Understanding the Operational Value of Big Data Analytics Capabilities for Firm Performance: A Meta-Analytic Structural Equation Modeling Approach

Eduard Anton
Universität Osnabrück

Thuy Duong Oesterreich
Universität Osnabrück

Frank Teuteberg
Universität Osnabrück

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Completed Research Paper

Eduard Anton
University of Osnabrück
Katharinenstraße 3, 49074 Osnabrück
eduard.anton@uos.de

Thuy Duong Oesterreich
University of Osnabrück
Katharinenstraße 3, 49074 Osnabrück
thuyduong.oesterreich@uos.de

Frank Teuteberg
University of Osnabrück
Katharinenstraße 3, 49074 Osnabrück
frank.teuteberg@uos.de

Abstract

To uncover the key mechanisms of how value is created through big data analytics (BDA), our main research objective is to integrate prior empirical findings on the relationship between BDA capabilities and firm performance. We conducted meta-analytic structural equation modeling based on 271 correlations and 33,281 observations collected from 63 individual studies. The findings confirm that creating business value from BDA is a complex and dynamic process affected by various value creation mechanisms. Aside from direct relationships between BDA capabilities and firm performance, we highlight the mediating role of operational performance in the value transmission to market and financial performance. Our study contributes to the rising debate on the business value of BDA by providing an integrated and novel picture of the value-adding pathways emanating from BDA capabilities. This informs future information systems research on theory building and assists practitioners in effectively formulating their objectives of BDA initiatives.

Keywords: Big data analytics, capabilities, business value, MASEM

Introduction

Similar to debates in the early 2000s, which centered on how to derive business value from IT (Carr 2003), the debate today has shifted to how to exploit data to impact firm performance (Baesens et al. 2016; Marchand and Peppard 2013; Mikalef et al. 2020). With the availability of large and complex data sets, often referred to as big data, the challenge lies in extracting the information value of those assets for improving organizational practices based on informed decision-making (Baesens et al. 2016). Data-driven decisions facilitate business action at an operational and strategic level and thereby contribute to value creation (Krishnamoorthi and Mathew 2018; Marchand and Peppard 2013). According to LaValle et al.'s (2011) survey of 3,000 managers and executives, big data analytics (BDA) is a means of generating business value, which is indicated by top performers' utilizing BDA to differentiate themselves in the market and generate a competitive advantage. For example, at an operational level, BDA initiatives in the realm of customer management provide insight into customer-facing processes which translate into a competitive advantage through improved customer relations at a strategic level (Asadi Someh and Shanks 2015). Moreover, information-enhanced business processes can transmit their informational value into financial performance such as cost reductions and revenue increases by rendering efficiency measures transparent (Aydiner et al. 2019). Irrespective of the benefits sought, extracting and exploiting the informational value of data require certain capabilities scattered across organizations and their workforce. Employees require technical skills to deal with tangible assets (such as data, technology, and the available infrastructure) and management capabilities to effectively leverage the gained information within the company. Furthermore, companies must bring along organizational capabilities such as the right data-driven culture and organizational learning to thrive with BDA use (Gupta and George 2016; Marchand and Peppard 2013; Mikalef et al. 2020).

Prior studies on BDA-enabled business value generally have three aspects in common. First, they focus on exploring the relationship between BDA and its business value in terms of firm performance (Akter et al. 2016; Mikalef et al. 2020; Rialti et al. 2019). Second, they assume certain technological (Côrte-Real et al. 2020; Hallikainen et al. 2020), managerial (Côrte-Real et al. 2017; Song et al. 2018), or organizational (Behl 2020; Raut et al. 2021) capabilities as a prerequisite to effectively employing BDA. Third, the examined BDA capabilities translate business value directly into operational (Asadi Someh and Shanks 2015; Torres et al. 2018), market (Ferraris et al. 2019; Hallikainen et al. 2020), or financial (Akter et al. 2016; Aydiner et al. 2019) benefits. The primary aim of this study is to challenge the third aspect. In particular, our objective is to examine the indirect effects of BDA capabilities on market and financial benefits through the mediating role of operational performance. Mediation through operational performance seems quite obvious, since improvements in firm-level measures such as the return on assets or market share are mostly the consequence of embedding BDA systems into the operational environment by supporting and improving organizational business processes for carrying out business and IT strategy (Shanks and Bekmamedova 2012; Torres et al. 2018). Nevertheless, research related to IT capabilities often examines direct paths to market and financial performance "since there are no market measures of business processes" (Dehning and Richardson 2002, p. 9). This is also the case with BDA research which has shown that investments in BDA capabilities can spill over directly into market aspects such as the ability to recognize market opportunities and fend off threats (Ghasemaghaei 2019) or the relationship between increasing financial metrics and sophisticated BDA capabilities (Akter et al. 2016; Ferraris et al. 2019).

The outlined heterogeneous studied pathways for generating BDA-enabled business value emanating from specific technological, managerial, or organizational capabilities constitute a research gap. This study therefore sets out to contribute to theory building and managerial practice in the area of BDA business value by revealing the relationship between BDA capabilities and business performance and the path through which BDA's effect is carried into business value. Our work complements previous research that has contributed to understanding "the nuances of [the] value creation mechanism" in BDA research (Krishnamoorthi and Mathew 2018, p. 643) and that has examined the role of BDA capabilities for generating business value (Mikalef et al. 2020). Our corresponding research questions (RQs) are stated as follows:

RQ1: To what extent do technical, managerial, and organizational BDA capabilities translate into business value in terms of firm performance?

RQ2: To what extent does operational performance play a mediating role in this translation process?

We address these RQs by conducting meta-analytic structural equation modeling (MASEM) (Cheung 2015), a method which supports our purpose in two ways: (1) It allows us to analyze and synthesize prior empirical research on the impact of BDA capabilities on business value through meta-analytic techniques, and (2) it enables us to exploit structural equation modeling (SEM) to fit the meta-analyzed data into a hypothesized structural path model. Our findings highlight organizational benefits of BDA initiatives and emphasize the mediating role of operational performance in improving market and financial performance through BDA capabilities.

Given the focus on BDA business value in this paper, we first provide a brief overview of prior research that emphasizes the role of BDA capabilities in enhancing business performance. We then present our proposed structural model. Next, we summarize the main steps of our methodological approach before presenting the MASEM results. Subsequently, we discuss the results in terms of their implications for research and practice, as well as the limitations of this study. Finally, a brief summary of this research is presented in the concluding section.

Theoretical Background

The digitization of business and society has led to a continuous increase of data from various sources, including structured data from databases and data warehouses as well as unstructured data generated from new sources such as web content and sensors (Grover et al. 2018). In research and practice, these huge volumes are often referred to as big data (Chen et al. 2012; Grover et al. 2018). The literature has highlighted the challenging nature of big data by using the 3 Vs framework to describe the magnitude of data (volume), the speed of data creation (velocity), and data's structural heterogeneity (variety) (Gandomi and Haider 2015; Grover et al. 2018). In this context, BDA is often used as an umbrella term for various advanced techniques and technologies for managing and leveraging big data to gain data insights for informed decision-making (Chen et al. 2012).

The impact of BDA on business performance has been discussed extensively in the IS literature, predominantly through the theoretical lens of the resource-based view (RBV) of the firm (Gupta and George 2016; Krishnamoorthi and Mathew 2018; Mikalef et al. 2020). Based on a broad interpretation of the resource concept (Bharadwaj 2000), the RBV postulates that differences in business performance result from variations in the configuration and allocation of resources. In particular, resources that are valuable, rare, non-imitable, and non-substitutable can distinguish firms within a market (Barney 1991). Studies employing this theoretical lens often take a competence-based view (Drnevich and Croson 2013), incorporating a mix of tangible resources, such as data, technology, and infrastructure, and intangible resources, such as organizational and human capabilities, to investigate their impact on business performance (Krishnamoorthi and Mathew 2018; Mikalef et al. 2020). However, distinguishing between tangible assets and capabilities is essential in the context of generating a competitive advantage, as tangible assets are mediated by their effective use (Brynjolfsson and Hitt 1998; Mooney et al. 1996). In line with the extant research, we consider capabilities as being the direct antecedents of deriving business value from BDA and define BDA capabilities following Amit and Schoemaker's (1993, p. 35) definition as "a firm's capacity to deploy resources, usually in combination, using organizational processes, to effect a desired end." With consideration of our RQs, the desired end of interest is business value. Business value is a broadly used construct in IS research for measuring the effectiveness of IT investments within a firm in terms of a dependent variable (Dehning and Richardson 2002). Measures of the business value construct vary widely and are typically operationalized through firm performance assessed by financial, market, or operations-related indicators (Venkatraman and Ramanujam 1986). This is consistent with the BDA literature, which includes various accounting (Chen et al. 2015; Yu et al. 2018) and customer- or market-related measures (Gupta and George 2016; Gupta et al. 2019) or which focuses on business process indicators at an operational level (Aydiner et al. 2019; Côrte-Real et al. 2017) for capturing business value.

