strong determinants of BDA business value. Through the combined lens of sociotechnical theory and the IS business value framework, we contribute to research and practice by enhancing the understanding of the main technical and social determinants of BDA business value at the firm level.

1. Introduction

The digital transformation of business and society has significantly increased the amount of data (Grover et al., 2018). In research and practice, these growing volumes of data are referred to as big data; this term is used for describing excessively large and complex datasets from various sources, which require advanced techniques for storage, management, analysis, and visualization (Chen et al., 2012). These advanced statistical, processing, and analytics techniques are well known under the term big data or business analytics (BDA) (Chen et al., 2012; Grover et al., 2018). From the technical viewpoint, the most common BDA concepts include advanced techniques with differing levels of intelligence, such as descriptive, predictive, prescriptive, and autonomous analytics, which in turn are expected to contribute to various levels of competitive advantage (Davenport & Harris, 2017). Aside from the technical component of BDA consisting of tangible assets, BDA is regarded as a sociotechnical concept that requires social factors such as human expertise and management capabilities as well as a nurturing organizational structure to be beneficial (Akter et al., 2016; Grover et al., 2018).

The view of BDA as a sociotechnical artifact is supported by previous research from the IS business value field, which similarly underscores its complementary elements, such as technical IT assets, and social factors such as IT human resources and IT management capabilities (Schryen, 2013). Given the potential economic and social value of big data, an increasing number of firms across the globe spend a considerable amount of their IT budget on BDA projects in an attempt to utilize their structured and unstructured data; however, the results reported on their business value are relatively heterogeneous (Grover et al., 2018). Creating the business value of big data is a complex and dynamic process involving sociotechnical factors and a multidimensional value-creating mechanism (Grover et al., 2018; Krishnamoorthi & Mathew, 2018). Additionally, assessing the monetary value of BDA is considered a challenging task due to the intangible and unique nature of big data (Grover et al., 2018). Nevertheless, addressing the questions of how, when, and why BDA can create value is essential for adopting firms to reap the benefits of their investments (Côrte-Real et al., 2017; Grover et al., 2018).

Given the important role of this topic, the business value of BDA has been investigated in numerous previous studies; however, many

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primary studies have reported mixed results (Torres et al., 2018). On the one hand, data-driven decision making has been found to have a positive impact on firm performance (Brynjolfsson & McElheran, 2016), indicating that firms using data and BDA for decision making achieve increased levels of output and productivity. According to a global survey of 3000 business managers, executives, and analysts across diverse industries and geographical areas (LaValle et al., 2011), top-performing organizations adopt advanced information and analytics approaches five times more often than low-performing organizations do. On the other hand, other studies have determined that BDA does not directly create value for a firm (Ghasemaghaei, 2019). Overall, numerous studies focusing on various BDA concepts with differing levels of sophistication and mixed results have been published on the business value of BDA (Akter et al., 2016; Božič & Dimovski, 2019b). Thus, the evidence remains unclear regarding the issue of whether BDA can contribute to competitive advantage as well as the factors that might account for the heterogeneous results. This mixed evidence has engendered the portrayal of big data as a *"glamorous"* topic, with a hype that *"may create unfounded pressure on firms to adopt BDA,"* along with warnings that *"the big data bubble could be about to burst"* (Grover et al., 2018, S. 390).

The heterogeneous research findings in this field generally constitute a research gap that can only be closed by a more aggregated and comprehensive investigation. In particular, the question regarding the key elements of BDA that are necessary to create business value from BDA and the specific role of the technical system of BDA within the sociotechnical concept of BDA is an important subject that merits increased attention (Grover et al., 2018). We address this research gap by integrating evidence on the business value of BDA through the lens of sociotechnical theory (Bostrom & Heinen, 1977a, 1977b). In essence, we aim to answer the following research questions (RQs):

> RQ1: What are the main technical and social factors of BDA, and to what extent do these factors contribute to enhancing firm performance?
> RQ2: To what extent does the technological sophistication of the BDA technical system contribute to enhancing firm performance?
> RQ3: What conditions may cause the sociotechnical system of BDA to have varying impacts on firm performance?

Consistent with the common view in the literature on IT business value (Kohli & Grover, 2008; Schryen, 2013) and BDA business value (Akter et al., 2016; Chen et al., 2015; Côrte-Real et al., 2017), we consider the business value of BDA as the firm-level impact of BDA on firm performance, which in turn can manifest itself through various measures at the operational, financial, or market level. Thus, we interchangeably use the terms business value and firm performance throughout the entire paper.

We conducted a comprehensive meta-analysis of 107 primary studies reported in 105 published and unpublished articles to answer our RQs. We applied meta-analysis as a quantitative review method to help us in synthesizing prior knowledge and resolving the inconsistent findings of individual studies (Jeyaraj & Dwivedi, 2020).

We organize the rest of this paper as follows. We briefly outline the theoretical background concerning the business value of BDA in Section 2. In Section 3, we develop the research framework and describe the structural and moderating variables of interest. In Section 4, we explain the main steps of our meta-analysis research approach. We then present the meta-analytic results in Section 5. We subsequently elaborate the implications for research and practice as well as the limitations of this study in Section 6. Finally, we provide the concluding remarks in Section 7.

2. Theoretical background

Since its introduction in the late 2000s, the term BDA has been used for describing analytical techniques for the storage, management, analysis, and visualization of data (Chen et al., 2012). The increasing digitization has resulted in massive and ever-growing volumes of data (Grover et al., 2018), with the "global data sphere" being forecasted to expand from 33 zettabytes (ZB) in 2018 to 175 ZB by 2025 (Reinsel et al., 2018, S. 6). From a technological viewpoint, the concept of big data is commonly described by using the three V's framework to highlight volume, velocity, and variety as its main characteristics. The emphasis of the term volume is on the magnitude of data (Gandomi & Haider, 2015); velocity refers to the speed of data creation, that is, real-time analysis and decision making (McAfee et al., 2012); and variety pertains to the structural heterogeneity of different data sources (Gandomi & Haider, 2015). Data can be structured or unstructured. Structured data can be found in relational databases from business applications such as enterprise resource planning (ERP), customer relationship management (CRM), and supply chain management (SCM) systems. By contrast, unstructured data emerge from a variety of sources such as social networks, sensors, mobile applications, and data from online shopping platforms (Gandomi & Haider, 2015; McAfee et al., 2012). The share of structured data is assumed to be only 5 %. Thus, 95 % of the total data volume is unstructured (Gandomi & Haider, 2015).

The extensive data growth has popularized the terms big data and BDA, describing the abundance of data of various types and sources and the corresponding analytical techniques. With the aid of BDA, big data can be leveraged for consistent and evidence-based business decisions and critical societal matters such as climate change (Dwivedi et al., 2022; Papadopoulos & Balta, 2022; Seddon et al., 2017). In particular, firms can gain valuable insights from big data by detecting new patterns and correlations prior to drawing conclusions (Walker, 2014). These insights, in turn, help managers in making better predictions and more informed decisions (McAfee et al., 2012). In research and practice, the advanced techniques and technologies necessary to handle big data are commonly referred to as business intelligence (BI), business analytics (BA), or BDA (Chen et al., 2012; Ranjan & Foropon, 2021). BA and BDA systems are distinguished from BI systems by their level of sophistication; they are considered an evolution of BI systems as they provide advanced techniques for the analysis and reporting of data (Someh et al., 2019). BA and BDA are technically based on data mining and statistical techniques (Chen et al., 2012). A common conceptual view of BDA pertains to the classification according to the advancement of concepts with differing levels of intelligence, such as descriptive, predictive, and prescriptive analytics as well as autonomous analytics (Davenport & Harris, 2017). These BDA concepts are expected to account for different levels of competitive advantage (Davenport & Harris, 2017).

Descriptive analytics techniques, as the concept with the lowest level of intelligence, only allow decision makers to answer the simple question *"What happened?"* based on historical data. More sophisticated concepts are offered by predictive and prescriptive analytics techniques, which focus not only on what might happen next but also on the provision of optimal behaviors and actions based on predictive modelling and rule-based systems (Davenport & Harris, 2017; Lepenioti et al., 2020). The highest level of intelligence is achieved by autonomous or augmented analytics techniques that employ AI to create self-learning and self-optimizing models with less involvement from human analysts (Davenport & Harris, 2017). In the context of this study, we adopt the broad definition of BDA proposed by Chen et al. (2012), who treat BI, BA, and BDA as related fields. We also refer to the conceptual view of BDA proposed by Davenport and Harris (2017) to define the technical components of BDA as concepts with differing levels of intelligence and competitive advantage. Viewing BDA as a technical concept with various technical levels enables us to examine the role of the BDA technical system in enhancing firm performance and to gain in-depth insights into the impact of technological advancement on the business value created from BDA, as addressed in RQ1 and RQ2.

Numerous studies have assessed the business value of BDA by providing valuable insights into the main technical and social factors of BDA (Maroufkhani et al., 2020; Zhu et al., 2021), but without presenting

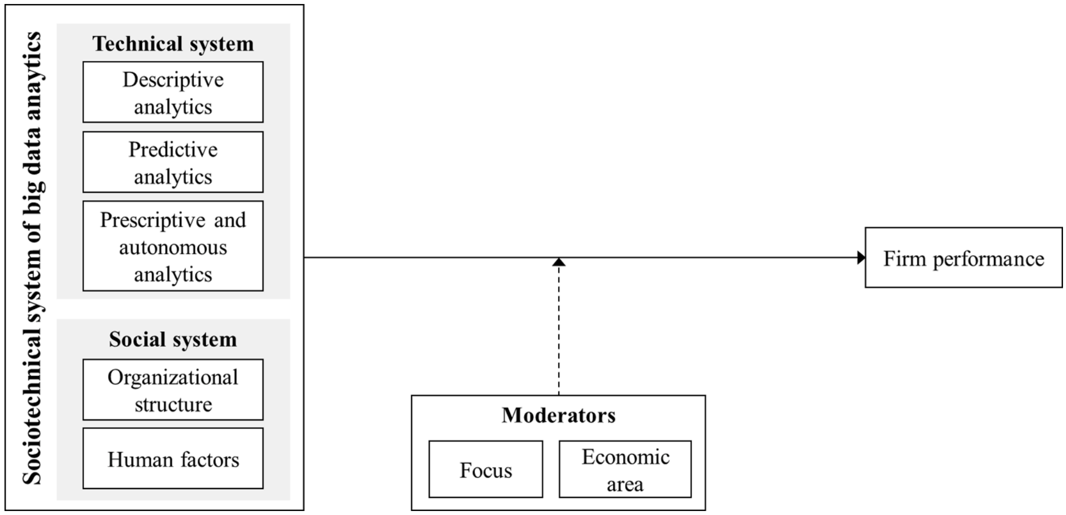

Fig. 1. Research model.

integrated, clear evidence of positive or negative impacts (Akter et al., 2016; Božič & Dimovski, 2019b). Beyond that, most prior studies have either focused on single BDA concepts, such as descriptive analytics (Fink et al., 2017; Ghasemaghaei & Calic, 2019), predictive analytics (Côrte-Real et al., 2020; Dubey et al., 2018; Gupta et al., 2019a), or more advanced techniques (Bag et al., 2021; Dubey et al., 2019b; Ghasemaghaei, 2019), leaving the question open of whether technical sophistication matters for the business value created from using this concept. In addition to this research gap in the BDA business value literature, to date no meta-analysis has provided an integrated picture of the impact of various technical and social factors of BDA on firm performance. Thus far, only Bogdan and Borza (2019) have attempted to meta-analyze prior studies addressing the relationship between BDA and firm performance. However, their research involves only 37 primary studies and is characterized by serious methodological flaws. Additionally, effect size measures such as path coefficients are misinterpreted as correlations. Furthermore, the authors did not attempt to explain the observed variability in effect sizes across the investigated studies, despite this question being fundamental to understanding the main rationales for this variability. Thus, to the best of our knowledge, we are the first to quantitatively meta-analyze the empirical evidence of prior studies to provide an integrated, comprehensive, and validated picture of the impact of the technical and social factors of BDA on firm performance.

