Realization of Data-Driven Business Models in Incumbent Companies

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Rahmenpapier: Realization of Data-Driven Business Models in Incumbent Companies

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Abstract

Data as a business fundament has become an essential element for company strategy, operations, and decisions. Originated in the digital and technology industry of Silicon Valley, data monetization is currently a topic for many industries to stay competitive in the market. In recent years, researchers have investigated manifold approaches to understanding data-driven businesses. Data monetization is a complex field, so data-driven business models (DDBMs) have become an important ideation tool for business research and managers. While the focus of recent research was on the design of DDBMs, research is still struggling to understand the challenges and strategies for realizing DDBMs. Current research has not yet investigated the realization of DDBM, although it is a phenomenon of increasing importance for practice.

To improve the understanding and knowledge in this research field, this work seeks to advance the knowledge about (1) the existing connection between DDBM literature and the realization of business models in general; (2) the understanding of periods for the realization of DDBM cases in incumbent companies; (3) the identification of required resources and capabilities through the DDBM realization (DDBMR) process; (4) the development of a DDBM realization tool to support the execution in practice; and (5) the utilization of data-driven business ventures (DDBV) for realizing DDBMs in incumbent companies.

To advance knowledge about DDBMR, this study applied a mixed-method approach. This work draws upon a systematic literature review, qualitative empirical research, and a design science research (DSR) approach. A systematic literature search was applied to summarize existing knowledge from research about DDBMs and business model realization. This review provides the foundation for planning and conducting qualitative semi-structured interviews with multiple DDBM experts. Through qualitative content analysis and open coding, these experts provided knowledge into how companies execute DDBM cases in practice and identified required periods, capabilities, and resources. To provide an artifact supporting DDBM realization, this work developed the "DDBM realization board" in two design iterations following the DSR process and principles.

This work provides multiple contributions to theory and practice. Previous studies have revealed a strong focus on the ideation, development, and strategies of DDBMs compared with the thesis at hand, which concentrates on the implementation and realization of DDBMs. The results of the qualitative-empirical study provide an improved understanding of the required periods, resources, and capabilities through the DDBM realization process. Furthermore, this work linked the research field of DDBM to the field of business model realization and digital

ventures. The identified DDBM realization periods, capabilities, and resources improve the understanding of the iterative realization process of DDBMs. The “DDBM realization board” designed in this thesis adds a useful tool for DDBMR validation, and DDBVs are a data-driven enhancement of digital venture research. For practice, the results offer managers and companies a better understanding of how the DDBM realization process is conducted in other companies. Current DDBM projects are executed mostly under high uncertainty, and the identified challenges and enablers will help make the realization more structured and problem-focused. The “DDBM realization board” will help companies through the realization process and validate its progress. The identified activities and capabilities required for DDBVs will help managers construct the right organizational forms in incumbent companies to realize DDBMs.

This thesis is not without limitations. With the regional focus of experts and companies in Germany, it might bear cultural or region-specific limitations. For further studies, it would be valuable to examine whether different cultural settings lead to different results. The interviewed experts were mostly from the operational rather than the higher company management levels. For further research, it would be valuable to connect experts from different hierarchical levels within one company to develop a richer picture of the DDBM strategy and execution. Moreover, it would be beneficial to construct a quantitative research design to enable a number-driven perspective on DDBMR and its influence on company performance.

Future research should focus on three research streams. First focus should be on an agile-oriented approach to DDBMR cases rather than on a traditional waterfall-like project execution of DDBMR cases. For this reason, this thesis recommends making a stronger connection between DDBMs and research on digital entrepreneurship and agile software development. The identified DDBMR periods offer a first approach to how these elements fit together, but future research could take a closer look at individual DDBM realization trajectories over time. The second research stream that should be developed is the concept of DDBVs. Digital ventures are a construct that has already been established in research. DDBV can be the right construct for research to understand how incumbent companies realize DDBM ideas. Third, it would be an important next step to focus on single-company case studies from practice in which the developed ideas, concepts, and tools are used. The results of this study were collected from multiple companies and experts with different levels of experience. Observation of a complete DDBMR case from start to market launch would provide an additional fine-grained understanding of DDBMR.