Along with this variance in measuring business performance and the focus on different BDA capabilities, the pathways leading from BDA capabilities to organizational benefits also diverge within BDA research (Krishnamoorthi and Mathew 2018). From studying the conceptualization of individual research models within BDA literature, we can observe both direct effects of BDA capabilities on operational business processes and financial and market measures at the firm level (e.g., Akter et al. 2016; Aydiner et al. 2019), as well as indirect effects via operational performance as a mediator (e.g., Côrte-Real et al. 2017; Someh et al. 2019). This heterogeneous conceptualization of indirect and direct pathways is not uncommon in IS research when it comes to examining the relationship between IT capabilities and firm performance (Dehning and Richardson 2002). However, as Krishnamoorthi and Mathew (2018, p. 644) have argued, the "value creation process is different for various technologies. Therefore, it is necessary to understand the unique value creation mechanism for BDA." Given this conceptualized heterogeneity, our goal is to integrate, synthesize, and analyze empirical research to draw on the results from several studies to gain a holistic view of the pathways, emanating from BDA capabilities, to improve business performance measuring and theory building.

Research Model

Guided by the competence-based frame of the RBV (Drnevich and Croson 2013) and the elaborations of the previous section, we propose the research model in Figure 1.

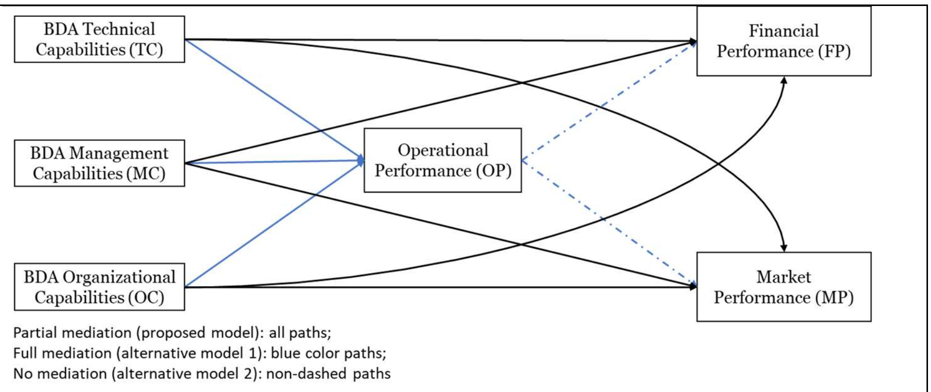

Figure 1. Proposed Structural Model

The conceptualization of the dependent variables within this model followed Steers' (1975, p. 546) suggestion that "a meaningful way to understand the abstract idea of effectiveness is to consider how researchers have operationalized and measured the construct in their work." Within BDA-related research, the operationalization of business value usually comprises firm performance measures in the realm of financial performance such as return on investment (ROI), return on assets (ROA), or return on sales (ROS) (Chen et al. 2015; Gupta et al. 2019; Yu et al. 2018); or market-based measures such as competitive advantage (Côrte-Real et al. 2017, 2020; Someh et al. 2019), customer retention (e.g., Ferraris et al. 2019), or market share (Gupta and George 2016; Gupta et al. 2019). Moreover, business value is measured at the process level by considering operational performance measures such business process performance (Aydiner et al. 2019; Côrte-Real et al. 2017) or decision-making effectiveness (Ghasemaghaei et al. 2018; Wang and Byrd 2017). We synthesize the various measures into containers of financial performance (noted as "FP"), market performance (noted as "MP"), and operational performance (noted as "OP").

Research in the context of the relationship between IT investments and firm performance typically focuses on either IT spending, IT strategy, or IT capabilities (Dehning and Richardson 2002). Our study is aligned with the latter area, as we consider BDA capabilities as an enabler of effectively leveraging existing assets (Božič and Dimovski 2019; Grover et al. 2018; Gupta and George 2016). Therefore, the direct antecedents of the performance measures in our research model are BDA capabilities. This competence-based view assumes that IT alone cannot meet all the criteria for a sustainable competitive advantage as imposed by Barney (1991) (e.g., inimitable or rare criteria) (Drnevich and Croson 2013). Thus, aside from technical assets, BDA use requires further capabilities to create value. Moreover, technical or managerial capabilities require the disposal of a workforce that possesses or can acquire a skills profile needed for mastering BDA (Akter et al. 2016). Such a complementary relationship between BDA resources and capabilities is aligned with the sociotechnical view of IS business value research, which highlights the interplay of IT assets, human IT resources, and IT capabilities to generate business value (Bharadwaj 2000). BDA research predominantly captures the complementary asset component within the capability constructs studied, without incorporating a dedicated asset level within the studies (Aydiner et al. 2019; Behl 2020; Dubey et al. 2019; Hallikainen et al. 2020). The complementary nature of the capability constructs is rendered evident when examining the independent variables in our research model: BDA technology capabilities (noted as "TC"), BDA management capabilities (noted as "MC"), and BDA organizational capabilities (noted as "OC"). BDA technical capabilities provide a container for capabilities related to the integration of data and software into an organization's infrastructure, the analysis and management of data, and the overall use of an organization's technology dimension in the context of big data, thus representing the interplay of human resources and technological BDA assets (Akter et al. 2016; Côrte-Real et al. 2020; Torres et al. 2018). BDA management capabilities comprise the container for constructs related to a firm's management capability to effectively leverage data insights in decision-making (Anand et al. 2016; Dubey et al. 2019; Mikalef and Krogstie 2020; Torres et al. 2018). While BDA technical and management capabilities are anchored at the individual level to implement and leverage BDA initiatives, organizational BDA capabilities are anchored at the firm level to promote and facilitate these initiatives. This nurturing environment for data-driven decision-making within an organization is typically operationalized through a data-driven culture or organizational learning within research (Gupta and George 2016; Gupta et al. 2019; Hallikainen et al. 2020; Mikalef et al. 2020; Ramakrishnan et al. 2020).

The proposed model, with all paths presented in Figure 1, represents a partially mediated structural path model in which the indirect and direct effects together yield the business value of BDA capabilities. This model is a combination of two alternate perspectives, i.e., a fully mediated and non-mediated model, that are commonly found in literature on the impact of general IT on business performance (Bharadwaj 2000; Dehning and Richardson 2002). The fully mediated perspective (alternative model 1) is embedded in a process-oriented IT business value model that views assets and capabilities as inputs to business processes driving firm-level performance (Melville et al. 2004). This perspective assumes the first-order effects of BDA capabilities by increasing the effectiveness and efficiency of business processes through transparency and information dissemination (Grover et al. 2018). Operational performance captures this intermediate mechanism of leveraging BDA assets and capabilities at the process level to generate output at the firm level (e.g., Asadi Someh and Shanks 2015; Ashrafi and Zare Ravasan 2018; Dubey et al. 2019; Torres et al. 2018). A mediation of operational performance also implies a temporal component of causality, which is reflected in literature on the time-lag effect. This suggests that IT investments impact firm performance only after a period of effectively operationalizing them (Campbell 2012). However, BDA is more than a simple information gathering tool that provides some basic performance indicators for operational transparency. Advanced analytics exhibits strategic value by allowing management to use discovery and prediction mechanisms for product innovation or improving customer relationships, in addition to the positive image and signals that a data-driven approach creates in the perception of the organization (Grover et al. 2018). This view is supported by research examining the direct effects (alternative model 2) between BDA capabilities and firm performance (e.g., Akter et al. 2016; Aydiner et al. 2019; Behl 2020; Božič and Dimovski 2019; Côrte-Real et al. 2017; Ferraris et al. 2019).

Since neglecting mediation or direct effects may cause between-study variance in effects, our focus is to examine the transmission pathways by synthesizing the empirical results of previous studies, thereby guiding theory building for future research. Therefore, to fully address our research questions, we compare our proposed partially mediated model with the alternative fully mediated and non-mediated models.