3. Sociotechnical research model of BDA business value

We examine the business value of BDA by viewing BDA as a sociotechnical system encompassing a set of technical and social factors that are necessary for creating business value. Therefore, we combine the well-established IS business value framework (Schryen, 2013) with the sociotechnical theory framework (Bostrom & Heinen, 1977a, 1977b) to conceptualize the firm-level impact of the BDA sociotechnical system as a whole. The IS business value framework (Schryen, 2013) employs a resource-based view (RBV) by assuming that IS resources are the main determinants of firm performance, which enable firms to gain competitive advantage (Melville et al., 2004). By contrast, the sociotechnical theory framework focuses on the view of IT artifacts as an interplay of both the technical and social subsystems (Bostrom & Heinen, 1977a, 1977b). The technical subsystem comprises all the technical components required for running the system as well as the tasks for which the system is used, whereas the social subsystem encompasses the organizational structure as well as the people, including their attitudes, knowledge, skills, values, and interrelationships (Bostrom & Heinen, 1977a, 1977b). Through the combined lens of sociotechnical theory and the IS business value framework, we aim to deepen the understanding of the main technical and social determinants of BDA business value at the firm level.

As shown in Fig. 1, our sociotechnical research model of BDA business value combines these theoretical lenses through the conceptualization of its structural and moderating variables. We detail these structural and moderating variables in the subsequent sections.

3.1. Business value of BDA

As depicted in Fig. 1, firm performance is the dependent variable of our research model. In the BDA business value literature, the precise meaning of creating business value from BDA is associated with a wealth of firm performance indicators. For example, some studies relied on market-level firm performance indicators such as competitive advantage (Côrte-Real et al., 2017, 2020; Shan et al., 2019; Someh et al., 2019; Wang et al., 2019), customer-based measures (Ferraris et al., 2019), as well as other market-based performance indicators, including market share, success rate of new products and services, and market entrance (M. Gupta & George, 2016; S. Gupta et al., 2019; Raguseo & Vitari, 2018), to conceptualize their dependent variables. Other studies adopted a mix of self-reported revenue- and profitability-based measures to conceptualize firm performance, such as return on investment (ROI), return on sales (ROS), return on assets (ROA), profitability enhancements, and revenue (S. Gupta et al., 2019a; Ji-fan Ren et al., 2017). Operational performance indicators are further common measures for assessing the business value of BA, with a particular focus on the impact of BDA on internal business processes (Côrte-Real et al., 2017; Nam et al., 2019), decision-making effectiveness (Ghasemaghaei et al., 2018), and other informational benefits such as fact-based decision making (Asadi Someh & Shanks, 2015) and firm agility (Ghasemaghaei et al., 2017).

All of these studies share a key feature: they consider the business value of BDA as the firm-level impact of BDA on firm performance, which in turn can manifest itself through various measures. In this study, we therefore adopt a similar broad view of business value, including the wealth of market-level, financial, and operational performance indicators as reported in the primary studies. Consistent with the common view in the IT business value literature (Kohli & Grover, 2008; Schryen, 2013), the term business value in the current study generally encompasses productivity gains, profitability enhancements, process improvements, increased consumer surplus, or improvements in supply chains or innovation at the organizational level as a result of BDA use. As commonly done in the BDA business value literature (Akter et al., 2016; Chen et al.,

Table 1
Independent variables employed to conceptualize the BDA sociotechnical system.

System	Variable	Definition	Exemplified Studies
BDA technical system	Descriptive analytics	A study examines the impact of descriptive analytics concepts on firm performance (often conceptualized as BI systems in a basic form)	(Fink et al., 2017; Ghasemaghaei & Calic, 2019)
	Predictive analytics	A study investigates the impact of predictive analytics concepts on firm performance (conceptualized as "predictive modeling," "predictive analytics," "big data analytics," or "forecasting")	(Côrte-Real et al., 2020; Dubey et al., 2018; Gupta et al., 2019a)
	Prescriptive and autonomous analytics	A study is focused on exploring the impact of prescriptive or autonomous analytics concepts on firm performance (conceptualized as "prescriptive analytics" or "AI-driven big data analytics")	(Bag et al., 2021; Dubey et al., 2019b; Ghasemaghaei, 2019)
BDA social system	Human factors	BDA human resources: employees with BDA skills or knowledge (e.g., analytics professionals, data scientists)	(Asadi Someh & Shanks, 2015; Fink et al., 2017; Torres et al., 2018; Yogev et al., 2012)
		BDA management capabilities: managers' ability to make solid business decisions based on BDA-enabled insights	(Dubey et al., 2019b; Torres et al., 2018; Anand et al., 2016)
	Organizational structure	Organizational culture that facilitates data-driven decision making, such as a "data-driven culture" or a "data-driven mindset"	(Grover et al., 2018; Mikalef et al., 2018b; Shamim et al., 2020; Wamba et al., 2020a)
		Information governance: the collection of mechanisms and guidelines on how to handle data and share knowledge	(Mikalef et al., 2020b; Shamim et al., 2020)

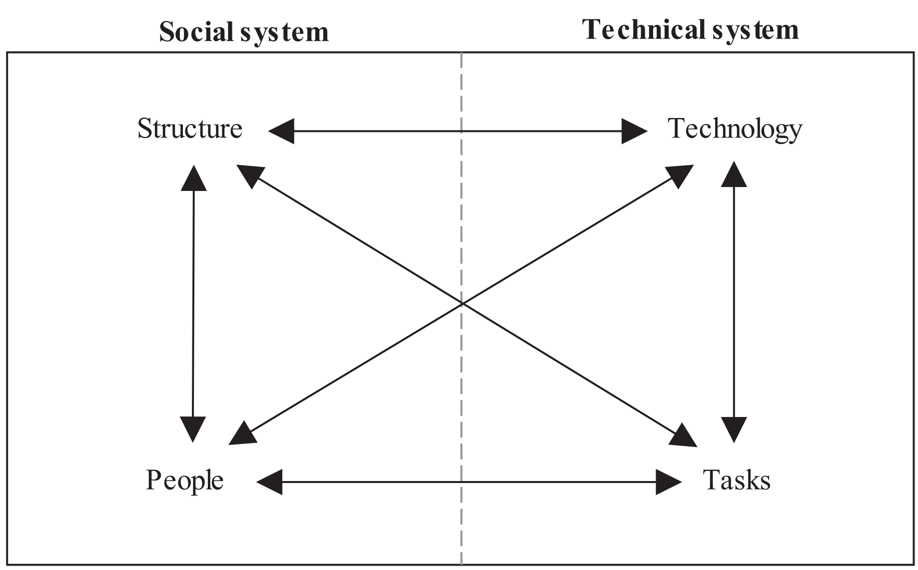

Fig. 2. Sociotechnical system framework , (Source: Adopted from Bostrom and Heinen, 1977a, 1977b).

2015; Côrte-Real et al., 2017), we also interchangeably use the terms business value and firm performance throughout the entire paper.

3.2. *Technical and social system of BDA*

When referring to BDA as the independent variable, we intentionally employ a sociotechnical lens to integrate the necessary technical and social factors as essential antecedents to business value creation. As summarized in Table 1, the variables that are used for conceptualizing BDA in primary studies include a set of technical and social factors. Most primary studies rely on the RBV of the firm (Wernerfelt, 1984) as well as the theory of dynamic capabilities (Teece et al., 1997) to explain the impact of BDA on firm performance, with BDA technical and BDA human resources as well as management capabilities being recognized as the most important factors that help firms to react and adapt to changing competitive environments (Chen et al., 2015; Ghasemaghaei et al., 2017). This RBV of IT as a combination of technology and humans is consistent with the perspective proposed by sociotechnical theory, according to which each IT system consists of an interplay of the technical and social subsystems (Bostrom & Heinen, 1977b, 1977a). According to sociotechnical theory (cf. Fig. 2), the technical component of a system includes IT assets such as software and hardware, system infrastructure, and methods and tools necessary for the use of the technology, as well as the tasks for which the technology is used (Bostrom & Heinen, 1977b, 1977a; Lyytinen & Newman, 2008).

Primary studies examining BDA business value consistently consider assets and tools (i.e., required software, hardware, infrastructure) as technical core components of the BDA sociotechnical system (Akter et al., 2016; Côrte-Real et al., 2020; Shan et al., 2019; Torres et al., 2018). Thus, the technological concept behind the investigated BDA systems and the tasks for which they are used are one central focus in our study. As previously stated, we adopt Davenport and Harris' (2017) conceptualization of BDA as four concepts ranging from descriptive over predictive to prescriptive and autonomous analytics. As these analytics concepts are intended to support internal business processes (Davenport & Harris, 2017), this conceptualization as process-supporting tools with various levels of advancement simultaneously encompasses the task-level components in accordance with sociotechnical theory.

Following this view, we aim to examine whether less sophisticated technological concepts such as descriptive analytics show a lower impact on firm performance than the more advanced concepts of predictive, prescriptive, or autonomous analytics. To distinguish the different technological levels, we include the variables (1) descriptive analytics, (2) predictive analytics, and (3) prescriptive and autonomous analytics in Table 1. We address prescriptive and autonomous analytics as one variable because these concepts have emerged only recently (Davenport & Harris, 2017; Lepenioti et al., 2020) and are not yet sufficiently diffused in organizational practice.

Table 2
Moderating variables.

Moderating Variable	Definition	Exemplified Studies
Study focus		
Technical focus (TF)	A study only integrates independent variables describing the BDA technical system into the research model	(Dubey et al., 2019a; Someh et al., 2019; Dong and Yang, 2020)
Social focus (SF)	A study merely integrates independent variables describing the BDA social system into the research model	(Ghasemaghaei et al., 2018; Shamim et al., 2020; Song et al., 2018)
Sociotechnical focus (STF)	A study includes both technical and social variables of the BDA system into the research model	(Akter et al., 2016; Božič & Dimovski, 2019b; Chen et al., 2015; Srinivasan & Swink, 2018)
Economic area		
Developed economy (DEVL)	Data stem from respondents located in a developed economy according to the classification of the United Nations (2019)	USA (Akter et al., 2016; Asadi Someh & Shanks, 2015; Torres et al., 2018);France (Raguseo & Vitari, 2018); Norway (Mikalef et al., 2020a)
Developing economy (DEVI)	Data stem from respondents located in a developing economy according to the classification of the United Nations (2019)	China (Shamim et al., 2020; Yu et al., 2021); India (Gupta et al., 2019a)
Diverse (DIV)	Studies in which data stem from respondents located in several geographical areas are referred to as diverse (DIV)	(Rialti et al., 2019; Srinivasan & Swink, 2018)

As shown in Table 1, the social subsystem, which consists of indispensable human and structural factors, constitutes the other core component of BDA. According to sociotechnical theory (cf. Fig. 2), each IS includes individuals or groups from the organizational environment in the social system, that is, employees, managers, users, customers, subcontractors, and suppliers (Lyytinen & Newman, 2008). In our context, human resources and management capabilities constitute the most important human factors of the BDA social system. Human resources, in turn, consist of employees with relevant skills and knowledge (e.g., data scientists), and they are widely considered a major precondition for successful value creation from BDA use (Asadi Someh & Shanks, 2015; Božič & Dimovski, 2019a; Fink et al., 2017; Torres et al., 2018; Yogev et al., 2012). Management capabilities represent the second source of human factors; they pertain to the managers' ability to take solid business decisions and perform core management tasks such as BDA planning, investment, coordination, and control (Akter et al., 2016). To add business value, managerial actions such as acquiring and analyzing critical information are essential for making sound decisions based on BDA insights (Anand et al., 2016; Torres et al., 2018).

