Delineating the Business Value of Data-driven Initiatives in Organizations – Findings from a Systematic Review of the Information Systems Literature

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Abstract

A key objective of data-driven transformations is to utilize big data analytics (BDA) to create data-driven business value (DDBV). While prior research shows the potential of BDA to achieve DDBV, the concept remains blurry and an overview of realizable DDBVs is still lacking. To better understand the multidimensionality of the DDBV concept and to obtain insights into the bandwidth of achievable DDBVs, we conducted a systematic review of the information systems literature. Based on our results, we present a comprehensive overview of 34 DDBVs, which are classified according to their tangibility and locus of value realization. Furthermore, we describe three research deficiencies: (1) the missing operationalization of the DDBV concept, (2) the lack of explanatory mechanisms for DDBV realization, and (3) missing qualitative, in-depth insights into DDBV realization processes. Future research may build upon our systematization and help closing these research gaps, thereby increasing the success likelihood of data-driven initiatives.

Keywords: Data-driven Business Value, Data-driven Organizations, Big Data Analytics, Literature Review

1. Introduction

Big data (BD) is frequently being hailed as the new oil for organizations (Wiener et al., 2020). Accordingly, BD as general topic and big data analytics (BDA) as the approach to extract value from BD are becoming ever more popular in academia and practice. Recent studies show that organizations can indeed benefit from the application of BDA in various ways. Often, BDA is therefore even viewed as facilitator of a data-driven transformation, fostering the emergence of data-driven organizations (DDO) as a whole (Schüritz et al., 2017).

Despite the promising results from early studies, however, the business value resulting from the use of BDA has remained blurry. So far, there exists no clear definition of data-driven business value (DDBV) as a concept. Related work instead mostly studied the effects of BDA usage on a few popular (comparatively generic) factors like competitive advantage or organizational performance. Other (more concrete) factors like process transparency have only been studied sporadically. Hence, current research lacks a holistic overview of the business values that can be achieved from the usage of BDA in organizations, thereby neglecting the multidimensionality of the concept. First steps to synthesize extant findings and categorize DDBVs can be found in literature (Elia et al., 2020; Vitari & Raguseo, 2020). Yet, the according approaches do not explain the identified business values in detail and rather focus on discussing prerequisites to realize them. A coherent systematization of DDBVs with detailed explanations is still missing. Without a precise definition of DDBV as a concept and understanding its multifaceted nature, it remains difficult to assess the potential of data-driven initiatives in concrete scenarios, however.

To contribute to the closure of this literature gap, we present the findings of a literature study, in which we aimed at identifying and systematizing the concrete business values that result from data-driven initiatives. We particularly examine the following research questions: "*Which business values can be achieved by data-driven initiatives in organizations? How can the term 'data-driven business value' and its multifaceted nature be conceptualized and systematized?*"

To answer these research questions, we conducted a systematic review of the information systems (IS) literature. Based on an in-depth analysis of 37 articles, we present 34 DDBVs and classify them according to the IS business value taxonomy of Schryen (2013). In addition, we delineate a research agenda based on three identified deficiencies in the current knowledge base: (1) a missing operationalization of the DDBV concept itself, (2) a lack of mechanisms that explain the realization of DDBVs, and (3) missing in-depth insights into the processes of DDBV realization.

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Our findings complement current research activities on the effects of data-driven initiatives in organizations in two ways: first, we present a unique overview of DDBVs and provide details regarding the business values themselves as well as the effects of their realization. Thereby, we go beyond discussing abstract values such as competitive advantage, thus describing the known bandwidth of realizable DDBVs and helping to better understand the multidimensional nature of the concept. Second, we provide concrete avenues for future research to further investigate und understand DDBV as a concept. Our research endeavor can thus be seen as a step to systematically unveil and depict the business value potentials of data-driven initiatives.

We proceed as follows: in section 2, we discuss the theoretical background, the data-driven business value concept, and related work. Thereafter, we describe the research methodology behind our literature review (section 3). The data-driven business values identified during the literature review are presented in section 4. In section 5, we discuss the findings and implications for research and practice. Section 6 concludes the paper.

2. Theoretical background

2.1 DDOs and the role of BDA

Big data (BD) is one of the most frequently discussed topics in organizational practice, IS research, and computer science today (McAfee et al., 2012; Wiener et al., 2020). It is characterized along several V's (Mikalef et al., 2018), emphasizing the extensive amount of data (*volume*), the diversity of data sources and types (*variety*), the speed of data generation (*velocity*), the authenticity of data (*veracity*), and the possible value implied in the data itself (*value*).