Research Methodology

As implied by the RQs, our main research objective is to quantitatively integrate empirical findings of prior studies on the relationship between BDA capabilities and firm performance, and thereby to explore the mediating role of operational performance in this relationship. To reach this objective, we apply meta-analysis as our method of choice for a systematic synthesis and the integration of findings for theory development (Hunter and Schmidt 2004). As a quantitative review method, meta-analysis offers scholars from across disciplines the opportunity to resolve inconsistencies in prior studies (Hwang 1996), increase the validity and statistical power of results (Hunter and Schmidt 2004, p. 75), and draw new conclusions out of past knowledge (Glass 1976). We rely on the multi-steps approach of Hunter and Schmidt (2004) that includes a defined set of steps and activities to ensure a transparent and rigorous research process. For the data analysis step, however, we refer to the MASEM approach as according to Cheung (2015). We describe the major steps of literature selection and coding as well as the MASEM approach in the following sub-sections.

Literature Selection and Coding

We follow the common guidelines found in the meta-analysis literature which recommend a broad search strategy to gather a comprehensive sample of studies (Rothstein et al. 2005). Given the interdisciplinary nature of the research field surrounding BDA, such a broad search strategy is especially important. The BDA-related literature stems from diverse disciplines, including the IS field, computer science, marketing, management, communication, and mathematics (Chen et al. 2012). Hence, we performed a comprehensive literature search in various databases and sources as well as a forward and backward search in all relevant studies (Hunter and Schmidt 2004, p. 467). We included the interdisciplinary databases EBSCOhost, ScienceDirect, Google Scholar, as well as the AIS Electronic Library into our literature search for the broadest possible search for journal articles, conference proceedings, and gray literature.

We applied a set of search terms that comprise the key word *analytics* to include diverse BA concepts (such as BDA, data analytics, business analytics, or predictive analytics) in the literature search, in combination with the keywords *performance*, *value*, *benefit*, and *advantage*, as well as *firm*, *company*, and *organization*. The combination of these terms enabled us to gather studies on the relationship between BDA and firm performance at the organizational level. In addition, we restricted the search to include only articles published in English. We performed the literature search in February 2021, which initially resulted in 2,003 articles. After removing 547 duplicates, the remaining 1,456 articles were screened for their relevance based on their titles and abstracts. Articles that we selected for the final sample must have satisfied the inclusion criteria summarized in Table 1. In the case of missing data, we followed the recommendations in the literature by contacting the authors and asking for the correlation matrix (Liberati et al. 2009).

Criteria	**Inclusion**	**Exclusion**
Focus and Scope	• Study reports quantitative findings on the relationship between BDA and firm performance at the organizational level	• Qualitative reviews and case studies • Study addresses the design and evaluation of BDA technical artifacts
Available Data	• Study contains relevant data, including: o Effect size measures reporting correlations between variables in the form of a correlation matrix o Sample sizes	• Does not contain original study data (e.g., editorials and research in progress) • Relevant data are not available (no correlations)
Publication Type	• Published studies, including journal articles, conference proceedings, and book chapters • Unpublished studies, including working papers and dissertations	• Duplicate studies • Bachelor's and master's theses, presentation slides

Table 1. Inclusion and Exclusion Criteria

One important aspect of all meta-analysis studies is concerned with the publication bias problem that highlights that significant results are more likely to be published than non-significant results (Rothstein et al. 2005). To mitigate the danger of publication bias, we included in the selected sample both published studies such as journal articles, conference proceedings, and book chapters as well as unpublished studies such as working papers and dissertations. In doing so, we support the notion in the meta-analysis literature that the inclusion of peer-reviewed and gray literature in the meta-analysis helps to capture the breadth and depth of available studies on the research topic while preventing publication bias (Rothstein et al. 2005). Based on this strict inclusion and exclusion scheme, the assessment step was conducted independently by two researchers with an interrater agreement (Cohen's Kappa) of 0.78 reported, which can be considered a substantial level of agreement (Landis and Koch 1977). Overall, we excluded 1,408 articles that did not match the inclusion criteria and identified 48 articles that could be included into the final sample. The subsequent forward and backward search yielded 13 articles that could be added to the selected sample. In sum, the final sample consisted of 61 papers published between 2013 and 2021, comprising 63 independent data sets that address the business value of BDA.[1]

For the subsequent coding step, we developed a coding scheme that allowed us to accurately extract and document the relevant characteristics and empirical data of interest from the selected studies (Hunter and Schmidt 2004, p. 470). Among others, we coded general study characteristics such as study ID, authors, reviewer ID, publication year, and publication type as well as sample sizes and effect size measures, as

[1] A detailed overview of the articles included in the final sample is available upon request.

mentioned in Table 1. When coding the effect size measures, we consequently followed a predefined set of coding rules that enabled us to consistently assign the independent variables to the distinct BDA capability categories and the dependent variables to the appropriate performance dimension. Therefore, we relied on the items of each study for obtaining the necessary information prior to deciding whether the respective independent variable represented technical, management, or organizational BDA capabilities and whether the dependent variable could be assigned to the operational, financial, or market performance dimension. We also used Cohen's Kappa (0.86) during this coding procedure to ensure reliability. Discrepancies were discussed and resulted in consensus. When coding the effect size measures, we ensured that only zero-order correlations were considered (e.g., Pearson's product-moment correlation coefficients, Spearman's rank-order correlations). Other studies using meta-analysis have also taken into account standardized path coefficients by simply equating beta with a correlation coefficient (Bogdan and Borza 2019). This assumption is only valid for zero-order relationships and was only considered by us in such cases (Peterson and Brown 2005). Furthermore, we also omitted the frequently used beta conversion of Peterson and Brown (2005), which is critically evaluated by fellow meta-analysts (Aloe 2015).

Meta-Analytical Structural Equation Modeling

We combined meta-analytical techniques and SEM to fit the structural models to the pooled data of the identified 63 studies. MASEM is particularly appropriate for the purpose of our study because not all studies provided correlations to all the proposed relationships in our research model, yet we were able to use the data of different approaches to fit the structural models (Jak 2015; Schlaegel and Koenig 2014). The sample comprised an overall sample size of N = 33,281 and 271 correlations. When a study examined multiple correlations of the same coding category, we followed the approach of Gerow et al. (2013) and used the Hunter and Schmidt (2004) formula (Equation 1) to calculate a composite correlation (where r_{xy_i} is the correlation between an independent variable x and a dependent variable y_i, $\bar{r}_{y_i y_j}$ represents the average correlation among the observed correlations of dependent variables, and n is the number of observed correlations of the same category):

$$r_{xy} = \sum r_{xy_i} / \sqrt{n + n * (n-1) * \bar{r}_{y_i y_j}} \quad (1)$$

In meta-analytical practice, there is a broad discussion about the necessity of correcting the composite correlation measures for attenuations (Cheung 2015). In psychometric meta-analyses, it is common to correct correlations for study-specific artifacts such as reliability scores (Hunter and Schmidt 2004). Other meta-analytic paradigms, however, refrain from this adjustment (Borenstein et al. 2009; Hedges and Olkin 1985). In a comprehensive study by Michel et al. (2011), several MASEM procedures were performed on real data to investigate the impact of the correction of these artifacts, with the result that the correction of reliability scores had no major impact in MASEM.[2] Therefore, we followed the meta-analysis paradigm of Hedges and Olkin (1985) by not correcting for reliability measures.

We applied the two-stage structural equation modeling (TSSEM) in R (Cheung 2015) for analyzing and synthesizing the prepared data by underlying a statistical model of random effects. We based the selection of the random effects model on the nature of our sample, which comprises a population of effect sizes that vary across studies (e.g., by study design, sample, etc.). In contrast, a fixed effects model is based on the assumption of a homogeneous population encompassing a single true effect size. Accordingly, the calculation of effect sizes within a random effects model takes into account not only within-study variability (as is the case with a fixed effects model), but also the variance that arises from the dispersion between studies (Borenstein et al. 2009). Therefore, in Stage 1 of TSSEM, we used conventional random effects meta-analytic techniques by first constructing a correlation vector r_i for each study i by accounting for within-type and between-study variability such that $r_i = \rho_i + u_i + e_i$, where ρ_i represents the correlation matrix, e_i the sampling covariance matrix, and u_i the between-study variance matrix for a study i (Cheung 2014, 2015). Then, we calculated the average correlation matrix $\hat{P}$, its corresponding sampling covariance matrix $\hat{v}$, and the matrix $\hat{T}$ that captures the between-study heterogeneity, using the maximum likelihood estimation method (Muthén et al. 1987). These calculated estimates were used in Stage 2 of the TSSEM to

[2] For interested readers, we also recommend Cheung's (2015) comments on this topic, in which he lists issues associated with correcting for reliability in the context of MASEM.

fit our proposed and alternate models by employing the weighted least squares (WLS) estimation method (Cheung 2015). The WLS uses the calculated asymptotic variances and covariances from Stage 1 as a weight matrix, thus taking into account the precision of each of the 63 samples (Jak 2015). We assessed model fit by calculating the root-mean-square error of approximation (RMSEA), standardized root-mean-square residual (SRMR), comparative fit index (CFI), and Tucker-Lewis index (TLI). Consistent with Joseph (2007), we also compared our hypothesized partially mediated model with an alternative fully mediated model via operational performance, as well as a no-mediation model via likelihood ratio tests.

