FROM DATA TO VALUE: REVISITING BUSINESS VALUE RESEARCH IN THE CONTEXT OF DATA-DRIVEN INSIGHT INITIATIVES

Completed Research Paper

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Abstract

The business value of data-driven insight initiatives (DDII), such as business intelligence or big data analytics, has been primarily studied from a variance perspective, often neglecting the process perspective. Although the variance perspective is well established and identifies key factors or capabilities critical to business value creation, the process perspective can provide explanations of how capabilities lead to business value. For organizations to fully understand how these capabilities impact the value-creation process and to prevent the failure of DDII, there is a need for prescriptive knowledge that encompasses both perspectives. Through a systematic literature review, this paper highlights the variance-focused conceptual landscape of DDII business value research. Based on these findings, along with an analysis of the (process-) explanations for this relationship, we introduce a hybrid explanation model that integrates the insights from both perspectives, thus providing a more comprehensive understanding of the mechanisms by which DDII capabilities lead to business value.

Keywords: Business Value, Big Data Analytics, Artificial Intelligence, Hybrid Model

1 Introduction

Creating business value from data analysis has been a prominent topic for research and industry in recent years (Abbasi et al., 2016; Günther et al., 2017; Mikalef and Gupta, 2021). The industry has deployed increasingly sophisticated technologies over time, such as business intelligence, big data analytics, and artificial intelligence, to leverage the inherent value of data through better decision-making and resulting actions (Torres et al., 2018). To specify this paper's scope, we summarize these initiatives – regardless of the respective technology or terminology zeitgeist – as data-driven insight initiatives (DDII). We understand DDII as an organization's effort to analyze data and turn the resulting insights into decisions and actions to create business value. Despite considerable effort and investments in relevant technologies and capabilities, the expected impact of DDII has not materialized to the extent that the hype surrounding these technologies would suggest. A survey of Fortune 1000 companies found that the results of these investments vary widely (Bean, 2017). Some even speak of a modern productivity paradox (Brynjolfsson et al., 2017).

One reason for this phenomenon, which has been much discussed in the literature, is that we do not yet fully understand the mechanisms by which DDII capabilities lead to business value (Grover et al., 2018; Günther et al., 2017; Torres et al., 2018). Accordingly, there is a need for prescriptive knowledge that not only identifies and guides investments in critical capabilities but also explicates how the acquired capabilities impact the value-creation process. Without a precise understanding of how capabilities impact the value-creation process, several concrete problems arise. First, it is difficult to identify potential breaking points in the value-creation process. Second, it is difficult to make targeted investments in specific capabilities because it is not known which capabilities impact different phases of the value-creation process. And third, it is difficult to determine the value of the investments made as long as it is not known what actions the acquired capabilities initiate. Ignoring the need for prescriptive knowledge leads to the risk of wasting investments in failing DDII.

Researches have explored various mediators to better comprehend DDII' value creation mechanisms from a variance perspective (Akter et al., 2019; Ferraris et al., 2019; Mikalef et al., 2020a; Olabode et al., 2022). The variance perspective examines independent variables (e.g., DDII capabilities) that cause changes in dependent variables (e.g., business value) (Webster and Watson, 2002). Because of its underlying causality (if X then Y) and due to the statistical machinery available for this perspective, it is well suited to determine factors that lead to business value and to identify corresponding mediators. Thus, the variance perspective can provide some of the necessary prescriptive knowledge (e.g., in which capabilities to invest). However, to gain further prescriptive knowledge, organizations also need to know how the capabilities they acquire impact the value-creation process. The variance perspective is not well suited for studying end-to-end processes, since the causality on which it is based assumes a direct influence of the independent variable on the dependent variable (Mohr, 1982). Therefore, it "often neglects to 'explain' exactly how or why the predictors and outcomes are related" (Newman and Robey, 1992, p. 250). While most research is conducted from a variance perspective, the process perspective is seldom used, despite some advantages: It is well suited to clarify how variables are related by describing the events that connect them (Mohr, 1982). It also allows exploring how the elements emerge, evolve, and interact with other events over time to produce outcomes. However, given that its underlying causality can lead to spurious relationships (Soh and Markus, 1995), the process view is not well suited to guide capability investment decisions.

Preventing the failure of DDII necessitates prescriptive knowledge from both the variance perspective (in which capabilities to invest) and the process perspective (how acquired capabilities impact the value-creation process). Consequently, we identify the need to integrate these perspectives to advance the research's applicability in practice. Recently, an increasing body of literature has elucidated the added value of employing these two perspectives in tandem (Burton-Jones et al., 2015; Ortiz de Guinea and Webster, 2017). Specifically, Burton-Jones & Mc Lean (2015) suggested that the process perspective can lead to a better understanding of variance relationships. Jewer and Compeau (2022) also demonstrated the use of hybrid models for research by creating a hybrid model based on the IS success model. To overcome treating the process and variance perspectives separately, we aim to develop a hybrid model and specifically ask:

RQ1: What capabilities critical to business value has research identified to date?

RQ2: How do these capabilities impact the value creation process?

To address the research questions, we employ a systematic literature review (Paré et al., 2016). We start with identifying and synthesizing variance theory elements (constructs, relationships, mediators) of the DDII capability – business value relationship and present them using a theory map. Subsequently, we examine the variance explanations provided so far since variance explanations implicitly use process arguments (Ortiz de Guinea and Webster, 2017; van de Ven, 2010) that can be utilized to understand the influence of capabilities on the value-creation process. We synthesize these arguments to better understand the mechanisms by which the capabilities studied within the DDII scope lead to business value. The analysis of these explanations yields several insights, which we present in a hybrid explanation model. The hybrid explanation model supports both practitioners in their pursuit of normative guidance and scholars in the development of new theories.

