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What translates big data into business value? A meta-analysis of the impacts of business analytics on firm performance

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ABSTRACT

The main purpose of this study is to examine the factors that are critical to create business value from business analytics (BA). Therefore, we conduct a meta-analysis of 125 firm-level studies spanning ten years of research from across 26 countries. We found evidence that the social factors of BA, such as human resources, management capabilities, and organizational culture show a greater impact on business value, whereas technical aspects play a minor role in enhancing firm performance. Through these findings, we contribute to the ongoing debate concerning BA business value by synthesizing and validating the findings of the body of knowledge.

1. Introduction

The disruptive impact of big data on various businesses and industries has been referred to as a "management revolution" [1] or "the next frontier" [2]. Others have even opined that "big data is possibly the most significant 'tech' disruption in business and academic ecosystems since the meteoric rise of the Internet and the digital economy" [3]. The advanced techniques and technologies necessary to handle big data are commonly referred to by the terms business intelligence (BI), business analytics (BA), or big data analytics (BDA) [4]. Given the enormous potential of BA to create value for business and society, an increasing number of studies from diverse research disciplines have attempted to examine the value creation mechanism of BA [5,6]. In the BA literature, technical and human resources, as well as management capabilities, are considered essential antecedents to business value creation [7–9]. Moreover, a data-driven culture [6,10,11] and contextual factors such as the competitive intensity [12] and industry dynamism [13] were found to have a major impact on the value created from BA. Some studies have noted that firms can only create value from BA when they manage to combine their resources and capabilities to gain benefits [14].

Overall, numerous studies with inconsistent results have been published on the business value of BA over the past decades [7,15,16]. Although most studies report a positive relationship between BA and firm performance, for example, by demonstrating the strong impact of data analytics competency on improving firm decision-making [14] or illustrating the major role that BDA use plays in enhancing asset productivity and business growth [17], some studies present a more nuanced picture of the conditions under which BA can create value for firms. In an attempt to explain the mixed results of prior studies, IS scholars have pointed to the essential role of contextual factors, such as a firm's structural readiness, and psychological readiness factors, which are needed to create value from BA [16]. In addition, whether BA is beneficial for firms depends on the fit between different factors, such as BA tools, data, people, and tasks [18]. Some IS scholars have similarly suggested that several factors, such as the inability to capture the indirect benefits of BA use, methodological issues, and inadequate consideration of environmental factors and time lags, are the main reasons for these mixed results [15].

Although the wealth of studies on the business value of BA has undoubtedly contributed to the body of knowledge by providing valuable insights into specific aspects of the value creation mechanism, recent work has highlighted the need for a more consistent picture, especially with regard to the question on how contextual factors influence the performance outcomes due to BA [5]. To date, few research efforts, whether in IS or in other disciplines, have attempted to provide a more integrated and consistent picture on the business value of BA based on empirical findings from prior studies. We address this gap by synthesizing quantitative evidence on this research topic from the rich body of knowledge. Thus, our main research objective is to provide a comprehensive and consistent picture of the main factors that contribute to

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Table 1
Overview of related works.

	This study	Trieu [42]	Günther et al. [43]	Mikalef et al. [44]	Maroufk-hani et al. [45]	Bogdan and Borza [47]	Paradza and Daramola [46]
Publication year	2022	2017	2017	2018	2019	2019	2021
Publication outlet	Information & Management	Decision Support Systems	Journal of Strategic Information Systems	Information Systems and e-Business Management	Information	Management and Economics Review	Sustainability
Research objective							
Data aggregation and integration	●					●	
Synthesis and integration of findings	●	●	●	●	●	●	●
Study design							
Theoretical review type	Meta-analysis	Descriptive review	Scoping review	Descriptive review	Descriptive review	Meta-analysis	Descriptive review
Nature of primary sources	Quantitative	Quantitative/ qualitative	Quantitative/ qualitative	Quantitative/ qualitative	Quantitative/ qualitative	Quantitative	Quantitative/ qualitative
Search strategy	Comprehensive	Selective (journals)	Comprehensive	Comprehensive	Selective (journals)	Selective (journals)	Selective (time period)
Review method							
Narrative synthesis	●	●	●	●	●	●	●
Bibliometric analysis		●			●		●
Statistical methods (meta-analytic techniques)	●					●	
Study sample							
Journal articles	●	●	●	●	●	●	●
Conference papers	●		●	●			●
Time period	2012–2021	2000–2015	2013–2016	2010–2017	2013–2019	2015–2019	2009–2020
Sample size	125	106	67	84	33	37	93
Study focus							
Technical concept							
• BI	●	●	●	●	●		●
• BA	●		●	●	●	●	
Units of analysis							
• BA resources and capabilities	●						
• Contextual factors	●						
• Firm performance	●						
BA impacts							
• General			●				●
• Directional	●	(●)		(●)		●	
Moderator analysis	●						
Research gaps	●	●	●	●			●
Future research directions	●	●	●	●			●

Abbreviations: BI = Business intelligence; BA = Business analytics

enhance the business value of BA, resolve the inconsistencies across studies, and achieve an enhanced understanding of the conditions under which BA's has varying impacts on firm performance. In doing so, we aim not only to synthesize qualitative findings from the body of knowledge but also to strive for a more valid picture of these findings based on the quantitative results of former studies. In particular, we aim to answer the following research questions (RQs):

> RQ1: What are the main BA resources and capabilities as well as contextual factors that are critical to create business value from business analytics?
> RQ2: To what extent do these factors contribute to enhancing firm performance and what conditions may cause business analytics to have varying impacts on firm performance?

To answer the RQs, we conduct a meta-analysis of 125 firm-level studies reported in 123 articles spanning ten years of research from across 26 countries and four continents. We consider meta-analysis to be an appropriate method for synthesizing the results of conflicting studies to resolve the inconsistencies [19] and increase the statistical power of these results [20]. The findings are expected to be of high importance for research and practice because answering the questions of how, when, and why it can create value is essential for companies to gain a competitive advantage [6,21]. For researchers, developing an enhanced understanding of the main determinants of the business value of IT would help to advance the development of theory in IS research. In business practice, such an enhanced understanding would help managers to increase the value of IT [22].

The remainder of this paper is structured as follows. In Sections 2 and 3, we explain the theoretical background concerning the business value of BA, describe the scope of our research, and develop the research framework, including identifying the dependent and independent variables of interest. In Section 4, we describe the relevant phases and activities of our meta-analysis research approach. The results of the meta-analysis are presented in Section 5. Implications for research and practice as well as the limitations of this study are described in Section 6. Finally, the concluding Section 7 presents a brief summary of this research.

2. Theoretical background

2.1. Business value of business analytics

In the literature, the term big data is often used to describe extremely large and complex data sets drawn from various sources that require advanced techniques, such as BI, BA, or BDA, for storage, management, analysis, and visualization [4]. In this context, the “three Vs” framework is often used to highlight volume (magnitude of data), velocity (speed of data creation), and variety (structural heterogeneity of data sources) as the main characteristics of big data. Additional Vs were later added to the framework, such as veracity and viscosity [23]. From a technical perspective, BA is based on data mining and statistical techniques [4]. A process-oriented view of BA was suggested by Phillips-Wren et al. [24] in their BDA framework that encompasses the underlying data sources as well as the data preparation, storage, analysis, access, and usage steps taken by business users, business analysts, and data scientists. Another conceptual view of BA is concerned with a classification according to the advancement of concepts with differing levels of intelligence, such as descriptive, predictive, and prescriptive analytics and autonomous analytics. These BA concepts, in turn, contribute to different levels of competitive advantage [25]. For this study, we adopt the definition proposed by Chen et al. [4], whereby BI, BA, and BDA are taken as related fields.

In essence, BA systems are considered an evolution of BI systems, offering advanced techniques for the analysis and reporting of data [26]. With the help of BA, new patterns and correlations can be detected in huge amounts of generated data [27]. Academics and practitioners alike acknowledge that better decisions can be made on the basis of data-based evidence rather than intuition [1,28]. Data-driven decision-making has been found to have a positive impact on firm performance, indicating that firms that use data and BA for decision-making achieve higher productivity [29]. In their “BDA business value framework,” Grover et al. [6] describe a capability-realization process in which the direct business value of BDA is created through various mechanisms to achieve valuable targets, such as improved organizational performance, business process improvement, products and services innovation, consumer experience, and market enhancement, all of which result in functional value (financial value such as return on investment [ROI] and return on sales [ROS]) and symbolic value (image, satisfaction, and industry leadership). This view of BDA business value as tangible manifestations in the operational, financial, and market performance metrics of the firm is consistent with the common terms used in the IT business value literature. Sabherwal and Jeyaraj [30] adopted the business value term proposed by Melville et al. [31], Schryen [32], and Kohli and Grover [22], which views the business value of IT as the firm-level impact of IT on organizational performance; this, in turn, can manifest itself through various measures. The measures used in the IT business value literature to evaluate the impact of IT on organizational performance include a comprehensive set of measures ranging from financial measures, such as ROI, to productivity- or output-based measures, such as production outputs or expenses [30], productivity gains, profitability enhancements, process improvements, increased consumer surpluses, improvements in supply chains, or innovation at the interorganizational level [22]. In their e-business value hierarchy, Zhu and Kraemer [33] conceptualize the value creation process of e-business as an hierarchy encompassing three layers, with the unique characteristics of the Internet (e.g., open standard, public network, and global connectivity) representing the bottom layer, which lead to value creation in terms of transactional efficiencies, market expansion, as well as information sharing and integration, which, in turn, result in tangible impacts on firm performance. In line with the definition of Grover et al. [6] and those in IT business value literature cited above, we define the business value of BA as the firm-level impact of BA on organizational performance, as operationalized in tangible metrics, such as operational, financial, and market performance measures. Similar to our definition, prior studies in the BA business value literature have viewed the business value of BA as improved firm performance that arises from BA, resulting in process improvements (operational dimension) and improved firm performance (financial dimension) [9, 34–38].

The business value creation process of BA has been acknowledged to be different from IT with respect to resource characteristics, implementation, and use [39]. IT creates value through process optimization, efficiency improvements, cost reductions, and productivity gains, whereas BA contributes to business value creation by facilitating managerial actions because it provides a basis for informed operational and strategic decision-making [39,40]. In general IT projects, the focus is on the deployment of technology, whereas in BDA projects, a further step is required in order to make meaningful use of information and generate valuable insights for value creation [39,41]. Despite these differences in the value creation process, we contend that the impact of BA implementation and use at the organizational level is similar to that of conventional IT because improved decision-making also contributes—although in a different manner—to process optimization, efficiency improvements, cost reductions, and productivity gains.

2.2. Related works

Given the benefits that BA offers for firms, numerous studies have assessed its business value but without yielding a clear and consistent picture of the main factors that contribute to enhancing firm performance [7,15]. As summarized in Table 1, six prior studies exist that can be considered as related works to our study. The most prominent attempts to integrate and synthesize the body of knowledge on the business value of BA have been made by Trieu [42], Günther et al. [43], and Mikalef et al. [44] in their systematic literature reviews. However, their studies primarily aimed at summarizing research patterns in the field, identifying research gaps, and proposing future research directions, rather than identifying and quantitatively assessing the main determinants and their impact on firm performance. Additionally, the descriptive review of Maroufkhani et al. [45] employs a bibliometric analysis, including an overview of publication practices and citation analysis, but it is based on a relatively small sample of only 33 primary studies and lacks further insights into research gaps and future research directions. The most recent literature review by Paradza and Daramola [46] shows a similar research focus to other related works, that is, qualitatively synthesizing prior literature on the research topic.

So far, only Bogdan and Borza [47] attempted to provide an integrated view of the business value of BA by conducting a meta-analysis of the impact of BDA on firm performance. Their meta-analysis, however, was based on a rather small sample of only 37 primary studies and thus fails to provide a comprehensive picture of the research topic. Moreover, their study focused on exploring the overall extent to which BDA contributes to enhancing firm performance, with BDA as the sole independent variable and firm performance as the dependent variable. This view of BDA as one independent variable does not take into account the multi-dimensional and complex nature of BDA and thus fails to provide a granular picture of the various BA resources and capabilities that contribute to enhancing firm performance. Further, Bogdan and Borza [34] did not make any attempt to explain the observed variability in effect sizes across the investigated studies.

Our study closes numerous gaps that the related works in Table 1 have not sufficiently addressed. Overall, our study aims at identifying the main BA resources and capabilities (BA technical resources, BA human resources, and BA management capabilities), data quality, as well as contextual factors (organizational culture and external pressure) that are critical for creating business value from BA and by exploring the extent to which this set of factors contributes to enhance firm performance. We additionally address the variability across individual studies by thoroughly conducting multiple subgroup analyses to further explore the conditions that may cause BA to have varying impacts on firm performance. In essence, we explore the moderating impact of the firm performance dimension, technical concept, economic area@, and time lag effects on the results. To the best of our knowledge, our work is the first to provide an integrated and consistent picture of the business value of BA based on the rich stream of research in the BA field. In doing so, we address the increasing need for more research integration and synthesis that has emerged from the IS discipline’s maturity [48]. Consistent with

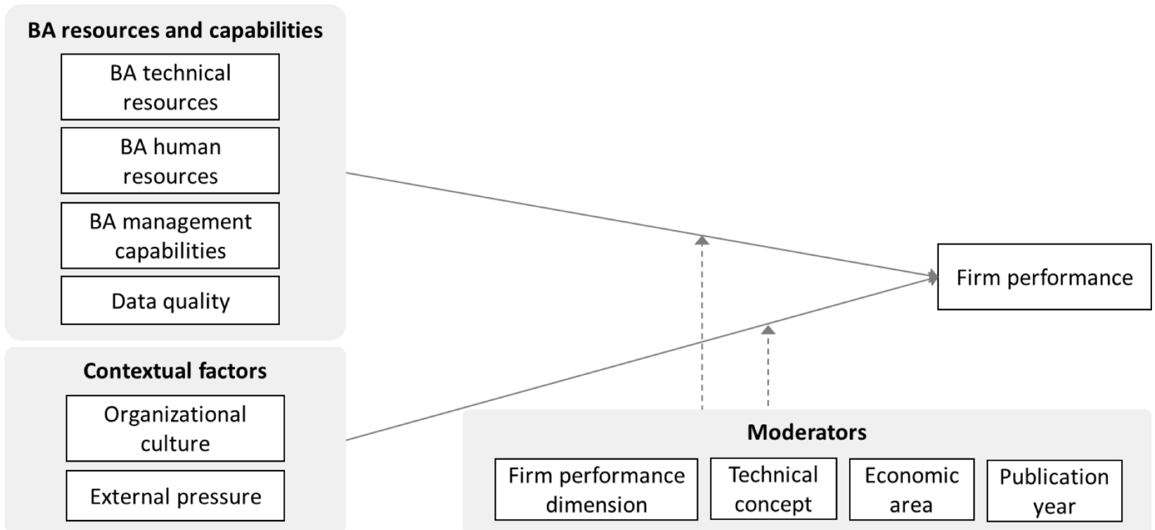

Fig. 1. Research model of BA business value.