To test how the effect of BDA capabilities is transmitted within the proposed structural model, we analyzed for mediation by assessing the indirect effects. For establishing and understanding mediating effects, we followed the guidelines of Zhao et al. (2010), who suggest first determining the significance of the indirect effects and then assessing the nature of the mediation based on the significance of the paths of the direct effects. Zhao et al. (2010) propose a bootstrapping procedure for the analysis of indirect effects, but when conducting a MASEM, bootstrapping entails some challenges due to the missing correlations within the primary studies, and so we used likelihood-based confidence intervals (LBCIs) as a suitable alternative to test the indirect effects (Cheung 2015). For this purpose, we employ the OpenMx package in R (Neale et al. 2016). In accordance with previous MASEM studies in IS (Gerow et al. 2013; Joseph et al. 2007) and to further provide robustness to the previous steps, we used the Sobel (1982) approach to validate the significance of indirect effects.

TSSEM and Mediation Analysis

We applied the outlined TSSEM procedure using the 63 empirical studies, 271 correlations, and a combined sample size of $N = 33{,}281$. The output of Stage 1 of the TSSEM is the pooled correlation matrix $\hat{P}$ encompassing the average correlation for each bivariate relationship with its corresponding precision (see the lower diagonal of Table 2) and the heterogeneity matrix $\hat{T}$ (see the upper diagonal of Table 2).

	TC	**MC**	**OC**	**OP**	**FP**	**MP**
TC	-	τ^2=.010, I^2 = 79%	τ^2=.039, I^2 = 93%	τ^2=.028, I^2 = 91%	τ^2=.029, I^2 = 91%	τ^2=.024, I^2 = 90%
MC	.618, k = 20, [.562, .673]	-	τ^2=.052, I^2 = 95%	τ^2=.036, I^2 = 93%	τ^2=.022, I^2 = 89%	τ^2=.021, I^2 = 89%
OC	.443, k = 21, [.353, .534]	.531, k = 18, [.420, .642]	-	τ^2=.043, I^2 = 94%	τ^2=.026, I^2 = 90%	τ^2=.05, I^2 = 95%
OP	.519, k = 28, [.450, .587],	.521, k = 21, [.434, .608]	.355, k = 18, [.253, .457]	-	τ^2=.029, I^2 = 92%	τ^2=.056, I^2 = 95%
FP	.4, k = 22, [.323, .477],	.482, k = 16, [.402, .564]	.427, k = 13, [.331, .523]	.509, k = 14, [.412, .606]	-	τ^2=.044, I^2 = 94%
MP	.433, k = 19, [.356, .510]	.502, k = 19, [.428, .575]	.433, k = 19, [.326, .539]	.475, k = 13, [.340, .610]	.548, k = 10, [.411, .685]	-

Lower diagonal: average correlation of bivariate relationship, k = number of studies, [CI 95% lower bound, CI 95% upper bound]; Upper diagonal: τ^2 = between-study variance, I^2 = ratio of between-study variance to overall variance

Table 2. TSSEM Stage 1 Results

The average correlation ranges from .355 to .618, with the relationship between OC and OP showing the lowest correlation and the relationship between TC and MC the highest correlation. All average correlations differ significantly from zero, as indicated by the 95% confidence interval (noted as "CI") which lies in the positive range, and are validated by the test of null, which reflects the statistical significance of the average effect expressed by significant Z scores ($p < .001$; Z scores range between 6.817 and 21.746, which are larger than the critical Z value of 3.29) (Lipsey and Wilson 2001). The magnitude of the average effects can be classified as medium to large according to the classification scheme of Lipsey and Wilson (2001) (small: ≤ .30; medium: between .30 and .50; large: between .50 and .67; very large: ≥ .67). The heterogeneity values τ^2 for each correlation indicate the variance that cannot be explained by sampling error alone. As these values are difficult to interpret, we augmented the information with the I^2 values, which indicate the proportion of between-study variance to total variance (combined sampling error plus τ^2) (Borenstein et al.

2009). The I^2 values range between 79% and 95%. This rather high between-study dispersion for all bivariate relationships is also reflected when conducting the Q test of homogeneity. As the Q value of 2370.089 ($p < .01$) exceeds the critical Q value on a χ^2 distribution with 256 degrees of freedom, we rejected the null hypothesis that the dispersion between the effect sizes can be explained by sampling error alone. This confirms our presumption of an underlying random effects model.

In Stage 2 of the TSSEM, we adjusted the calculated estimates to fit the structural models while considering the potential role of operational performance (partial, full, or no mediation). Table 3 summarizes the model fit indices and differences between the three tested models. The proposed partially mediated model fits the data best, with RMSEA = .012 and SRMR = .044, thus yielding values below the limit of .08 (Hu and Bentler 1999) and, with CFI = .997 and TLI = .955, exceeding the threshold of .9 for a good fit (Bentler and Bonett 1980). In comparison, a fully mediated model through OP (RMSEA = .013, SRMR = .099, CFI = .977, TLI = .951, χ^2 = 49.266, df = 7, $p < .01$) and a model of solely direct effects between the BDA capability variants and the performance measures (RMSEA = .016, SRMR = .076, CFI = .987, TLI = .933, χ^2 = 27.589, df = 3, $p < .01$) show inferior values. In addition, the likelihood ratio test underlines that the partially mediated model fits the data best compared to the full mediation model ($\Delta\chi^2$ = 42.75, Δ df = 6, $p < .05$) and the no mediation model ($\Delta\chi^2$ = 21.07, Δ df = 2, $p < .05$).

Model	RMSEA	SRMR	CFI	TLI	χ^2	df	p	$\Delta\chi^2$	Δdf	p
Partial mediation	.012	.044	.997	.955	6.519	1	<.05			
No mediation	.016	.076	.987	.933	27.589	3	<.01	21.069	2	<.01
Full mediation	.013	.099	.977	.951	49.266	7	<.01	42.747	6	<.01

Table 3. Model fit and fit difference between models

The resulting path estimates of the partially mediated model are depicted in Figure 2. The parameters show that MC has a direct relationship with MP (β = .21, $p < .05$) and FP (β = .2, $p < .05$) and an indirect relationship via OP (β = .27, $p < .01$). In contrast, TC has no direct relationship with FP (β = -.01, $p > .05$) and MP (β = .03, $p > .05$), but only an indirect relationship via OP (β = .33, $p < .01$). The other exogenous variable OC has only direct relationships with FP (β = .22, $p < .01$) and MP (β = .22, $p < .01$), but no relationship with OP (β = .05, $p > .05$). OP and FP show the strongest relationship (β = .36, $p < .01$), and the relationship between OP and MP show a similar strong effect (β = .33, $p < .01$).

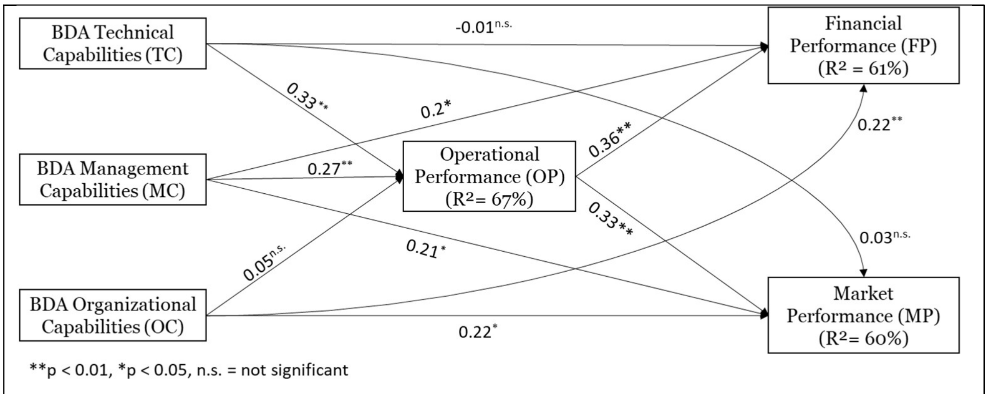

Figure 2. Results of the TSSEM Stage 2 (partial mediation)