2 Theoretical Background

2.1 Business value creation in data-driven insight initiatives

Over the past years and decades, research has investigated various technological approaches to leverage the value of data for organizations, driven by the respective technological developments of the time. In the early 2000s, scholars primarily associated business intelligence with structured data analysis, while in the 2010s, big data analytics emerged, enabling the analysis of massive unstructured datasets through affordable storage solutions and enhanced processing capabilities (Delen and Ram, 2018). Advances in artificial intelligence, particularly machine learning, have brought these terms to the forefront of recent debates (Mikalef and Gupta, 2021). As research also discusses additional terms such as business analytics or data analytics, it is becoming increasingly challenging to overview the development of the field. This is also complicated as many terms are used interchangeably in the literature (Holsapple et al., 2014). Additionally, concepts such as business intelligence are defined differently by various scholars (Mortenson et al., 2015). Mortenson et al. (2015) offer two explanations for the similarities of the terms. First, they are all part of a larger movement. Mortenson et al. (2015) label this movement as the dianoetic management paradigm, referring to the development of the last decades in which decisions were increasingly made less based on intuition and more based on data. Second, they all share a similar purpose: Improving business operations and decision-making with information, quantitative analysis, and/or technology. This view is in line with Delen and Zolbanin (2018), who state that the purpose of these technologies is to "employ internal or external, structured or unstructured data for actionable insight" (p. 187). We follow this line of thought and understand DDII as an organization's effort to analyze data and turn the resulting insights into decisions and actions to create business value. To further clarify this definition and establish DDII' scope, we relate it to the information value chain (see Figure 1). The DDII' process flow is as follows: Data is first converted into information and then transformed into knowledge. These process steps constitute the knowledge-building phase, which creates a value potential that is eventually realized in the knowledge-realization phase. In this phase, knowledge is used to make decisions and initiate actions that ultimately lead to business value (Abbasi et al., 2016). We define business value thereby as the organizational performance impacts of DDII at both the intermediate operational and the organizational-wide levels, comprising both efficiency and competitive impacts (adapted from (Melville et al., 2004).

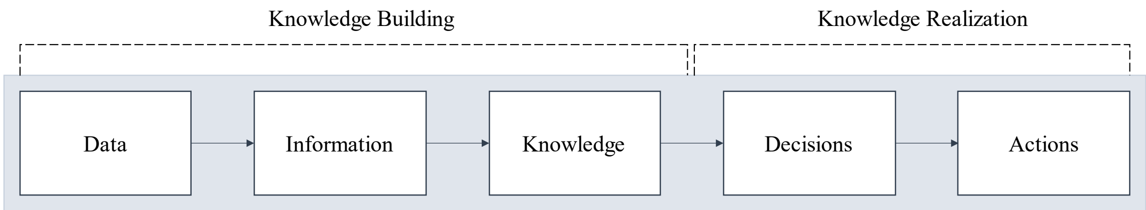

Figure 1. DDII' process (based on the information value chain).

2.2 Integrating the variance and process perspective in hybrid models

Research on DDII business value creation is predominantly conducted from either a variance or process perspective. The variance perspective, which is more prevalent, investigates independent variables that induce changes in dependent variables and is based on the assumption that outcomes will invariably occur if the necessary and sufficient conditions are present, irrespective of the temporal order of these conditions (Mohr, 1982; Ortiz de Guinea and Webster, 2017; Webster and Watson, 2002). This perspective aims to identify "the few critical factors that are necessary and sufficient conditions for the effect" (Poole et al., 2000, p. 33). However, despite its predominance, this approach is limited in that it offers only a snapshot of reality and struggles to explain the why or reasoning behind the relationships of variables, often resorting to 'process thinking' to theoretically justify these relationships (Ortiz de Guinea and Webster, 2017).

Conversely, the process perspective employs events and states to articulate the relationship between variables over time, assuming that outcomes do not necessarily occur even when favorable conditions are present and that the temporal order in which conditions combine is consequential (Mohr, 1982; Ortiz de Guinea and Webster, 2017). It seeks to "focus on critical events and conjunctions of events to explain development and change" (Poole et al., 2000, p. 41), providing a dynamic view of reality where necessary conditions must occur in a specific sequence. This characteristic allows the process perspective to generate "highly satisfying explanations" (Soh and Markus, 1995, p. 30) and is therefore indispensable for understanding the mechanisms and temporal aspects contributing to value creation, as highlighted by Grover et al. (2018) who show how big data analytics capabilities enable multiple value-creation mechanisms affecting various business aspects, and by Seddon et al. (2017) who outline the paths of decisions enabled by business analytics that lead to organizational benefits.

Despite the recognized value of both perspectives, contemporary research has shown a preference for the variance approach, which, despite identifying numerous capabilities and mediators that influence business value creation (see results section), only provides a limited understanding of the prescriptive knowledge needed to understand the mechanisms by which these capabilities translate into business value. Recognizing the complex nature of effective value creation, a hybrid approach that integrates both variance and process perspectives may offer a more comprehensive understanding. Such an approach would align with recent calls in the literature to merge these perspectives and directly address the identified gap by examining the interplay between DDII capabilities and their temporal deployment in the value creation process (Burton-Jones et al., 2015; Ortiz de Guinea and Webster, 2017).

3 Research Method

To lay the foundation for a hybrid explanation model, we conducted a systematic literature review. A systematic literature review is well suited for our paper as it allowed us to identify and conceptually synthesize the variance studies conducted to date on the relationship between DDII capabilities and business value. Drawing on the process of Pare et al. (2016), we describe each phase of the review in detail to support transparency and demonstrate our approach's systematicity.