The extraction of *value* from BD is embodied in the notion of BDA. As such, BDA can be viewed as a "holistic process that involves the collection, analysis, use, and interpretation of data" (Akter & Wamba, 2016, p. 178). BDA further describes a means for "advancing business" (Grover et al., 2018, p. 390), and generating competitive advantages (Vitari & Raguseo, 2020). Thereby, researchers and practitioners agree that value creation represents the key objective of BDA. We define BDA as technologies, techniques, and processes for using BD to realize business value.

While BDA as a concept has been clarified, specific characterizations of firms that use BDA for value realization are mostly lacking. Schüritz et al. (2017) define a DDO as an organization that "heavily relies on data to make decisions and take actions" (p. 394). While this definition emphasizes the relevance of creating actionable insights, the business value resulting from data-driven initiatives is left unclear.

Extant research has identified elements of a DDO, including technical aspects like data science, managerial aspects such as data-driven business models, and organizational aspects including a data-driven culture (Hupperz et al., 2021). Establishing a DDO moreover requires the holistic diffusion of analytical capabilities in several functional areas (Hagen & Hess, 2020).

With a particular emphasis on the objective of business value realization, we define a DDO as an organization that holistically establishes BDA and infrastructure capabilities to implement data-centric sense-making mechanisms and employs data-driven insights for business advancements (e.g., through data-driven business models or innovations) to realize data-driven business value.

2.2 Business value of data-driven initiatives

The resource-based view (RBV) is regarded as the most prominent theoretical paradigm to explain BDA value realization (Akter et al., 2016; Grover et al., 2018). Extant research determined the establishment of a BDA capability as a necessary prerequisite to realize business value (Mikalef et al., 2018). Following the RBV, a BDA capability requires the orchestration of technical, human, and management-related resources (Grover et al., 2018). Thereby, the data and the BDA infrastructure are assigned to the technical resource component (Gupta & George, 2016). Technical and business knowledge are attributed to the human resource (Mikalef et al., 2018). Concerning management resources, a BDA capability entails elements such as BDA governance mechanisms as well as a data-driven culture (Gupta & George, 2016; Mikalef et al., 2018).

Further research on business value realization originates from the debate on IS business value. The RBV perspective is also frequently applied in IS business value models that refer to assets, resources, and capabilities to explain IS business value realization (Schryen, 2013). To grasp the multidimensionality of IS business value, Schryen (2013) proposes a taxonomy that classifies its manifestations along their tangibility and their locus of value realization (p. 151).

The first criterion distinguishes intangible and tangible business values. Performance-related business values depict a popular example of tangible business values as they are measurable. In contrast, intangible business values like an improved organizational agility can be hardly quantified but can be interpreted qualitatively.

The differentiation between internal and external business values depicts the second criterion of the taxonomy. Internal business values discuss beneficial effects within an organization, for instance an improved decision-making. External business values comprise market- and competition-oriented business values, taking the environment of an organization into account.

Similarly, research on the effects of data-driven initiatives has illustrated the multidimensionality of the DDBV concept by identifying values like competitive advantage (Brynjolfsson et al., 2011) or operational performance (Akter et al., 2016). We conclude that the DDBV concept has several forms of manifestation, allowing for an application of the IS business value perspective in our research context.

Accordingly, we define *data-driven business value* as the multidimensional beneficial effects resulting from the establishment and utilization of data-driven resources and capabilities, which are observable within an organization and in interaction with its competitive environment.

2.3 Related work

So far, research has mostly focused on examining particular business values resulting from BDA usage, among them competitive advantages, decision-making support, or innovation (Duan & Cao, 2015; Vitari & Raguseo, 2020). Accordingly, findings regarding the effects of BDA usage are scattered across the literature.

There also exist first steps to synthesize these findings and to delineate the DDBV concept (Elia et al., 2020; Vitari & Raguseo, 2020). Elia et al. (2020) present a BDA value creation model with a set of business values identified from management and computer science literature. While the model contributes to a better understanding of the multidimensional nature of the DDBV concept, the paper does not provide detailed explanations of specific BDA business values.

In addition, values such as "hiring of big data experts" or "use of scalable open source technologies" (Elia et al. 2020, p. 622) rather seem to characterize prerequisites for value realization than actual outcomes of BDA application. The presented systematization of BD business values hence still seems to lack a detailed, coherent perspective. Another shortcoming concerns the omission of the IS literature despite its importance with respect to research on BDA. In addition, the model only covers findings published from 2013 to 2017, thus calling for an update.