Organizational structure is another important dimension of the BDA sociotechnical system; it represents the fifth independent variable of our research model. The structural dimension is defined by institutional arrangements, such as formal work organization, communication, and authority structure, including values, norms, general role expectations, and behavioral patterns (Lyytinen & Newman, 2008). In the BDA business value literature, two factors are considered key structural enablers, namely a *data-driven culture* (Grover et al., 2018; Mikalef et al., 2018b; Shamim et al., 2020) and an *information governance mechanism*. Prior research has emphasized the major role of a data-driven culture for creating value from BDA (Grover et al., 2018). Primary studies examining the impact of the organizational culture on firm performance have shown that a *data-driven culture* positively impacts data-driven decision making and firm performance (Mikalef et al., 2018b; Shamim et al., 2020; Wamba et al., 2020a).

In addition, an *information governance mechanism* enables firms to make accurate and timely decisions, which in turn contributes to the enhancement of firm performance (Shamim et al., 2020), especially in business environments with high market dynamism (Mikalef et al., 2020b). In line with prior studies (Mikalef et al., 2020b; Shamim et al., 2020), we therefore define information governance as mechanisms and guidelines on how to handle data and share knowledge across organizational boundaries. Given the major role of *data-driven culture* and *information governance*, we use them for building the structural component of the BDA sociotechnical system in our model.

3.3. Moderating variables

Furthermore, we integrate two moderators into the research model to investigate the variability of findings across studies (cf. Table 2). The moderators help us to differentiate between *study focus* and *economic area*. The moderator *study focus* is associated with the question of whether the individual study employs a rather technical, social, or sociotechnical view of BDA. We consider the study focus as technology-centric when a study merely integrates independent variables describing the BDA technical system. When a study simply examines variables that conceptualize the social components of BDA, we assume a social study focus. A study is considered to have a sociotechnical focus when it includes both technical and social variables into the research model. According to the core ideas of sociotechnical theory, the interplay between the technical and social components of a system is necessary to achieve satisfactory IT usage (Bostrom & Heinen, 1977b, 1977a; Lyytinen & Newman, 2008). Thus, a purely technology-centric or social view of BDA is likely to yield weaker results regarding the created business value. Overall, the analysis of *study focus* is worthwhile because it provides different and unique insights into the context of the conceptual design or theoretical framing of the individual study.

Economic area is the next moderator in our meta-analysis that accounts for geographical differences in BDA value creation. Previous research indicates that the macro-environmental context, including country-specific factors such as economic or cultural characteristics, may explain differences in the value created from BDA (Wang et al., 2019). When examining geographical study characteristics, prior studies commonly refer to economic regions (Mandrella et al., 2020; Sabherwal & Jeyaraj, 2015) or continents (Cram et al., 2019) to explore national and cultural differences that might account for the variability of results. By contrast, we deliberately select economic area as a moderator to investigate the moderating impact of economic regions on the created business value according to the country classifications proposed by the United Nations (2019).

4. Meta-analysis

We conduct a meta-analysis to quantitatively integrate and synthesize empirical evidence on the business value of BDA based on multiple individual studies. Since its introduction in the 1970s (Glass, 1976), meta-analysis has become an important research method in multiple research disciplines, including medicine, pharmacology, epidemiology, education, psychology, business, and ecology, as well as various domains of the natural and social sciences (Borenstein et al., 2011, S. 24; Hwang, 1996; Schmidt et al., 2009). In the IS field, meta-analysis has gained considerable attention as a method for synthesizing prior knowledge and resolving the inconsistent findings of individual studies (Jeyaraj & Dwivedi, 2020). Moreover, meta-analysis is a useful means of increasing the statistical power of results (Hunter & Schmidt, 2004, S. 75).

From a methodological viewpoint, meta-analysis is a formalized and systematic review method (Glass, 1976). Similar to literature reviews, the primary aim of meta-analysis is to integrate and synthesize literature from a specific research area. In the typology of literature reviews

Theoretical review types	Narrative review	Descriptive review	Scoping review	Meta-analysis	Qualitative systematic review	Umbrella review	Theoretical review	Realist review	Critical review
Methods for synthesizing and analyzing findings	Narrative summary	Content analysis/ frequency analysis	Content or thematic analysis	Statistical methods (meta-analytic techniques)	Narrative synthesis	Narrative synthesis	Content analysis or interpretive methods	Mixed-methods approach	Content analysis or critical interpretive methods
Overarching goal	Summarization of prior knowledge			**Data aggregation or integration**			Explanation building		Critical assessment of extant literature

Fig. 3. Comparison of meta-analysis with other literature review types according to Paré et al. (2015).

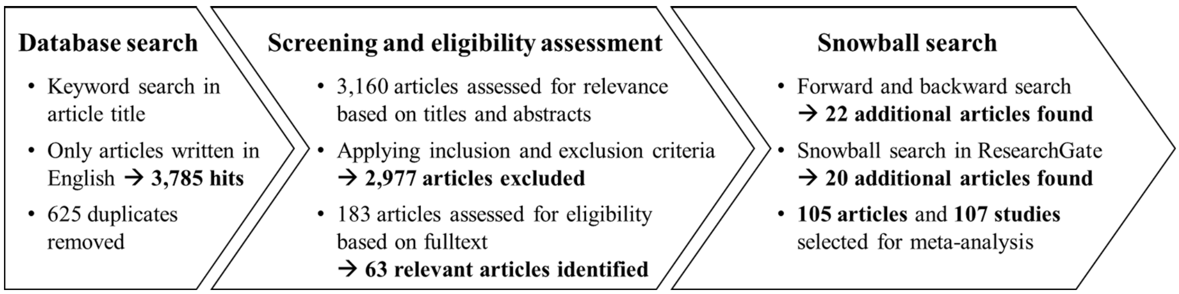

Fig. 4. Literature search and selection process.

proposed by Paré et al. (2015), nine literature review types based on seven distinct dimensions are suggested (cf. Fig. 3).

Within the proposed typology, meta-analysis is described as a type of literature review that is focused on aggregating quantitative data across studies. The quantitative nature of the applied methods for synthesizing and analyzing the results is used for differentiating various types of literature reviews. However, qualitative systematic reviews or umbrella reviews use narrative syntheses to integrate the findings, whereas meta-analyses require specific data extraction techniques and statistical methods to summarize the results (Paré et al., 2015).

The use of meta-analysis is worthwhile especially in research domains where the number of empirical studies is already sufficiently large (Hunter & Schmidt, 2004; Hwang, 1996). Given more than two decades of research in the field of BI and BDA, this research area is already at an early stage of maturity (Asadi Someh & Shanks, 2015; Conboy et al., 2020), with many primary studies reporting inconsistent findings regarding the business value of BDA (Torres et al., 2018). For this reason, we consider the use of meta-analysis to be particularly appropriate for examining the business value of BDA.

4.1. Selection of relevant studies

Due to the interdisciplinary nature of the BDA research field with various interfaces to related disciplines such as computer science, marketing, management, communication, and mathematics (Chen et al., 2012), we conducted a correspondingly comprehensive, interdisciplinary literature search to capture a large sample of studies. This approach also complies with prior recommendations of meta-analysis researchers (Cooper et al., 2009; Rothstein et al., 2005). To enhance transparency and reproducibility, we thoroughly documented the entire search and coding process in accordance with the PRISMA guidelines (Liberati et al., 2009). In addition, we applied interrater reliability (IR) to ensure the objectivity and validity of the search results throughout the search process. Therefore, two researchers independently performed the literature search, with an IR (Cohen's Kappa) of 0.82 reported (Landis and Koch, 1977; LeBreton & Senter, 2008), which can be considered a substantial agreement according to Landis and Koch (1977). In the case of disagreement, conflicts were resolved through final discussions to reach an overall agreement.

As shown in Fig. 4, we conducted a three-step literature search process in February and March 2021 to identify both published and unpublished studies on the business value of BDA. This procedure allowed us to "accumulate a relatively complete census of relevant literature" (Webster & Watson, 2002, S. 16) and thus to capture the breadth and depth of available studies on the research topic while avoiding publication bias (Kepes & Thomas, 2018; Rothstein et al., 2005). In meta-analyses, publication bias (also known as file-drawer problem) refers to the major limitation that studies reporting significant results are more likely to be accepted for publication, whereas studies with non-significant findings may remain unpublished (Rothstein et al., 2005). We overcome this limitation by including both published studies in journal papers and conference proceedings and identified unpublished studies in the so-called "gray literature" such as working papers and dissertations.

The first step of the search process involves a comprehensive keyword search in four interdisciplinary databases, namely EBSCOhost, Scopus, Google Scholar, and the AIS Electronic Library (AISeL), which not only offer published articles in leading journals and conferences from the IS field but also cover various unpublished studies from related research disciplines. We used the search terms "*big data*," *analytics*, and "*business intelligence*" to identify topics related to the BDA, BA, and BI concepts, in combination with the keywords *performance*, *value*, *benefit*, and *advantage*, as well as *firm*, *company*, and *organization* to find organizational-level studies.[1] The initial search in the article titles was restricted to articles written in English, which yielded 3,785 hits. After removing 625 duplicates, we continued with the screening process in which 3,160 articles were assessed for relevance based on their titles and abstracts. To pass this assessment step, an article must focus on studying the business value of BDA at the organizational level and report qualitative or quantitative findings on the relationships between the variables of interest as presented in Section 3. Based on these criteria, we excluded all those articles with another focus as well as articles that did not report original study data, such as short papers and editorials.

Through a detailed evaluation of the full texts, we identified 183 relevant articles. To be selected as relevant for the final sample, articles had to fulfill the aforementioned inclusion criteria and contain pertinent

[1] For a complete overview of the applied search terms, please refer to Table A1 in Appendix A.

Table 3
Coded data from the study sample (n = 107).

Categories	Extracted Data
General study characteristics	▪ Study ID, authors ▪ Publication date, publication type ▪ Study focus (social, technical, sociotechnical) ▪ Economic area according to the country of the respondents (developed and developing economy)
Measures	Effect size measures reporting correlations between the independent and dependent variables: ▪ Descriptive/predictive/prescriptive and autonomous analytics → firm performance ▪ Organizational structure (data-driven culture, information governance) → firm performance ▪ Human factors (BDA human resources and management capabilities) → firm performance When correlations are unavailable: ▪ Only path coefficients that reflect a simple bivariate (zero-order) Other measures: ▪ relationship between two variables Sample sizes

data such as study characteristics, sample size, and effect sizes for the extraction and coding step. In case relevant data were missing, we directly retrieved them from the studies' authors (Liberati et al., 2009). When we could not obtain the missing information in this manner, we excluded the study from the quantitative synthesis. Additionally, we omitted duplicate studies because they represent a threat to the validity of the results (Wood, 2008). Based on this selection scheme, we identified 63 relevant quantitative studies, 25 of which stem from Scopus, 17 from EBSCOhost, 7 from AISeL, and 14 from Google Scholar. In addition to the database search, we conducted a thorough forward and backward search according to Webster and Watson (2002) to broaden the literature base, which resulted in the inclusion of additional 22 studies in the study sample. We also performed a snowball search in the large interdisciplinary academic social website ResearchGate by typing the title of the 63 articles that had passed the eligibility step in the search function. We subsequently accessed each primary study and screened the articles that were possibly related to the research of the study; this procedure yielded another 20 studies.