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List of Abbreviations

BDA	Big Data Analytics
BM	Business Model
BMR	Business Model Realization
B2B	Business-to-Business
B2C	Business-to-Consumer
B2G	Business-to-Government
DBM	Digital Business Model
DDBM	Data-Driven Business Model
DDBMR	Data-Driven Business Model Realization
DDBV	Data-Driven Business Venture
DSR	Design Science Research
GDPR	General Data Privacy Regulation
MMP	Minimum Marketable Product
MMV	Minimum Marketable Venture
MVP	Minimum Viable Product
MVV	Minimum Viable Venture
RBV	Resource-Based View
RG	Research Goal
RQ	Research Question

1 Introduction

1.1 Motivation

Over the last decades, the use of data in business strategy, operations, and processes has become an increasingly essential asset for companies in many industries. With a view of the fast scalability of modern data-based Internet and digital business models from Silicon Valley tech companies, incumbent companies from traditional industries such as engineering, retail, energy, or transport also want to benefit from these valuable data assets for business success. Topics such as “big data,” “data monetization,” or “data science” have become very popular in computer science and information systems literature and led to an increasing number of publications (Davenport and Patil 2012; Lavalle et al. 2011; Najjar and Kettinger 2014). “Rushing for gold” or “data as the new oil” were expressions used in previous research papers in the context of creating value from big data (Günther, Hosein, et al. 2017; Hartmann et al. 2016).

An important action to create this value for a company is to establish the right data analytics capabilities, enabling the processing of all these big data sources and entries (Anand et al. 2016a; Chen et al. 2012). Research on big data and data analytics has improved by searching for the right capabilities for data monetization (Günther, Mehrizi, et al. 2017; Loebbecke and Picot 2015; Mikalef et al. 2018). On the one hand, understanding of the required technical infrastructure has improved. On the other hand, research has recognized the need for a strategy and a plan for data monetization (Baesens et al. 2016; Mikalef et al. 2017; Woerner and Wixom 2015). However, researchers and business leaders are still struggling to overcome the challenge of realizing the promised benefits (Davenport and Malone 2021; Dremel et al. 2020; Klee et al. 2021). In particular, incumbent companies struggle with the challenges of establishing a comprehensive data-driven business strategy.

A starting point for understanding the development and realization of data-driven business strategies was set by Hartmann et al. (2016), who highlighted the role of start-ups in the development of data-driven business models (DDBMs). On the basis of the ideas of multiple traditional business model frameworks as an important element in fostering a business strategy, Hartmann et al. developed the DDBM framework (Chesbrough and Rosenbloom 2002; Johnson et al. 2008; Osterwalder and Pigneur 2010). This framework was used to analyze 100 existing data-driven startup companies and to identify DDBM clusters. The previous studies were a starting point to view data as an important element of business models, but they also increased the awareness that a DDBM must be designed with elements different from traditional business approaches. The development of a DDBM is a complex task, especially when conducted by a firm in a traditional industry with a long-established business focus, in contrast to a startup with excellent data analytics and software technology know-how.

Several researchers have followed the perspective of DDBMs and evolved the approach used by Hartmann et al. to develop tools for DDBM ideation (Brownlow et al. 2015; Bulger et al. 2014; Hartmann et al. 2016). On the basis of this perspective, multiple case studies focused on how companies innovate and develop DDBMs in their incumbent organizations were conducted. Chen et al. (2017) described how the German aviation company Lufthansa tried to modernize its business model with the support of big data. The researchers analyzed and presented multiple use cases for data in the business processes and delivered the first design principles, which are required for successful development of a DDBM. Alfaro et al. (2019) described use cases based on multiple data monetization projects of the Spanish bank BBVA. The results provided a wide knowledge about the various ideas for DDBMs in a company and about the big challenges that occur, especially in a very regulated banking industry.

However, these studies mostly focused on the ideation phase of the DDBM process and did not consider the challenges and tactics involved in the realization process. It is important to have the right tools to develop DDBM ideas, but it is much more important to be able to execute these ideas. Otherwise, these ideas are not valuable and cannot support company data-driven revenue goals. Studies on DDBM realization (DDBMR) are scarce and inadequate to provide an understanding of how companies realize their DDBM ideas. To stay competitive in the market, incumbent companies need the appropriate approach, resources, and capabilities to successfully complete the DDBMR endeavor. Especially at the operational level, which means how DDBM cases are executed in project teams, valuable insights are missing.