To delve deeper into the causality of how BDA capabilities translate to business value, we checked for mediation to test the significance of the indirect effects of BDA capability variants on the BDA-enabled financial and market performance via OP. This allows us to have a formalized understanding of the mechanisms that determine whether and how OP mediates the effects of BDA capabilities (see Table 4). According to Zhao et al. (2010), the first step is to test the significance of the indirect effects, for which we calculate the effect variation in the form of the 95% LBCIs. The calculations indicate the strongest indirect effects emanating from TC, followed by those emanating from MC, and the smallest indirect effects resulting from OC, where the 95% LBCIs do not cross zero for all pathways except for the paths OC → OP → FP and OC → OP →MP. Therefore, we conclude that the indirect effects MC → OP → FP, MC → OP → MP, TC → OP → FP, and TC → OP → MP are significant. To confirm this conclusion, we conducted the Sobel (1982) test, showing significant Z values for the indirect effects of MC on FP ($Z = 2.417$, $p < .05$), MC on MP ($Z = 2.140$, $p < .05$), TC on FP ($Z = 3.183$, $p < .01$), and TC on MP ($Z = 2.619$, $p < .01$) via the mediator OP. The paths from OC to FP and to MP via OP are not significant, with $p > .05$, indicating no mediation.

Because the direct paths from MC to FP and MC to MP are significant, the effect of MC on FP and of MC on MP is partially mediated by OP. As the sign between the multiplication of a, b, and the direct effect c ($a * b * c$) is positive, the relationship constitutes a complementary mediation. In contrast, the effect of TC on FP and of TC on MP is fully (only) mediated by OP, as there is no significant direct effect c (Zhao et al. 2010).

Path	Indirect Effect	95% LBCI: [LB, UB]	a	b	s_a	s_b	Z Value
MC→OP→FP	.099	[.028, .138]	.274	.364	.096	.080	2.417*
MC→OP→MP	.092	[.025, .20]	.274	.334	.096	.103	2.140*
TC→OP→FP	.118	[.052, .215]	.325	.364	.073	.080	3.183**
TC→OP→MP	.109	[.037, .213]	.325	.334	.073	.103	2.619**
OC→OP→FP	.020	[-.054, .083]	.054	.364	.085	.080	.634$^{\text{n.s.}}$
OC→OP→MP	.018	[-.052, .082]	.054	.334	.085	.103	.628$^{\text{n.s.}}$

LB: lower bound of the 95% likelihood-based CI; UB: upper bound of the 95% likelihood-based CI; a: path of the independent variable to the mediator; b: path of the mediator to the dependent variable; s_a: standard error of a; s_b: standard error of b; $Z = (a * b)/\sqrt{b^2 * s_a^2 + a^2 * s_b^2}$;
significance: ** $p < .01$, * $p < .05$, not significant (n.s.) for $p > .05$

Table 4. Results from the Mediation Analyses

Discussion

Key Findings

Following recent calls for more research that enhances understanding of the business value creation process of BDA (Grover et al. 2018), one major research objective of our study was to integrate empirical findings of prior individual studies on the relationship between BDA capabilities and firm performance. In particular, we aimed to explore the extent to which technical, managerial, and organizational BDA capabilities translate into business value in terms of firm performance (RQ1). With regard to RQ1, we found an interesting picture showing diverse nuances of direct relationships between the variables of interest in our theoretical model.

Most notably, our study results clearly show that BDA management capabilities have a positive relationship with operational, market, and financial performance, which underlines the major role that BDA management capabilities play in the BDA value creation process in all firm performance dimensions. BDA technical capabilities, on the contrary, have been found to have direct effects on neither market nor financial performance. However, we do observe a direct relationship between BDA technical capabilities and operational performance. This finding supports the competence-based view, according to which IT spending on technological assets and infrastructure and their effective deployment is an essential prerequisite of success, because without assets such as an efficient infrastructure, the availability of data, and BDA systems, even the best capabilities are of no use (Gupta and George 2016). However, at the same time, the question emerges why BDA technical capabilities only show a direct impact on operational performance but not on market and financial performance. In this context, the literature on IT investment appraisals has shown that investments in new IT are associated with high initial expenditures for IT assets which first negatively impact the financial performance of a firm, whereas the corresponding returns on investment manifest themselves in later periods (Oesterreich and Teuteberg 2018). This observed phenomenon points to the existence of so-called time-lag effects, since firms must align their processes and structure to the new systems in the first years prior to reaping the benefits of their investment (Campbell 2012). Thus, while BDA technical capabilities visibly impact the operational performance of a firm (e.g., by rendering internal tasks and processes more efficient), they may not directly impact the firm's financial and market performance. The reason for BDA's limited direct impact on the financial and market performance dimension becomes clearer when considering Grover et al.'s BDA business value framework (2018). It describes a capability-realization process in which the business value of BDA is created through various mechanisms. The use of BDA first helps firms improve their business processes in the short run (operational performance). It then enhances organizational performance (financial performance) and creates competitive advantage by increasing market shares, improving customer experiences, and offering product/service innovation (market performance) in the long run.

The predominant role of BDA management capabilities, as revealed by the results of our study, supports the common view in BDA business value research that the social components of BDA play a more important role in enhancing firm performance (Grover et al. 2018). With consideration of the BDA context, key tangible assets are the availability of big data and BDA systems, as well as an infrastructure that can support the analytic processes (Grover et al. 2018). Yet, BDA "encompasses the notion of going behind the surface of the data to link a set of explanatory variables to a business response or outcome" (Baesens et al. 2016, p. 808), which is not feasible with the mere possession of data or investment in sophisticated BDA systems (Božič and Dimovski 2019; Grover et al. 2018; Gupta and George 2016). This is because the components of the technical dimension, such as software and tools, are imitable noncore resources, whereas BDA management capabilities, such as data interpretation and decision-making, are core capabilities that create value (Huang et al. 2018).

With regard to the direct impact of BDA organizational capabilities on the distinct firm performance dimensions, our results show a clear picture. We observed a direct relationship between BDA organizational capabilities and both firm and market performance, but no direct relationship between BDA organizational capabilities and operational performance. This finding is not surprising when one recognizes that establishing such organizational capabilities provides the foundation on which management and staff "understand, nurture, align, and cultivate a data-analytics based value chain and operational processes" (Ramakrishnan et al. 2020, p. 723). Thus, BDA organizational capabilities are the basis of an analytical environment for generating business value from BDA initiatives (Mikalef et al. 2020). In addition, firm-level capabilities, such as establishing an organizational culture, enable and promote data-driven decision-making (Marchand and Peppard 2013). Overall, BDA organizational capabilities may have a sustainable impact on a firm's success in terms of financial and market performance, while the impact on internal processes is limited.

Another interesting picture emerges regarding the mediating role of operational performance in the relationship between BDA capabilities and the distinct firm performance dimensions, as addressed in RQ2. In answering RQ2, we gained several interesting insights that contribute to enhancing the understanding of how business value is created (see Table 5). First, the study results confirm the major role of operational performance in the value creation process, regarding the strong direct relationships between operational performance and both financial and market performance. Apart from these direct relationships, we also observed the mediating role of operational performance in several relationships of the theoretical model. In particular, operational performance fully mediates the relationships between BDA technical performance and financial and market performance, whereas there is a partial mediation between BDA management capabilities and financial and market performance. This finding indicates that operational performance should be considered an important intermediate performance indicator when one assesses the business value of BDA. This finding is supported by recent studies, according to which the business value of BDA is created at an operational level. For example, Aydiner et al. (2019) observed a significant relationship between BDA and business process performance, which in turn impacts firm-level performance, whereas they could not confirm a direct impact on firm-level performance. They rather concluded that the positive effect of BDA is only evident through the indirect mediating role of business process performance.