3.1 Review plan

We employed a search protocol to rigorously plan and document all literature search activities (vom Brocke et al., 2015). In line with Pare et al. (2016), we used the protocol as a living document to record and transparently document changes to the original plan as the review progressed. To answer our first research question, we identified and synthesized the theory elements (concepts, relationships, mediators) of the relationship between DDII capabilities and business value in a theory map. Specifically, we aimed to identify and define the capability elements critical to business value creation studied within the DDII scope. In addition, we analyzed the type of relationship (direct or via mediators) and synthesized and defined these mediators. To answer our second research question, we examined the explanations research has provided so far for the relationship between DDII capabilities and business value. Synthesizing these explanations provided several insights into how capabilities impact the value-creation process, which we present in a hybrid explanation model. We describe the remaining elements of the search protocol in the following sections.

3.2 Literature identification

A critical decision in a systematic literature review is determining its scope, which has implications for all subsequent steps. Our guiding principle is to optimize the balance between sensitivity (a high proportion of relevant studies) and specificity (a low proportion of irrelevant studies) (Petticrew and Roberts, 2006). Since our goal was to find articles that explore the relationship between DDII capabilities and business value, our search term consisted of a logical AND combination of DDII terms[1], capability terms[2] and business value terms[3]:

(“business intelligence” OR “business analytic*” OR “data analytic*” OR “big data” OR “artificial intelligence” OR “machine learning” OR “data-driven”**)**[1] **AND (**“Capability*” OR “asset*” OR “resource”**)**[2] **AND (**“business value” OR “firm performance” OR “organi*ational performance” OR “organi*ational value” OR “organi*ational benefit*” OR “business performance” OR “competitive performance” OR “competitive advantage” OR “process innovation” OR “process performance”**)**[3].

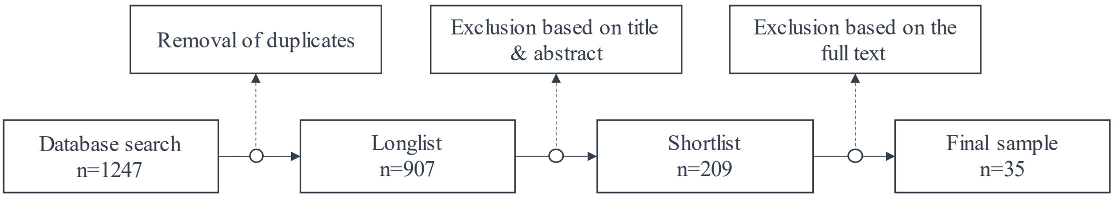

Figure 2. Article screening and selection (adapted from Steininger et al., 2021).

On the one hand, the search terms resulted from the examination of the prior business value research. On the other hand, following the recommendation of vom Brocke et al. (2015), we compared the resulting search terms with the search terms of other reviews (Ain et al., 2019; Eggert and Alberts, 2020; Enholm et al., 2021; Günther et al., 2017; Melville et al., 2004; Mikalef et al., 2018; Schryen, 2013; Trieu, 2017) and adjusted them accordingly. To search the widest possible selection of journals, we conducted a database search in the areas of Information Systems, Information Technology, and Business. The selected databases include Web of Science, Ebsco Host (Business Source Complete & EconLit), ACM, IEEE, Taylor & Francis, and Emerald Insight. To find conference papers, we also searched the AISel database. We searched within the title, abstract, and keywords as far as the databases offered this functionality. After removing 340 duplicates, this approach resulted in a longlist of 907 articles (see Figure 2). We screened the remaining articles based on their titles and abstracts. Using the exclusion criteria (see Table 1) resulted in an initial shortlist of 209 articles. We went through all the full texts for the remaining articles, thereby removing 169 articles. This resulted in a final sample of 35 articles.

Exclusion Criteria	Rationale	Examples of Papers Excluded
The article does not investigate the relationship between DDII capabilities and business value	To ensure relevance to the review’s focus on the relationship between DDII capabilities and business value, articles that do not address this specific relationship will be excluded.	Jöhnk et al., 2021; Reis et al., 2020
The article does not employ a variance approach	To extract implicit process explanations, the review focuses solely on variance articles. The limited number of published process articles will be considered in the discussion to highlight the hybrid explanatory model’s differences from previous models.	Grover et al., 2018; Mikalef et al., 2019; Seddon et al., 2017
The topic doesn’t match the DDII definition	To maintain consistency and clarity in the review, articles that do not align with the definition of DDII will be excluded. This ensures that all included articles are relevant to the topic at hand.	Huang et al., 2018; Irfan and Wang, 2019
The article is mainly technical	The focus of the review is on the business value derived from DDII capabilities, rather than technical aspects of DDII implementation.	Huang et al., 2018; Remita et al., 2017
Books, discussions, reports, non-scholarly work, dissertation, in-progress research, opinion article	The goal of the review is to include only high-quality, peer-reviewed scholarly articles to ensure the credibility and reliability of the evidence being reviewed. Non-scholarly work, in-progress research, etc. may not have undergone rigorous peer review.	Madhala et al., 2022; Reis et al., 2019

Table 1. Exclusion criteria (adapted from Günther et al., 2017).

3.3 Data extraction and analysis

We used a theory extraction worksheet (Okoli, 2019) as a methodological tool to systematically analyze existing literature. This approach allowed for the extraction and categorization of theory elements (concept definitions, mediators, etc.) essential to the development of a theory map that serves to classify and evaluate the findings of prior research on the relationship between capabilities and business value.