Previous research on business models have presented the first approaches for structured realization, but most of them did not work with a DDBMR focus or concentrate mainly on ideation (Fichman et al. 2014; Geissdoerfer et al. 2016; de Reuver et al. 2013). Najjar and Kettinger (2014) described the first structured approach to a data monetization journey from retail with the help of multiple capabilities. The journey reflects a very good first idea about the required steps and elements but remains on a very high and abstract level. Hunke et al. (2017) developed a process model for DDBM innovation and identified many important elements through the realization process. However, a concrete understanding of how organizations execute these DDBM elements through coordinated activities is lacking.

Deeper examination of previous research has clarified that DDBMs are an important element of the digital innovation and transformation initiatives of incumbent companies. For this, it is important to connect DDBM research with knowledge of digital business models and venture development. Many elements of the realization of digital ventures can be adopted in DDBMR because the requirements for digital products, technologies, and operations are similar to those for DDBMs (Huang et al. 2017; Lehmann and Recker 2022; Nambisan and Baron 2019). Data-driven business ventures (DDBVs) are an important element for successful DDBMR in incumbent companies. Previous publications have not built this connection. However, DDBVs are an important element of practice that clearly needs more attention in further research.

A review of the existing literature revealed a research gap. Previous research has mostly focused on the ideation of DDBMs; however, the realization of these DDBMs in practice is not yet well understood. Generating ideas for DDBMs as a concept is only the first step in the complex field of DDBMR. Only if a company can execute their DDBMs in their organization will it add value to them. Previous research has not provided this knowledge. Research must shift its focus from DDBM ideation to a more comprehensive DDBMR. Motivated by these research gaps, this thesis aimed to examine how incumbent companies realize their DDBMs in practice and presents structured guidance for researchers and practitioners for successfully executing DDBMR cases and ventures.

1.2 Problem Statement and Research Goals

Previous research has shown that an understanding of the ideation of DDBMs already exists, but it does not cover how companies and managers execute these ideas in their organizations (Bulger et al. 2014; Dehnert et al. 2021; Wiener et al. 2020). The authors refer to it as big data business, data monetization, or DDBMs but have been mostly investigating different approaches to generate ideas for data-driven products or services, which can be offered to customers, or to optimize the company processes. In particular, incumbent companies are struggling with the topic of monetizing data because digital technologies and data analytics are mostly not part of their traditional business models and organizations (Metzler and Muntermann 2020; Sebastian et al. 2017; Svahn et al. 2017). However, to stay competitive in the market, they are driven to generate new ideas for new data-driven income streams, products, and business models.

Multiple frameworks for DDBM ideation have been developed to provide supporting tools for the DDBM design phase based on business model canvas philosophies (Fruhwirth et al. 2020; Hartmann et al. 2016; Kühne and Böhmann 2019). These tools are important for identifying the basic elements of a DDBM and for making a first short validation of a company's ability to develop DDBM ideas. However, DDBM ideation is only a very small step in the complex process of implementing these ideas in companies. Case studies from practice help understand the complexity and manifold opportunities of incumbent companies to monetize data (Alfaro et al. 2019; Chen, Kazman, Schütz, et al. 2017). However, Chen et al. (2017) also addressed the big "deployment gap" between the literature and practical execution. The literature review of Wiener et al. (2020) revealed the requirement to understand potential deployment drivers for realization. Researchers must understand which capabilities, resources, and approaches are required to transform DDBM ideas in practice. This includes a comprehensive overview of the required periods, tasks, and actions. This also requires tools to help researchers and managers understand DDBMR through execution in the incumbent organization.

To develop an improved understanding of DDBMR, this thesis followed five research goals (RG):

RG_1: Identify knowledge about DDBMR in existing literature

As mentioned earlier, previous studies have mostly referred to the ideation of DDBMs but have been less focused on realization. Nevertheless, it is important to understand the existing elements and approaches to realizing DDBM from the literature. Parts of the DDBM ideation literature are also important in the more complex DDBMR process (Anand et al. 2016b; Najjar and Kettinger 2014). Moreover, results from the traditional business model literature, which focuses on business model realization (BMR), provide important concepts for this work (Frishammar and Parida 2019; de Reuver et al. 2013). RG_1 will help to understand existing research knowledge and improve the empirical research design and interview quality of subsequent studies. It also enables the additional validation of the identified research gap.