While previous research made first steps towards systemizing DDBVs, the approaches lack conceptual clarity and a holistic overview. With our study, we aim at complementing these approaches by providing a new perspective on the multifaceted nature of DDBVs with a particular focus on findings from IS research. Through the development of a categorization of DDBVs, we aim at delineating the DDBV concept and defining it more precisely. We also identify concrete avenues for future research to better understand the concept.

3. Research methodology

To identify and systematize DDBVs, we conducted a systematic literature review that follows the procedure proposed by vom Brocke et al. (2009). As we intend to delineate the term DDBV, we screened the extant body of knowledge to identify benefits of BDA usage before classifying them into a coherent concept according to the IS business value taxonomy of Schryen (2013).

For the first step of defining the review type, we built upon the framework of Cooper (1988). Our goal was to integrate extant research outcomes on DDBVs covered in the IS domain in a conceptual manner, thereby taking a neutral perspective with the goal to inform practitioners and scholars (Cooper, 1988).

In a second step, we determined key concepts for our research endeavor. We emphasized BD as well as BDA and "data-driven" as key terms for the data-related domain. We complemented these terms with different notions of business value, such as benefits, advantages, and other termini. Based on these terms, we created the following search string:

(("BDA" OR "Big Data Analytics" OR "data analytics" OR "advanced analytics" OR "data driven") AND (value OR "business value" OR benefi* OR advantage* OR perform* OR achiev* OR increase* OR success* OR profit* OR accept* OR adoption*))*

The third step entailed the search for publications. Since we adopted an IS business value-oriented stance, we only searched for publications within the IS domain. Hence, we browsed the AIS Electronic Library using our search string. Additionally, we employed the Web of Science search engine to select relevant publications from the Senior Scholars Basket of IS Journals. As a result, we identified 459 initial hits. In our selection funnel, we defined distinct inclusion and exclusion criteria to establish a collection of relevant articles. Only articles that discuss DDBV facets were included in the final sample. Furthermore, selected publications that are not characterized as completed research were excluded. In addition, we limited the time frame for relevant publications from 2010 onwards, since the hype around BD in both industry and academia surfaced at the beginning of this decade (McAfee et al., 2012; Wiener et al., 2020). To ensure the selection of high-quality papers, we focused on leading IS conferences and journals according to current rankings. Thereby, we reduced the initial sample to 201 articles. Subsequently, we performed a title- and abstract-screening to identify articles that discuss DDBVs in detail. Concludingly, we analyzed the resulting 75 articles in an independent full-text screening. After iterative discussions, we defined a final sample of 37 articles.

In a fourth step, we performed an in-depth analysis of the 37 articles, aiming at identifying distinct DDBVs. To extract and systematize the multiple facets of DDBV, we adhered to a grounded theory approach suggested by

Gioia et al. (2013) to establish a coherent data structure. Our procedure entails three consecutive steps: data extraction, aggregation, and synthesis. In the initial step of data extraction, we scrutinized the articles in our review sample for statements that explicitly mention a particular DDBV. We extracted 217 text fragments, which were then labelled according to the depicted DDBV in an open coding step. As a result, we identified 34 single DDBVs. Subsequently, we aggregated the 34 DDBVs into 11 2nd order business value themes in an axial coding step. Thereby, we clustered closely related DDBVs that emphasize a similar value target of DDBV realization. For instance, we grouped *improved decision-making* and *better-informed planning decisions* into the 2nd order theme ***decision-making support***, since both address a similar aspect of DDBV realization. In a final step, we classified the 11 2nd order business values themes according to the IS business value taxonomy proposed by Schryen (2013), thereby performing a selective and theory-informed coding. For example, the 2nd order theme ***decision-making support*** was categorized as an internal and intangible value, as decision-making embodies an intra-organizational process and improves an organization's capability to make efficient high-quality decisions (Schryen, 2013). Note that we also found a DDBV called "improved organizational performance", which we classified as internal and tangible business value. While we rather consider organizational performance to be a business value theme, several papers do not further disaggregate this generic business value. We discuss this "blurriness" of some business values in more detail in chapter 5.1.

To substantiate our understanding of the DDBV concept, we depict the 34 identified DDBVs according to the IS business value taxonomy. We also provide illustrative statements from literature to delineate the beneficial effects of data-driven initiatives. In addition, we present an agenda for future research and managerial practice to further investigate the multifaceted nature of DDBV, as proposed by vom Brocke et al. (2009).