Table 2
Independent variables employed to conceptualize BA.

Dimension	Variable	Description
BA resources and capabilities	BA technical resources (BATC)	Technological components of BA, including required software, hardware, and infrastructure [7,53,55]
	BA human resources (HBAR)	Personnel with BA skills or knowledge and analytics professionals such as data scientists who are able to use BA [35,51,53,54]
	BA management capabilities (BAMC)	Management activities, such as planning, investment, coordination, and control; management's ability to make solid business decisions; search and select efforts of managers; entrepreneurial orientation [53,56]
	Data quality (DQ)	The access to consistent, accurate, credible, and complete data [6,53,55]
Contextual factors	Organizational culture (OC)	Organizational culture that facilitates data-driven decision-making, such as an "data-driven culture" or a "data-driven mindset" [6,10,11]
	External pressure (EP)	The intensity of competition [12,13] and environmental dynamism in an industry [57]

the dominant view in the IT business value literature, we use the terms business value and firm performance interchangeably throughout the entire paper.

3. Research model

We combine the broad view of the business value term of BA proposed by Grover et al. [6] with the well-established IS business value framework [32] to examine the impact of BA on firm performance at the organizational level for several reasons. First, the IS business value framework [32] provides a sociotechnical conceptualization of IS as investments in important IS resources and capabilities such as technical assets, human resources and management capabilities, and non-IS investments (such as organizational structure) that have multi-dimensional impacts on firm performance. This sociotechnical view of IS investments fits well with the sociotechnical nature of BA systems that comprise technical IT infrastructure, human, and organizational system components [7]. The BDA value creation framework [6] extends this view of IS as sociotechnical resources and capabilities with a more process-oriented view of the BDA value creation mechanism that enables us to better take into account the dynamic nature of BA, including a rich set of moderating factors, such as competitive dynamics and data-driven culture that may also have impacts on the manifestation of BA's value. Thus, our research model draws on both frameworks to conceptualize BA as a set of resources and capabilities that must be combined with contextual factors prior to creating business value at an organizational level that is manifest in firm performance measures.

As shown in Fig. 1, our research model integrates a set of structural and moderating variables that enables us to answer the questions of whether and under what conditions BA can create value. We explain these structural and moderating variables in detail in the following sections.

3.1. *Structural variables*

Primary studies have mostly relied on the resource-based view (RBV) of the firm [49] as well as the theory of dynamic capabilities (DC) [50] to explain the impact of BA on firm performance, with BA resources being seen as DC that helps firms to react and adapt to changing competitive environments [18]. Similar to prior literature in this line of research, we assume that IT resources constitute a main determinant of firm performance that enables a firm to gain a competitive advantage [31]. As summarized in Table 2, the independent variables of our research model are comprised of various sociotechnical factors which are considered essential to create business value from BA at the organizational level. We intentionally adopt a sociotechnical lens to integrate a multidimensional perspective of BA comprising the necessary technical and human resources as well as management capabilities as essential antecedents to business value creation.

In primary studies, BA has commonly been referred to as *BDA resources and capabilities* [7–9]. For example, Akter et al. [7] describe BDA technology capability (physical component), BDA talent capability (human component), and BDA management capability (organizational component) as the three major BDA antecedents of BA business value. This conceptualization of BA as a sociotechnical artifact is consistent with the existing view in IS business value research, which similarly underlines the complementary elements of BA such as IT assets, human IT resources, and IT management capabilities [32].

BA technical resources constitute the technological core components of BA by highlighting the physical nature of BA, including its technical components, such as required software, hardware, and infrastructure [7]. *BA human resources* refer to a firm's personnel with BA skills or

Table 3
Performance measures employed to evaluate the impact of BA on firm performance.

Performance dimension	Value targets
Market performance (MA)	Competitive advantage [21,26,55,60,61] Customer retention [8] Other market performance indicators (market share, success rate of new products and services, market entrance, etc.) [9,37,58]
Financial performance (FI)	ROI, return on assets (ROA), ROS, profitability enhancements, and revenue [36–38, 58]
Operational performance (OP)	Business process performance [21,34] Decision-making effectiveness/performance [14,62,63] Innovation ambidexterity and organizational innovation [15,64] Firm agility [18,65] Informational benefits (fact-based decision-making, real-time decisions, and a "single version of the truth") [51]

Table 4
Moderating variables included in the moderator analysis.

Moderating variable	Definition	Description
Firm performance dimension	Operational performance (OP)	Impact on the operational performance dimension level of BA is examined by employing the operational performance measures as described in Table 3
	Financial performance (FI)	Impact on the financial performance dimension level of BA is examined by employing the financial performance measures as described in Table 3
	Market performance (MA)	Impact on the market performance dimension level of BA is examined by employing the market-based performance measures as described in Table 3
	Diverse (DIV)	Studies that report at least two types of performance measures are referred to as diverse
Technical concept	Business intelligence (BI)	A study is focused on examining the impact of BI on firm performance
	Business analytics (BA)	A study is focused on examining the impact of BA on firm performance
Economic area	Developed economy (DEVD)	Data were collected from respondents located in a developed economy according to the classification of the United Nations [69]
	Developing economy (DEVG)	Data were collected from respondents located in a developing economy according to the classification of the United Nations [69]
	Diverse (DIV)	Studies that report data collected from respondents located in several geographical areas are referred to as diverse (DIV)
Publication year	-	The year in which the study was published or available

knowledge, persons who are, in most cases, analytics professionals, such as data scientists being able to perform required tasks using BA [7]. Among others, technical knowledge, technology management knowledge, business knowledge, and relational knowledge are considered essential to their skills profile [7]. In the literature, BA human resources are widely viewed as a major precondition for successfully creating value from BA use [35, 51–54]. In line with the RBV of the firm, BA human resources are considered non-imitable and thus constitute a major source of competitive advantage [14].

BA management capabilities, as the organizational component of BA, refer to a firm's management's ability to make solid business decisions with respect to core management tasks, such as BDA planning, investment, coordination, and control [7]. The strategic role of managerial actions in developing competitive actions is considered essential to an enhanced understanding of how business value is created from BA [56]. More specifically, researchers have argued that BA-enabled managerial efforts in acquiring and analyzing critical information for decision-making help to create business value [53,56] because insights gained from data do not automatically result in performance gains. Acquired knowledge is useless without someone to make sense of it for decision-making and action-taking purposes [52]. When conceptualizing BA resources and capabilities, primary studies frequently consider *data quality* as another critical factor on the way to business value creation. Anecdotal evidence has shown that the access to consistent, accurate, credible, and complete data plays a major role in gaining competitive advantage [6,53,55]. Thus, aside from the focus on the technical, human, and managerial components of BA, we additionally include data quality as another independent variable in our research model.

Contextual factors constitute another important dimension to be considered when examining the impact of IT on firm performance. This is because firm, industry, and macro-economic factors can account for facilitating or hampering conditions for business value creation [32]. One important firm-level factor that may contribute to enhancing BA business value is often referred to as an "data-driven culture" or a "data-driven mindset" [6]. Prior studies have emphasized that without an *organizational culture* that facilitates data-driven decision-making, firms cannot reap benefits from BA [10,11]. Market-level factors are other important contextual variables in primary BA business value studies since they may trigger firms toward BA adoption and use. For example, the intensity of competition in the market [12,13] and environmental dynamism in an industry [57] may cause BA to have varying impacts on the business value created since they constitute an *external pressure* for firms.

Firm performance is the dependent variable of our research model. In line with prior studies on the business value of BA, we employ a multidimensional set of firm performance measures to conceptualize the business value term, including variables that evaluate the impact of BA on the firm's market, financial, and operational performance (cf. Table 3). In the context of Grover et al [6], these variables are viewed as value targets that specify the various operational (e.g., business process or decision-making improvement) and strategic entities (e.g., product and service innovation, customer experience, or market improvement) that are affected by BA capabilities. These value-creating entities have a tangible impact on the productivity (operational) as well as on market and financial metrics (i.e., impact variables). Respondents' assessment of the BA's impact on these value targets represents the quantification of the effects. An alternative approach would be to use objective indicators such as productivity KPIs or financial metrics as impact variables of the surveyed companies. In the BA literature, however, expense-based measures are not employed; instead, self-reported income-based measures are used. Therefore, we interpreted the Grover et al. [6] framework in terms of performance measures as the self-reported quantification of value targets. This interpretation of Grover et al.'s [6] framework is consistent with previous work and approaches to measuring business value [36,38,58,59]. Thus, in line with the literature, we consider BA business value as the tangible impact of BA on firm performance by employing measures of firm performance, that is, operational, financial, and market performance.

In the BA business value literature, the *market performance* dimension is often evaluated by means of market-based measures such as competitive advantage [21,26,55,60,61], customer-based measures [8], as well as other market performance indicators, such as market share, success rate of new products and services, and market entrance [9,37, 58] to conceptualize their dependent variables. In doing so, they aimed to examine whether BA helps firms to not only improve their position in the market compared with their competitors [9,37] but also sustain this competitiveness [21,55]. As far as the *financial performance* is

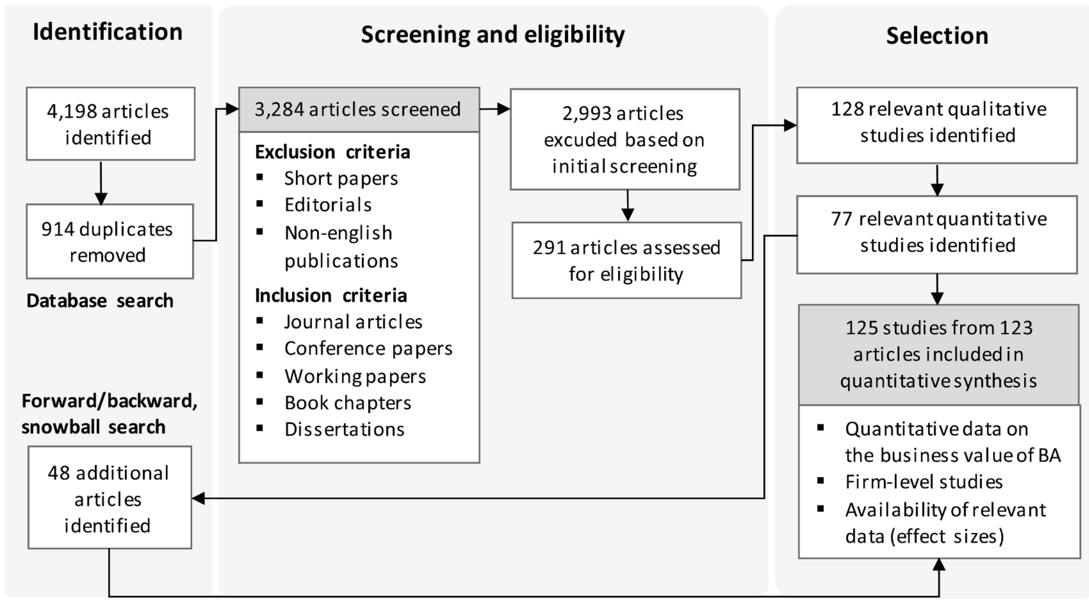

Fig. 2. Literature search process according to the PRISMA flowchart.

concerned, a mix of revenue- and profitability-based measures is commonly used to conceptualize firm performance, such as ROI, return on assets (ROA), ROS, profitability enhancements, and revenue [36–38, 58].

In the BA business value literature, operational performance is the most frequently used firm performance measure to assess the business value of BA, with a particular focus on its positive impact on internal business processes. Operational performance measures were used in 58% of all individual studies of our sample (n = 125), whereas 42% of the studies used market performance and only 36% relied on financial performance measures. Performance-based measures for BA include decision-making effectiveness, which focuses on the mechanisms through which BA improves decision-making and the extent to which a company can make real-time decisions, respond to change, and understand customers on the basis of the insights gained through BA [62]. Other operational performance outputs include, among others, the conceptualization of BA impact as innovation ambidexterity, firm DC [15], firm agility, and informational benefits [18]. Given this wealth of firm performance measures in the primary studies, we consistently adopt a broad definition of firm performance to conceptualize the business value of BA, whether the measures are referred to as market, financial, or operational performance measures.

3.2. Moderating variables

The second major purpose of this study is to understand the conditions under which BA may have varying impacts on firm performance. As shown in Table 4, the moderators of interest include a set of three variables that enables us to differentiate between firm performance dimensions, economic area, and publication year. The first moderating variable refers to the *firm performance dimension* of the dependent variable, as described in the preceding section. Previous meta-analyses have presented evidence that the nature of the dependent variable is significantly related to the business value created from IT. For example, Kohli and Devaraj [66] found that primary studies that used productivity-based measures reported higher firm performance than those that used profitability-based measures. Sabherwal and Jeyaraj [30] similarly concluded that profitability measures are less likely to demonstrate the business value of IT. Liang et al. [67] also found that IT contributes to both financial performance and internal efficiency; the latter is similar to operational performance, and a higher positive effect from IT was found on internal efficiency than on financial performance. Further evidence suggests that the impact of IT investments and market-based measures show marginally higher correlations in the case of accounting-based measures [68]. In line with these findings, we expect the moderator *firm performance dimension* to be helpful in explaining the variability in the overall findings of the primary studies.

The second moderating variable of interest in our study relates to the *technical concept* that is central in the primary studies. As stated previously, the BA term that we adopt refers to the broad definition proposed by Chen et al. [4], who suggested that business intelligence and analytics (BI&A) and BDA are taken as related fields. However, in the BA literature, BA systems are considered an evolution of BI systems because they offer more advanced techniques for the analysis and reporting of data compared to BI systems [26]. Thus, we assume that less sophisticated technological concepts such as BI generate less business value than does BA.