To answer RQ1, we first had to identify capabilities (as the independent variable) and the mediators of the theory map from the literature. Toward this goal, we synthesized the capabilities studied within the DDII scope. Capabilities are usually structured hierarchically in research (e.g., divided into first, second, and third-order capabilities). The two most commonly used second-order capability categorizations are the classification into technological, management, and talent capabilities (e.g., Akter et al., 2016; Wamba et al., 2017) and the classification into tangible, intangible, and human resources (e.g., Gupta and George, 2016; Mikalef and Gupta, 2021). As these categorizations are both challenging to reconcile and rooted in more general IS business value research, we utilized our DDII definition to develop a novel categorization. The fundamental approach to ascertain specific capabilities involved disassembling the various capability categorizations found in our sample at the most granular (first-order) level and then reassemble them based on our DDII definition. This process resulted in the identification of specific capabilities pertinent to the knowledge-building and knowledge-realization phases. In addition to DDII capabilities, the theory map also consists of the mediators considered in research to date. We used the theory extraction worksheet to identify the mediators for which empirical support was found.

To answer RQ2, we had to delve deeper into the relationship between the concepts of the theory map. Toward this goal, we extracted all explanations of why DDII capabilities lead to business value. The individual explanations can be single sentences or paragraphs forming a coherent argument. They can refer to why DDII capabilities influence a mediator, why the mediator influences business value, or why DDII capabilities influence business value. To facilitate the analysis of the various explanations, we have converted them into a standardized form. This was necessary since the structure of the argumentation was often non-linear. For example, we converted the sentence: “Consequently, value from a BDAC is a result of improved decision making and repositioning in relation to external needs and opportunities” (Mikalef et al., 2020a, p. 5) into the following form: BDAC → improved decision making & repositioning in relation to external needs and opportunities → value. This procedure resulted in 239 standardized explanations. We decomposed the individual arguments and divided the argument parts into different categories. The DDII capability category explains the impact of the various DDII capabilities on the success of the DDII process. Arguments in the knowledge-building mechanism category explain how and what kind of knowledge is gained from data. Arguments in the value-realization category explain how this knowledge is finally transformed into value via decisions and actions. Classifying the explanations into the described categories and matching the process flow found in the explanations with the DDII process led to several insights. These insights were eventually the basis for the creation of the hybrid explanation model, which helps us to understand how capabilities impact the value-creation process. We present the hybrid model in the results section and address the insights that led to the model in the discussion.

4 Results

The analysis of variance papers studying the relationship between DDII capabilities and business value resulted in a theory map (see Figure 3). It consists of the capabilities found within the DDII scope and business value, and of the relationships between them. The analysis of the explanations for these relationships resulted in a hybrid explanation model (see Figure 4).

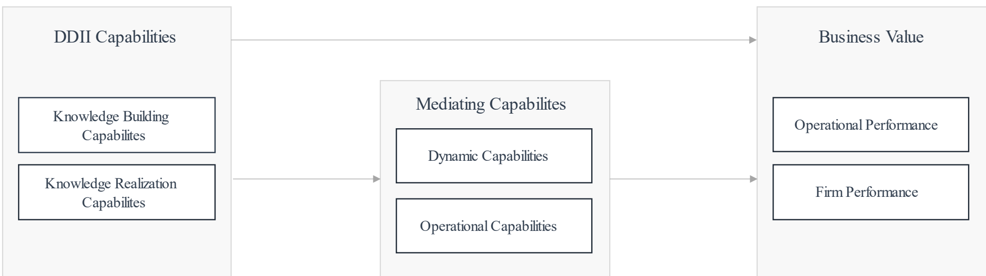

Figure 3. Theory map of the relationship between DDII capabilities and business value.

4.1 DDII capabilities and business value

Following our definition, business value consists of the constructs 'operational performance' and 'firm performance'. The result of the synthesized DDII capabilities is presented in Table 2. It consists of two second-order and eight first-order constructs.

Construct		Definition	Contributing Papers
Knowledge Building Capabilities		Capabilities supporting the transformation of data into knowledge	
	Infrastructure Capability	The ability to deploy IT infrastructure (i.e., platform technology, communication technologies, and software) so that firms can generate, capture and identify data from multiple sources (adapted from Wu et al., 2022)	Akter et al., 2019; Akter et al., 2016; Fosso Wamba and Akter, 2019; Gupta and George, 2016; Kristoffersen et al., 2021; O'Neill and Brabazon, 2019; Torres et al., 2018; Wamba et al., 2017
	Data Governance Capability	The ability to integrate, manage, and pre-process data to form data formats that meet the requirements of architecture and quality for further analysis (adapted from Wu et al., 2022)	Akter et al., 2019; Gupta and George, 2016; Kristoffersen et al., 2021; Mikalef and Gupta, 2021; O'Neill and Brabazon, 2019; Torres et al., 2018
	Analytics Capability	The ability to develop advanced and complex analytics models (e.g., machine learning, cloud computing, distributed computing) to produce information batch-wise, in real-time or near real-time (adapted from Wu et al., 2022)	Akter et al., 2019; Akter et al., 2016; Fosso Wamba and Akter, 2019; Gupta and George, 2016; Kristoffersen et al., 2021; O'Neill and Brabazon, 2019
	Information Processing Capability	The ability to gather, interpret and synthesize information, thus discovering hidden knowledge toward the quality of decision-making (Wu et al., 2022)	Akter et al., 2019; Akter et al., 2016; Fosso Wamba and Akter, 2019; Wamba et al., 2017
	Knowledge Management Capability	The ability to acquire knowledge from information and convert it to be useful for decision-making and action (adapted from Ferraris et al., 2019)	Ferraris et al., 2019; Gupta and George, 2016
Knowledge Realization Capabilities		Capabilities supporting the transformation of knowledge into decisions and actions	
	Data-driven Decision-making Capability	The ability to systematically collect, evaluate, and analyze knowledge gained from analytics to enhance decision-making quality and efficiency (adapted from Chen et al., 2022)	Akter et al., 2016; Chen et al., 2022; Wamba et al., 2017
	Data-driven Culture Capability	The extent to which organizational members are committed to DDII and make decisions based on insights derived from data (adapted from Kristoffersen et al., 2021)	Gupta and George, 2016; Kristoffersen et al., 2021; O'Neill and Brabazon, 2019; Torres et al., 2018
	Change-Management Capability	The ability to minimize friction and inertia associated with a change to enable and pursue the implementation of plans (adapted from Mikalef and Gupta, 2021)	Mikalef and Gupta, 2021

Table 2. DDII capabilities.