Through this three-step search and selection process, we identified 105 articles with 107 primary studies[2] for our meta-analysis. The sample consisted of 93 journal articles, 10 conference papers, 1 thesis, and 1 working paper. Moreover, we included additional qualitative studies when interpreting and discussing the results; this step is considered beneficial because it allows us to overcome the weaknesses of a purely quantitative meta-analysis (Guzzo et al., 1987).

4.2. Documentation and coding of studies

Documentation and coding refers to the systematic extraction of relevant data from the selected studies (Hunter & Schmidt, 2004, S. 470). To facilitate this step, we developed a coding scheme containing all necessary information shown in Table 3.

First, we coded the study attributes as follows: general study characteristics relevant to our study (e.g., study ID, authors, publication date, and publication type); the study focus when examining BDA business value (social, technical, or sociotechnical); the economic area from which the respondents stem (developed or a developing area); and, following the general recommendations of meta-analysis researchers (Brown et al., 2003; King & He, 2005), the sample sizes and effect size measures reporting the relationship between independent and dependent variables. The majority of primary studies in our sample used structural equation modeling, multiple regression, or factor analysis techniques to examine their topic of interest based on a formative research model, with β coefficients mostly used for reporting the relationship between the variables of interest. In these cases, we followed the recommendations of Peterson and Brown (2005) and Hunter and Schmidt (2004) by referring to the zero-order correlation matrices of the articles. We also included Pearson's product-moment correlation coefficients and Spearman's rank-order correlations among the coded effect size measures. When correlation coefficients were unavailable in the study, we only coded β coefficients reflecting a simple bivariate (zero-order) relationship between two variables in accordance with the suggestion of Peterson and Brown (2005). Otherwise, we excluded the primary study due to missing information.

For the sake of consistent coding, all the coders consequently applied previously established coding rules. With regard to BDA resources and capabilities, we relied on the items of each study prior to assigning the variables to the technical concept or human factors instead of solely referring to the information given in the studies. In some studies, assigning the independent variables to the different variables based on the given information within the research models was not possible. In these cases, we obtained the necessary information from the items to decide whether the respective variables represent the technological, human, or structural aspects of BDA in accordance with the conceptualized variables in Section 3.

4.3. Data analysis and synthesis

We implemented the analysis steps using the Comprehensive Meta-Analysis software (Borenstein et al., 2005) and adhered to the meta-analytic paradigm of Hedges and Olkin (1985) and Borenstein et al. (2011). We conducted a separate meta-analysis for each relationship between a component of the BDA sociotechnical system and firm performance. The meta-analyzed relationships are based on a sample ranging from 8 to 72 studies.

To ensure the independence of the samples included, we formed mean scores when the research models of the primary studies examined more than one correlation of the same hypothesized relationship (Cram et al., 2019; Mandrella et al., 2020). The coded correlations were subjected to a Fisher's *Z* transformation to normalize the values and perform the meta-analytic calculations. As recommended by Borenstein et al. (2011), we transformed these values back into correlations for reporting the results. The calculations are based on a random effects (RE) model because our meta-analysis is founded on different effect sizes of varying samples of a larger population (Tamilmani et al., 2019). By contrast, a fixed effects model assumes a homogeneous population and a single underlying true effect, in which the variations in effect sizes between studies are simply attributed to a sampling error (Borenstein et al., 2011). However, as is evident from the literature coding, the studies were defined by various distinguishing sample and study characteristics as well as contextual and technological factors, suggesting between-study variance as an additional explanatory factor for differing true effects (Mandrella et al., 2020). The RE model was therefore applied as the underlying meta-analysis approach to calculate the summary effect sizes.

In addition, meta-analysis researchers concur that the examination of heterogeneity is considered an important yet challenging task (Haidich, 2010). Therefore, to account for heterogeneity and moderator effects, we conducted partition tests to split the between-study variance into the pre-defined moderator groups and compare the summary effect sizes without the influence of group dependence (Borenstein et al., 2011).

5. Meta-analytic results

In this section, we present the meta-analytic results concerning the impact of the main social and technical factors of BDA on firm performance. We also delve deeper into the findings of the moderator analysis.

[2] See Table B1 in Appendix B for a complete overview of the included articles.

Table 4
Meta-analytic results.

n	*N*	*k*	Est. eff.	CI 95 %	PI 80 %	*Z*-value	τ^2	Fail-safe *N*
Descriptive analytics → firm performance								
14	3,133	20	0.422	0.317–0.517	0.140–0.641	7.229**	0.048	1,867, 134†
Heterogeneity: Q-value = 147.078**, *df* (Q) = 13, I^2 = 91 %								
Predictive analytics → firm performance								
63	32,804	90	0.446	0.395–0.494	0.164–0.661	15.117**	0.058	54,302, 862†
Heterogeneity: Q-value = 1311.202**, *df* (Q) = 62, I^2 = 95 %								
Prescriptive and autonomous analytics → firm performance								
8	1,833	10	0.504	0.359–0.625	0.171–0.734	6.094**	0.062	1,118, 140†
Heterogeneity: Q-value = 103.845**, *df* (Q) = 7, I^2 = 93 %								
Organizational structure → firm performance								
14	2,918	26	0.467	0.369–0.554	0.204–0.667	8.376**	0.045	2,190, 157†
Heterogeneity: Q-value = 129.442**, *df* (Q) = 13, I^2 = 90 %								
Human factors → firm performance								
72	16,388	131	0.472	0.431–0.512	0.232–0.658	19.204**	0.045	73,945, 1,027†
Heterogeneity: Q-value = 790.395**, *df* (Q) = 71, I^2 = 91 %								

Notes: *n* = number of studies; *N* = sample size; *k* = number of correlations; Est. eff. = estimated summary effect size; CI = 95 % confidence interval; PI = 80 % prediction interval; significance: $^{**}p < .01$, $^{*}p < .05$, not significant (n.s.) for $p > .05$; τ^2 = between-study variance; I^2 = proportion of variance attributed to between-study variance; † indicates the number of missing studies necessary for each identified study to nullify the effect (calculated as fail-safe *N* divided by *n*); *df* = degree of freedom.

5.1. Impact of the sociotechnical system on firm performance

We conducted five separate meta-analyses, each reflecting the relationship between a component of the BDA's sociotechnical system and firm performance. The results of these analyses are presented in Table 4. The summary effect sizes quantify the relationship between the variables (weighted mean; the relative weight for each study is calculated as the inverse of the sum of sampling error and between-study variance based on the underlying RE model) (Borenstein et al., 2011).

The meta-analyses yielded weighted summary effect sizes ranging between 0.422 and 0.504. All 95 % CIs are in the positive range, indicating that they are significantly different from null, which is confirmed by the test of null providing an indication of the validity of our estimate by reflecting the statistical significance for the overall effect (Cram et al., 2019). The *Z*-value of the summary effect sizes ranges between 6.094 ($p < .001$) and 19.204 ($p < .001$), which is larger than the critical *Z* of 3.29 (two-tailed), allowing us to reject the null hypothesis, which denotes that the components of the BDA's sociotechnical system have no effect on firm performance. Therefore, we concluded that our calculated estimates are statistically significant (with a significance level of $\alpha = 0.05$). We evaluated the summary effect sizes by relying on the categorization of Lipsey and Wilson (2001), who classify the outcomes as a medium effect size, except for the relationship between prescriptive and autonomous analytics and firm performance, which shows a tendency toward a large effect size (small: ≤ 0.30, medium: between 0.30 and 0.50, large: between 0.50 and 0.67, and very large: ≥ 0.67).

To strengthen the robustness of the findings, we assessed the potential influences originating from outliers and the publication bias. To exclude outliers, we first visually examined the distribution of effect sizes using forest plots and explored the influence of individual studies by performing separate meta-analyses, removing one study at a time and assessing the effect of that intervention on the summary effect size. Both the visual test and the separate meta-analyses could not identify clear outliers but only marginal summary effect variations (King & He, 2005). We also conducted cumulative meta-analyses to examine temporal trends or outliers in the data. For this purpose, we added one study after another in chronological order and computed the cumulative summary effect sizes (Trikalinos & Ioannidis, 2006). We could not find any clear outliers in this visual analysis either.

In addition, we tested for the influences of a potential publication bias, which can compromise the validity of the results. For this purpose, we calculated Rosenthal's (1979) fail-safe *N*, a robustness check that factors in the number of studies without any effect that are necessary to cancel out the summary effect size ($p > .05$). The calculated values of our meta-analyses exceeded the critical threshold of $5 \times k + 10$ to indicate validity issues (Rosenthal 1979). The calculated high fail-safe *N*s (1,118–73,945) would require that we incorporate hundreds to thousands of studies of no effect to reach a nonsignificant value of $p > .05$ (see Table 4).

5.2. Moderator analysis

As previously mentioned, we assume a statistical model of random effects, which considers between-study variance due to heterogeneous study artifacts such as design and sample, among others. High between-study variance is an indicator of moderator influences (Borenstein et al., 2017). Therefore, we first quantified the heterogeneity (τ2, I2) and statistically assessed the significance of the dispersion by conducting the Cochran's (1954) Q-test of homogeneity. As shown in Table 4, all the Q-values of the investigated five relationships exceed the critical Q-value on a χ^2 distribution with $n - 1$ degrees of freedom (*df*) (n as the number of studies). Therefore, we can reject the null hypothesis that the dispersion is solely caused by sampling error (Borenstein et al., 2017). The between-study variance is given by τ^2 and put in proportion by I^2 (τ^2 in relation to the total variance) (IntHout et al., 2016). I^2 varies between 91 % and 95 %; thus, the between-study variance represents a significant

Table 5
Results of the subgroup analysis.