4. Delineating data-driven business value

A quantitative analysis of the literature sample shows that most of the identified studies employed a quantitative methodology (n=25). Seven studies used a qualitative approach and five built upon mixed methods. 21 articles were published within the last five years, thus highlighting the recent debate on DDBV realization. More details of our quantitative analysis can be found online: *doi.org/10.6084/m9.figshare.20894191*. In our qualitative analysis, we classified the identified DDBVs according to the IS business value taxonomy of Schryen (2013), taking their tangibility and locus of realization into account. Table 1 provides a summary of the results. It contains the individual DDBVs, the overarching value themes, and depicts corresponding articles that discuss the respective DDBV. In the following subsections, we delineate those DDBVs and present illustrative statements from literature to provide an inside view.

4.1 Tangible and internal DDBVs

During our literature analysis, we identified the DDBV themes ***prediction capability, operational performance***, and ***firm & organization performance*** as part of the **tangible and internal** dimension. In the ***prediction capability*** theme, *improved forecasting* was found as a significant benefit for DDOs. By using BDA, order forecasting can be realized with an extended timespan (Dremel et al., 2017). Procurement generally profits from BDA, as procurement plans for upcoming seasons can be based on sales forecasts, while real-time sales data can be leveraged to adapt plans for the current situation (Du et al., 2020). Hence, the *accuracy* of predictions was found to be *improved* by BDA. As stated by Du et al. (2020), "the shipping accuracy increased from 60 % to 85 %" (p. 130), indicating better demand prediction. In a similar vein, BDA was found to better predict the static stability in air cargo scenarios, also being "faster than a regular physics engine" (Mazur et al., 2022, p. 12). This implies that BDA can provide more accurate predictions faster.

Data-driven initiatives were also found to improve the internal ***operational performance*** of DDOs. Generally, the usage of BDA has a potential to increase an organization's *process performance*. Various organizational processes were found to be improved by BDA, for instance delivery processes (Grover et al., 2018), palletizing processes in the air cargo domain (Mazur et al., 2022), and investment processes in the venture capital sector (Weibl & Hess, 2019). More concretely, *process efficiency* was increased significantly. Efficiency gains especially concern the temporal dimension of process execution (Eggers et al., 2021; Weibl & Hess, 2019). As stated by Du et al. (2020), the application of BDA shortens "the average production cycle from 9 to 5 days" (p. 130). A reduced cycle time, indicating higher efficiency, can for instance be achieved by automating process steps (Gust et al., 2017; Müller et al., 2018). Similarly, *increased productivity* was identified in several cases. Apparently, BDA as an "information processing capability" (D. Chen et al., 2015, p. 27) helps to increase a firms asset productivity. Moreover, several authors noted the influence of BDA on productivity-based metrics (Brynjolfsson et al., 2011; Müller et al., 2018). Besides optimized productivity (D. Chen et al., 2015), BDA also enables *improved resource utilization* (Grover et al., 2018). Particularly, idle times of resources were

Table 1. A classification of data-driven business values along the taxonomy of Schryen (2013)

Dimension	Value Theme	Data-driven Business Value (DDBV)	Authors	∑
Tangible / Internal	*Prediction Capability*	Improved Forecasting	[12, 13, 18, 24, 27, 28]	6
		Improved Accuracy	[13, 25]	2
	Operational Performance	Increased Process Efficiency	[13, 15, 18, 25, 26, 27, 32, 34]	8
		Increased Productivity	[5, 9, 26]	3
		Improved Resource Utilization	[13, 17, 18, 31, 33]	5
		Reduced Waste	[29]	1
		Increased Process Performance	[2, 15, 17, 18, 25, 27, 28, 31, 34, 37]	10
	Firm & Organization Performance	Improved Organizational Performance	[6, 13, 22, 26, 32]	5
Tangible / External	*Strategic & Competitive Performance*	Increased Competitive Advantage	[5, 7, 11, 14, 21]	5
		Increased Market Value	[5]	1
		Improved Market Perception	[17]	1
		Improved Inter-Organizational Collaboration	[13, 27, 34]	3
		Improved Supply Chain Performance	[10]	1
	Financial Performance	Realization of Cost Savings	[17, 18, 27, 29, 31, 34]	6
		Increased Revenue	[4, 13, 17, 19, 22, 33]	6
		Increased Return on Investment	[34]	1
	Customer Benefits	Improved Customer Experience	[1, 17]	2
		Improved Customer Treatment	[17, 27]	2
		Improved Customer Satisfaction	[2, 13, 17]	3
		Improved Fraud Prevention	[17]	1
Intangible / Internal	*Decision-Making Support*	Generally Improved Decision-Making	[6, 8, 12, 13, 16, 18, 19, 24, 31, 32]	10
		Improved Decision Quality	[16, 18]	2
		Improved Decision-Making Efficiency	[16]	1
		Better-Informed Planning Decisions	[13, 18, 23, 25]	4
	Knowledge Generation & Usage	Improved Generation of Business Insights	[3, 12, 15, 17, 23, 32, 37]	7
		Increased Process Transparency & Awareness	[15, 18]	2
	Organizational Flexibility & Adaptability	Increased Organizational Agility	[20]	1
		Reduced Time to Market	[32]	1
		Increased Business Growth	[9]	1
Intangible / External	*Customer Approach*	Improved Customer Acquisition	[1, 4, 12, 13, 17, 23, 31, 36]	8
		Improved Customer Retention	[17, 31, 34]	3
	Service & Innovation Capability	Increased Innovation Capability	[3, 14, 30, 35]	4
		Increased Potential for new data-driven Services	[12, 26, 34]	3
		Continuous Service Optimization	[12, 15]	2