4.2 Direct path and mediating capabilities

The relationship between DDII capabilities and business value is addressed diversely in the studies in our sample. Of the 35 articles, 12 consider a direct relationship, 12 discuss both direct and mediated relationships, and 11 solely examine mediated relationships. The synthesized categorization of mediators (see Table 3) draws upon the resource-based view, which posits that an organization comprises various complementary capabilities (Schryen, 2013). Consequently, we aggregated the mediators identified in our sample into corresponding capabilities. For instance, we aggregated the mediators 'agility', 'market responsiveness agility', and 'operational adjustment agility' into a higher-level 'agility' capability. The analysis of the mediators found in our sample, together with the analysis of explanations of why DDII capabilities lead to business value, revealed a distinction between dynamic and operational capabilities. Dynamic capabilities, on the one hand, are directed toward the strategic change of operational capabilities (Steininger et al., 2021). The empirical studies in our sample show that these capabilities positively impact operational capabilities and business value. Operational capabilities, on the other hand, determine how a firm makes its living in the short term (Mikalef et al., 2020a).

Construct	Definition	Contributing Papers
Dynamic Capability	Capabilities directed towards the strategic change of operational capabilities (adapted from Steininger et al., 2021)	Danielsen et al., 2021; Mikalef et al., 2020a; Torres et al., 2018; Wamba et al., 2017
Agility Capability	The ability of a business to renew itself and react quickly when necessary (adapted from Teece et al., 2016)	Rialti et al., 2019; Xie et al., 2022
Creativity Capability	The ability of a firm to create novel and valuable ideas (Ferraris et al., 2019)	Chen et al., 2022; Mikalef and Gupta, 2021
Innovation Capability	The ability to introduce and define innovative ideas and deploy them in designing new products or enhancing the current products (adapted from Ramadan et al., 2020)	Ramadan et al., 2020; Rialti et al., 2019; Zhang et al., 2022
Business Model Capability	The ability to develop an infrastructure strategy of how to create value as well as a value strategy of how to shape competitive advantage (adapted from Song et al., 2022)	Kristoffersen et al., 2021; Olabode et al., 2022; Song et al., 2022
Resource Management Capability	The ability to manage resources efficiently with respect to the use of existing resources and the integration of new resources (adapted from Huang et al., 2022)	Huang et al., 2022; Kristoffersen et al., 2021
Operational Capability	Capabilities through which a firm makes its living in the short term (Mikalef et al., 2020a)	Danielsen et al., 2021
Supply Chain Capability	The ability to identify, utilize, and assimilate internal and external resources in order to enhance the entire supply chain activities (Wu et al., 2006)	Dubey et al., 2019; Fosso Wamba and Akter, 2019; Gu et al., 2021
Marketing Capability	The ability of the firm to serve certain customers based on the collective knowledge, skills, and resources related to market needs (Mikalef et al., 2020a)	Asadi Someh and Shanks, 2015; Mikalef et al., 2020a; Suoniemi et al., 2020
Technological Capability	The ability of a firm to convert inputs into outputs (adapted from Mikalef et al., 2020a)	Mikalef et al., 2020a

Table 3. Mediating capabilities.

4.3 A hybrid explanation model

The articles we examined on the relationship between DDII capabilities and business value provide a variety of explanations as to why this relationship exists. In some cases, these explanations differ considerably as existing models consider a variety of different mediators. The goal of our hybrid explanation model (see Figure 4) is to integrate these explanations from both a variance perspective (see theory map) and a process perspective (see DDII process). The hybrid explanation model consists of three separate processes (knowledge-building, capability-development, and value-realization), the theory map elements (DDII capabilities, mediating capabilities, and business value), and their relationships (effect and process flow). In this way, it represents an organizational DDII perspective and goes beyond a single instantiation of the information value chain in a data science project. The rationale for considering elements of the variance perspective (theory map) and process perspective (DDII process) simultaneously in one model is that the variance articles we consider often implicitly use process logic to explain the relationship between two variance variables (e.g., between DDII capabilities and business value). The hybrid explanation model allows these explanations to be made explicit, representing them with (orange) effect arrows and (black) process arrows.

In the following we explain the flow of the hybrid model. Through investments, knowledge-building capabilities are obtained. This increases the chance that the right projects will be launched at the right time, initiating the knowledge-building process. Knowledge-building capabilities (see Table 2) enable the transformation of data into information and knowledge. At the end of the knowledge-building process, this knowledge enhances mediating capabilities (dynamic or operational). Dynamic capabilities are improved by identifying opportunities and threats (Mikalef et al., 2020a; Xie et al., 2022; Zhang et al., 2022). Additionally, knowledge enhances the organization's ability to seize opportunities by providing more decision-making options and innovative ideas (Kristoffersen et al., 2021; Mikalef et al., 2020a; Ramadan et al., 2020). Operational capabilities are improved, for example, by increasing knowledge of customer behavior to enhance marketing capabilities (Asadi Someh and Shanks, 2015; Mikalef et al., 2020a), by increasing knowledge of supplier spending patterns to enhance supply chain capabilities (Dubey et al., 2019; Gu et al., 2021), or by increasing knowledge of internal operational inefficiencies and deviations to enhance technological capabilities (Mikalef et al., 2020a). Note that the DDII process flow was interrupted by the effect of knowledge on mediating capabilities.