IV	Subgroup	*n*	*N*	*k*	Est. eff.	CI 95 %	PI 80 %	*Z*-value	FS
Study focus									
Subgroup abbreviations: SC = sociotechnical, T = technical, S = social									
Predictive analytics	ST	39	8,599	54	0.424	0.355–0.489	0.133–0.648	10.873**	16,003
	T	24	24,205	36	0.479	0.396–0.555	0.176–0.699	9.945**	11,321
	Heterogeneity: $Q_{between}$ (Total) = 1.078$^{n.s.}$, *df* (Q) = 1; Q_{within} (ST) = 510.657**, *df* (Q) = 38; Q_{within} (T) = 630.771**, *df* (Q) = 23								
Human factors	S	26	7,081	42	0.484	0.414–0.548	0.241–0.670	11.868**	12,247
	ST	46	9,307	89	0.466	0.412–0.516	0.216–0.659	14.897**	25,965
	Heterogeneity: $Q_{between}$ (Total) = 0.169$^{n.s.}$, *df* (Q) = 1; Q_{within} (ST) = 321.096**, *df* (Q) = 25; Q_{within} (T) = 467.867**, *df* (Q) = 45								
Economic area									
Subgroup abbreviations: DEVL = developed countries, DEVI = developing countries, DIV = diverse									
Predictive analytics	DEVL	25	20,170	35	0.417	0.335–0.493	0.197–0.597	9.093**	7,788
	DEVI	31	6,928	47	0.466	0.396–0.530	0.157–0.692	11.617**	13,265
	DIV	7	2,187	8	0.454	0.302–0.583	−0.005–0.755	5.401**	862
	Heterogeneity: $Q_{between}$ (Total) = 0.868$^{n.s.}$, *df* (Q) = 2; Q_{within} (DEVL) = 295.158**, *df* (Q) = 24; Q_{within} (DEVI) = 475.162**, *df* (Q) = 30; Q_{within} (DIV) = 189.484**, *df* (Q) = 6								
Human factors	DEVL	30	5,334	52	0.446	0.378–0.510	0.224–0.624	11.438**	8,059
	DEVI	37	9,363	69	0.492	0.436–0.545	0.269–0.665	14.722**	25,131
	DIV	5	1,691	10	0.468	0.303–0.605	−0.069–0.817	5.116**	547
	Heterogeneity: $Q_{between}$ (Total) = 1.129$^{n.s.}$, *df* (Q) = 2; Q_{within} (DEVL) = 203.494**, *df* (Q) = 30; Q_{within} (DEVI) = 380.417**, *df* (Q) = 37; Q_{within} (DIV) = 165.149**, *df* (Q) = 4								

Notes: IV = independent variable; *m* = moderator; *n* = number of studies; *N* = sample size; *k* = number of correlations; Est. eff. = estimated summary effect size; CI = 95 % confidence interval; PI = 80 % prediction interval; FS = fail-safe *N*; significance: ***p* < .01, **p* < .05, not significant (n.s.) for *p* > .05; *df* = degree of freedom

proportion of the total variance in all the examined relationships. Previous meta-analyses in the IS area interpreted I^2 as indicative of the magnitude of the variance of true effects and concluded high, moderate, or low heterogeneity in effects (Pelaez et al., 2019). Nevertheless, this approach constitutes a misinterpretation of I^2 because it does not provide information on the true effect size variation (Borenstein et al., 2011; IntHout et al., 2016). This information is instead expressed by the prediction interval (Borenstein et al., 2017; Whitener, 1990). The prediction interval is a probability-based range (similar to the credibility interval used in psychometric meta-analyses) that reflects the array of true effects expected to emerge in future studies using similar study artifacts as the studies included in our sample (IntHout et al., 2016). Our analyses reveal the broad spectrum of the 80 % prediction intervals in all the relationships. This information, together with the other evidence described previously, suggests moderator influences.

Our attempt to account for these moderator influences is based on partition tests centered on our hypothesized categorical variables *study focus* and *economic area*. For conducting partition tests, studies are first assigned to the coded categories of the moderators that partition the variance induced by this group dependence (King & He, 2005). We subsequently performed separate meta-analyses within the individual groups and compared the differences between the summary effect sizes. A major weakness of partition tests is that partitioning reduces the number of studies as a basis for meta-analysis; thus, this type of analysis requires an initial large number of studies. Thus, with our sample, we can perform partition tests on the relationships of predictive analytics (n = 63) and human factors (n = 72) with firm performance; for other relationships with n < 15 studies, further partitioning into smaller categories would provide results without any validity. The results of the performed partition tests are shown in Table 5.

The results indicate that group membership to any of the moderator groups has no effect on the fact that both predictive analytics and human factors continue to have a decisive positive effect on firm performance (summary effect sizes vary in the range of 0.417 to 0.492, resulting in significant *Z*-values). To assess the robustness of the findings, we calculated the fail-safe *N* for each subgroup, which yielded no problematic values. In our examination of the differences in effects between the subgroups, we find that the moderator *study focus*, for both predictive analytics and human factors as independent variables, the sociotechnical perspective has a smaller effect than the purely technical or social perspective. However, the Q-tests show that these differences are not statistically significant. The subgroup analyses of the moderator economic area exhibit a consistent pattern for predictive analytics and human factors with DEVI > DIV > DEVL; however, these differences are once again only marginal and not of statistical significance. Although we can show the differences in effect sizes dependent on the group affiliation, these differences are marginal; furthermore, other moderator influences may explain the remaining within-type heterogeneity in each group. This result is also indicated by the generally wide 80 % prediction intervals.

6. Discussion

Many research efforts across research disciplines have attempted to answer this question: “*What are the main determinants of the business value of BDA, and to what extent do they contribute to enhancing firm performance?*” We found that 107 studies have already examined the impact of BDA on firm performance, yet with heterogeneous results. Therefore, we aim to resolve this fragmented picture by integrating these studies’ empirical findings and individual insights into the business value of BDA. Aside from the integrated view of prior research, we provide in-depth insights into the reasons for variability across studies by

Table 6
Main findings, implications for research and practice, and future research directions.

Main Findings	Implications and Future Research Directions
RQ1: What are the main technical and social factors of BDA, and to what extent do these factors contribute to enhancing firm performance?	
BDA systems consist of both a technical and a social subsystem.	• Contribution to the understanding of the mechanisms leading to BDA-induced business value to guide future theory building Managers and decision makers should pay more attention to the sociotechnical nature of BDA when launching new BDA projects.
Social factors have a stronger impact on enhancing firm performance than technical components, except for the most advanced concept of prescriptive and autonomous analytics.	• Company managers need to focus more on building a skilled workforce and establishing adequate organizational structures, for example through a nurturing organizational environment in which employees can be upskilled through training, and recruitment programs that help to find qualified personnel. Policy makers and curriculum developers should integrate industry requirements to develop appropriate educational programs for future analytics personnel and to close the skills gap in the market.
RQ2: To what extent does the technological sophistication of the BDA technical system contribute to enhancing firm performance?	
More advanced BDA concepts such as predictive or prescriptive analytics have a stronger impact on firm performance than less advanced concepts .such as descriptive analytics.	• Focus on the business value impact of specific BDA techniques that contribute to an overview at a more granular level. Further research is needed to explore the mechanism leading to the business value creation of more advanced analytics concepts such as prescriptive and autonomous analytics. Research could address the following questions: To what extent will the major role of human factors change through the introduction of AI-enabled autonomous analytics concepts? Are human factors still essential or even more important to facilitate value creation? Does the increasing level of automation in more advanced analytics concepts cause a shift in the roles of the social and technical components of the sociotechnical BDA system?
RQ3: What conditions may cause the sociotechnical system of BDA to have varying impacts on firm performance?	
In the case of predictive analytics and human factors, studies with a sociotechnical focus report smaller effects on the relationship between BDA and firm performance compared to studies with a purely technical or social perspective.	• Moderator analysis contributes to the understanding of how certain conditions (study focus, economic area) affect the translation of BDA adoption to business value.More research is needed on the role of technological and social components of BDA, such as the role shift among the components of the BDA sociotechnical system (cf. RQ2) .
The relationship between BDA and firm performance for the variables predictive analytics and human factors is higher in developing than in developed economies.	• Further research is needed with a particular focus on the role of differing data protection and data security regulations and the impact of cultural factors on the business value of BA. Firms using BDA have to comply with local regulations, especially in industry sectors with highly sensitive data (e.g., health care) . Firms need to establish adequate organizational structures and a governance mechanism to ensure compliance on the way to value creation.

investigating the moderating effects of study focus and economic area.

Overall, the contribution of our study is threefold. First, we enrich the research stream in the field around the business value of BDA by providing a consistent and validated view of the role of the social and technical components of the BDA system in creating business value. Second, we contribute to advancing the use of meta-analysis as a method of inquiry in IS research and respond to the frequent calls for more meta-analyses in IS research (Hwang, 1996; Jeyaraj & Dwivedi, 2020; King & He, 2005). Third, we provide an advanced understanding of the business value of IT as an important research area in IS research (Kohli & Grover, 2008; Schryen, 2013). We believe that the findings are of high importance for research and practice because understanding the business value of IT is considered fundamental to the IS discipline, especially with respect to the questions of whether, how, when, and why IT creates value (Kohli & Grover, 2008; Schryen, 2013). As stated by Kohli and Grover (2008, p. 24), *"if IT is not valuable, then we are engaging in research on something that is not valuable, and hence we are not valuable!"* Profound insights into the conditions of positive or negative firm performance help firms to understand the key success factors and increase their value from BDA (Grover et al., 2018).

We summarize the main findings of this meta-analysis, the corresponding implications for research and practice, and the future research directions in Table 6. We then elaborate them in the succeeding sections.

6.1. Implications for research and practice

Research often draws on RBV and process-oriented business value models to explain the effects of specific IS resources on business value (Melville et al., 2004; Schryen, 2013). By using the sociotechnical lens and highlighting that not individual IS resources are crucial, but the bundle of IS and sociotechnical factors, we significantly contribute to the research in this field. Referring to ***RQ1***, we identify numerous technical and social factors as major determinants of the BDA business value. The findings of our meta-analysis reveal that social factors have a stronger impact on enhancing firm performance than technical components, except for the most advanced concept of prescriptive and autonomous analytics. Among the social factors, human aspects have a stronger impact on firm performance than organizational structure. These findings confirm the common view in BDA research, according to which human resources and management capabilities play essential roles in creating business value from BDA. Furthermore, the outcomes support the research notion that IT should be considered as a sociotechnical system when examining the business value of such systems (Schryen, 2013). The reason is that human factors such as skilled personnel or management capabilities in interpreting data insights and data-enabled decision making are non-imitable core capabilities that create value; by contrast, the technical components of BDA such as BDA tools and software are recognized as imitable noncore resources (Bekmamedova & Shanks, 2014; Huang et al., 2018). Hence, solely investing in BDA technology does not create value (M. Gupta & George, 2016; Someh et al., 2019). As implied by the sociotechnical view of IS, an interplay of technical and social subsystems is required to run the system (Bostrom & Heinen, 1977a, 1977b). Thus, firms need complementary technical assets and social system components to develop unique capabilities to ultimately create value (Božič & Dimovski, 2019b; Ferraris et al., 2019). Contributing to existing research (Abbasi et al., 2016; Gupta & George, 2016; Krishnamoorthi & Mathew, 2018), our findings provide an understanding of the mechanisms leading to BDA-induced business value and guide future theory building. They also offer key implications for decision makers in business and policy. For example, decision makers should pay more attention to sociotechnical aspects when launching BDA projects. Accounting for the major role of personnel and management resources in the value creation process, establishing a skilled workforce (Asadi Someh & Shanks, 2015; Božič & Dimovski, 2019a; Fink et al., 2017; Grover et al., 2018; Torres et al., 2018; Yogev et al., 2012) and adequate management capabilities and structures is essential (Anand et al., 2016; Torres et al., 2018). To facilitate the use of BDA, firms should therefore create a nurturing organizational environment in which employees can be upskilled through training or qualified personnel can be recruited (Mikalef et al., 2018a). However, recruiting qualified personnel with analytics skills is challenging (Grove et al., 2018; Mikalef et al., 2018a). Extant research highlighted an increasing skills gap in the market, as the rising demand for personnel with data science skills does not match the actual skills of graduates and professionals in the industry (Mikalef et al., 2018a; Pappas et al., 2018). Although addressing this skills gap is a major challenge for policy makers, it is an essential prerequisite for technology diffusion. Industry demand for highly skilled analysts entails the incorporation of data science skills into academic curricula at the tertiary level. Policy makers and curriculum developers should therefore integrate industry requirements to develop appropriate educational programs to close this gap (Mikalef et al., 2018a; Pappas et al., 2018).