[1] Abhari et al. (2021)
[2] Adjerid et al. (2018)
[3] Alexander and Lyytinen (2019)
[4] Bragge et al. (2013)
[5] Brynjolfsson et al. (2011)
[6] Cao and Duan (2015)
[7] Cao and Duan (2014)
[8] D. Chen et al. (2021)
[9] D. Chen et al. (2015)
[10] W. Chen et al. (2020)
[11] Danielsen et al. (2021)
[12] Dremel et al. (2017)
[13] Du et al. (2020)
[14] Duan and Cao (2015)
[15] Eggers et al. (2021)
[16] Ghasemaghaei et al. (2018)
[17] Grover et al. (2018)
[18] Gust et al. (2017)
[19] He et al. (2021)
[20] Hyun et al. (2020)
[21] Kamioka et al. (2017)
[22] Kitchens et al. (2018)
[23] Kucklick et al. (2020)
[24] Lash and Zhao (2016)
[25] Mazur et al. (2022)
[26] Müller et al. (2018)
[27] Oesterreich et al. (2020)
[28] Papapanagiotou et al. (2021)
[29] Seubert et al. (2020)
[30] Shuradze and Wagner (2018)
[31] Sodenkamp et al. (2015)
[32] Someh and Shanks (2015)
[33] Wagner et al. (2015)
[34] Weibl and Hess (2019)
[35] Wölfl et al. (2017)
[36] Yao et al. (2012)
[37] Zhang et al. (2014)

reduced, indicating higher exploitation of resource capacity (Du et al., 2020; Wagner et al., 2015). Seubert et al. (2020) also describes the potential of BDA to *reduce waste* in operating processes as a concrete DDBV. Compared to human planning, BDA yielded a waste reduction of up to 55 % (Seubert et al., 2020).

BDA moreover has a potential to ***improve firm performance***. Scholars frequently noted *improved organizational performance* as a consequence of BDA usage (Cao & Duan, 2015; Du et al., 2020; Kitchens et al., 2018; Müller et al., 2018). In particular, informational benefits created through BDA can “lead to superior firm performance” (Someh & Shanks, 2015).

4.2 Tangible and external DDBVs

Tangible and external DDBVs can be divided into ***strategic & competitive performance, financial performance***, and ***customer benefits.*** Several authors describe a higher strength of the competitive position of the firm. Here, the most prominent DDBV manifests as *increased competitive advantages*. Generally, “an organization’s ability to process data […] and utilize insights […] can enhance business competitiveness” (Cao & Duan, 2014, p. 12). Due to enhanced innovation capabilities enabled by BDA, organizations can achieve further competitive advantages (Duan & Cao, 2015). Also, firms that adopt BDA and thereby increase their level of IT capital show tendencies of higher *market value*. This holds especially true for the application of BDA for organizational decision-making (Brynjolfsson et al., 2011). Similarly, applying BDA as an innovative technical artifact has been found to lead to reputational benefits, indicating an *improved market perception*. This can be particularly attributed to "being on the forefront of BDA" (Grover et al., 2018, p. 407). Concerning the position of a firm within a business sector, BDA use helps to *improve inter-organizational collaboration*. For instance, the adoption of BDA in the supply chain of an organization supported "increased commitment from manufacturing and retail partners" (p. 130) in the case of Du et al. (2020). In this vein, cross-organizational data platforms also contribute to an increased data exchange (Weibl & Hess, 2019). Concerning the collaboration of industry partners, W. Chen et al. (2020) also report an *improved supply chain performance*, as "BDA would help organizations better implement […] agile supply chain strategies to improve supply chain performance" (W. Chen et al., 2020, p. 13).