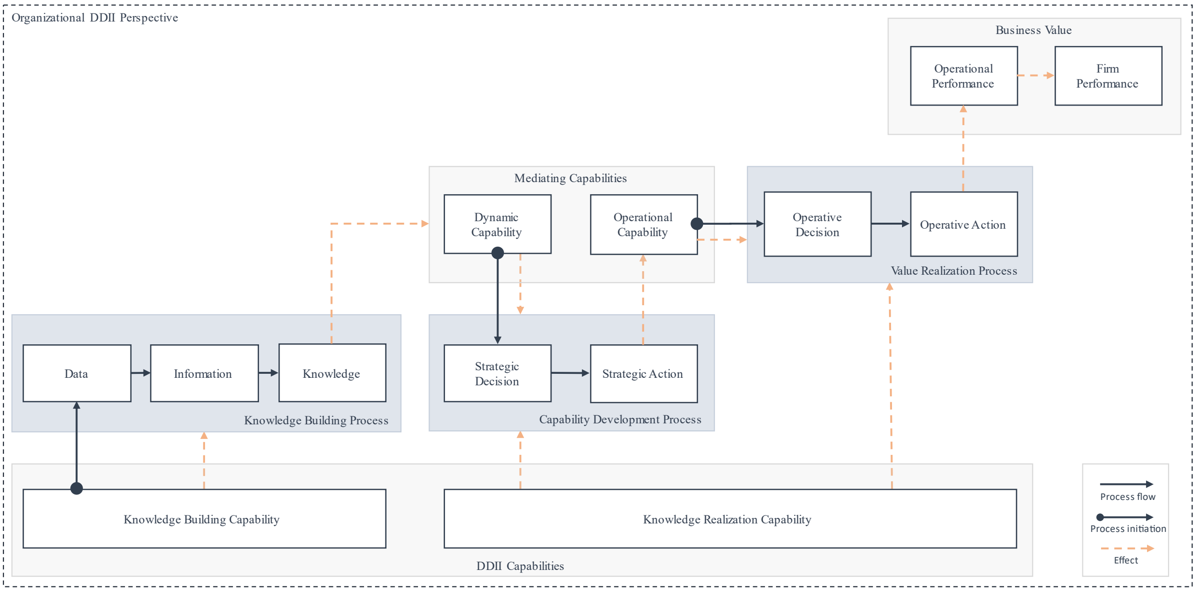

Figure 4. Hybrid explanation model.

Dynamic capabilities improved by knowledge increase the chance that this knowledge will be used for strategic decisions, which initiates the capability-development process. Dynamic capabilities (see Table 3), along with knowledge-realization capabilities (see Table 2), enable the transformation of strategic decisions into strategic actions. At the end of the capability-development process, the executed strategic action improves operational capabilities, by enhancing technical skills needed to develop new products and services (Zhang et al., 2022), aligning and reconfiguring internal processes and routines (Ramadan et al., 2020; Torres et al., 2018) and improving the rate and efficiency of resource transformation and integration (Huang et al., 2022; Kristoffersen et al., 2021).

Operational capabilities, enhanced by knowledge, increase the chance that this knowledge will be used for operative decisions, initiating the value-realization process. It is important to note that knowledge impacts operational capabilities directly through (operational) knowledge and indirectly through (strategic) knowledge influence on the capability-development process and the resulting strategic action. Operational capabilities (see Table 3), along with knowledge-realization capabilities (see Table 2), enable the transformation of operational decisions into operational actions. At the end of the value-realization process, the operational action leads to improved operational performance. Examples of these actions include person-specific, context-specific, and location-specific offerings and communication, faster and cheaper experiments with the marketing mix (Suoniemi et al., 2020), or the prioritization of target customers and segments (Mikalef et al., 2020a). In the supply chain, distribution networks can be created and optimized (Gu et al., 2021), and inputs can be effectively and efficiently transformed into outputs (Mikalef et al., 2020a). The various actions thus impact several operational performance variables such as process performance, product and service improvements, or customer satisfaction. As there are numerous examples of operational performance improving firm performance in the explanations we analyzed, and this relationship is well established in IS business value research (Melville et al., 2004; Schryen, 2013), we also included this effect in our model.

5 Discussion

The hybrid explanation model has yielded several significant insights that help better understand the mechanisms by which DDII capabilities lead to business value. All insights have in common that they are based on the combined consideration of the variance and process perspective. This allowed us to analyze the impact of capabilities on processes and of process outputs on variance elements. Our analysis of these insights also highlighted several research gaps that merit further exploration. To make the rather abstract discussion more tangible, in each section we describe examples of how our hybrid model can be applied in real-world scenarios.

5.1 The role of mediating capabilities as a breeding ground

During the analysis of the explanations, it became apparent that the studies examined do not always make a clear distinction between the reason for improving a capability and the effect of improving a capability. Many explanations for the relationship between DDII capabilities and mediating capabilities do not give a reason for this relationship but describe the effects of operational or dynamic capabilities that are improved by DDII capabilities. For example, big data-driven insights in marketing lead to person-specific, context-specific, and location-specific offers and communication (Suoniemi et al., 2020). These improvements, however, represent the effect of an improved operational marketing capability, not the improvement in the capability itself. The improvement in the operational marketing capability results from the knowledge gained in the knowledge-building process. This distinction is important as it clarifies the role of mediating capabilities in extracting business value from data.

In the discourse on mediating capabilities within the context of variance articles, a notable inconsistency arises. Research such as that by Danielsen (2021) and Mikalef et al. (2020a) diverges in conceptualizing the influence of dynamic and operational capabilities on competitive performance. This disparity underscores a broader issue: the ambiguous role of knowledge in shaping these mediators. Current process models, including those by Grover et al. (2018) and Hirschlein and Dremel (2021), largely overlook the significance of mediators. Even in models such as Seddon et al. (2017), which include organizational resources, there is a lack of explicit clarification regarding the direct influence of knowledge on these resources.