With regard to the impact of the BDA sociotechnical system on firm performance, an imbalance between the technical (i.e., analytical tools, tasks, and data) and social components (i.e., human resources) can even have a negative impact on the value creation mechanism (Ghasemaghaei et al., 2017). These results challenge the simplistic assumption commonly found in the literature that the adoption of new technologies manifests in corporate efficiency and performance gains. As a result, the IS business value literature has proposed the unanticipated consequences of IS use, which can be positive and/or negative, as another worthwhile avenue for future research (Schryen, 2013). Among the unanticipated negative consequences of IS use is the well-known phenomenon of the rebound effect. Previous studies revealed that efficiency gains from IT-enabled information processing do not necessarily increase work efficiency (Gossart, 2015; Hilty et al., 2006; Hörning et al., 1999). Hence, a deeper understanding of the conditions of BDA deployment is of significant importance to IS business value research, as it would help project managers avoid pitfalls with negative effects in BDA implementation, optimize the development of coordinated IT strategies, and increase the added value of BDA.

In our study, we examine the impact of specific BDA techniques on firm performance (**RQ2**), which provides insights at a more granular level. Our results indicate that the reported business value created from more advanced concepts (e.g., predictive, prescriptive, and autonomous analytics) is higher than that of less advanced concepts (e.g., descriptive analytics), which is consistent with the common view in the literature (Davenport & Harris, 2017). Nonetheless, the idea that more advanced concepts contribute to better decision making is not surprising. From a technical viewpoint, descriptive analytics techniques merely allow decision makers to answer questions on the past based on historical data (*"What happened?")*. On the contrary, predictive analytics concepts enable decision makers to take into account future developments based on quantitative techniques such as predictive modelling and rule-based systems and thus to predict *"what might happen next,"* including the provision of optimal behaviors and actions (Davenport & Harris, 2017). Recent studies similarly argue that the improvement of firm performance requires the integration of BDA into decision making, business processes, as well as products and services (Božič & Dimovski, 2019b; Ghasemaghaei et al., 2018). BDA is expected to create value by enabling firms to make the right decisions, adapt more quickly to changes such as consumer needs, and improve their products and services accordingly (Ghasemaghaei et al., 2017).

By identifying further research opportunities, we make a meaningful contribution. For example, researchers should dedicate more attention to the mechanisms that lead to the value creation of more advanced analytics concepts such as predictive, prescriptive, or augmented analytics. The most advanced concepts are "autonomous" or "augmented" analytics that rely on machine learning techniques to build self-learning and self-optimizing models with less involvement from human analysts (Davenport & Harris, 2017; Prat, 2019). Augmented analytics is praised for its numerous advantages over conventional BDA techniques. First, the processes of discovery, exploration, explanation, prediction, and prescription of findings in augmented analytics are automated through AI and executed in near real time (Kronz, 2019). Second, the ability to automate virtually any process step through augmented analytics (from data preparation over data analysis to the recognition of patterns and correlations) (Prat, 2019) enables the uncovering of hidden insights and the formulation of faster, better, and more trustworthy decisions without human biases, for example, subjective assumptions (LaPlante, 2019). Third, augmented analytics helps overcome the skills shortage in the data science market (Davenport & Harris, 2017; LaPlante, 2019; Prat, 2019). However, the potential of augmented analytics to automate significant tasks of analytics professionals also constitutes a challenge to the view of BDA as a sociotechnical system that requires technological assets, human resources, and management capabilities as complementary elements to create value (Grover et al., 2018). In particular, the extent to which the principal role of human factors as the social component of the BDA sociotechnical system is challenged by the introduction of such AI-enabled autonomous analytics needs to be investigated. Furthermore, the following exemplary questions need to be answered in future research: Does the increasing level of automation in more advanced analytics, as is the case with the autonomous analytics concept, cause a shift in the roles of the social and technical components of the sociotechnical BDA system? Will the role of human factors remain essential or become even more important to facilitate value creation?

When examining the role of the BDA technical system, another significant yet under-researched question relates to data characteristics. As stated in the introduction, the focus of our study is on the requisite techniques for handling big data. However, some recent technical developments have challenged the role of BDA techniques in organizational practice. For instance, Gartner Inc. (2021) predicts a shift of focus from big data to "small data" and "wide data" in about 70 % of organizations by 2025. The wide data approach includes analytics techniques for data from small and large as well as unstructured and structured data sources, whereas the small data approach refers to techniques for building analytics models with less data to create "less data hungry models" (Gartner Inc., 2021, S. 10). Less data-hungry techniques would help firms overcome the "lack of data" problem and reduce the entry barriers for the use of analytics techniques (Gartner Inc., 2021). Hence, future studies could explore and compare the impacts of different techniques for the data approaches, including big data, small data, and wide data, on the created business value.

Another focus of our meta-analysis is the examination of the moderating effects of study focus and economic area on the business value created from BDA (***RQ3***). Such moderator analyses can explain the occurrence of inconsistencies between primary studies (Brynjolfsson & McElheran, 2016; Ghasemaghaei, 2019) and the specific impact of moderators. Although we could not find a statistically significant explanation for the high variance between studies, we summarized the empirical knowledge on pre-defined moderator categories for the BDA community. With regard to study focus, the findings indicate that studies examining the business value of prescriptive analytics concepts from a purely technical perspective find a higher impact on firm performance than studies adopting a sociotechnical view. This result highlights the predominant role of technology in more advanced BDA concepts, where the social component may not be required to create business value. As previously explained, the role of the sociotechnical system may be increasingly challenged when sophisticated BDA concepts are used, as the social components may then become obsolete. At the same time, individual studies exploring the human factors of BDA from a purely social angle reveal a stronger relationship between these factors and firm performance than studies with a sociotechnical focus, which underlines the essential role of the human factors. These findings indicate that BDA studies show stronger effects when employing a single perspective, be it technical or social, whereas studies with a sociotechnical view find weaker effects. However, given the fact that the differences between the subgroups are relatively small and not statistically significant, we must refrain from deriving any implications from these findings. Instead, we call for further research on the mechanisms that may lead to these observations.

Moreover, we consider different geographical areas as a notable moderator. At first glance, the question may arise as to the variations that can be expected across different geographical areas when analyzing the business value created from BDA. Advanced concepts in BDA, such as cloud computing and analytics as a service, recently allow firms to operate more flexibly, making locations less important. However, as BDA is a sociotechnical system, we also expect social factors such as human and management factors to be essential antecedents to business value creation. The findings of our moderator analysis reveal that the relationship between BDA and organizational performance is higher in developing than in developed economies. Studies that collected data from firms located in developing economic regions, such as China, India, and Malaysia, reported higher business value than studies that gathered data from developed economic regions, such as the US, the UK, France, and Norway. This finding is surprising because prior research on the diffusion of innovation assumed that innovations are more likely to emerge from well-developed areas with technological infrastructure than from areas with insufficient infrastructure (Depietro et al., 1990; Feldman & Florida, 1994). Guided by this assumption, we expected the relationship between BDA and firm performance to be stronger in geographical areas with more developed technological infrastructure, such as European countries, than in less developed areas such as Asian countries. However, when looking beyond the economic aspects, varying legal environments could play a role.

To facilitate managerial actions based on informed operational and strategic decision making through BDA technology, firms have to use their data appropriately (Krishnamoorthi & Mathew, 2018). In other words, business value can only be created from BDA when companies successfully manage to make sense of their data (Bekmamedova & Shanks, 2014; Huang et al., 2018). This premise raises certain questions as to whether differing data protection and data security regulations may constitute reasons for the observed variability across individual studies. Anecdotal evidence shows that organizations from developing countries tend to reap more benefits from big data because the regulation and legislation in such countries may lag behind those in developed countries (Günther et al., 2017). Recent studies suggest that compliance with data protection and privacy regulations provides a competitive advantage. More specifically, compliant organizations outperform their noncompliant counterparts by an average of 20 % (Capgemini, 2019). Hence, compliance with local regulations (e.g., with regard to the handling of personal data, data storage, and data exchange across country borders) represents a major challenge for companies that intend to use BDA. Particularly in sectors dealing with highly sensitive data (e.g., health care), compliance is of utmost importance (Günther et al., 2017). In addition, appropriate information governance structures should be established to ensure compliance and value creation (Grover et al., 2018). Future research should guide companies on how to comply with the respective local data protection and data security regulations to maximize their benefits from data use. However, we reiterate that the interpretation of the results of the moderator analysis on study focus entails the recognition that the differences between the subgroups are rather small and not statistically significant.

Overall, the findings of our study show that all components of the BDA sociotechnical system play an important role in the business value creation process. Regardless of whether technical or social factors contribute more to BDA value creation, managers and decision makers must pay equal attention to the technical system, human factors, and the organizational structure. To create value, BDA systems must be integrated into the operational system, organizational business processes, and managerial decision making routines, while being aligned with the organization's business and IT strategy and continuously adapted to changes (Shanks & Bekmamedova, 2012). Thus, exploring the value creation mechanism of the BDA sociotechnical system remains a major challenge in the future, both for research and business practice.

6.2. Limitations and future research directions

Despite our efforts to enhance transparency and consistency throughout the research process, our study has several limitations that should be considered in the interpretation of the results. First, the methodological limitations relate to the use of meta-analysis and the aforementioned publication bias problem, which may weaken the validity of results. To address this issue, we thoroughly documented our literature search, selection, and coding and consequently applied the IR concept to establish consistency in the rating processes (LeBreton & Senter, 2008) and validate the robustness of our findings by calculating Rosenthal's (1979) failsafe N. We also integrated the qualitative insights from the BDA literature to complement the quantitative findings of our meta-analysis in an attempt to overcome the limitation that arises from its quantitative focus on effect sizes (King & He, 2005).

Further limitations relate to the scope of our research. As previously described, we conceptualized the term business value as a comprehensive set of firm performance indicators at the market, financial, and operational levels. The underlying assumption of this conceptualization is that organizations strive to maximize economic value; this view is grounded in the 10 principles of economics as proposed by Gregory Mankiw (2011, S. 4). However, this assumption may not apply to all organizations. Nonprofit organizations, for instance, may act in accordance with other principles and strive for other ideals such as sustainability or social values. Hence, future studies could further examine the impact of BDA on firm performance, with a particular focus on social or environmental performance.

Another limitation of our research pertains to its focus on the organizational unit. More specifically, our meta-analysis focuses on analyzing the value added that individual organizations yield by using BDA. However, this focus might be too narrow to capture the real value of BDA. In this context, recent literature suggests that firms should collaborate in a big data business ecosystem to reap the full benefits of BDA by creating new products and services based on rich data environments (Curry, 2016; Pappas et al., 2018). Such a big data business ecosystem would consist of different key micro-, meso-, and macroscale stakeholders such as academic institutions, organizations, government departments, and civil society, all of which generate and use data and simultaneously benefit from this ecosystem in particular ways. Exploring this intersectional value creation process could help to understand the value of BDA in co-creation processes and capture the real value of BDA (Pappas et al., 2018), especially given that the value of certain data is expected to significantly increase when combined with other sources (Grover et al., 2018). In Gartner's "Top Trends in Data and Analytics for 2021," the ability for data-sharing collaboration is even considered as a core competency that helps organizations gain a competitive advantage (Gartner Inc., 2021). In such data-sharing economies, questions concerning open source solutions and open data become increasingly relevant. For example, organizations need data-sharing agreements and governance frameworks that enable them to effectively share their data while taking into account relevant aspects such as access control, anonymization, data protection, and privacy (Grover et al., 2018). Therefore, future research should shed more light on the mechanisms required in data-sharing economies and big data business ecosystems and thus provide an understanding of how open data can be shared and used across organizations. Furthermore, although beyond the scope of this study, technical and managerial questions with regard to outsourcing, centralization versus decentralization, and technology-induced organizational change, need to be posed and explored in future studies.