Furthermore, we also aim to study *economic area* and *publication year* as further potential factors that might account for variation across individual studies. The moderator economic area points to geographical differences in the results of individual studies. Geographical differences in the value creation process of BA are considered under-researched factors that deserve more attention, since the macro-environmental context, including country-specific factors, such as the economic or cultural characteristics of a country, may account for differences in the value created from BA [61]. When examining geographical study characteristics, prior studies have commonly referred to economic regions [30,70] to explore differences that might account for the variability of results. Similarly, we aim to examine the moderating role of economic regions according to the country classifications proposed by the United Nations [69] on the created business value.

The last moderating variable in our research model is *publication year* which helps us to examine the impact of time lag effects on the results, as also conceptualized in the IS business value model [32]. Devaraj and Kohli [66] argued that time lags in measuring the return on IT investments can lead to inconsistent results in empirical studies. Time lag effects can occur because companies often have to adjust to new technologies and processes and master change management before the business value of IT becomes apparent [71]. Accordingly, the measured BA business value of the individual studies may depend on the timing of the observations, which is taken into account by integrating the publication year as moderating variable into the research model.

Table 5
Data to be extracted, coded, and documented from the selected studies (n = 125).

Extracted data	Examples
General study characteristics	■ Study ID, authors, reviewer ID ■ Publication date, publication type
Effect size measures	■ Effect size measures reporting correlations between variables ■ When correlations unavailable: Only path coefficients that reflect a simple bivariate (zero-order) relationship between two variables
Other measures	■ Sample sizes ■ Moderating variables (cf. Section 3)

4. Meta-analysis

We chose to conduct a meta-analysis because such a research approach facilitates the achievement of our primary goals—integrating, synthesizing, and analyzing the quantitative results of multiple individual studies to draw new conclusions from past knowledge [72]. Moreover, meta-analysis is a useful means by which to increase the statistical power of results [20]. Since being introduced in the 1970s, meta-analysis has become an important research method in multiple research disciplines of the natural and social sciences [19,73,74]. Thus, meta-analysis enables us to re-examine the results of prior studies on the business value of BA in a manner that can extend our understanding of how BA can create value.

4.1. Selection of relevant studies

We employed a multidimensional search strategy that enables us to gather a comprehensive sample of studies. This broad search strategy is necessary due to the interdisciplinary nature of the big data and BA research field at the interfaces to various related disciplines such as computer science, marketing, management, communication, and mathematics [4]. Therefore, we conducted a literature search in various databases and sources as well as an additional forward and backward search in all relevant studies [20]. For the sake of transparency and reproducibility, we followed the PRISMA guidelines [75] for a detailed documentation of the search process and selection criteria (cf. Fig. 2).

In the first step, we searched several sources, including the interdisciplinary databases EBSCOhost, Scopus, Google Scholar, as well as the AIS Electronic Library (AISeL), which comprises various leading journals and conferences from the IS field. The search terms applied for this database search include the keywords *analytics* and *"business intelligence"* to represent various BA concepts, in combination with the keywords *performance, value, benefit,* and *advantage*, as well as *firm, company, organization*, and *organization* that enable us to gather primary studies on the business value of BA at the organizational level. The initial search in December 2021 resulted in 4198 articles, 914 of which were duplicates and were removed prior to carrying out the screening process. Subsequently, a total of 3284 articles were screened based on their titles and abstracts. In this screening step, we only selected articles for the eligibility assessment step that explicitly focus on examining the business value of BA at the organizational level. Therefore, the articles must report qualitative or quantitative findings on the relationship between BA and firm performance. Articles with another primary focus, e.g., development and evaluation of technical artifacts [76], case study reports on the adoption of BA [77,78], and more general aspects of BA [79] have been excluded. Furthermore, we excluded short papers [80,81] and editorials [82,83] without original study data as well as studies not written in English. Following the call for more comprehensive literature searches [84], we did not restrict our literature search to journal papers and conference proceedings but rather attempted to include working papers, book chapters, dissertations, and so-called "gray literature." We did this with the primary aim to "accumulate a relatively complete census of relevant literature," as suggested by Webster and Watson [84] in order to avoid publication bias. The publication bias problem constitutes a major limitation arising from the fact that significant results are more likely to be published than non-significant findings, given the attention that significant results may attract in publications [85]. Thus, the inclusion of various types of literature, including peer-reviewed and gray literature in the meta-analysis, can help to capture the breadth and depth of available studies on the research topic [85,86].

Based on this inclusion and exclusion scheme, 291 articles were selected to be assessed for eligibility. This assessment step entailed a detailed and thorough evaluation of article content based on its full text with a primary aim of deciding whether to include the study for qualitative or quantitative synthesis. In this step, the focus of the article, as well as the availability of relevant data, were key factors to be assessed. To be included in the final meta-analysis, an article had to report quantitative findings on the impact of BA on firm performance and include the independent and dependent variables of interest defined in Section 3. Second, relevant information such as study characteristics, sample size, effect sizes, and other measures and data had to be reported and thus be available for extraction and coding in the subsequent step. When relevant data were missing, we contacted the authors of the study to obtain the missing information [75]. Subsequently, a study was excluded from the quantitative synthesis when the relevant information was still lacking. Based on this selection scheme, 77 relevant articles were identified.

The subsequent forward and backward search resulted in the inclusion of additional 23 articles to the study sample. We also performed a snowball search in the large interdisciplinary academic social website ResearchGate to gather more primary studies, with 25 additional articles yielded. Finally, this assessment process resulted in a total of 123 articles comprising 125 primary studies[1] that were included for quantitative synthesis (meta-analysis), and 176 studies were selected for inclusion in the qualitative synthesis. In the context of this study, the inclusion of qualitative data in the synthesis step helped us to complement the purely quantitative findings of a meta-analysis with qualitative results from the body of literature and to provide a more comprehensive view of the RQ and objectives [87].

The entire search process was performed independently by two researchers according to the interrater reliability concept to justify the similarity in rating processes (Cohen's Kappa: 0.84) [88,89]. According to Landis and Koch [88], the reported Cohen's Kappa statistic of 0.84 can be considered a substantial agreement and thus demonstrates the objectivity and validity of the search results.

4.2. Documentation and coding of studies

In the next step, we focused on documenting and coding the relevant characteristics and quantitative data of the selected studies [20]. Therefore, we developed a coding scheme that enabled us to systematically collect the key information of each study (cf. Table 5). An essential information in primary studies is the effect size, representing the magnitude of the effect observed with regard to the correlations between variables or groups [90]. We followed the recommendations of Peterson and Brown [91] and Hunter and Schmidt [20] by referring to the zero-order correlation matrices reported in the articles. Where neither correlation coefficients nor a zero-order correlation matrix was available in the text, we only coded β coefficients reflecting a simple bivariate (zero-order) relationship between two variables in accordance with Peterson and Brown's [91] suggestion. Otherwise, the primary study was excluded due to missing information. This restrictive

[1] The number of included studies is higher than the number of articles because one article comprised three independent studies [12]. See Appendix A for a complete overview of the included articles.

Table 6
Meta-analysis results.

IV	n	N	k	Est. eff.	CI 95%	PI 80%	Z-value	τ^2	Fail-safe N
BATC	91	39,246	127	0.452	0.409–0.493	0.162–0.670	17.917**	0.062	113,108 1243†
Heterogeneity: Q-value = 1920.153**, DF (Q) = 90, I^2 = 95.31%									
HBAR	42	9219	61	0.494	0.444–0.541	0.276–0.663	16.602**	0.038	27,276 650†
Heterogeneity: Q-value = 379.967**, DF (Q) = 41, I^2 = 89.21%									
BAMC	69	16,074	94	0.477	0.433–0.519	0.221–0.672	18.102**	0.051	70,822 1027†
Heterogeneity: Q-value = 861.169**, DF (Q) = 68, I^2 = 92.10%									
DQ	14	3088	18	0.434	0.328–0.528	0.155–0.649	7.374**	0.048	1908 137†
Heterogeneity: Q-value = 142.257**, DF (Q) = 13, I^2 = 90.86%									
OC	18	3698	28	0.472	0.391–0.546	0.229–0.659	10.037**	0.041	3724 207†
Heterogeneity: Q-value = 153.939**, DF (Q) = 17, I^2 = 88.96%									
EP	17	3644	30	0.165	0.036–0.288	-0.194–0.485	2.503*	0.069	522 31†
Heterogeneity: Q-value = 248.937**, DF (Q) = 16, I^2 = 93.57%									

Notes: IV = independent variable; 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

approach was a critical and necessary step to strengthen the validity and rigor of our meta-analysis.

For coding the data, we referred to the detailed overview of the main independent, dependent, as well as moderating variables as introduced in Tables 1 2 3 of Section 3. Additionally, we defined a set of coding rules that are consequently and consistently applied to the variables of interest. During the coding process, we primarily relied on the information given in the studies to apply these coding rules. With respect to the BA resources and capabilities as well as firm performance dimensions, we additionally relied on the items of each study prior to coding the variables instead of solely referring to the information given in the studies. The reliance on the items was necessary to ensure accuracy and consistency during the coding process. Similar to the literature search, the development of the coding scheme as well as the coding process was conducted independently by two different researchers, with an inter-rater reliability of 0.82 reported. In the case of disagreement, the conflicts were resolved through a final discussion to achieve the overall agreement.

4.3. Data analysis and synthesis

The included quantitative studies (n = 125) were analyzed using comprehensive meta-analysis software [92]. The sample comprised k = 358 identified relationships between independent and dependent variables. For those studies that examined more than one effect between variables of the same category, we calculated a mean score. This common approach prevented independent consideration of each variable relationship with its correlation and corresponding sample size, which would hamper the comparison of the effects between the outcomes because the overall sample would not reflect the reality of the individual observations [70,93]. We then applied a Fisher's Z transformation to the coded, converted, or obtained data to normalize the correlations [90]. The next step involved computing additional estimates for each study, including the confidence intervals (CIs), *p*-values, standardized residuals, and relative weights in relation to the sample size. For presentation purposes, we have retranslated the estimates into correlations [73].

We use the guidelines of Borenstein et al. [73] to perform the analytical steps based on the meta-analytical methods of Hedges and Olkin [94]. The statistics were calculated for the random effect (RE) model [92]. The most significant conceptual difference between the fixed effect (FE) and RE models relates to their underlying assumptions about the population on which studies are based [95]. The FE model assumes that the "true" effect size is the same for all the included studies, but the RE model assumes that the population effect sizes are not fixed but vary from study to study. As a consequence, calculations of the weights required for both models differ because FE models only refer to within-study variability, whereas RE models also consider between-study variability. Due to these differences in the calculation of weights, standard errors are consequently larger in RE models than in FE models [74,96]. Given these considerations, the calculations made for our meta-analysis were based on an RE analysis because our meta-analysis was founded on different effect sizes of varying samples of a larger population. To obtain insight into the reasons for the observed heterogeneity, we conducted a partition test for categorical variables (firm performance and economic area) and a meta-regression for the continuous variable (publication year) to examine the effect sizes and variance within subgroups [95]. The partition test entailed a meta-analysis of each of the grouped moderator categories to compare the summary effects [73].

5. Results

The results of the meta-analysis of the 125 studies and 358 effect sizes are summarized in Table 6. We conducted six separate meta-analyses, each examining the relationship between an independent variable and firm performance. Each of the studies was assigned a relative weight, which is the inverse of the sum of the sampling error and the between-study variance. The relative weight for each study provides the basis for calculating the weighted mean reflected by the summary effect size [73].[2]

The meta-analyses yielded in weighted summary effect sizes ranging between 0.165 [.036; 0.288] for the analysis with external pressure as an independent variable and 0.494 [.444; 0.541] for human BA resources as the independent variable. The 95% CIs for the individual summary effects are all in the positive range, indicating significant values. The test of null provides an indication of the validity of our estimates by reflecting the statistical significance for the overall effects

[2] We provide an overview of the detailed estimates for each study and a visual presentation of the analysis in the form of forest plots in Appendix B.

Table 7
Results of the partition test (firm performance dimensions).

IV	Subgroup	n	N	k	Est. eff.	CI 95%	PI 80%	Z-value
Economic area								
Subgroup abbreviations: DEVD = developed countries, DEVG = developing countries, DIV = diverse								
BATC	DEVD	36	25,662	51	0.420	0.351–0.485	0.176–0.616	10.774**
	DEVG	47	10,860	67	0.482	0.426–0.534	0.206–0.687	14.663**
	DIV	8	2724	9	0.408	0.258–0.538	-0.072–0.735	5.033**
	Heterogeneity: $Q_{between}$ (Total) = 2.455$^{n.s.}$, DF (Q) = 2; Qwithin (DEVD) = 507.115**, DF (Q) = 35; Qwithin (DEVG) = 656.773**, DF (Q) = 46; Qwithin (DIV) = 269.445**, DF (Q) = 7							
BAMC	DEVD	27	5232	39	0.468	0.393–0.537	0.207–0.667	10.764**
	DEVG	37	9151	49	0.484	0.422–0.541	0.244–0.668	13.333**
	DIV	5	1691	6	0.474	0.296–0.620	-0.109–0.814	4.814**
	Heterogeneity: $Q_{between}$ (Total) = 0.107$^{n.s.}$, DF (Q) = 2; Qwithin (DEVD) = 267.132**, DF (Q) = 26; Qwithin (DEVG) = 417.057**, DF (Q) = 36; Qwithin (DIV) = 168.709**, DF (Q) = 4							
Firm performance dimension								
Subgroup abbreviations: FI = financial performance, OP = operational performance, MA = market performance, DIV = diverse								
BATC	FI	14	21,158	15	0.520	0.411–0.614	0.184–0.747	8.107**
	OP	30	6794	30	0.430	0.350–0.504	0.102–0,674	9.495**
	MA	17	4604	17	0.514	0.416–0.600	0.154–0.754	8.905**
	DIV	30	6690	65	0.403	0.321–0.479	0.193–0.578	8.856**
	Heterogeneity: $Q_{between}$ (Total) = 5.016$^{n.s.}$, DF (Q) = 3; Q_{within} (FI) = 351.303**, DF (Q) = 13; Q_{within} (OP) = 492.060**, DF (Q) = 29; Q_{within} (MA) = 398.457**, DF (Q) = 16; Q_{within} (DIV) = 211.785**, DF (Q) = 29							
BAMC	FI	9	1992	9	0.484	0.353–0.597	0.299–0.634	6.493**
	OP	26	6664	26	0.507	0.434–0.573	0.223–0.712	11.685**
	MA	14	3665	14	0.449	0.342–0.544	0.129–0.685	7.495**
	DIV	20	3753	45	0.454	0.366–0.535	0.190–0.657	8.994**
	Heterogeneity: $Q_{between}$ (Total) = 1.277$^{n.s.}$, DF (Q) = 3; Q_{within} (FI) = 34.127**, DF (Q) = 8; Q_{within} (OP) = 406.518**, DF (Q) = 25; Q_{within} (MA) = 225.828**, DF (Q) = 13; Q_{within} (DIV) = 183.403**, DF (Q) = 19							
Technical concept								
Subgroup abbreviations: BA = business analytics, BI = business intelligence								
BATC	BA	82	37,369	115	0.453	0.407–0.497	0.163–0.671	16.946**
	BI	9	1877	12	0.444	0.296–0.572	0.179–0.649	5.431**
	Heterogeneity: $Q_{between}$ (Total) = 0.014$^{n.s.}$, DF (Q) = 1; Q_{within} (BA) = 1837.753**, DF (Q) = 81; Q_{within} (BI) = 65.707**, DF (Q) = 8							
BAMC	BA	63	14,690	87	0.486	0.440–0.529	0.240–0.674	18.008**
	BI	6	1384	7	0.378	0.205–0.529	-0.001–0.662	4.103**
	Heterogeneity: $Q_{between}$ (Total) = 1.702$^{n.s.}$, DF (Q) = 1; Q_{within} (BA) = 748.301**, DF (Q) = 62; Q_{within} (BI) = 67.227**, DF (Q) = 5							

Notes: IV = independent variable; m = moderators; 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:
*$p < .05$, not significant (n.s.) for $p > .05$; R^2 = proportion of variance accounted by subgroup membership; DF = degree of freedom
** $p < .01$,

[93]. The Z-values were all larger than the critical Z of 1.96 (for $p < .05$) and 3.29 (for $p < .001$), respectively, allowing us to reject the null hypothesis, which reflects BA having no effect on creating business value; hence, 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 [97], which classifies the outcome as small for the relationship EP and firm performance and medium for the remaining effect sizes (small: ≤ 0.30, medium: between 0.30 and 0.50, large: between 0.50 and 0.67, and very large: ≥ 0.67).