Implications and Main Contributions

The presented key findings have several important implications for business practices, namely firms planning to establish BDA projects (cf. Table 5). First, firms should acknowledge the sociotechnical nature of BDA and create the appropriate conditions when investing in it. The mere adoption of a BDA tool or software does not effectively enable improvements to business performance (Gupta and George 2016; Someh et al. 2019). Instead, its success requires personnel with the ability to understand business needs, technical skills to extract relevant information from the data, and management skills to effectively utilize fact-based decision-making to create value (Akter et al. 2016; Anand et al. 2016). Data analyses only provide the corresponding added value if the insights are actually exploited, for example, making processes more efficient or taking appropriate operational or strategic measures based on the data (Ramakrishnan et al. 2020). Therefore, management capabilities, such as planning, investment, coordination, and control are necessary to make solid business decisions (Anand et al. 2016; Dubey et al. 2019; Mikalef and Krogstie 2020; Torres et al. 2018). Thus, along with investments in BDA tools and technical infrastructure, firms should establish the necessary internal knowledge by providing employees opportunities to develop skill sets in BDA management through formal trainings. In addition, recruitment programs can help firms acquire qualified personnel with such BDA skill sets (Mikalef et al. 2018). However, finding qualified BDA personnel is still a major challenge for firms given the skills gap, since the actual BDA skills of graduates and professionals in industry often do not match the rising demand from organizations for such personnel (Mikalef et al. 2018; Pappas et al. 2018). To close this gap, policy makers and curriculum developers are well advised to establish teaching programs in higher education where data science skills can be taught at a tertiary level (Mikalef et al. 2018; Pappas et al. 2018).

For managers and decision-makers in firms engaging in BDA implementation projects, another implication arises from the strong direct impact of BDA use on operational performance. The mediating effect of operational performance implies that managers should pay more attention to operational performance indicators when assessing the business value of BDA instead of solely relying on financial or market performance indicators. A strict focus on financial indicators would not take into account the whole business value of BDA. For research, an important aspect emerges from this finding: The question of how exactly this mediating effect is created remains an under-researched topic in the BDA business value field (Grover et al. 2018). Therefore, a promising avenue for future research is to explore the different pathways of business value creation to shed more light on the question of how BDA business value is actually created at different levels of firm performance.

The picture that arises from the results of our study confirms that creating business value from BDA is a complex and dynamic process that is affected by various value creation mechanisms (Grover et al. 2018). In this respect, anecdotal evidence has shown that BDA business value can only be created when different capabilities are adequately combined and matched in the value creation process (Ghasemaghaei et al. 2017). In a similar manner, Shanks and Bekmamedova (2012) emphasize the importance of embedding and fitting BDA systems within organizations at five levels as a major precondition for business value creation. Aside from an integration of BDA technical systems and tools into a firm's operational system (1), BDA usage must be aligned with internal processes (2), harmonized with the culture of decision-making (3), integrated into the firm's business and IT strategy (4), and constantly adapted to changes (5). Given the complex interplay between the BDA capabilities and the generated business value, future research efforts should be focused on the question of how different BDA capabilities can be combined and orchestrated to develop these unique capabilities (Mikalef and Krogstie 2020). The answer to this question would contribute to an enhanced understanding of how, when, and why BDA can create value (Côrte-Real et al. 2017; Grover et al. 2018).

Overall, the presented findings summarized in Table 5 are expected to be of value for research and practice in many ways. For business practice, deeper insights into the main antecedents of BDA business value and the corresponding firm performance measures would help a firm to allocate its efforts toward developing the most important BDA capabilities and use the appropriate performance indicators to measure the business value of BDA. This, in turn, would enable decision-makers and managers to better manage their BDA projects and improve on the business value derived from BDA. For researchers in the IT business value field, the presented findings as well as the raised RQs represent further worthwhile future research avenues. In addition, the results of our study have highlighted the mediating role of operational performance that should be adopted by scholars when studying the business value of BDA. In addition, IS scholars wishing to use the MASEM approach to integrate empirical findings on a particular research question in the IT business value field can use this study as a guideline. To the best of our knowledge, we are the first to apply MASEM as a method of choice to integrate prior research findings on BDA business value, combining heterogeneous fragments of knowledge into one comprehensive and consistent picture. In sum, our study contributes to the rising debate on the business value of BDA by providing an integrated and validated picture of the business value of BDA, thus adding important insights to the existing body of knowledge.

Main Findings (MF)	**Implications and Propositions**
RQ1: To what extent do technical, managerial, and organizational BDA capabilities translate into business value in terms of firm performance?	
MF1a: BDA management capabilities are direct antecedents of operational, market, and financial performance MF1b: BDA technical capabilities have direct effects on neither market nor financial performance, but do directly impact operational performance MF1c: BDA organizational capabilities directly impact both firm and market performance, but not operational performance	• Firms planning to adopt BDA should acknowledge the sociotechnical nature of BDA by consequently creating the appropriate conditions, including o internal BDA knowledge and o a data-driven culture promoting data-driven decision-making • Policy makers and curriculum developers should establish teaching programs in higher education to close the BDA skills gap • BDA technical capabilities are imitable resources and should solely serve as tools to improve operational performance • Existence of time-lag effects must be taken into account when measuring BDA business value
RQ2: To what extent does operational performance play a mediating role in this translation process?	
MF2a: There is a strong direct relationship between operational performance and both financial and market performance MF2b: Operational performance fully mediates the relationship between BDA technical performance and financial and market performance MF2c: Operational performance partially mediates the relationship between BDA management capabilities and financial and market performance	• Operational performance should be considered an important intermediate performance indicator when assessing the business value of BDA • Managers should pay more attention to operational performance indicators when assessing the business value of BDA instead of solely relying on financial or market performance indicators: → Future research is needed to explore how BDA business value is actually created at different levels of firm performance • Creating business value from BDA is a complex and dynamic process that is affected by various value creation mechanisms: → Future research is needed to examine how different BDA capabilities can be combined and orchestrated to create value

Table 5. Main Findings, Implications, and Propositions

Limitations

Despite our attempt to follow a rigorous methodological approach (Cheung 2015; Hunter and Schmidt 2004), this study has several methodological limitations that should be taken into account when interpreting the results. First, meta-analysts are often confronted with the "apples and oranges" problem, which posits that aggregating different constructs from multiple studies involving different research designs and measures compromises the validity of results (Hwang 1996). Yet, following Smith et al.'s (1980, p. 47) perspective, we do "mix apples and oranges, as one necessarily would do in studying fruits." We justify the aim of our study to aggregate results from different studies and render the aggregation criteria transparent in order to shed light on previous research and provide considerations for theory building for future primary studies, while we establish the coding reliability by considering the interrater agreement of two researchers who coded the literature independently. Second, we fitted our structural path model based on a correlation matrix as opposed to a covariance matrix, an approach that has been criticized in primary studies using SEM, but with proper techniques as conducted in this study, there is no objection to performing MASEM based on correlation matrices (Cheung 2015; Joseph et al. 2007). Third, meta-analyses draw data from empirical studies yet neglect qualitative findings. We have attempted to compensate for this limitation by including findings from qualitative studies in our interpretation of the results. Fifth, we detected a high between-study variance in the effects. This is not unusual for meta-analyses (Gerow et al. 2013), but the results suggest moderator influences that should be focused upon in future studies. Investigating the impact of moderators on the relationships between BDA and different firm performance levels would help provide in-depth insights on how the conditions in which the business value created from BDA may differ depending on contextual factors (e.g., application area, industry sector, or culture).

Additional limitations pertain to the data used in our meta-analysis study. In this context, it is important to emphasize that the measures of firm performance in all studies are based on self-reported data from participants in the primary studies. We cannot verify the accuracy of this information via objective financial data, as the company names or other identifying information are mostly undisclosed in the primary studies. In addition, measuring the return on IT investments can involve time lags, leading to inconsistent results depending on when a study was conducted (Campbell 2012). We cannot conclusively rule out time-lag effects, but we did check the temporal dynamics of the firm performance effects by performing a cumulative meta-analysis as a robustness test. A cumulative meta-analysis is a visual test that provides information about temporal trends and outliers in data by adding one study at a time in a temporal sequence and calculating the successive summary estimates (Rothstein et al. 2005). We were unable to identify any temporal trends based on this test. Two important implications for future research emerge from this limitation. First, future studies could examine the impact of BDA on different firm performance levels based on secondary financial data (e.g., company financial statements and annual reports) instead of using self-reported data. Study results based on secondary financial data could help verify the objectivity of prior studies that relied on perceptual data, as was provided by the individual studies of our sample. Second, analyzing secondary financial data enables scholars to study the time lag effect, e.g., by comparing the impact of BDA on the key performance indicators reported in the financial statements at different time points (t=0, t=1, t=n). The findings would help validate the conclusions made in this study and contribute to a deeper understanding of the monetary impact of BDA on firm performance.

Conclusion

Given the heterogeneous conceptualization in research in regard to the relationship between BDA capabilities and BDA business value, we conducted a MASEM to synthesize and analyze past research to render the value-adding pathways transparent. With our results, we have been able to show that firms' value-creating mechanisms depend on the BDA capabilities studied and the targeted performance dimension. Technical BDA capabilities have a positive relationship with operational performance and have an indirect impact on financial and market performance. Managerial BDA capabilities, on the other hand, have a direct impact on the financial and market dimensions, but their positive effect is also transmitted via the operational dimension. Organizational BDA capabilities create the foundation for BDA initiatives and thereby directly impact financial and market metrics. Our meta-analytic and SEM-based results shed new light on previous work in the area of BDA business value and serve to inform future theory building. In addition, our findings help management to effectively formulate the goals of BDA initiatives by providing insight into the value-generating mechanisms.