The results of the partition tests revealed differences in the summary effect sizes between the moderator subgroups, but these differences are not statistically significant. Indeed, partition tests often suffer from low statistical power, especially when the number of studies or empirical observations is small (Hedges & Pigott, 2004; Valentine et al., 2010). Despite the absence of a universal valid benchmark for n and the fact that N guarantees sufficient power for meta-analysis, IS meta-analysts often base their meta-analysis on thresholds from three or more studies (Tao et al., 2020) to at least 15 studies (Yun et al., 2014). We refrained from establishing a study threshold because statistical power can be determined not only by the number of studies but also by the sample size and the split of studies between subgroups (Hedges & Pigott, 2004; Valentine, 2019). Nevertheless, as Hunter and Schmidt (2004, p. 12) underscore, "there need be no concern with statistical power when point estimates and confidence intervals are used to analyze data in studies and meta-analysis is used to integrate findings across studies.".

7. Conclusion

In this study, we integrated empirical evidence on the business value of BDA through a meta-analysis of 107 studies from 105 articles to provide in-depth insights into the role of the technical and social components of the BDA sociotechnical system in enhancing firm performance. We also attempted to explore the moderating impact of study focus and economic area on the reported business value. The findings suggest that social components such as the BDA system's human factors, including human resources and management capabilities, contribute more to business value creation compared to technological factors. Furthermore, both the underlying technological concept and the economic area have impacts on the relationship between BDA and firm performance. However, regardless of these moderating influences, both the BDA technical and social factors remain a significant determinant of BDA business value. Our findings contribute to research and practice by providing a consistent and validated picture of the main social and technical factors that are necessary to create value from BDA, while raising questions for future research. For business practice, this validated picture can serve as a checklist to guide BDA projects and enable organizations to understand the mechanisms in the value creation process and thus to increase the value they derive from BA.

CRediT authorship contribution statement

Thuy Duong Oesterreich: Conceptualization, Methodology, Investigation, Data curation, Validation, Writing – original draft, Visualization, Project administration, Software. **Eduard Anton:** Investigation, Formal analysis, Validation, Writing – original draft, Visualization. **Frank Teuteberg:** Writing – review & editing, Supervision. **Yogesh K Dwivedi:** Writing – review & editing, Supervision.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix A:. Search terms applied for the database search

Table A1
Search terms applied for the database search.

Database	Search terms
Scopus	("big data" OR analytics OR "business intelligence") AND (value OR benefit OR advantage)
	("big data" OR analytics OR "business intelligence") AND performance AND (firm OR company OR organization OR organisation)
EBSCO	("big data" OR analytics OR "business intelligence") AND (value OR benefit OR advantage)
	("big data" OR analytics OR "business intelligence") AND performance AND (firm OR company OR organization OR organisation)
AISEL	("big data" OR analytics OR "business intelligence" AND value OR benefit OR advantage)
	("big data" OR analytics OR "business intelligence") AND performance AND (firm OR company OR organization OR organisation)
GoogleScholar	allintitle:("big data" OR analytics OR "business intelligence") AND (value OR benefit OR advantage)
	allintitle:("big data" OR analytics OR "business intelligence") AND performance AND (firm OR company OR organization OR organisation)

Appendix B:. Articles included in the meta-analysis

Table B1
Articles included in the meta-analysis (n = 105 articles/107 studies).

					Social System		Technical System		
Authors (Year)	**Title**	**Publication type**	**Publication name**	**Sample size**	**HF**	**OS**	**DA**	**PA**	**AA**
Ahmed et al. (2020)	The role of supply chain analytics capability and adaptation in unlocking value from supply chain relationships	Journal article	Production Planning & Control	254				0.528	
Akhtar et al. (2019)	Big data-savvy teams' skills. big data-driven actions and business performance	Journal article	British Journal of Management	240	0.500				
Akter et al. (2016)	How to Improve Firm Performance Using Big Data Analytics Capability and Business Strategy Alignment?	Journal article	International Journal of Production Economics	152	0.345			0.345	
Ali et al. (2020)	How Big Data Analytics Boosts Organizational Performance: The Mediating Role of the Sustainable Product Development	Journal article	Journal of Open Innovation: Technology. Market. and Complexity	372	0.448			0.556	
Alkatheeri et al. (2020)	The Mediation Effect of Management Information Systems on the Relationship between Big Data Quality and Decision making Quality	Journal article	Test Engineering and Management	398	0.509				
Al-Serhan (2020)	Big data analytics and sustainable business performance: does internal business process matter in it?	Journal article	PalArch's Journal of Archaeology of Egypt/ Egyptology	438	0.416				
Anand et al. (2016)	Realizing value from business analytics platforms: The effects of managerial search and agility of resource allocation processes	Conference paper	ICIS 2016 Proceedings	72	0.527			0.381	
Anwar et al. (2018)	Big Data Capabilities and Firm's Performance: A Mediating Role of Competitive Advantage	Journal article	Journal of Information & Knowledge Management	312	0.350			0.290	
Asadi Someh and Shanks (2015)	How Business Analytics Systems Provide Benefits and Contribute to Firm Performance?	Conference paper	ECIS 2015 Completed Research Papers	98	0.536		0.554		
Ashrafi and Ravasan (2018)	How market orientation contributes to innovation and market performance: the roles of business analytics and flexible IT infrastructure	Journal article	Journal of Business & Industrial Marketing	114	0.130				
Awan et al. (2021)	Big data analytics capability and decision-making: The role of data-driven insight on circular economy performance	Journal article	Technological Forecasting and Social Change	109	0.565			0.540	
Aydiner et al. (2019)	Business analytics and firm performance: The mediating role of business process performance	Journal article	Journal of Business Research	204			0.345	0.360	0.370
Bag et al. (2020)	Big data analytics as an operational excellence approach to enhance sustainable supply chain performance	Journal article	Resources. Conservation and Recycling	520	0.715				
Bag et al. (2021)	Role of institutional pressures and resources in the adoption of big data analytics powered artificial intelligence. sustainable manufacturing practices and circular economy capabilities	Journal article	Technological Forecasting and Social Change	219	0.373				0.249
Baker and Chasalow (2015)	Factors Contributing to Business Intelligence Success: The Impact of Dynamic Capabilities	Conference paper	AMCIS 2015 Proceedings	30	0.559				
Behl (2020)	Antecedents to firm performance and competitiveness using the lens of big data analytics: a cross-cultural study	Journal article	Management Decision	502		0.320		0.305	
Benzidia et al. (2021)	The impact of big data analytics and artificial intelligence on green supply chain process integration and hospital environmental performance	Journal article	Technological Forecasting and Social Change	168					0.760
Božič and Dimovski (2019b)	Business intelligence and analytics use. innovation ambidexterity. and firm performance: A dynamic capabilities perspective	Journal article	International Journal of Information Management	97	0.521			0.350	
Bronzo et al. (2013)	Improving performance aligning business analytics with process orientation	Journal article	International Journal of Information Management	368	0.765			0.736	
Chae et al. (2014a)	The impact of supply chain analytics on operational performance: a resource-based view	Journal article	International Journal of Production Research	537			0.054		

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Table B1 (*continued*)

					Social System		Technical System		
Authors (Year)	**Title**	**Publication type**	**Publication name**	**Sample size**	**HF**	**OS**	**DA**	**PA**	**AA**
Chae et al. (2014b)	The impact of advanced analytics and data accuracy on operational performance: A contingent resource based theory (RBT) perspective	Journal article	Decision Support Systems	533	0.263			0.069	
Chakphet et al. (2020)	The Role of Big Data Analytics in the Relationship among the Collaboration Types. Supply Chain Management and Market Performance of Thai Manufacturing Firms	Journal article	International Journal of Supply Chain Management	196				0.888	
Chatterjee et al. (2021)	How does business analytics contribute to organisational performance and business value? A resource-based view	Journal article	Information Technology & People	306				0.327	
Chen et al. (2015)	How the Use of Big Data Analytics Affects Value Creation in Supply Chain Management	Journal article	Journal of Management Information Systems	161	0.276			0.296	
Cheng and Lu (2018)	The Impact of Big Data Analytics Use on Supply Chain Performance—Efficiency and Adaptability as Mediators	Conference paper	Proceedings of The 18th International Conference on Electronic Business	245				0.355	
Cheng et al. (2021)	Linkages between big data analytics. circular economy. sustainable supply chain flexibility. and sustainable performance in manufacturing firms	Journal article	International Journal of Production Research	320	0.527			0.391	
Côrte-Real et al. (2019)	Unlocking the drivers of big data analytics value in firms	Journal article	Journal of Business Research	175				0.585	
Côrte-Real et al. (2020)	Leveraging internet of things and big data analytics initiatives in European and American firms: Is data quality a way to extract business value?	Journal article	Information & Management	618				0.306	
Daneshvar Kakhki and Palvia (2016)	Effect of Business Intelligence and Analytics on Business Performance	Conference paper	AMCIS 2016 Proceedings	116				0.434	
Dong and Yang (2020)	Business value of big data analytics: A systems-theoretic approach and empirical test	Journal article	Information & Management	18,816				0.219	
Dubey et al. (2018)	Examining the role of big data and predictive analytics on collaborative performance in context to sustainable consumption and production behaviour	Journal article	Journal of Cleaner Production	190				0.500	
Dubey et al. (2019a)	Empirical investigation of data analytics capability and organizational flexibility as complements to supply chain resilience	Journal article	International Journal of Production Research	213				0.135	
Dubey et al. (2019b)	Big data analytics and artificial intelligence pathway to operational performance under the effects of entrepreneurial orientation and environmental dynamism: A study of manufacturing organisations	Journal article	International Journal of Production Economics	256	0.590				0.610
Dubey et al. (2019c)	Big data analytics capability in supply chain agility: The moderating effect of organizational flexibility	Journal article	Management Decision	173				0.425	
Dubey et al. (2019d)	Big Data and Predictive Analytics and Manufacturing Performance: Integrating Institutional Theory. Resource-Based View and Big Data Culture	Journal article	British Journal of Management	195	0.105			−0.120	
Eidizadeh et al. (2017)	Analysing the role of business intelligence. knowledge sharing and organisational innovation on gaining competitive advantage	Journal article	Journal of Workplace Learning	213			0.520		
Elbashir et al. (2013)	Enhancing the Business Value of Business Intelligence: The Role of Shared Knowledge and Assimilation	Journal article	Journal of Information Systems	347	0.126				
El-Kassar and Singh (2019)	Green innovation and organizational performance: the influence of big data and the moderating role of management commitment and HR practices	Journal article	Technological Forecasting and Social Change	215	0.443	0.145			
Ferraris et al. (2019)	Big data analytics capabilities and knowledge management: impact on firm performance	Journal article	Management Decision	88	0.213			0.354	
Fink et al. (2017)	Business intelligence and organizational learning: An empirical investigation of value creation processes	Journal article	Information & Management	159	0.502		0.558		
Ghasemaghaei et al. (2017)	Increasing firm agility through the use of data analytics: The role of fit	Journal article	Decision Support Systems	215					0.165
				151	0.688				

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Table B1 (*continued*)