5.1. Assessment of outliers and publication bias

We further conducted an assessment of the influence of outliers and publication bias which is considered an essential step to demonstrate the accuracy and trustworthiness of findings [86]. To investigate the effects of potential outliers, we conducted a visual examination of the forest plots (cf. Appendix B) and additionally conducted a multitude of meta-analyses for each relationship when removing one study at a time. The visual examination revealed a high dispersion in effect sizes between the studies but did not reveal a clear outlier. The findings from the meta-analyses incorporating n-1 studies for each iteration resulted in only slight deviations for each examined relationship. Because these analyses demonstrated only a small effect size variation, we concluded outliers had no major effect [95].

As mentioned in Section 3.2., we also tested for deviations and outliers over time that may be caused by time lag effects to examine the impact of the timing of the observations on the measured BA business value of the individual studies. Since comprehensive information on BA adoption processes or longitudinal data such as financial performance indicators of the companies included in the empirical studies of our literature sample is sparse, we cannot conclusively examine the temporal dynamics within these studies. However, we can "display the pattern of the [business value] evidence over time" by conducting a cumulative meta-analysis [73]. A cumulative meta-analysis can render temporal trends and outliers in the data transparent by adding one study after another in a chronological sequence and calculating the successive summary estimates [98]. A relatively constant forest plot, including small deviations as in our analyses, does not indicate temporal trends in the data [98]. However, it should be noted that these are visual robustness tests without definitely excluding a time lag effect.

To further strengthen the validity of the summary effect sizes, we tested for the possibility of publication bias. Publication bias, also known as the "file drawer problem" [99], arises from the fact that in many cases, only significant results are published by scientific journals or submitted by researchers, implying the potential risk that meta-analyses reflect inferences from studies with cherry-picked significant results [100,101]. To avoid and validate this, we included

Table 8
Meta-regression test statistics.

IV	Covariate	Coefficient	Standard error	CI 95%	Z-value	Two-sided p-value
BATC	Intercept	-36.264	26.909	-89.005–16.477	-1.35 $^{n.s.}$	0.178
	Publication year	0.018	0.013	-0.008–0.044	1.37 $^{n.s.}$	0.172
Test of the model: Simultaneous test that all coefficients (excluding intercept) are zero: $Q = 1.87^{n.s}$, DF (Q) = 1, $R^2 = 0\%$						
BAMC	Intercept	-27.701	27.782	-82.153–26.751	-1.00 $^{n.s.}$	0.319
	Publication year	0.014	0.014	-0.013–0.041	1.02 $^{n.s.}$	0.310
Test of the model: Simultaneous test that all coefficients (excluding intercept) are zero: $Q = 1.03^{n.s}$, DF (Q) = 1, $R^2 = 0\%$						

Notes: Significance: ** $p < .01$, * $p < .05$, not significant (n.s.) for $p > .05$; R^2 = proportion of total between-study variance explained by the meta-regression model; DF = degree of freedom

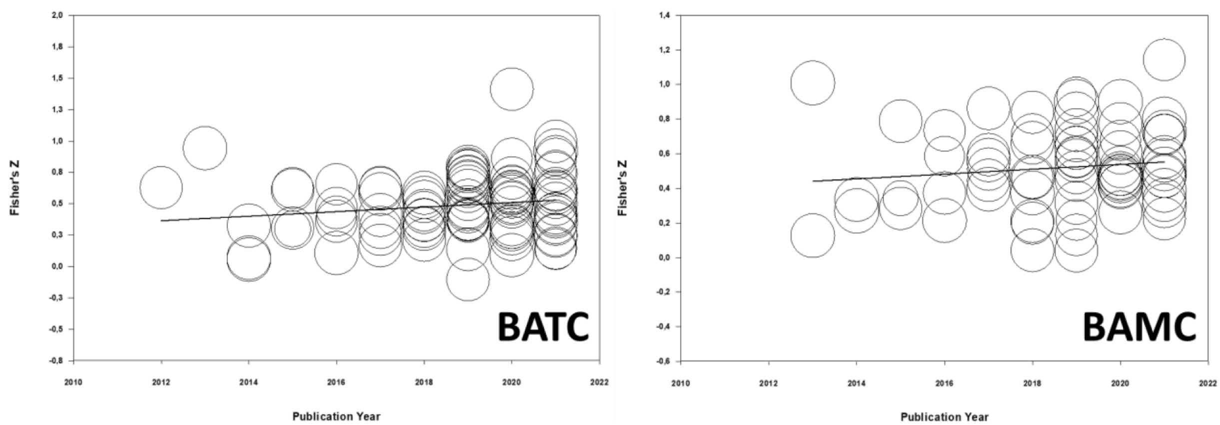

Fig. 3. Meta-regression scatterplot with publication year.

unpublished studies in the research corpus. Furthermore, we used Rosenthal's [99] fail-safe N as a statistical method to check for evidence that the significant impact of BA on business value is solely attributed to publication bias [73]. Rosenthal's [99] fail-safe N is the number of studies necessary to yield a point estimate of null before the *p*-value for the meta-analysis yields a non-significant value ($p > .05$). The calculated fail-safe Ns of our meta-analyses exceed the threshold of 5*k+10 [99]. Accordingly, we can conclude that all examined relationships are not exposed to a major validity threat of publication bias.

5.2. Moderator analysis

We further assessed the findings to determine whether moderator influences are causing effect size dispersions between studies by calculating various statistics testing for heterogeneity (cf. Table 6). Starting with the Cochran's [102] Q-test of homogeneity, we assumed, as a null hypothesis, that each study has the same true effect and variations in effect size are solely caused by sample error.

We first calculated the Q-value for each relationship between an independent variable and firm performance expressing the dispersion about the mean of observed effects [103]. We rejected the null hypothesis if Q was greater than the critical Q on a χ^2 distribution with $n-1$ degrees of freedom (df), where n is the number of analyzed studies [93,103,104]. The resulting Q-values are all significant ($p < .001$); therefore, we concluded that the heterogeneity cannot be explained by sampling error alone and there is a statistically significant between-study variance that supports the underlying RE model [104]. This between-study variance is expressed by τ^2 with an estimate ranging between 0.038 and 0.069. The ratio between τ^2 and the observed variance (sum of τ^2 and the sampling error) is reflected by I^2 (ranging between 88.96%–95.31%) [103]. The information on the true effect size variation is provided by the prediction interval [103,105], a probability-based range reflecting the spectrum of true effects likely to manifest in future studies that examine the BA business value in contexts similar to our sample studies [106]. We computed the 80% prediction intervals in accordance with previous meta-analyses in the IS field that calculated the Hunter and Schmidt [20] pendant, i.e., 80% credibility interval [70,93,107]. The calculated broad prediction intervals (BATC, HBAR, BAMC, DQ, and QC) next to a prediction interval that include zero (EP) indicates the influence of moderators [105,108].

The previous tests led us to suspect moderator effects that might explain the variance of true effects. In accordance with our research model, we coded and analyzed several moderators as categorical variables. The exception to this was the publication year of each study, which we incorporated as a continuous variable. For the partition test analyzing moderator effects, we first assigned the studies to moderator subgroups that were introduced in Section 3. This partitioning process leaves only an available subset of the studies from the original analysis for further processing. Although there is no universally valid benchmark for *n* that guarantees sufficient power for meta-analysis, IS meta-analysts often base their meta-analysis on thresholds from 3 or more studies [109] to at least 15 studies [110]. We decided to only perform a subgroup analysis if the partition provides at least 5 studies within a subgroup. Thus, we only included the variables BAMC and BATC for subgroup analysis. We conducted a separate meta-analysis for each of those subgroups in the respective examined relationship and computed the summary effect sizes and their variances. To compare the results within subgroups, we performed a Q-test on the basis of the analysis of variance [73]. Table 7 depicts the results of the 18 separate analyses.

The significant summary effect sizes range between 0.378 and 0.520 across moderators. All 95% CIs are positive and do not cross zero. The corresponding Z-tests reflect the statistical significance of the calculated summary effect sizes and confirm that the effects differ significantly from zero for all subgroups ($p < .01$). When examining the 95% CIs of the individual subgroups, overlaps can be observed within the moderator categories, which indicate that the summary effect sizes do not differ significantly [70]. We performed a Q-test based on the analysis of variance to confirm this impression [73]. The results revealed that Q is lower than the critical Q on a χ^2 distribution with the respective DF; therefore, we accepted the null hypothesis that the magnitudes of summary effects are not significantly different between subgroups within a moderator category.

In addition, while the partition tests explained a small portion of between-study variance, the tests were unable to explain most of the observed heterogeneity. We conducted a Q-test for the within subgroup dispersion to demonstrate its statistical significance ($p < .01$). Furthermore, the 80% prediction intervals of the subgroups were relatively large or included negative values in some cases, supporting the conclusion of high heterogeneity within the subgroups [106]. The dispersion between the studies remained largely unexplained, suggesting other influences. Nevertheless, Q-tests are a measure of statistical significance, and differences often remain undetected when the effect is small or the power is insufficient in statistical tests [73]. Other meta-analyses in the field of IS have typically avoided using Q-statistics to compare effect sizes in partition tests [70,93]. This is probably the result of adopting the Hunter and Schmidt [20] approach, which does not emphasize the use of Q-statistics, unlike Borenstein et al. [73]. Regardless of the statistical power, mostly small differences were evident between the individual subgroups when comparing the effect sizes, which can be essential for management decisions and thus can have practical significance [111].

In addition to the partition test, we conducted meta-regressions to determine the influence of the publication year on the effect size (cf. Table 8). Fig. 3 displays the corresponding scatterplots (the circle size is proportional to the study weight). The regression coefficients indicate that the effect size increases slightly with each year for BATC and BAMC. Yet, the Z-tests indicated non-significance of the slopes.

6. Discussion

The main research objective of our study was to integrate the empirical evidence of previous studies regarding the business value of BA to achieve a consistent and enhanced understanding of the impact of BA on firm performance. Moreover, we were interested in answering the question of under what conditions BA can create value. We found evidence that BA has an overall positive impact on organizational performance in terms of operational, financial, and market performance. In addition, we gained insights regarding the moderating effects of various variables, which we expect to be of value for research and practice in several ways. These findings enable us to further elaborate on the questions of which BA factors matter and offer a helpful starting point for further lines of research.

Overall, our study contributes to the ongoing debate in the IT literature concerning the business value of BA by providing a synthesis of a comprehensive set of literature including 125 primary studies from 123 articles that validated the business value of BA. We also responded to calls for more meta-analyses in IS research [19,95] while attempting to shed light on the business value of IT as a research area that is fundamental to the IS discipline [22,32]. In the following Sections 6.1 and 6.2, we further explain the implications for research and practice that emerge from the findings of our study and propose future research directions in terms of a research agenda to advance theory development.

6.1. Implications for research

Several implications for research can be derived from the findings of this study. First, contrary to prior meta-analysis studies on the business value of IT and IS [66,112], we did not find evidence for the well-known "productivity paradox" reported with regard to the impact of BA on firm performance. Rather, the findings clearly indicate that all BA variables positively impact organizational performance. The productivity paradox is a widely discussed topic in IS research that points to the ambiguity arising from the inconsistent and contradictory empirical results of former studies on the economic impact of IT and IS investments [66]. Previous meta-analyses from the IS field have attempted to resolve this productivity paradox by examining the factors that may account for the varying results of individual studies. The impact of IT on firm performance has been found to be moderated by study design and study characteristics, such as sample size, data sources, and industry sector, and by methodological issues. Additionally, the choice of the dependent variable has been found to account for the disparate results [30,66]. Overall, these meta-analysis studies have helped to identify how previous studies obtained conflicting results about IT investment payoffs. In line with prior studies examining the business value of BDA, the results of our meta-analysis indicate that the productivity paradox does not exist with regard to BA. Hence, IS scholars studying the business value of BA should redirect their attention to the questions of how and when BA can create value rather than exploring whether and to what extent BA impacts firm performance. In particular, the following future research direction (RD) emerges:

RD1: *More research is needed that focuses on investigating the mechanism of the value creation process of BA on different levels of analysis (micro, meso, and macro level).*

Another important finding relates to the major role of human resources, management capabilities, and organizational culture as key enablers of performance gains. In line with the literature, the results of our meta-analysis demonstrate that the social factors are among the most important ingredients in creating business value from BA. This finding confirms the common view in IS business value research that IT must be viewed as a sociotechnical system [32]. When considering BA as a sociotechnical system consisting of technical and social components, prior studies have confirmed that BA assets and technical capabilities constitute imitable and thus outsourceable noncore resources, whereas the ability to interpret data insights as well as make decisions on the basis of such insights are core internal capabilities that create value [113,114]. Investments in BA assets alone do not enable firms to create value. Instead, organizational performance gains can only be achieved when BA assets are complemented with higher-order DC such as absorptive capacity for knowledge creation and innovation ambidexterity performance [15,52]. This is because firms can only achieve performance gains when they manage to develop unique capabilities with the help of BA [8,15], such as firm agility [18].