BDA use can furthermore improve the ***financial performance***. Here, BDA can support the *realization of cost savings*, i.e. operational costs (Someh & Shanks, 2015; Weibl & Hess, 2019). In the case of UPS, BDA helped to "reduce fuel consumption, […] and maintenance costs" (Grover et al., 2018, p. 408). Besides cost savings, *increased revenue* can be realized through BDA usage (Grover et al., 2018; Kitchens et al., 2018). As sales figures increased due to optimized data-driven services (Bragge et al., 2013; Wagner et al., 2015), significant increases in the resulting revenue were observed (Du et al., 2020). Similarly, investments augmented by data-driven insights have proven to lead to a *higher return on investment* (Weibl & Hess, 2019).

Another DDBV theme that affects the external organizational environment concerns ***benefits for the customers***. As a first business value, the application of BDA has shown to generally improve the *customer experience* (Grover et al., 2018). In addition, the adoption of BDA supports the establishment of increased overall customer equity for the firm (Abhari et al., 2021). The improved customer experience can be achieved by granting the employees "more autonomy to participate in customer experience co-creating and co-delivery in the way they prefer" (Abhari et al., 2021, p. 7). Likewise, BDA use improves *customer treatment*, especially in the healthcare sector. For instance, BDA supports "effective and personalized treatment decisions" (Grover et al., 2018, p. 406), leading to "better and individualized therapies" (Oesterreich et al., 2020, p. 12). This causes a *higher satisfaction of the customers*, i.e., increasing patient satisfaction in individualized therapies through data-driven insights (Adjerid et al., 2018; Grover et al., 2018; Oesterreich et al., 2020). This holds also true for improved customer satisfaction in a business context (Du et al., 2020; Grover et al., 2018). Adding to the customer satisfaction, *fraud prevention* depicts another DDBV, since BDA supports the detection of abnormalities, thereby reducing fraud probability (Grover et al., 2018).

4.3 Intangible and internal DDBVs

Next, we assess DDBVs in the **intangible and internal** value dimension. As overarching themes, we identified ***decision-making support, knowledge generation & usage*** and ***organizational flexibility & adaptability***. A central purpose of data-driven initiatives depicts an improved ***decision-making support.*** This particularly addresses *organizational decision-making in general*. Typically, BDA enhances an organization's decision-making capability (D. Chen et al., 2021; He et al., 2021) by "augmenting decision makers rather than replacing them" (Du et al., 2020, p. 133). In addition, using multiple data sources also makes business decisions more robust (Gust et al., 2017). Taking a closer look at decision-making, both *decision quality* as well as *decision-making efficiency* can be enhanced by using BDA. As such, Ghasemaghaei et al. (2018) report that "employing big data […] increases the quality of […] decisions" (p. 10), thereby improving the overall accuracy (Gust et al., 2017). Furthermore, decision-making can be performed more efficiently with the help of BDA (Ghasemaghaei et al., 2018). As another facet, BDA helps firms make *better-informed planning decisions*. Based on BDA-driven insights, organizations can improve their capacity and resource planning (Kucklick et al., 2020). In comparison to human planning, recommendations based on BDA yield better results than human judgement (Du et al., 2020).

Another prominent business value theme depicting intangible and internal DDBVs concerns ***knowledge generation and usage***. Several authors highlight the ability of BDA to *improve the generation of business insights*. As such, BDA helps organizations "to gain insights into their business, customers and markets" (Someh & Shanks, 2015, p. 13). In this vein, extracting insights from large data streams (e.g., social media) "[enhances an] organizations management practice" (Zhang et al., 2014, p. 16). Since new data-driven insights foster an increased transparency, BDA also provides benefits on the process level. In this regard, BDA usage enables *increased process transparency and awareness*. For instance, using process mining as a data-driven technology helps organizations create process transparency (Eggers et al., 2021), thereby "achieving alignment of processes across departments" (p. 502).

As a last theme, BDA can help firms improve their ***flexibility and adaptability***. While depicting a small theme, the DDBVs within this theme illustrate the potential for organizations to constantly evolve even in volatile environments. In this vein, BDA adoption was found to stimulate the *agility of an organization* (Hyun et al., 2020). As with agile methodologies, the agility from BDA insights can lead to a *reduced time to market* (Someh & Shanks, 2015). As a further benefit, organizations can leverage BDA to stimulate their *business growth*, particularly "to an even greater degree in dynamic environments" (D. Chen et al., 2015, p. 28).

4.4 Intangible and external DDBVs

Lastly, we identified **intangible and external** DDBVs. The DDBV themes herein include ***customer approach*** and ***service & innovation capability***.