By integrating insights from both variance and process models, our hybrid perspective clarifies the role of mediating capabilities in the dynamic interplay between DDII capabilities and business value, especially highlighting the effect of knowledge on these capabilities. Mediating capabilities can be interpreted as a breeding ground for value, which is enriched through the value potential created by knowledge gained in the knowledge-building process. The value potential must be leveraged through its use in the capability development and value realization processes. The underlying logic is that value can only be created if it is leveraged through subsequent action. Thus, improving mediating capabilities through knowledge only adds value if the subsequent processes are initiated. Specifically, the knowledge-enriched mediating capabilities (dynamic and operational) must initiate the subsequent capability development and value realization processes. However, this is not an automatism, so that a potential breaking point in the value creation process arises. The emergence of a breaking point cannot be understood with a pure variance approach, since the variance perspective is based on a linear the more the better model. With this approach, it is very well possible to determine capabilities that have the greatest possible influence on mediating capabilities or business value. However, the action-guiding connection to the sequential activities is missing, so that potential breaking points in the creation of business value do not become apparent.

Practical example: Consider a scenario where a company's CIO aims to harness data analytics for improved product development. Despite having advanced analytics tools (knowledge-building capabilities), the expected innovation surge is not materializing. Utilizing our hybrid model, the CIO identifies a lack of dynamic capabilities, particularly in agile decision-making and resource reallocation, as a critical mediating capability acting as a 'breeding ground' for business value. By focusing on enhancing these dynamic capabilities, the company can better translate analytics insights into actionable changes in product development.

Path for future research: Understanding breaking points in the value creation process is critical for organizations, as it can help them develop strategies to overcome challenges and maximize value creation. While we have identified where possible breaking points exist in the value creation process, the question remains as to what barriers prevent the initiation of the subsequent process and how these can be overcome through successful process initiation. In this context, it is also crucial to understand how the initiation of processes is related to the investment in DDII. While the relationship between the investment in a capability and the initiation of processes seems to be more direct for the knowledge-building process, this is not the case for the capability development and value realization processes. For these processes in particular, the question arises as to why the knowledge acquired in the knowledge-building process is sometimes used to initiate a process and why this is not the case elsewhere.

5.2 The first split of the DDII' process: knowledge building vs. realization

The analysis of the explanations showed that the knowledge-building phase and the knowledge-realization phase of the DDII process require capabilities that are clearly distinguishable. This distinction is important to ensure that the necessary capabilities are available to the various processes at the right time. Instead of investing in DDII capabilities in general and expecting them to solve existing problems, the distinction enables a better understanding of problems and, as a result, more targeted investments.

The existing classification of capabilities in variance literature into categories such as technology, management, and talent, or tangible, intangible, and human resources, presents a notable conceptual gap. This classification, employed in studies like Akter et al. (2016) and Gupta and George (2016), does not adequately distinguish between the specific capabilities required for different phases of the value-creation process. Particularly, it does not address the distinction between knowledge-building and knowledge-realization capabilities. In addition, knowledge-realization capabilities are less represented than knowledge-building capabilities and the individual elements (e.g., building a data-driven culture or change management) are more dispersed and less consistent in previous research. Previous process models also do not consider this distinction (Grover et al., 2018; Seddon et al., 2017).

By splitting DDII capabilities into knowledge-building and knowledge-realization capabilities, we extend the previous process and variance research in this important aspect and demonstrate again the advantage of a hybrid perspective. Our model reveals the effect of the various capabilities on the respective process phases. In particular, we emphasize that it is not enough to improve operational or dynamic capabilities through knowledge. From an organizational DDII perspective, additional knowledge-realization capabilities are needed, such as building a data-driven culture or change management capabilities, so that initial investments actually translate into business value.

Practical Example: Continuing the practical example, under the CIO's guidance, the company begins integrating enhanced dynamic capabilities, focusing on product development. Despite this integration, the expected market impact remains below forecasts. This scenario underscores a gap not in generating insights, but in actualizing these insights into strategic actions that redefine the company's direction. The company then realizes the importance of reinforcing knowledge-realization capabilities, particularly through solidifying a data-driven culture and advancing change management practices. These steps ensure insights from data analytics are actively transformed into strategic actions, steering the company towards new opportunities and innovative solutions.

Path for future research: Understanding and effectively managing DDII capabilities in both the knowledge-building and knowledge-realization phases are critical for organizations to fully realize the value potential of their data. While our discussion has highlighted the distinct impacts of knowledge-building and knowledge-realization capabilities on their respective process phases, the precise mechanisms underlying these capabilities remain to be fully elucidated. Specifically, a key question for future research is how DDII capabilities influence these processes. Given that both the capability-development and value-realization processes are impacted by knowledge-realization capabilities in conjunction with mediating capabilities, it is essential to understand how these capabilities interact and contribute to the successful completion of the processes.

5.3 The second split of the DDII' process: strategic vs. operative actions

During the analysis of the explanation, it became noticeable that the explanations often refer to strategic ("change the business") decisions and actions or to operational ("run the business") decisions and actions without this difference being explicitly addressed by the authors. This distinction is important since different capabilities enable these two processes, and the respective actions have different effects. Due to the different effects of the respective processes, these should be measured differently to render the realization of value sufficiently transparent.