However, as shown by the results of our study, technical factors such as BA technical resources and data quality remain major antecedents that exhibit lower, but equally important impacts on the business value created from BA. This finding supports the common view in the literature that technical assets and infrastructure and their effective deployment are considered the basic but essential prerequisite of success. Without the basic conditions such as an efficient infrastructure, the access to consistent and credible data, and BA systems, even the best capabilities do not contribute to value creation [9,44]. Ghasemaghaei et al. [18] argue that firm agility represents a higher-order capability that arises when lower-order capabilities (such as IT and other resources) are combined and matched in an adequate manner. Interestingly, they also found that a mismatch between analytical tools, data, people, and tasks would result in an even lower degree of firm agility. Hence, under unfavorable conditions, data analytics use can result in even lower firm performance than would be the case without data analytics use. As already outlined in RD1, future research efforts should pay more focus on examining what exactly is needed to establish the necessary human skills, management capabilities, and a nurturing organizational culture over time and how they can be combined and orchestrated to develop non-imitable and unique capabilities [5]. In this context, another worthwhile direction for future research is concerned with the benefit realization process. In IS business value research, benefits realization from IS and IT is considered one of the most important tasks to be accomplished when investing in new technologies [115]. Thus, we suggest the following:

RD2: *Qualitative research in long-term case studies could help develop an understanding of how to facilitate the benefits realization process.*

When considering the technical concept as a potential moderator, we found that the reported business value created from BA is slightly higher than that of BI. This finding is in line with the common view in the literature that assumes that concepts with higher levels of sophistication (such as predictive or prescriptive analytics) also contribute to a higher competitive advantage than less advanced concepts such as BI do [25]. However, since the differences between BI and BA are only marginal, more research is needed to examine the varying impact of the technical concept on the created business value. In particular, a worthwhile avenue for future research includes applying greater focus to the following issue:

RD3: *Future research should direct their attention to answering the question whether more advanced analytics concepts contribute more to enhancing firm performance compared to less advanced techniques.*

For example, the most sophisticated level of intelligence would include so-called "autonomous" or "augmented" analytics techniques, which employ machine learning to develop self-learning and self-optimizing models with less involvement from human analysts [25, 116]. Autonomous analytics concepts are intended to automate a great portion of analysts' and managers' tasks and thus may constitute a challenge to the conceptualization of BA as a socio-technical system. In this context, the following research direction emerges:

RD4: *Another interesting question is whether more advanced analytics concepts such as autonomous/augmented analytics techniques with less human involvement make human and management factors less important.*

Alongside with these future research directions, the following corresponding research propositions can be developed based on the discussed findings:

Proposition 1: *Firms adopting more advanced analytics concepts based on artificial intelligence techniques such as prescriptive or autonomous analytics may report a higher firm performance in terms of operational, financial, and market performance compared to firms adopting less advanced techniques.*

Proposition 2: *Firms adopting more advanced analytics concepts based on artificial intelligence techniques such as prescriptive or autonomous analytics may be less dependent on qualified analytics personnel and managers due to the automated analysis and decision-making routines.*

With regard to external pressure as the sixth independent variable in our research model, we found a significant, but rather weak relationship with firm performance. Individual studies differ strongly in their findings, with studies reporting no impacts of contextual factors such as environmental dynamism on firm performance [57], while others underline the important impact of factors such as competitive intensity on the value created from BA [12]. However, given the small number of the included individual studies (n = 11), we were not able to conduct a subgroup analysis on this variable. As a worthwhile avenue for future research, we, therefore, recommend IS researchers to direct their attention to the following issue:

RD5: *Future studies should examine the impact of other important contextual factors on the created business value by integrating industry sector or industry-related characteristics as a moderating variable (e.g., information intensity or competitiveness of an industry).*

In their econometric study, for example, Müller et al. [117] found substantial differences in the relationship between BDA assets and firm productivity when considering the industry sector of the firms. Their findings further indicated that firms in information technology-intensive or highly competitive industries exhibit higher value created from BDA assets than do firms outside these industry groups [117]. Accordingly, the following corresponding research proposition can be posed:

Proposition 3: *Firms operating in information-intensive industry sectors may report a higher firm performance in terms of operational, financial, and market performance compared to firms operating in less information-intensive industry sectors when using BA.*

As indicated by the findings of prior studies, firm size matters when it comes to IT adoption and use [118,119]. This is because firm size is an important indicator for the availability of resources [33] (e.g., financial and human resources) and may account for the extent to which a firm is capable of making use of BA. With regard to BA adoption and use, we, therefore, suggest the following RD and corresponding proposition:

RD6: *Examine firm size as a potential factor moderating the business value created by BA.*

Proposition 4: *The business value of BA in terms of operational, financial, and market performance will differ for small-sized, medium-sized, and large firms.*

The results of our moderator analyses further indicate that the business value of BA is significant at all dimensions of firm performance, including the operational, financial, and market level, with no significant differences between dimensions. This finding challenges the results presented by prior meta-analyses on the business value of IT and IS, which found that primary studies using financial measures reported lower business value than did studies using operational or market-based measures [30, 66–68]. Thus, one worthwhile avenue for future research is as follows:

RD7: *Future research should focus on investigating the interrelationship between various performance dimensions to better understand the real impact of BA on an organization as a whole.*

As implied by the multi-level constructs provided in Grover et al.'s [6] BDA business value framework, the value creation process can take several possible pathways. The different value creation mechanism, for instance, can translate BDA capabilities in distinct value targets, ranging from business process improvement, products and services innovation, consumer experience and market enhancement, and improved organization performance, all of which were conceptualized as tangible operational, financial, and market performance in the BA business value literature and our meta-analysis. Although Grover et al. [6] stated that these value targets are interrelated, they remain silent on the question of how this interrelation may occur. Although we were not able to find statistically significant differences between the different performance dimensions, the results of the subgroup analyses indicate slight differences that deserve more attention in future studies. For example, we found that BA management capabilities exhibit a stronger impact on operational performance than financial and market performance, revealing that BA management capabilities may have a direct positive impact on decision-making and process improvement, whereas the effect on the financial and market performance level may be less predominant. In Melville et al.'s [31] process-oriented IT business value model, IT assets and capabilities are considered as inputs to business processes which, in turn, impact firm-level performance [120]. Following this view, the assumption is near that operational performance (such as business process improvement) may play a mediating role on the way to financial and market performance. Hence, the following research proposition can be posed:

Proposition 5: *In the BA value creation process, operational performance plays a mediating role on the way to enhancing firm performance in terms of financial and market performance.*

Furthermore, when examining the business value of BA in different geographical areas according to the country classification proposed by the United Nations [69], we surprisingly found that studies with data from firms located in developing economic regions reported higher business value than did studies that collected data from firms located in developed economic regions. This is an unexpected finding because prior research on the diffusion of innovation assumed that innovations emerge in geographical areas that offer well-developed technological infrastructures rather than in those that do not provide sufficient infrastructure [121,122]. Based on this assumption, we expected that the business value created from BA would be higher in geographical areas with more developed technological infrastructure and contextual factors, such as in developed economies, than in less developed areas such as developing economies. At a second glance, however, this expectation might have reflected a too oversimplified view with respect to BA.

From a technical viewpoint, BA is an advanced technique that is required to handle big data [4]. Thus, investing in BA means that firms aim to make sense of their data to facilitate managerial actions based on informed operational and strategic decision-making [39]. As a logical consequence, the business value of BA can only be created when companies endeavor to use and make sense of their data, as commonly acknowledged by prior studies [113,114]. Thus, differing data protection and data security regulations between countries may account for the observed variability in the results of individual studies. Anecdotal evidence has suggested that organizations can take considerable advantage of using big data, especially in developing countries, because the regulation and legislation in developing countries may lag behind those in developed countries [43]. In this context, recent studies have found that compliance with data protection and privacy regulations is a major source of competitive advantage for organizations [123]. Thus, the following research direction and proposition emerge:

RD8: *Future research should provide guidance on how firms can comply with data protection and data security regulations in their country to optimally reap benefits from their data.*

Proposition 6: *Firms located in geographical areas with strict data protection and data security regulations may report a lower firm performance in terms of operational, financial, and market performance compared to firms operating in less strict data protection and data security regulations.*

6.2. Implications for practice

In addition to the research implications, the findings of our study also have several implications for business practices and are relevant to professionals such as managers and decision-makers who are engaged in BA implementation initiatives as well as policy-makers who are responsible for the development of conditions to facilitate technology diffusion. First, given the significant impact of BA on firm performance, BA should be considered an integral part of a firm's business strategy [6]. Thus, one important future research direction that emerge from this implication is the question:

RD9: *How can BA be integrated into a firm's business strategy to maximize the strategic value of BA?*

However, when investing in BA, companies should keep in mind the sociotechnical nature of BA and the major role that personnel resources, management capabilities, and a nurturing organizational culture play within the value creation process, as revealed by the findings of this study. Simply implementing a BA tool does not necessarily give a company a competitive advantage [9,26]. Rather, they must focus on strategic issues by establishing necessary knowledge and skills as well as adequate organizational structures, with human resources as one major precondition for successfully creating value from BA use [6,35, 51–54] as well as BA-enabled managerial efforts in acquiring and analyzing critical information for decision-making [53,56]. This is because personnel and management capabilities cannot be easily imitated and are, therefore, an important source of competitive advantage [6,9,14]. To establish necessary internal knowledge, firms adopting BA need to provide opportunities for their employees to develop the required skill sets for BA through formal trainings or establish recruitment programs to acquire qualified personnel with comprehensive skills or knowledge in data science practices [124].

In this context, recent studies have emphasized that finding qualified personnel with the required set of skills constitutes a major challenge for companies given the high skills gaps [6,124]. McKinsey has forecasted that there will be a shortage of 140,000 to 190,000 people with analytical skills as well as a shortfall of 1.5 million managers and analysts for BDA and decision-making roles [2]. This skills gap has emerged because of the difference between the rising demand from organizations seeking personnel with data science skills and the actual skills that are possessed by graduates and professionals in industry [124,125]. For policy-makers, this issue has important implications for their future work. Given the apparent skills gap, data science skills must be taught at a tertiary level to adequately prepare graduates for the skills demanded in industry. Thus, policy-makers and curriculum developers are advised to include the industry's needs and requirements for data science skills of future personnel into academic curricula and integrate these new requirements into educational settings in a timely manner through efforts such as joint initiatives [124,125].

In addition to the major role of BA human resources and management capabilities, the organizational culture is another essential factor to be considered when firms intend to make use of BA. Without an organizational culture that facilitates data-driven decision-making, firms cannot create business value from BA [10,11]. Firms need to establish a data-driven culture that shifts away from opinion-based decisions to fact-based decisions [11] while promoting data-driven decision-making and continuous learning [10]. Thus, one important related question emerges that should be central in future studies:

RD10: *How can firms develop and establish a data-driven organizational culture that facilitates effective BA use and data-driven decision-making?*

The final implication for practice relates to the geographical area and thus the regulations concerning data protection and data security of the country in which a firm operates. As stated earlier, compliance with data protection and privacy regulations has been found to be a major source of competitive advantage for organizations [123]. More specifically, compliant organizations outperform their noncompliant counterparts by an average of 20% [123]. Hence, firms should find a way to comply with the regulations in their countries, especially with regard to the handling of personal data, data storage, and data exchange across country borders. This is of special importance for organizations from industry sectors that deal with highly sensitive data and thus must comply with a strict and limited data collection and use policy, such as health care [43]. Aside from data protection, data security, and privacy issues, companies should establish the necessary organizational structures and governance frameworks to ensure compliance and value creation [6].

6.3. Limitations

As with any research, our study has several limitations that must be considered when interpreting the results. Some limitations related to the use of meta-analysis as a research method. The most common limitation of meta-analyses is the well-known publication bias, also known as the file-drawer problem. Notwithstanding our efforts to comprehensively search for both published and unpublished primary studies in a number of different interdisciplinary databases and sources, we only found two unpublished studies that could be included in the final sample. In addition, we calculated Rosenthal's fail-safe N [99] to diagnose the presence of publication bias and provide evidence of the robustness of the findings. The results indicate no major threat of a potential publication bias.

Our results should also be examined in light of the partition test results, which failed to provide evidence of statistically significant differences between the effect sizes of the moderator subgroups. Partition tests are often insufficiently meaningful to detect significant differences because the assessment of dispersion in RE models is driven by the sample size and the number of studies included. Accordingly, the conclusions in regard to heterogeneity for subgroups comprising a small n and N must be considered against the background of potential low power [126]. Nevertheless, Hunter and Schmidt [20] emphasize that meta-analyses serve to integrate results from different studies using effect sizes and CIs, and that this consolidation of knowledge benefits science without the support of significance tests. Therefore, although we draw attention to the potentially low power of meta-analysis using a small n and N [73], we consider and interpret the results of our moderator analysis because even small differences in financial, operational, or market performance can influence decisions at the management level in light of practical significance [111]

We intentionally employed a broad view of the independent and dependent variables of interest while bearing in mind the commonly known “apples and oranges” problem. In this context, it must be kept in mind that we have integrated and synthesized individual studies with varied research objectives, research designs, research variables, and measures, which could raise concerns about the comparability and integrability of these results [19,127]. The question of which studies can be considered appropriate to be integrated into a meta-analysis is controversial. Some researchers have suggested combining so-called “perfect replication studies with the same dependent and independent variables and the same measures involved” [97], whereas others have emphasized that the strength of meta-analysis lies in the opportunity to compare the results of heterogeneous studies with various research designs and measures to create new and more valuable results [128]. We support the latter view regarding the impact of BA on the business value of BA to examine a highly relevant topic of interest, the study of which has yielded mixed results in recent decades. As noted by Smith et al. [129], “Indeed the approach does mix apples and oranges, as one necessarily would do in studying fruits.” In this meta-analysis study, our fruits refer to the diversity of business value concepts as well as the various conceptualizations of BA in individual studies that form the dependent and independent variables in the research model.