References

Akter, S., Wamba, S. F., Gunasekaran, A., Dubey, R., and Childe, S. J. 2016. "How to Improve Firm Performance Using Big Data Analytics Capability and Business Strategy Alignment?," *International Journal of Production Economics* (182), Elsevier, pp. 113–131.

Aloe, A. M. 2015. "Inaccuracy of Regression Results in Replacing Bivariate Correlations," *Research Synthesis Methods* (6:1), pp. 21–27.

Amit, R., and Schoemaker, P. J. H. 1993. "Strategic Assets and Organizational Rent," *Strategic Management Journal* (14:1), pp. 33–46.

Anand, A., Sharma, R., and Coltman, T. 2016. "Realizing Value from Business Analytics Platforms: The Effects of Managerial Search and Agility of Resource Allocation Processes," in *Thirty Seventh International Conference on Information Systems*, Dublin, Ireland.

Asadi Someh, I., and Shanks, G. 2015. "How Business Analytics Systems Provide Benefits and Contribute to Firm Performance?," in *Twenty-Third European Conference on Information Systems (ECIS)*, Münster, Germany.

Ashrafi, A., and Zare Ravasan, A. 2018. "How Market Orientation Contributes to Innovation and Market Performance: The Roles of Business Analytics and Flexible IT Infrastructure," *Journal of Business & Industrial Marketing* (33:7), pp. 970–983.
Aydiner, A. S., Tatoglu, E., Bayraktar, E., Zaim, S., and Delen, D. 2019. "Business Analytics and Firm Performance: The Mediating Role of Business Process Performance," *Journal of Business Research* (96), pp. 228–237.
Baesens, B., Bapna, R., Marsden, J. R., Vanthienen, J., and Zhao, J. L. 2016. "Transformational Issues of Big Data and Analytics in Networked Business," *MIS Quarterly* (40:4), pp. 807–818.
Barney, J. 1991. "Firm Resources and Sustained Competitive Advantage," *Journal of Management* (17:1), pp. 99–120.
Behl, A. 2020. "Antecedents to Firm Performance and Competitiveness Using the Lens of Big Data Analytics: A Cross-Cultural Study," *Management Decision* (ahead-of-p:ahead-of-print).
Bentler, P. M., and Bonett, D. G. 1980. "Significance Tests and Goodness of Fit in the Analysis of Covariance Structures.," *Psychological Bulletin* (88:3), pp. 588–606.
Bharadwaj, A. S. 2000. "A Resource-Based Perspective on Information Technology Capability and Firm Performance: An Empirical Investigation," *MIS Quartely* (24:1), pp. 169–196.
Bogdan, M., and Borza, A. 2019. "Big Data Analytics and Organizational Performance: A Meta-Analysis Study," *MANAGEMENT AND ECONOMICS REVIEW* (4:2), pp. 147–162.
Borenstein, M., Hedges, L. V., Higgins, J. P. T., and Rothstein, H. R. 2009. "Introduction to Meta-Analysis," *Introduction to Meta-Analysis*, Chichester, UK: John Wiley & Sons, Ltd.
Božič, K., and Dimovski, V. 2019. "Business Intelligence and Analytics for Value Creation: The Role of Absorptive Capacity," *International Journal of Information Management* (46), pp. 93–103.
Brynjolfsson, E., and Hitt, L. M. 1998. "Beyond the Productivity Paradox," *Communications of the ACM* (41:8), pp. 49–55.
Campbell, M. 2012. "What a Difference a Year Makes: Time Lag Effect of Information Technology Investment on Firm Performance," *Journal of Organizational Computing and Electronic Commerce* (22:3), pp. 237–255.
Carr, N. G. 2003. "IT Doesn't Matter," *Harvard Business Review* (81), pp. 41–49.
Chen, Chiang, and Storey. 2012. "Business Intelligence and Analytics: From Big Data to Big Impact," *MIS Quarterly* (36:4), p. 1165.
Chen, D. Q., Preston, D. S., and Swink, M. 2015. "How the Use of Big Data Analytics Affects Value Creation in Supply Chain Management," *Journal of Management Information Systems* (32:4), pp. 4–39.
Cheung, M. W. L. 2014. "Fixed- and Random-Effects Meta-Analytic Structural Equation Modeling: Examples and Analyses in R," *Behavior Research Methods* (46:1), pp. 29–40.
Cheung, M. W. L. 2015. "Meta-Analysis," *Meta-Analysis: A Structural Equation Modeling Approach*, Chichester, UK: John Wiley & Sons, Ltd.
Côrte-Real, N., Oliveira, T., and Ruivo, P. 2017. "Assessing Business Value of Big Data Analytics in European Firms," *Journal of Business Research* (70), pp. 379–390.
Côrte-Real, N., Ruivo, P., and Oliveira, T. 2020. "Leveraging Internet of Things and Big Data Analytics Initiatives in European and American Firms: Is Data Quality a Way to Extract Business Value?," *Information & Management* (57:1), p. 103141.
Dehning, B., and Richardson, V. J. 2002. "Returns on Investments in Information Technology: A Research Synthesis," *Journal of Information Systems* (16:1), pp. 7–30.
Drnevich, P. L., and Croson, D. C. 2013. "INFORMATION TECHNOLOGY AND BUSINESS-LEVEL STRATEGY: TOWARD AN INTEGRATED THEORETICAL PERSPECTIVE," *MIS Quartely* (37:2), pp. 483–509.
Dubey, R., Gunasekaran, A., and Childe, S. J. 2019. "Big Data Analytics Capability in Supply Chain Agility," *Management Decision* (57:8), pp. 2092–2112.
Ferraris, A., Mazzoleni, A., Devalle, A., and Couturier, J. 2019. "Big Data Analytics Capabilities and Knowledge Management: Impact on Firm Performance," *Management Decision* (57:8), pp. 1923–1936.
Gandomi, A., and Haider, M. 2015. "Beyond the Hype: Big Data Concepts, Methods, and Analytics," *International Journal of Information Management* (35:2), pp. 137–144.
Gerow, J. E., Ayyagari, R., Thatcher, J. B., and Roth, P. L. 2013. "Can We Have Fun @ Work? The Role of Intrinsic Motivation for Utilitarian Systems," *European Journal of Information Systems* (22:3), pp. 360–380.
Ghasemaghaei, M. 2019. "Are Firms Ready to Use Big Data Analytics to Create Value? The Role of Structural and Psychological Readiness," *Enterprise Information Systems* (13:5), pp. 650–674.