Using BDA enables firms to take a more targeted ***customer approach***. This particularly concerns *customer acquisition*, as BDA helps firms to address their target groups and "thus [makes] marketing activities more effective and efficient" (Dremel et al., 2017, p. 87). Moreover, BDA supports the identification of customer purchase patterns (Grover et al., 2018), enabling efficient marketing campaigns (Sodenkamp et al., 2015; Yao et al., 2012). BDA also allows firms to monitor the customer and optimize the customer journey (Bragge et al., 2013; Du et al., 2020), while identifying "reasons for customer attrition" (Grover et al., 2018, p. 408). BDA similarly facilitates *customer retention* by improving the quality of customer "interactions […] and discover[ing] customer opportunities and problems" (Grover et al., 2018, p. 408). In this vein, BDA-driven insights allow to "increase customer retention [and] strengthen customer engagement" (Sodenkamp et al., 2015, p. 14). Existing services optimized through BDA can also provide ways of binding the customer "more closely to the company" (Wagner et al., 2015, p. 13).

As another interlinked business value theme, BDA allows firms to achieve a superior ***service & innovation capability***. Here, *increased innovation capability* manifests itself through "enhanced new product novelty and meaningfulness" (Duan & Cao, 2015, p. 12). In addition, the use of BDA intensifies "radical as well as incremental innovations" (Shuradze & Wagner, 2018, p. 4230). As a result, adopting BDA "can payoff in terms of higher innovation performance" (Wölfl et al., 2017, p. 9). In addition, BDA offers *potential for generating new data-driven services* (Dremel et al., 2017), realizable by designing "products and services that offer superior value to the customer and are distinct from competition" (Müller et al., 2018, p. 504). In a similar vein, data-driven services (Dremel et al., 2017) and personal services, particularly in the healthcare industry (Oesterreich et al., 2020), can be enhanced through *continuous service optimization* based on BDA.

5. Discussion and Implications

5.1 Delineating a research agenda for DDBVs

During our analysis, we identified a variety of DDBVs that demonstrates the multifaceted nature of the concept. As one remarkable result, the use of BDA not only generates DDBVs within the firm, but also proves beneficial in the competitive environment and in the interaction with the customer. Our study, however, also reveals deficiencies in BDA research. In the following, we discuss three research deficiencies (RD) of extant BDA literature to guide future research that aims at better understanding DDBV as a concept.

RD1: Missing operationalization of DDBVs

A first shortcoming of BDA research concerns the blurriness of the DDBV concept. Despite a variety of researchers that emphasize the potential of BDA to realize DDBV, the operationalization of the beneficial effects frequently remains rather coarse and on a high level of abstraction. Our systematic review accentuates the need to further disaggregate certain DDBVs. This is particularly apparent in the case of process performance (Adjerid et al., 2018), organizational performance (Someh & Shanks, 2015), competitive advantage (Kamioka et al., 2017), and the generation of business insights (Kucklick et al., 2020). While it has been found that the usage of BDA may lead to the realization of such business values in general, it is left somewhat unclear which concrete values can be achieved. In contrast, other DDBVs were conceptualized in greater detail. As an example, Ghasemaghaei et al. (2018) delved deeper into the beneficial effects on decision-making, stating that BDA use leads to an improved decision-making performance and discussed improved decision quality and decision-making efficiency as concrete values. Further publications depict DDBVs in a more graspable way. These include - among others - increased revenue (Du et al., 2020; Wagner et al., 2015), reduced waste (Seubert et al., 2020), and cost savings (Gust et al., 2017). Based on this observation, we encourage future research to analyze DDBVs on a more detailed level.

RD2: Lacking explanatory mechanisms of DDBV realization

A second relevant aspect concerns the mechanisms that lead to a distinct DDBV. While the RBV depicts a frequently employed concept to theoretically explain business value realization mechanisms (Mikalef et al., 2018), other theoretical approaches to delineate DDBV realization are needed for further clarification. One possibility to further sharpen the understanding of

DDBV realization is to consider extant research in the business intelligence (BI) domain (Shiau et al., 2022). Several articles have developed theoretical explanations for BI business value realization, for instance through the lens of absorptive capacity or the general systems theory (Trieu, 2017). As a consequence, research about DDBV realization could be informed by extant findings and perspectives from the BI domain (Marjanovic et al., 2022; Shiau et al., 2022).

Another avenue for future research is to examine the interplay between distinct DDBVs and its potential to facilitate DDBV realization. Several studies indicate relationships among DDBVs. For instance, Gust et al. (2017) mention that an improved forecasting results in the realization of cost savings. Likewise, Wagner et al. (2015) depict the optimization of resource utilization through BDA resulting in reduced idle time, which in turn led to an increased revenue. DDBV realization should hence not only be attributed to distinct data-driven resources, but future research should also examine the interplay of several DDBVs, drawing a more holistic picture of DDBV realization processes.