Another well-known methodological limitation of the meta-analysis method is the “personal bias” problem, which arises when the overall outcome of a meta-analysis is affected by the researcher’s personal selection of studies [87]. We attempted to solve this problem by employing a detailed documentation of the literature search and coding process in which the process of inclusion and exclusion of each primary study is transparently described as well as by assessing interrater reliability to justify the similarity in rating processes [89]. Another major limitation of the meta-analysis method lies in its quantitative nature. Due to its quantitative focus on effect sizes, meta-analysis does not enable researchers to integrate qualitative findings on each topic of interest [95]. We have made attempts to overcome this methodological limitation by integrating insights from qualitative studies to inform the findings from the meta-analysis through a triangulation approach [87].

In addition to these methodological issues, further limitations on the scope of our research must be stated. One simplifying assumption made in this research is that the adoption of new technologies such as BA is manifest in efficiency gains, which, in turn, result in performance gains at the organizational level. However, this assumption that IT-induced efficiency gains always result in savings of resources (e.g., time and labor costs) has proven to be invalid under certain circumstances [130]. For instance, a recent study on the impact of big data on firm performance found that data volume, one of the major characteristics of big data, does not positively impact firm performance, whereas other characteristics such as variety and velocity do show positive impacts on firm performance. This finding underlines the business value of big data, while revealing the “dark side” of data volume as one unintended consequence of big data. Thus, the statement “big data is better data” must be considered with caution [131]. The literature on IS business value has proposed the unanticipated consequences of IS use, which can be positive and/or negative, as another worthwhile avenue for future research [32]. The unanticipated negative consequences of IS use constitute a well-known phenomenon, the so-called “rebound effect.” Previous studies found that efficiency gains from IT-enabled information processing did not necessarily result in higher work efficiency [132–134]. Nevertheless, rebound effects have not attracted much attention in industry economics to date [130,132,135]. Hence, this research gap constitutes another future research direction that could be of interest in IS business value research. Another simplifying assumption stems from the inclusion of self-reported data from participants in primary studies as a measure of performance, which cannot be objectively validated by financial or other metrics because the companies surveyed are not disclosed. Future primary studies should rely on objective data to validate subjective impressions.

7. Conclusion

With the primary purpose of providing a comprehensive and consistent picture of the main factors that contribute to enhancing the business value of BA, we conducted a meta-analysis of 125 studies from 123 articles to answer the questions of whether and when BA can create business value for organizations. More specifically, we examined the impact of BA resources, capabilities, and contextual factors on firm performance, as well as potential moderating effects that might account for the variability across primary studies. Overall, we found evidence that BA has a positive impact on firm performance in terms of operational, financial, and market performance. Moreover, the results indicate that social aspects such as human resources, management capabilities, and organizational culture play a major role in the business value creation process, whereas technological factors, such as the BA technical assets and data quality, are less important. Beyond that, the contextual factor external pressure has been shown to have only a moderate impact on firm performance. Based on the findings of our meta-analysis, we propose ten worthwhile directions for future research and suggest six research propositions that should be central in future studies. Through these findings, we have contributed to the ongoing debate concerning BA business value by synthesizing and validating the findings of the body of knowledge. Furthermore, the enhanced understanding of the conditions under which BA can have varying impacts on firm performance helps to raise new RQs and has uncovered possible avenues for future research, which may, in turn, help to advance theory development in IS research while offering organizations the opportunity to improve 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. **Eduard Anton:** Investigation, Formal analysis, Validation, Writing – original draft, Visualization. **Frank Teuteberg:** Writing – review & editing, Supervision.

Appendix A: Articles included in the meta-analysis

Table A1

Table A1
Articles included in the meta-analysis (n = 123 articles / 125 studies).

Authors (Year)	Title	Publication type	Publication name	Publication year	Sample size
Ahmed et al. [136]	The role of supply chain analytics capability and adaptation in unlocking value from supply chain relationships	Journal article	Production Planning & Control	2020	254
Akhtar et al. [137]	Big data-savvy teams' skills. big data-driven actions and business performance	Journal article	British Journal of Management	2019	240
Akter et al. [7]	How to Improve Firm Performance Using Big Data Analytics Capability and Business Strategy Alignment?	Journal article	International Journal of Production Economics	2016	152
Ali et al. [138]	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	2020	372
Aljumah et al. [139]	Organizational performance and capabilities to analyze big data: do the ambidexterity and business value of big data analytics matter?	Journal article	Business Process Management Journal	2021	650
Alkatheeri et al. [140]	The Mediation Effect of Management Information Systems on the Relationship between Big Data Quality and Decision making Quality	Journal article	Test Engineering and Management	2020	398
Almazmomi et al. [141]	The impact of business analytics capability on data-driven culture and exploration: achieving a competitive advantage	Journal article	Benchmarking: An International Journal	2021	272
Al-Serhan [142]	Big data analytics and sustainable business performance: does internal business process matter in it?	Journal article	PalArch's Journal of Archaeology of Egypt/Egyptology	2020	438
Anand et al. [56]	Realizing value from business analytics platforms: The effects of managerial search and agility of resource allocation processes	Conference paper	ICIS 2016 Proceedings	2016	72
Anwar et al. [143]	Big Data Capabilities and Firm's Performance: A Mediating Role of Competitive Advantage	Journal article	Journal of Information & Knowledge Management	2018	312
Asadi Someh and Shanks [51]	How Business Analytics Systems Provide Benefits and Contribute to Firm Performance?	Conference paper	ECIS 2015 Completed Research Papers	2015	98
Asare and Boateng [144]	Examining the Relationship Between Enterprise Resource Planning (ERP) Implementation: The Role of Big Data Analytics Capabilities and Firm Performance	Conference paper	The 7th Annual ACIST Proceedings (2021)	2021	74
Ashrafi et al. [145]	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	2018	114
Awan et al. [146]	Big data analytics capability and decision-making: The role of data-driven insight on circular economy performance	Journal article	Technological Forecasting and Social Change	2021	109
Aydiner et al. [34]	Business analytics and firm performance: The mediating role of business process performance	Journal article	Journal of Business Research	2019	204
Bag et al. [147]	Big data analytics as an operational excellence approach to enhance sustainable supply chain performance	Journal article	Resources. Conservation and Recycling	2020	520
Bag et al. [148]	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	2021	219
Bahrami and Shokouhyar [149]	The role of big data analytics capabilities in bolstering supply chain resilience and firm performance: a dynamic capability view	Journal article	Information Technology & People	2021	167
Baker and Chasalow [150]	Factors Contributing to Business Intelligence Success: The Impact of Dynamic Capabilities	Conference paper	AMCIS 2015 Proceedings	2015	30
Behl [151]	Antecedents to firm performance and competitiveness using the lens of big data analytics: a cross-cultural study	Journal article	Management Decision	2020	502
Benzidia et al. [152]	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	2021	168
Božič and Dimovski [15]	Business intelligence and analytics use, innovation ambidexterity, and firm performance: A dynamic capabilities perspective	Journal article	International Journal of Information Management	2019	97
Bronzo et al. [153]	Improving performance aligning business analytics with process orientation	Journal article	International Journal of Information Management	2013	368
Chae et al. [154]	The impact of supply chain analytics on operational performance: a resource-based view	Journal article	International Journal of Production Research	2014	537
Chae et al. [155]	The impact of advanced analytics and data accuracy on operational performance: A contingent resource based theory (RBT) perspective	Journal article	Decision Support Systems	2014	533
Chakphet et al. [156]	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	2020	196
Chatterjee et al. [157]	How does business analytics contribute to organisational performance and business value? A resource-based view	Journal article	Information Technology & People	2021	306
Chen et al. [17]	How the Use of Big Data Analytics Affects Value Creation in Supply Chain Management	Journal article	Journal of Management Information Systems	2015	161

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Table A1 (*continued*)

Authors (Year)	Title	Publication type	Publication name	Publication year	Sample size
Cheng and Lu [158]	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	2018	245
Cheng [159]	Linkages between big data analytics, circular economy, sustainable supply chain flexibility, and sustainable performance in manufacturing firms	Journal article	International Journal of Production Research	2021	320
Côrte-Real et al. [21]	Assessing business value of Big Data Analytics in European firms	Journal article	Journal of Business Research	2017	175
Côrte-Real et al. [160]	Unlocking the drivers of big data analytics value in firms	Journal article	Journal of Business Research	2019	175
Côrte-Real et al. [55]	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	2020	618
Daneshvar Kakhki and Palvia [161]	Effect of Business Intelligence and Analytics on Business Performance	Conference paper	AMCIS 2016 Proceedings	2016	116
Dong and Yang [162]	Business value of big data analytics: A systems-theoretic approach and empirical test	Journal article	Information & Management	2020	18,816
Dubey et al. [163]	Examining the role of big data and predictive analytics on collaborative performance in context to sustainable consumption and production behavior	Journal article	Journal of Cleaner Production	2018	190
Dubey et al. [164]	Empirical investigation of data analytics capability and organizational flexibility as complements to supply chain resilience	Journal article	International Journal of Production Research	2019	213
Dubey et al. [165]	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	2019	256
Dubey et al. [13]	Big data analytics capability in supply chain agility: The moderating effect of organizational flexibility	Journal article	Management Decision	2019	173
Dubey et al. [166]	Big Data and Predictive Analytics and Manufacturing Performance: Integrating Institutional Theory, Resource-Based View and Big Data Culture	Journal article	British Journal of Management	2019	195
Eidizadeh et al. [64]	Analysing the role of business intelligence, knowledge sharing and organisational innovation on gaining competitive advantage	Journal article	Journal of Workplace Learning	2017	213
Elbashir et al. [167]	Enhancing the Business Value of Business Intelligence: The Role of Shared Knowledge and Assimilation	Journal article	Journal of Information Systems	2013	347
El-Kassar et al. [168]	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	2019	215
Ferraris et al. [8]	Big data analytics capabilities and knowledge management: impact on firm performance	Journal article	Management Decision	2019	88
Fink et al. [35]	Business intelligence and organizational learning: An empirical investigation of value creation processes	Journal article	Information & Management	2017	159
Ghasemaghaei et al. [18]	Increasing firm agility through the use of data analytics: The role of fit	Journal article	Decision Support Systems	2017	215
Ghasemaghaei et al. [14]	Data analytics competency for improving firm decision making performance	Journal article	The Journal of Strategic Information Systems	2018	151
Ghasemaghaei [16]	Are firms ready to use big data analytics to create value? The role of structural and psychological readiness	Journal article	Enterprise Information Systems	2019	179
Ghasemaghaei and Calic [169]	Does big data enhance firm innovation competency? The mediating role of data-driven insights	Journal article	Journal of Business Research	2019	280
Ghasemaghaei and Calic [131]	Assessing the impact of big data on firm innovation performance: Big data is not always better data	Journal article	Journal of Business Research	2020	239
Ghasemaghaei [170]	Improving Organizational Performance Through the Use of Big Data	Journal article	Journal of Computer Information Systems	2020	140
Ghasemaghaei [171]	Understanding the impact of big data on firm performance: The necessity of conceptually differentiating among big data characteristics	Journal article	International Journal of Information Management	2021	143
Gu [172]	Exploring the relationship between supplier development, big data analytics capability, and firm performance	Journal article	Annals of Operations Research	2021	108
Gupta and George [9]	Toward the development of a big data analytics capability	Journal article	Information & Management	2016	108
Gupta et al. [58]	Achieving superior organizational performance via big data predictive analytics: A dynamic capability view	Journal article	Industrial Marketing Management	2019	209
Gupta et al. [59]	Role of cloud ERP and big data on firm performance: a dynamic capability view theory perspective	Journal article	Management Decision	2019	231
Hallikainen et al. [173]	Fostering B2B sales with customer big data analytics	Journal article	Industrial Marketing Management	2020	417
Hosoya and Kamioka [174]	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)	2018	107
Hossain and Akter [175]	Why doesn't our value creation payoff: Unpacking customer analytics-driven value creation capability to sustain competitive advantage	Journal article	Journal of Business Research	2021	327
Hung and Chen [176]				2020	168

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Table A1 (*continued*)