The prevailing research in the realm of variance articles, while extensive, exhibits a significant conceptual limitation: it predominantly focuses on the impact of dynamic and operational capabilities on firm performance without sufficiently unpacking the underlying mechanisms of value creation. This prevalent approach, despite its merits, often glosses over the nuanced interplay between these capabilities and the actual processes of capability development and value realization. The critical issue here is not just the identification of the capabilities themselves but, more importantly, understanding how these capabilities translate into tangible organizational outcomes. Exceptions in the literature, such as the works of Fink et al. (2017) and Bordeleau et al. (2020), which attempt to differentiate between operational and strategic business values, and Mikalef et al. (2020a), which explores the direct impacts of dynamic capabilities, signify an awareness of this gap. However, these studies are still constrained by a variance-focused lens, which limits their ability to fully capture the complexity of the value creation process. The deficiencies of the existing research are further highlighted by models like Seddon's (2017), which, while distinguishing between different types of organizational actions, do not fully articulate the varied effects of mediating capabilities.

This also highlights the advantage of considering the variance and process perspectives together in one model. We can clearly distinguish through the hybrid model the effects of mediating capabilities on different processes. Dynamic capabilities influence the capability-development process, while operational capabilities impact the value-realization process. Moreover, the impact of the different actions of these processes becomes evident through a hybrid model. Strategic actions in the capability-development process enhance operational capabilities, and operative actions in the value-realization process improve operational performance. This further indicates that the value potential gained in the knowledge-building process and incorporated into the breeding ground has different effects and must be measured differently depending on whether dynamic or operational capabilities are improved.

Practical Example: After implementing the strategies outlined in sections 5.1 and 5.2, the CIO of the company takes a further step to distinguish between strategic and operational actions. Acknowledging that these require different capabilities, the CIO institutes a clear framework to evaluate their distinct impacts on the company's performance. Strategic actions, such as the introduction of new data analytics tools, are measured for their long-term impact on product innovation and market positioning. In contrast, operational actions, like the application of these tools in daily product development tasks, are assessed for immediate efficiency and customer satisfaction improvements. This approach ensures that the value generated from both types of actions is correctly understood and quantified.

Path for future research: Recognizing the distinction between strategic and operational actions and their effects is critical for organizations to effectively manage and develop their capabilities. Although our work has established the importance of distinguishing between strategic and operational actions, more research is needed to explore the nuances of their interrelationships and impact on value creation. Future studies should explore how strategic and operative actions affect the initiation of the capability-development and value-realization processes and investigate the extent to which the effects of the capability-development and value-realization processes need to be measured differently.

6 Conclusion

Research on creating business value through data analysis is conducted under various terms, such as business intelligence and big data analytics. Based on the information value chain, we developed a definition of data-driven insight initiatives (DDII) that focuses on the common underlying purpose of these technologies: Analyze data and turn the resulting insights into decisions and actions to create business value. Building on this, we conducted a literature review to synthesize previously studied DDII capabilities and recategorized them based on our DDII definition. We also synthesized the mediators of the relationship between DDII capabilities and business value and created a theory map of this relationship. In addition, we analyzed the explanations for this relationship and developed a hybrid explanation model. This model integrates the discovered explanations, thereby shedding light on the mechanism through which DDII capabilities lead to business value and detailing the role of mediating capabilities. Finally, we identify key areas and possible approaches for future research.

To ensure rigorous validation of our hybrid model, future research should directly address the distinctions and interactions highlighted in our discussion, particularly between knowledge-building and knowledge-realization capabilities and their impact on business value creation. Empirical testing could include deploying case study methodologies to observe how organizations navigate the transition between these two phases of DDII or employing longitudinal studies to track the evolution and effects of implementing strategic versus operational actions as guided by the model. Although we conducted the review carefully, three limitations should be mentioned. First, our model considers only the process and variance perspectives. While these two perspectives make up most of the DDII business value research, there are also other approaches (e.g., systems perspective and configurational perspective). Second, we have placed a strong emphasis on the RBV by examining the relationship between DDII capabilities and business value. We acknowledge that there are other important theory-based perspectives on the value creation of DDII. And third, the methodological approach of our literature review is not without limitations. In particular, our findings are limited by the databases searched and search terms used. Although we tried to integrate as many databases as possible, studies from psychology or sociology could provide further insights.

Despite these limitations, this study makes several theoretical contributions to the business value literature of DDII. First, we develop a capability categorization that is adapted to the characteristics of DDII. This allows us to obtain a clear picture of the capabilities that have been researched to date, thus answering our first research question. In doing so, we have revealed that knowledge-realization capabilities have been less considered in research, which presents an interesting opportunity for further research. Second, we respond to Mikalef et al.'s (2020b) and Trieu's (2017) call to identify the mediators through which DDII leads to business value. Their large number makes it difficult for researchers to keep track of the mediators already studied. By classifying the found mediators into dynamic and operational capabilities and stating contributing authors, we provide a structure upon which future research can build. Third, we present a hybrid explanation model that synthesizes the various explanations of how DDII capabilities lead to business value, thus answering our second research question. In doing so, we approached business value research in a new way. We consider this methodological approach a promising tool for DDII and, more generally, for IS business value research. Since the variance perspective can only explain to a limited extent why, for example, DDII capabilities and business value are related, our approach can make the implicitly given process explanations explicit so that an overall explanation for this relationship emerges.

In addition to its theoretical contributions, our model provides three actionable insights for organizations. First, it illustrates why expected outcomes may not always be achieved by identifying potential causes of DDII failure. We highlight several possible breaking points in the value chain and emphasize the importance of process initiation. Second, our model helps to target investments more effectively. In particular, the separation into knowledge-building and knowledge-realization capabilities can be used to review an organization's investment to determine whether they support DDII from start to end. And third, the explanations provide a theoretical but actionable basis for identifying and addressing problems and opportunities within the organization. In conclusion, our research not only advances the understanding of DDII and its value-creation mechanisms but also provides prescriptive knowledge that enables organizations to harness the potential of data-driven insights more effectively.

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