RD3: Missing in-depth insights into DDBVs

Although the field is still nascent, our analysis shows that a majority (n=25) of articles employs a quantitative stance to examine the potential of BDA for DDBV realization. Yet, qualitative studies revealed more accurate explanations of DDBVs and provided a larger bandwidth of DDBVs (Dremel et al., 2017; Du et al., 2020; Gust et al., 2017). This RD is interwoven with the two preceding RDs, as missing insights into successful data-driven initiatives and the lack of explanations of value realization mechanisms may stem from rather high-level approaches found in a considerable number of quantitative studies. While quantitative studies allow to confirm relationships between BDA usage and beneficial effects, qualitatively uncovering the breadth of DDBVs appears more promising. We therefore encourage future research to use qualitative approaches to derive more comprehensive explanations of DDBV realization, particularly producing insights on the interplay between DDBVs. Once a more holistic perspective is established, quantitative studies may complement this perspective to confirm the identified relationships.

5.2 Theoretical and practical implications

Our results have implications for academia and practice alike. As regards academia, we provide an updated perspective on DDBV realization forms and established a coherent systematization of the concept. In doing so, we complement previous systematizations (Elia et al., 2020) by delving deeper into the bandwidth of possible DDBVs and the multidimensionality of the concept. Thereby, we also shed light on previously overlooked DDBVs like reduced waste (Seubert et al., 2020) and increased organizational agility (Hyun et al., 2020). Moreover, we provide characteristic quotes from literature to describe each DDBV in detail. The variety of newly identified DDBVs indicates that the business value realization potential in data-driven initiatives yet needs to be fully uncovered. We also identified several intangible business values, thereby extending the so far performance-oriented business value discussion in the BDA domain (Vitari & Raguseo, 2020). This extension is in analogy to Marjanovic et al. (2022), who propose to re-think the current business value understanding in the BI domain, especially with respect to the consideration of more intangible business values. To further investigate and understand DDBV as a concept, we moreover provide concrete directions for future research and particularly call for qualitative studies to obtain more in-depth insights.

For practice, the presented classification of DDBVs delivers an instrument to plan and evaluate data-driven capabilities in a goal-oriented approach. Organizations ought to define a vision that accentuates their key objectives and the DDBVs that should be realized when implementing BDA. Our classification can guide organizations to decide whether to pursue internal DDBVs, for instance to optimize operational efficiency, or to focus on strengthening its competitiveness and position in the market. Additionally, our findings can help DDOs to identify areas where DDBVs are not yet realized, allowing them to take appropriate actions to further unfold their data-driven value realization potential and thus serving as a means of benchmarking.

5.3 Limitations

Our findings are not without limitations. While we assessed articles individually to avoid a subjective bias, a residual probability of having excluded potentially relevant articles remains. Nonetheless, we deem the sample to be representative for the IS research domain. A second limitation also relates to the representativeness of the sample. Since we only focused on publications from the IS research domain, recent articles from related fields (e.g., computer science) are not included in our sample. Given the breadth of facets in our article, however, we believe that the identified DDBVs still depict the quintessence of DDBVs in BDA research. Future research may complement our findings by updating the perspectives from other domains, thereby further extending the DDBV concept. Lastly, we solely adopted a positive perspective on BDA to identify the benefits of BDA application. Potential downsides like privacy invasion (Sodenkamp et al., 2015) were out of scope, thus potentially portraying a deceptive picture.

Comparing the dark side of BDA with the identified DDBVs presents itself as an avenue for future research that could lead to a more balanced conception of BDA.

6. Concluding remarks

While the potential of BDA as the new oil for firms (Wiener et al., 2020) is widely acknowledged, the concretely achievable DDBVs still remain somewhat unclear. The results of our literature study contribute to the closure of this literature gap. Our systematization of 34 DDBVs provides a unique overview and shows the breadth of potentially achievable business values. Thereby, we extend previous understandings by also taking intangible business values like organizational agility into consideration. Although the knowledge base is still nascent and in-depth insights are often lacking, we found several indications, which support the claim that BDA depicts a central strategic asset for firms to thrive in the future (McAfee et al., 2012).

The identified research deficiencies moreover provide concrete avenues for future endeavors to further investigate the value realization mechanisms of BDA. In so doing, we hope to contribute to the body of literature that aims at explaining the vast potential to realize DDBVs with the organizational use of BDA and intends to close the so-called BDA deployment gap (Wiener et al., 2020).

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