Authors (Year)	Title	Publication type	Publication name	Publication year	Sample size
	The Role of Organizational Support and Problem Space Complexity on Organizational Performance - A Business Intelligence Perspective	Journal article	Pacific Asia Journal of the Association for Information Systems		
Hyun et al. [177]	The Moderating Role of Democratization Culture: Improving Agility through the Use of Big Data Analytics	Journal article	PACIS 2019 Proceedings	2019	304
Irfan and Wang [178]	Data-driven capabilities, supply chain integration and competitive performance: Evidence from the food and beverages industry in Pakistan	Journal article	British Food Journal	2019	240
ji-fan ren et al. [36]	modeling quality dynamics, business value and firm performance in a big data analytics environment	Journal article	International Journal of Production Research	2017	287
Kasasbeh et al. [179]	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	2021	300
Kristoffersen et al. [180]	The effects of business analytics capability on circular economy implementation, resource orchestration capability, and firm performance	Journal article	International Journal of Production Economics	2021	125
Li et al. [181]	Understanding usage and value of audit analytics for internal auditors: An organizational approach	Journal article	International Journal of Accounting Information Systems	2018	209
Mandal [182]	An examination of the importance of big data analytics in supply chain agility development: A dynamic capability perspective	Journal article	Information Technology & People	2018	176
Mandal [183]	The influence of big data analytics management capabilities on supply chain preparedness, alertness and agility: An empirical investigation	Journal article	Information Technology & People	2019	173
Maroufkhani et al. [184]	Big data analytics adoption: Determinants and performances among small to medium-sized enterprises	Journal article	International Journal of Information Management	2020	171
Medeiros et al. [185]	Competitive advantage of data-driven analytical capabilities: the role of big data visualization and of organizational agility	Journal article	Management Decision	2021	173
Mikalef et al. [10]	Complementarities between information governance and big data analytics capabilities on innovation	Journal article	Journal of Business Research	2018	175
Mikalef et al. [124]	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)	2018	113
Mikalef et al. [186]	Information governance in the big data era: aligning organizational capabilities	Conference paper	Proceedings of the 51st Hawaii International Conference on System Sciences	2018	158
Mikalef et al. [187]	Exploring the relationship between big data analytics capability and competitive performance: The mediating roles of dynamic and operational capabilities	Journal article	Information & Management	2020	202
Moreno et al. [188]	Does Business Intelligence and Analytics Leverage Dynamic and Operational Capabilities? An Empirical Study in a Brazilian Telecommunications Company	Conference paper	AMCIS 2018 Proceedings	2018	131
Muhammad et al. [189]	Big data analytics capability as a major antecedent of firm innovation performance	Journal article	The International Journal of Entrepreneurship and Innovation	2021	394
Nam et al. [190]	Business analytics use in CRM: A nomological net from IT competence to CRM performance	Journal article	International Journal of Information Management	2019	170
Nasrollahi [191]	The Impact of Big Data Adoption on SMEs Performance	Working paper	Research Square	2020	224
Nji [192]	Big Data Predictive Analytics and Performance: The Role of Transformational Leadership	Journal article	Turkish Journal of Computer and Mathematics Education (TURCOMAT)	2021	145
O'Neill and Brabazon [193]	Business analytics capability, organisational value and competitive advantage	Journal article	Journal of Business Analytics	2019	64
Park et al. [194]	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)	2020	200
Peters et al. [60]	Business intelligence systems use in performance measurement capabilities: Implications for enhanced competitive advantage	Journal article	International Journal of Accounting Information Systems	2016	324
Qureshi et al. [195]	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	2020	303
Raguseo and Vitari [37]	Investments in big data analytics and firm performance: an empirical investigation of direct and mediating effects	Journal article	International Journal of Production Research	2018	200
Rahman et al. [196]	Does marketing analytics capability boost firms' competitive marketing performance in data-rich business environment?	Journal article	Journal of Enterprise Information Management	2021	250
Ramadan et al. [197]	Sustainable Competitive Advantage Driven by Big Data Analytics and Innovation	Journal article	Applied Sciences	2020	117
Raman et al. [198]	Impact of big data on supply chain management	Journal article	International Journal of Logistics Research and Applications	2018	287
Ramakrishnan et al. [199]	An Integrated Model of Business Intelligence & Analytics Capabilities and Organizational Performance	Journal article	Communications of the Association for Information Systems	2020	154
Razaghi and Shokouhyar [200]	Impacts of big data analytics management capabilities and supply chain integration on global sourcing: a survey on firm performance	Journal article	The Bottom Line	2021	158
Rialti et al. [201]	Big data analytics capabilities and performance: Evidence from a moderated multi-mediation model	Journal article	Technological Forecasting and Social Change	2019	259
Richards et al. [202]	AN EMPIRICAL STUDY OF BUSINESS INTELLIGENCE IMPACT ON CORPORATE PERFORMANCE MANAGEMENT	Conference paper	PACIS 2014 Proceedings	2014	337

(*continued on next page*)

Table A1 (*continued*)

Authors (Year)	Title	Publication type	Publication name	Publication year	Sample size
Saleem et al. [203]	An empirical investigation on how big data analytics influence China SMEs performance: do product and process innovation matter?	Journal article	Asia Pacific Business Review	2020	312
Samsudeen [204]	Impact of big data analytics on firm performance: mediating role of knowledge management	Journal article	International Journal of Advanced Science and Technology	2020	107
Sangari and Razmi [205]	Business intelligence competence, agile capabilities, and agile performance in supply chain: An empirical study	Journal article	The International Journal of Logistics Management	2015	184
Shamim et al. [206]	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	2019	108
Shamim et al. [207]	Connecting big data management capabilities with employee ambidexterity in Chinese multinational enterprises through the mediation of big data value creation at the employee level	Journal article	International Business Review	2019	308
Shamim et al. [11]	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	2020	108
Shan et al. [208]	Big data analysis adaptation and enterprises' competitive advantages: the perspective of dynamic capability and resource-based theories	Journal article	Technology Analysis & Strategic Management	2019	219
Shaqrah and Alzighaibi [209]	Linking knowledge management capabilities and the mediating role of the big data capabilities for enterprise value-adding processes	Journal article	VINE Journal of Information and Knowledge Management Systems	2021	120
Singh and El-Kassar [210]	Role of big data analytics in developing sustainable capabilities	Journal article	Journal of Cleaner Production	2019	215
Someh et al. [26]	Reconceptualizing synergy to explain the value of business analytics systems	Journal article	Journal of Information Technology	2019	201
Song et al. [211]	Creating Sustainable Innovativeness through Big Data and Big Data Analytics Capability: From the Perspective of the Information Processing Theory	Journal article	Sustainability	2020	294 477 632
Song et al. [12]	Data analytics and firm performance: An empirical study in an online B2C platform	Journal article	Information & Management	2018	309
Srinivasan and Swink [212]	An Investigation of Visibility and Flexibility as Complements to Supply Chain Analytics: An Organizational Information Processing Theory Perspective	Journal article	Production and Operations Management	2018	191
Suoniemi et al. [213]	Big data and firm performance: The roles of market-directed capabilities and business strategy	Journal article	Information & Management	2020	301
Thirathon [214]	Competitive advantage through big data analytics	Thesis	Thesis	2017	163
Torres et al. [53]	Enabling firm performance through business intelligence and analytics: A dynamic capabilities perspective	Journal article	Information & Management	2018	137
Wamba et al. [38]	Big data analytics and firm performance: Effects of dynamic capabilities	Journal article	Journal of Business Research	2017	297
Wamba et al. [215]	Big data analytics-enabled sensing capability and organizational outcomes: assessing the mediating effects of business analytics culture	Journal article	Annals of Operations Research	2020	202
Wamba et al. [57]	The performance effects of big data analytics and supply chain ambidexterity: The moderating effect of environmental dynamism	Journal article	International Journal of Production Economics	2020	281
Wang et al. [61]	Harnessing business analytics value through organizational absorptive capacity	Journal article	Information & Management	2019	600
Wang et al. [216]	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	2020	260
Wang and Byrd [63]	Business analytics-enabled decision-making effectiveness through knowledge absorptive capacity in health care	Journal article	Journal of Knowledge Management	2017	152
Waqas et al. [217]	Big data analytics as a roadmap towards green innovation, competitive advantage and environmental performance	Journal	Journal of Cleaner Production	2021	294
Wieder and Ossimitz [218]	The Impact of Business Intelligence on the Quality of Decision Making – A Mediation Model	Journal article	Procedia Computer Science	2015	33
Wilkin et al. [219]	Big data prioritization in SCM decision-making: Its role and performance implications	Journal article	International Journal of Accounting Information Systems	2020	84
Yadegaridehkordi et al. [220]	The impact of big data on firm performance in hotel industry	Journal article	Electronic Commerce Research and Applications	2020	418
Yogev et al. [54]	HOW BUSINESS INTELLIGENCE CREATES VALUE	Conference paper	ECIS 2012 Proceedings	2012	159
Yoo and Roh [221]	Value Chain Creation in Business Analytics	Journal article	Journal of Global Information Management	2021	268
Yu et al. [222]	Data-driven supply chain capabilities and performance: A resource-based view	Journal article	Transportation Research Part E: Logistics and Transportation Review	2018	329
Yu et al. [223]	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	2021	105
Zhu et al. [224]	A longitudinal study of the actual value of big data and analytics: The role of industry environment	Journal article	International Journal of Information Management	2021	89
Zotoo et al. [225]	Big data management capabilities and librarians' innovative performance: The role of value perception using the theory of knowledge-based dynamic capability	Journal article	Journal of Academic Librarianship	2021	299

Appendix B: Forest plot of the selected sample

Fig. B1, Fig. B2, Fig. B3, Fig. B4, Fig. B5, Fig. B6, Fig. B7

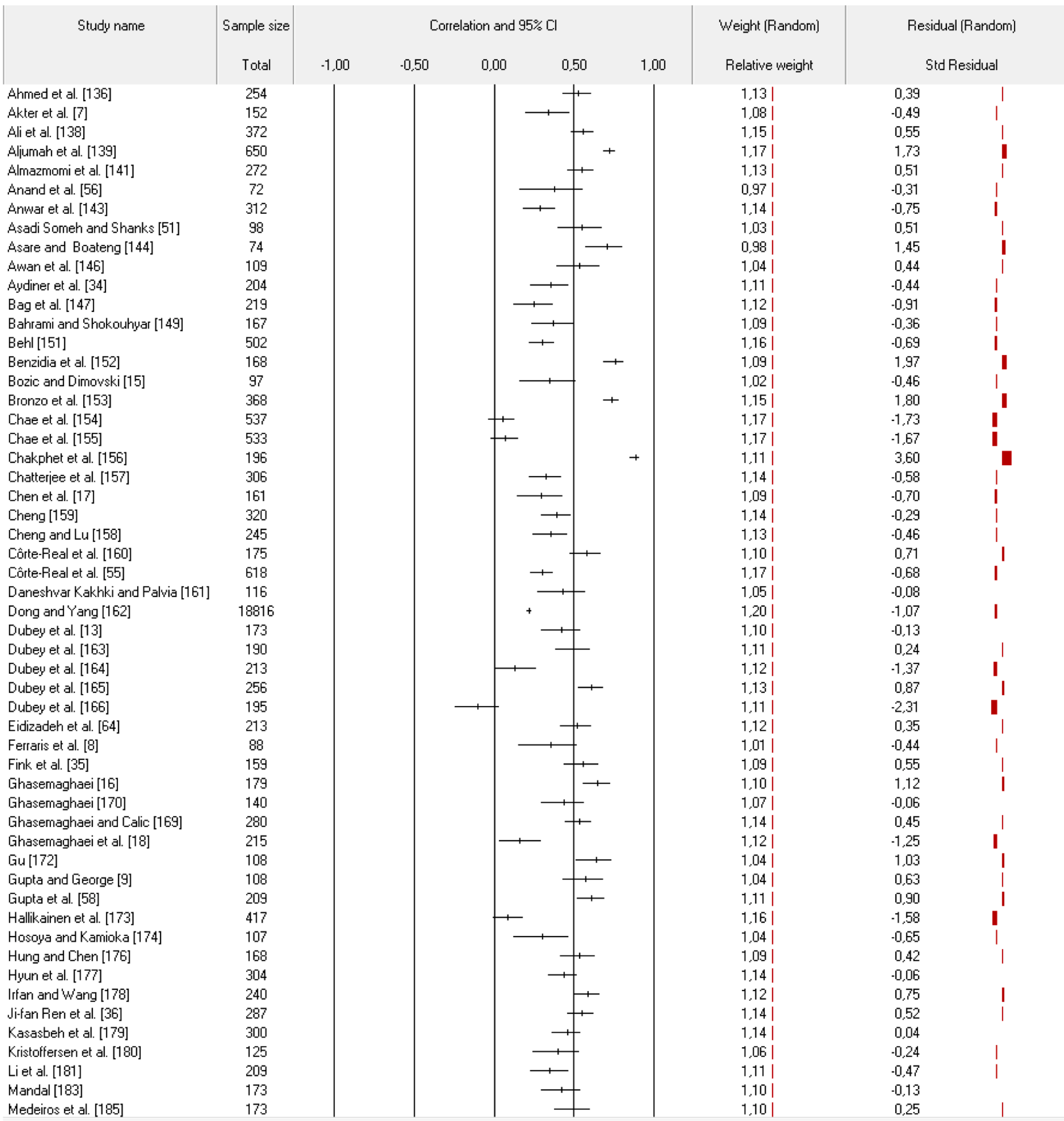

Fig. B1. Forest plot of the selected sample (BATC → Firm performance) (1/2).

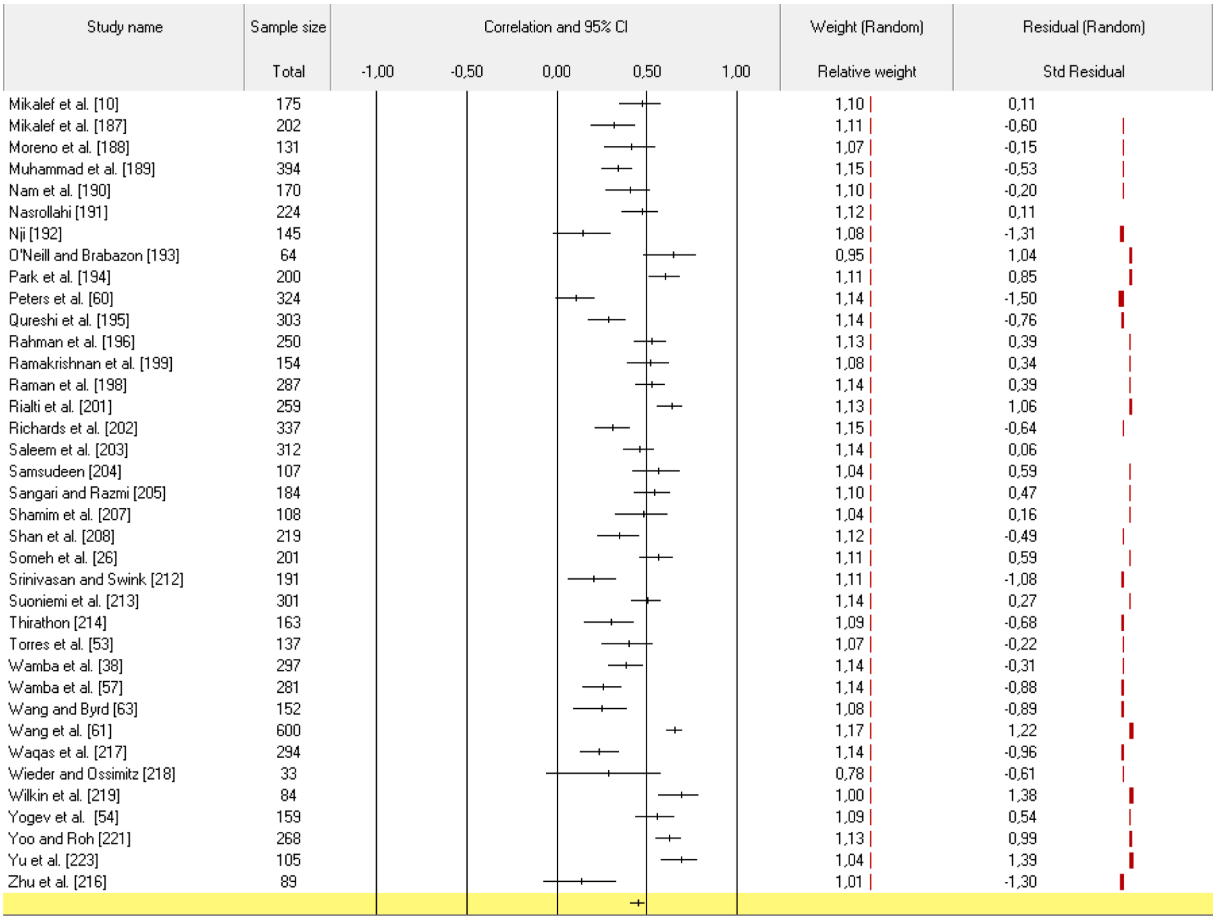

Fig. B2. Forest plot of the selected sample (BATC → Firm performance) (2/2).