Ghasemaghaei, M., Ebrahimi, S., and Hassanein, K. 2018. "Data Analytics Competency for Improving Firm Decision Making Performance," *The Journal of Strategic Information Systems* (27:1), pp. 101–113.
Ghasemaghaei, M., Hassanein, K., and Turel, O. 2017. "Increasing Firm Agility through the Use of Data Analytics: The Role of Fit," *Decision Support Systems* (101), pp. 95–105.
Glass, G. V. 1976. "Primary, Secondary, and Meta-Analysis of Research," *Educational Researcher* (5:10), p. 3.
Grover, V., Chiang, R. H. L., Liang, T.-P., and Zhang, D. 2018. "Creating Strategic Business Value from Big Data Analytics: A Research Framework," *Journal of Management Information Systems* (35:2), Routledge, pp. 388–423.
Gupta, M., and George, J. F. 2016. "Toward the Development of a Big Data Analytics Capability," *Information & Management* (53:8), pp. 1049–1064.
Gupta, S., Qian, X., Bhushan, B., and Luo, Z. 2019. "Role of Cloud ERP and Big Data on Firm Performance: A Dynamic Capability View Theory Perspective," *Management Decision* (57:8), pp. 1857–1882.
Hallikainen, H., Savimäki, E., and Laukkanen, T. 2020. "Fostering B2B Sales with Customer Big Data Analytics," *Industrial Marketing Management* (86), pp. 90–98.
Hedges, L. V., and Olkin, I. 1985. *Statistical Methods for Meta-Analysis*, Academic Press, Inc.
Hu, L., and Bentler, P. M. 1999. "Cutoff Criteria for Fit Indexes in Covariance Structure Analysis: Conventional Criteria versus New Alternatives," *Structural Equation Modeling: A Multidisciplinary Journal* (6:1), pp. 1–55.
Huang, C.-K., Wang, T., and Huang, T.-Y. 2018. "Initial Evidence on the Impact of Big Data Implementation on Firm Performance," *Information Systems Frontiers* (22), pp. 475–487.
Hunter, J. E., and Schmidt, F. L. 2004. *Methods of Meta-Analysis*, Thousand Oaks, California: Sage Publications, Inc.
Hwang, M. I. 1996. "The Use of Meta-Analysis in MIS Research," *ACM SIGMIS Database: The DATABASE for Advances in Information Systems* (27:3), pp. 35–48.
Jak, S. 2015. *Meta-Analytic Structural Equation Modelling*, SpringerBriefs in Research Synthesis and Meta-Analysis, Cham: Springer International Publishing.
Joseph, D., Ng, K.-Y., Koh, C., and Ang, S. 2007. "Turnover of Information Technology Professionals: A Narrative Review, Meta-Analytic Structural Equation Modeling, AND Model Development," *MISQ* (31:3), pp. 547–577.
Krishnamoorthi, S., and Mathew, S. K. 2018. "Business Analytics and Business Value: A Comparative Case Study," *Information & Management* (55:5), Elsevier, pp. 643–666.
Landis, J. R., and Koch, G. G. 1977. "The Measurement of Observer Agreement for Categorical Data," *Biometrics* (33:1), p. 159.
LaValle, S., Lesser, E., Shockley, R., Hopkins, M. S., and Kruschwitz, N. 2011. "Big Data, Analytics and the Path From Insights to Value," *MIT Sloan Management Review* (52:2), pp. 21–31.
Liberati, A., Altman, D. G., Tetzlaff, J., Mulrow, C., Gotzsche, P. C., Ioannidis, J. P. A., Clarke, M., Devereaux, P. J., Kleijnen, J., and Moher, D. 2009. "The PRISMA Statement for Reporting Systematic Reviews and Meta-Analyses of Studies That Evaluate Healthcare Interventions: Explanation and Elaboration," *BMJ* (339:jul21 1), pp. b2700–b2700.
Lipsey, M. W., and Wilson, D. B. 2001. *Practical Meta-Analysis*, London, UK: SAGE Publications.
Marchand, D. A., and Peppard, J. 2013. "Why IT Fumbles Analytics," *Harvard Business Review* (91:1), pp. 104–112.
Melville, Kraemer, and Gurbaxani. 2004. "Review: Information Technology and Organizational Performance: An Integrative Model of IT Business Value," *MIS Quarterly* (28:2), p. 283.
Michel, J. S., Viswesvaran, C., and Thomas, J. 2011. *Conclusions from Meta-Analytic Structural Equation Models Generally Do Not Change Due to Corrections for Study Artifacts*, (December 2017).
Mikalef, P., Giannakos, M. N., Pappas, I. O., and Krogstie, J. 2018. "The Human Side of Big Data: Understanding the Skills of the Data Scientist in Education and Industry," in *2018 IEEE Global Engineering Education Conference (EDUCON)*, pp. 503–512.
Mikalef, P., and Krogstie, J. 2020. "Examining the Interplay between Big Data Analytics and Contextual Factors in Driving Process Innovation Capabilities," *European Journal of Information Systems* (29:3), Taylor and Francis Ltd., pp. 260–287.
Mikalef, P., Krogstie, J., Pappas, I. O., and Pavlou, P. 2020. "Exploring the Relationship between Big Data Analytics Capability and Competitive Performance: The Mediating Roles of Dynamic and Operational Capabilities," *Information and Management* (57:2), Elsevier B.V., p. 103169.
Mooney, J. G., Gurbaxani, V., and Kraemer, K. L. 1996. "A Process Oriented Framework for Assessing the

Business Value of Information Technology," *ACM SIGMIS Database: The DATABASE for Advances in Information Systems* (27:2), pp. 68–81.

Muthén, B., Kaplan, D., and Hollis, M. 1987. "On Structural Equation Modeling with Data That Are Not Missing Completely at Random," *Psychometrika* (52:3), pp. 431–462.

Neale, M. C., Hunter, M. D., Pritikin, J. N., Zahery, M., Brick, T. R., Kirkpatrick, R. M., Estabrook, R., Bates, T. C., Maes, H. H., and Boker, S. M. 2016. "OpenMx 2.0: Extended Structural Equation and Statistical Modeling," *Psychometrika* (81:2), pp. 535–549.

Oesterreich, T. D., and Teuteberg, F. 2018. "Looking at the Big Picture of IS Investment Appraisal through the Lens of Systems Theory: A System Dynamics Approach for Understanding the Economic Impact of BIM," *Computers in Industry* (99), pp. 262–281.

Pappas, I. O., Mikalef, P., Giannakos, M. N., Krogstie, J., and Lekakos, G. 2018. "Big Data and Business Analytics Ecosystems: Paving the Way towards Digital Transformation and Sustainable Societies," *Information Systems & E-Business Management* (16:3), pp. 479–491.

Peterson, R. A., and Brown, S. P. 2005. "On the Use of Beta Coefficients in Meta-Analysis.," *Journal of Applied Psychology* (90:1), pp. 175–181.

Ramakrishnan, T., Khuntia, J., Kathuria, A., and Saldanha, T. J. V. 2020. "An Integrated Model of Business Intelligence & Analytics Capabilities and Organizational Performance," *Communications of the Association for Information Systems* (46:31), pp. 722–750.

Raut, R. D., Yadav, V. S., Cheikhrouhou, N., Narwane, V. S., and Narkhede, B. E. 2021. "Big Data Analytics: Implementation Challenges in Indian Manufacturing Supply Chains," *Computers in Industry* (125), p. 103368.

Rialti, R., Zollo, L., Ferraris, A., and Alon, I. 2019. "Big Data Analytics Capabilities and Performance: Evidence from a Moderated Multi-Mediation Model," *Technological Forecasting and Social Change* (149), p. 119781.

Rothstein, H. R., Sutton, A. J., and Borenstein, M. 2005. *Publication Bias in Meta-Analysis: Prevention, Assessment and Adjustments*, Wiley.

Schlaegel, C., and Koenig, M. 2014. "Determinants of Entrepreneurial Intent: A Meta-Analytic Test and Integration of Competing Models," *Entrepreneurship Theory and Practice* (38:2), pp. 291–332.

Shanks, G., and Bekmamedova, N. 2012. "Achieving Benefits with Business Analytics Systems: An Evolutionary Process Perspective," *Journal of Decision Systems* (21:3), pp. 231–244.

Smith, M. L., Glass, G. V., and Miller, T. I. 1980. *The Benefits of Psychotherapy*, Baltimore, Maryland: The John Hopkins University Press.

Sobel, M. E. 1982. "Asymptotic Confidence Intervals for Indirect Effects in Structural Equation Models," *Sociological Methodology* (13:1982), p. 290.

Someh, I., Shanks, G., and Davern, M. 2019. "Reconceptualizing Synergy to Explain the Value of Business Analytics Systems," *Journal of Information Technology* (34:4), pp. 371–391.

Song, P., Zheng, C., Zhang, C., and Yu, X. 2018. "Data Analytics and Firm Performance: An Empirical Study in an Online B2C Platform," *Information and Management* (55:5), pp. 633–642.

Steers, R. M. 1975. "Problems in the Measurement of Organizational Effectiveness," *Administrative Science Quarterly* (20:4), pp. 546–558.

Torres, R., Sidorova, A., and Jones, M. C. 2018. "Enabling Firm Performance through Business Intelligence and Analytics: A Dynamic Capabilities Perspective," *Information & Management* (55:7), pp. 822–839.

Venkatraman, N., and Ramanujam, V. 1986. "Measurement of Business Performance in Strategy Research: A Comparison of Approaches," *The Academy of Management Review* (11:4), pp. 801–814.

Wang, Y., and Byrd, T. A. 2017. "Business Analytics-Enabled Decision-Making Effectiveness through Knowledge Absorptive Capacity in Health Care," *Journal of Knowledge Management* (21:3), pp. 517–539.

Yu, W., Chavez, R., Jacobs, M. A., and Feng, M. 2018. "Data-Driven Supply Chain Capabilities and Performance: A Resource-Based View," *Transportation Research Part E: Logistics and Transportation Review* (114), pp. 371–385.

Zhao, X., Lynch, J. G., and Chen, Q. 2010. "Reconsidering Baron and Kenny: Myths and Truths about Mediation Analysis," *Journal of Consumer Research* (37:2), pp. 197–206.