Authors (Year)	Title	Publication type	Publication name	Sample size	Social System		Technical System		
					HF	OS	DA	PA	AA
Ghasemaghaei et al. (2018)	Data analytics competency for improving firm decision making performance	Journal article	The Journal of Strategic Information Systems						
Ghasemaghaei (2019)	Are firms ready to use big data analytics to create value? The role of structural and psychological readiness	Journal article	Enterprise Information Systems	179	0.600	0.470			0.650
Ghasemaghaei and Calic (2019)	Does big data enhance firm innovation competency? The mediating role of data-driven insights	Journal article	Journal of Business Research	280			0.520	0.575	0.520
Ghasemaghaei and Calic (2020)	Assessing the impact of big data on firm innovation performance: Big data is not always better data	Journal article	Journal of Business Research	239	0.542				
Ghasemaghaei (2020)	Improving Organizational Performance Through the Use of Big Data	Journal article	Journal of Computer Information Systems	140	0.600			0.440	
Gu et al. (2021)	Exploring the relationship between supplier development. big data analytics capability. and firm performance	Journal article	Annals of Operations Research	108				0.641	
Gupta and George (2016)	Toward the development of a big data analytics capability	Journal article	Information & Management	108	0.573	0.485		0.575	
Gupta et al. (2019a)	Achieving superior organizational performance via big data predictive analytics: A dynamic capability view	Journal article	Industrial Marketing Management	209	0.627			0.615	
Gupta et al. (2019b)	Role of cloud ERP and big data on firm performance: a dynamic capability view theory perspective	Journal article	Management Decision	231	0.756				
Hallikainen et al. (2020)	Fostering B2B sales with customer big data analytics	Journal article	Industrial Marketing Management	417		0.103		0.089	
Hosoya and Kamioka (2018)	Understanding How the Ad Hoc use of Big Data Analytics Impacts Agility: A Sensemaking-Based Model	Conference paper	2018 International Conference on Advances in Big Data. Computing and Data Communication Systems (icABCD)	107	0.430			0.305	
Hung and Chen (2020)	The Role of Organizational Support and Problem Space Complexity on Organizational Performance - A Business Intelligence Perspective	Journal article	PACIS 2020 Proceedings	168			0.535		
Hyun et al. (2019)	The Moderating Role of Democratization Culture: Improving Agility through the Use of Big Data Analytics	Journal article	PACIS 2019 Proceedings	304		0.500		0.440	
Irfan and Wang (2019)	Data-driven capabilities. supply chain integration and competitive performance: Evidence from the food and beverages industry in Pakistan	Journal article	British Food Journal	240				0.590	
Ji-fan Ren et al. (2017)	Modelling quality dynamics. business value and firm performance in a big data analytics environment	Journal article	International Journal of Production Research	287	0.510			0.550	
Kasasbeh et al. (2021)	The moderating effect of entrepreneurial marketing in the relationship between business intelligence systems and competitive advantage in Jordanian commercial banks	Journal article	Management Science Letters	300			0.461		
Li et al. (2018)	Understanding usage and value of audit analytics for internal auditors: An organizational approach	Journal article	International Journal of Accounting Information Systems	209				0.352	
Mandal (2018)	An examination of the importance of big data analytics in supply chain agility development: A dynamic capability perspective	Journal article	Information Technology & People	176	0.517				
Mandal (2019)	The influence of big data analytics management capabilities on supply chain preparedness. alertness and agility: An empirical investigation	Journal article	Information Technology & People	173				0.425	
Mikalef et al. (2018a)	The human side of big data: Understanding the skills of the data scientist in education and industry	Conference paper	2018 IEEE Global Engineering Education Conference (EDUCON)	113	0.290				
Mikalef et al. (2018b)	Information governance in the big data era: aligning organizational capabilities	Conference paper	Proceedings of the 51st Hawaii International Conference on System Sciences	158		0.344			
Mikalef et al. (2020a)	Exploring the relationship between big data analytics capability and competitive performance: The mediating roles of dynamic and operational capabilities	Journal article	Information & Management	202	0.274			0.322	

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Table B1 (*continued*)

Authors (Year)	Title	Publication type	Publication name	Sample size	Social System		Technical System		
					HF	OS	DA	PA	AA
Mikalef et al. (2020b)	The role of information governance in big data analytics driven innovation	Journal article	Information & Management	175	0.563	0.523		0.475	
Moreno et al. (2018)	Does Business Intelligence and Analytics Leverage Dynamic and Operational Capabilities? An Empirical Study in a Brazilian Telecommunications Company	Conference paper	AMCIS 2018 Proceedings	131	0.610			0.420	
Nam et al. (2019)	Business analytics use in CRM: A nomological net from IT competence to CRM performance	Journal article	International Journal of Information Management	170	0.485			0.410	
Nasrollahi et al. (2021)	The Impact of Big Data Adoption on SMEs Performance	Working paper	Research Square	224	0.418	0.487		0.474	
Nji (2021)	Big Data Predictive Analytics and Performance: The Role of Transformational Leadership	Journal article	Turkish Journal of Computer and Mathematics Education (TURCOMAT)	145	0.315			0.144	
O'Neill and Brabazon (2019)	Business analytics capability. organisational value and competitive advantage	Journal article	Journal of Business Analytics	64	0.745	0.700		0.650	
Park et al. (2020)	The Relationships between Capabilities and Values of Big Data Analytics	Conference paper	Proceedings of the 9th International Conference on Smart Media and Applications (SMA 2020)	200				0.607	
Peters et al. (2016)	Business intelligence systems use in performance measurement capabilities: Implications for enhanced competitive advantage	Journal article	International Journal of Accounting Information Systems	324	0.210		0.107		
Qureshi et al. (2020)	The Role HR Analytics. Performance Pay and HR Involvement in influencing Job Satisfaction and Firm Performance	Journal article	International Journal of Advanced Science and Technology	303				0.287	
Raguseo and Vitari (2018)	Investments in big data analytics and firm performance: an empirical investigation of direct and mediating effects	Journal article	International Journal of Production Research	200	0.208				
Ramadan et al. (2020)	Sustainable Competitive Advantage Driven by Big Data Analytics and Innovation	Journal article	Applied Sciences	117	0.445				
Raman et al. (2018)	Impact of big data on supply chain management	Journal article	International Journal of Logistics Research and Applications	287				0.527	
Ramakrishnan et al. (2020)	An Integrated Model of Business Intelligence & Analytics Capabilities and Organizational Performance	Journal article	Communications of the Association for Information Systems	154		0.623		0.520	
Rialti et al. (2019)	Big data analytics capabilities and performance: Evidence from a moderated multi-mediation model	Journal article	Technological Forecasting and Social Change	259	0.589			0.639	
Richards et al. (2014)	An empirical study of business intelligence impact on corporate performance management	Conference paper	PACIS 2014 Proceedings	337	0.323		0.314		
Saleem et al. (2020)	An empirical investigation on how big data analytics influence China SMEs performance: do product and process innovation matter?	Journal article	Asia Pacific Business Review	312				0.430	0.520
Samsudeen (2020)	Impact of big data analytics on firm performance: mediating role of knowledge management	Journal article	International Journal of Advanced Science and Technology	107	0.480			0.567	
Sangari and Razmi (2015)	Business intelligence competence. agile capabilities. and agile performance in supply chain: An empirical study	Journal article	The International Journal of Logistics Management	184	0.657		0.543		
Shamim et al. (2019a)	Role of big data management in enhancing big data decision-making capability and quality among Chinese firms: A dynamic capabilities view	Journal article	Information & Management	108	0.440	0.505		0.485	
Shamim et al. (2019b)	Connecting big data management capabilities with employee ambidexterity in Chinese multinational enterprises through the mediation of big data value creation at the employee level	Inter	International Business Review	308	0.680				
Shamim et al. (2020)	Big data analytics capability and decision making performance in emerging market firms: The role of contractual and relational governance mechanisms	Journal article	Technological Forecasting and Social Change	108	0.620	0.613			
Shan et al. (2019)	Big data analysis adaptation and enterprises' competitive advantages: the perspective of dynamic capability and resource-based theories	Journal article	Technology Analysis & Strategic Management	219	0.306			0.348	

(*continued on next page*)

Table B1 (*continued*)

Authors (Year)	Title	Publication type	Publication name	Sample size	Social System		Technical System		
					HF	OS	DA	PA	AA
Singh and El-Kassar (2019)	Role of big data analytics in developing sustainable capabilities	Journal article	Journal of Cleaner Production	215	0.508				
Someh et al. (2019)	Reconceptualizing synergy to explain the value of business analytics systems	Journal article	Journal of Information Technology	201				0.564	
Song et al. (2020)	Creating Sustainable Innovativeness through Big Data and Big Data Analytics Capability: From the Perspective of the Information Processing Theory	Journal article	Sustainability	294	0.393				
Song et al. (2020)	Creating Sustainable Innovativeness through Big Data and Big Data Analytics Capability: From the Perspective of the Information Processing Theory	Journal article	Sustainability	477	0.433				
Song et al. (2020)	Creating Sustainable Innovativeness through Big Data and Big Data Analytics Capability: From the Perspective of the Information Processing Theory	Journal article	Sustainability	632	0.389				
Song et al. (2018)	Data analytics and firm performance: An empirical study in an online B2C platform	Journal article	Information & Management	309	0.357				
Srinivasan and Swink (2018)	An Investigation of Visibility and Flexibility as Complements to Supply Chain Analytics: An Organizational Information Processing Theory Perspective	Journal article	Production and Operations Management	191	0.042			0.207	
Suoniemi et al. (2020)	Big data and firm performance: The roles of market-directed capabilities and business strategy	Journal article	Information & Management	301	0.450			0.505	
Thirathon (2017)	Competitive advantage through big data analytics	Thesis	Thesis	163	0.418			0.301	
Torres et al. (2018)	Enabling firm performance through business intelligence and analytics: A dynamic capabilities perspective	Journal article	Information & Management	137	0.223		0.405		
Wamba et al. (2017)	Big data analytics and firm performance: Effects of dynamic capabilities	Journal article	Journal of Business Research	297	0.395			0.388	
Wamba et al. (2020a)	Big data analytics-enabled sensing capability and organizational outcomes: assessing the mediating effects of business analytics culture	Journal article	Annals of Operations Research	202	0.647	0.607			
Wamba et al. (2020b)	The performance effects of big data analytics and supply chain ambidexterity: The moderating effect of environmental dynamism	Journal article	International Journal of Production Economics	281				0.257	
Wang et al. (2019)	Harnessing business analytics value through organizational absorptive capacity	Journal article	Information & Management	600	0.712			0.659	
Wang et al. (2020)	Corporate social responsibility. Green supply chain management and firm performance: The moderating role of big-data analytics capability	Journal article	Research in Transportation Business & Management	260	0.295				
Wang and Byrd (2017)	Business analytics-enabled decision-making effectiveness through knowledge absorptive capacity in health care	Journal article	Journal of Knowledge Management	152	0.470			0.250	
Wilkin et al. (2020)	Big data prioritization in SCM decision-making: Its role and performance implications	Journal article	International Journal of Accounting Information Systems	84	0.589			0.697	
Wieder and Ossimitz (2015)	The Impact of Business Intelligence on the Quality of Decision Making – A Mediation Model	Journal article	Procedia Computer Science	33	0.330		0.290		
Yadegaridehkordi et al. (2020)	The impact of big data on firm performance in hotel industry	Journal article	Electronic Commerce Research and Applications	418	0.550				
Yogev et al. (2012)	How business intelligence creates value	Conference paper	ECIS 2012 Proceedings	159	0.473		0.556		
Yu et al. (2018)	Data-driven supply chain capabilities and performance: A resource-based view	Journal article	Transportation Research Part E: Logistics and Transportation Review	329	0.433				
Yu et al. (2021)	Role of big data analytics capability in developing integrated hospital supply chains and operational flexibility: An organizational information processing theory perspective	Journal article	Technological Forecasting and Social Change	105				0.695	

HF = Human factors; OS = Organizational structure; DA = Descriptive analytics; PA = Predictive analytics; AA = Prescriptive and autonomous analytics.

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