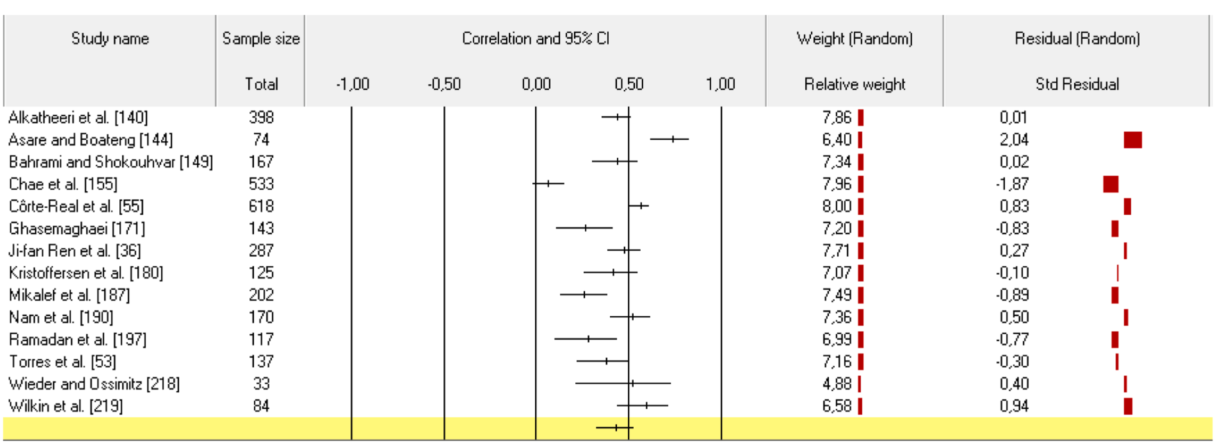

Fig. B3. Forest plot of the selected sample (DQ → Firm performance).

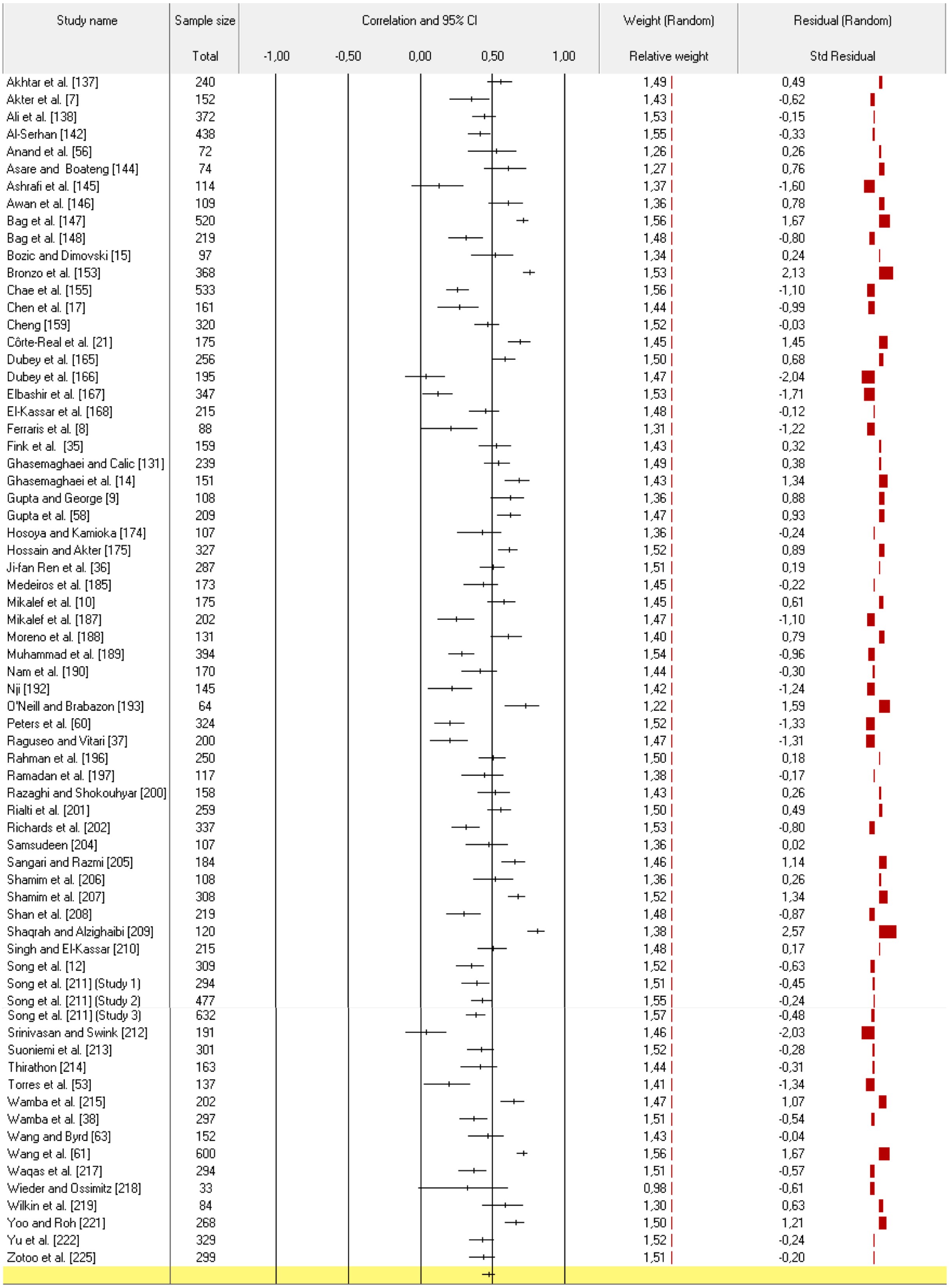

Fig. B4. Forest plot of the selected sample (BAMC → Firm performance).

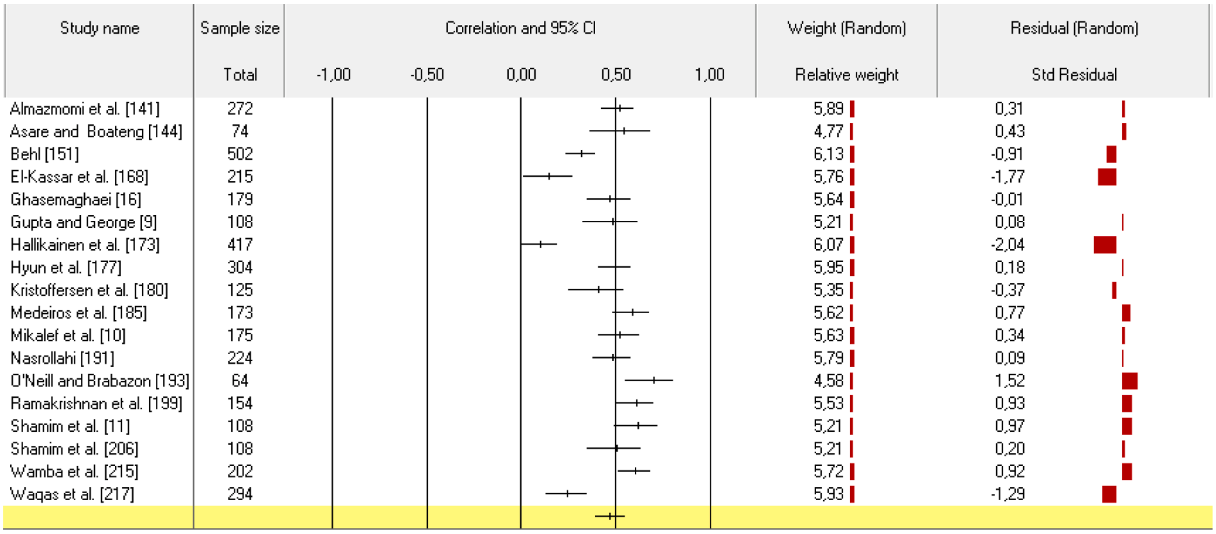

Fig. B5. Forest plot of the selected sample (OC → Firm performance).

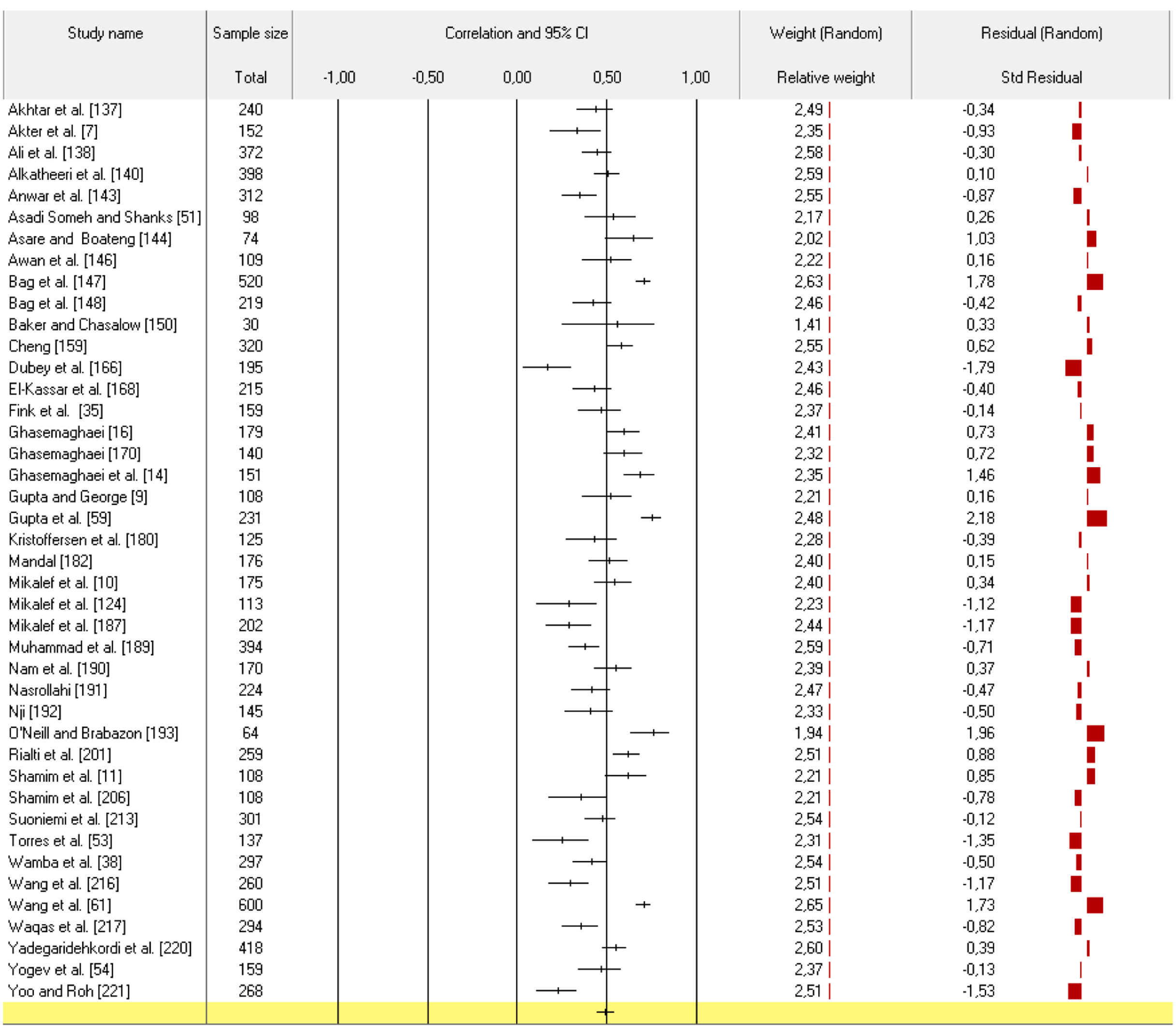

Fig. B6. Forest plot of the selected sample (HBAR → Firm performance).

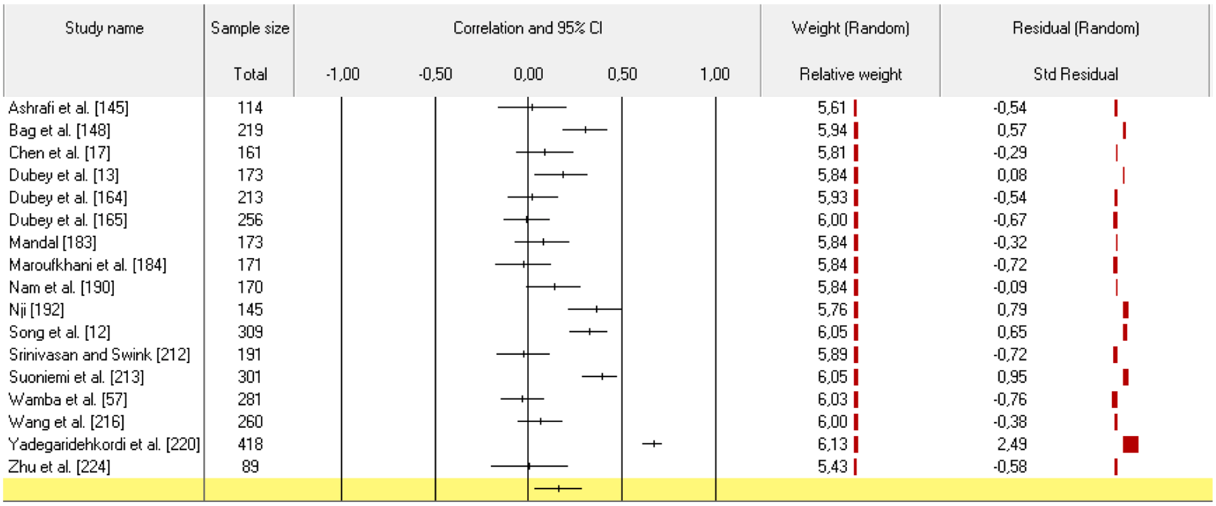

Fig. B7. Forest plot of the selected sample (EP → Firm performance).

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