RG_2: Understand how incumbent companies realize DDBMs and compare it to recent research

On the basis of the literature, this thesis seeks to reveal how incumbent companies realize their DDBMs in practice. Previous studies have tried to explain this by constructing process-oriented execution models or by explaining how different data monetization approaches function in companies (Alfaro et al. 2019; Hunke et al. 2017). These learnings are important but do not help to increase the understanding of how people from an operational level execute DDBMs in their project teams. The aim of this research was to improve this understanding by asking the right questions to real-life DDBMR experts. By connecting recent DDBM research with insights from experts, this thesis will provide a valuable impact for theory and practice. RG_2 will help to emphasize the actions of DDBMR and enhance the existing knowledge for further research.

RG$_3$: Identify challenges and enablers of DDBMR in the execution process

Given the knowledge of how companies realize DDBMs, an understanding of which challenges and enablers influence the realization process is needed. Multiple resources (tangible, intangible, and human skills), capabilities, and actions are required to execute a valuable DDBMR approach. Previous DDBM research has barely focused on this topic, describing multiple required elements and the challenges in developing a DDBM but not which resources are required within the realization periods (Ermakova et al. 2021; Jensen et al. 2019). To identify these resources, research connected big data and the resource-based view (RBV) in the research field of big data analytics (BDA) to measure firm performance (Gupta and George 2016; Mikalef et al. 2020; Wamba et al. 2017). With the help of the RBV and by following RG$_3$, this study identified relevant DDBMR challenges and enablers in the execution process.

RG$_4$: Acquire design knowledge for a guidance tool within the DDBMR process

As previous research has focused on the design and ideation of DDBMs, the developed DDBM frameworks offer guidance through the ideation process and lead people to structure ideas in a useful way (Brownlow et al. 2015; Fruhwirth et al. 2020; Kühne and Böhmann 2019). Owing to the missing focus on DDBMR, research does not offer structured tools that support key decision makers in DDBMR cases. The realization of a DDBM is a very complex task and requires multiple validation steps for adjustments and improvements through execution. Previous approaches described in the literature can help fix this, but most of them do not work fully in the context of DDBMR (Dellermann et al. 2019; Linde et al. 2021). On the basis of the design science research (DSR) methodology of Peffers et al. (2007), the goal is to build such a validation tool, supporting research and companies in making better decisions during their DDBMR cases. Companies with little technical or digital background will hugely benefit from such a tool.

RG$_5$: Improve the understanding of how digital ventures support DDBMR in incumbent companies

Previous research goals have focused on the relationship of practice to previous DDBM research, the identification of required DDBMR periods/resources, and the development of a helpful realization tool for researchers and companies. An open question remains: Which entity should incumbent companies choose to realize their DDBMs? However, the missing experience and organizational ability to execute DDBM cases in existing company structures is a big challenge for incumbent companies. This is not a specific problem of DDBMR but is also an issue in the realization of digital business models and ventures with a strong connection to DDBMR.

To realize digital business models, companies can create digital ventures as units where digital experts can work independently from traditional cultures, software, or structures (Berger et al. 2021; Lehmann and Recker 2022; Nambisan 2017). These ideas of digital ventures have been adopted for DDBV. With DDBVs, incumbent companies have a scalable unit that can be used to execute DDBM ideas independently from the incumbent company industry background. DDBVs are an important starting point for further research, especially by connecting them more to digital ventures and business research. For practice, this can be evolved into a complete step-by-step guidance on how to realize a DDBM in their organizations.

1.3 Research Questions

To achieve the research goals ($RG_{1–5}$), this thesis formulated multiple research questions ($RQ_{1–5}$), which provide guidance through the research process. DDBMR is a complex and still not well-researched topic. For better knowledge and to achieve the RGs, this thesis is divided into multiple articles to understand the current research literature status; obtain information from DDBMR experts and compare it to recent research; identify resources, challenges, and enablers for DDBMR; create a DDBMR tool to support and validate the realization process; and connect DDBMR to digital ventures to construct DDBVs. Each publication advances knowledge to answer the following RQs and applies the right methods to obtain useful understandings.
As mentioned previously, RG_1 is to understand the existing knowledge about DDBMR in the current literature. On the one hand, this study can draw on the required activities for DDBMR that have already been identified in previous publications. On the other hand, it should help to construct a first systematic literature-based approach with the phases and activities of how companies realize a DDBM. Hence, RQ_1 was formulated as follows:

RQ_1: Which activities are required to realize a DDBM, and how can they be integrated and structured in a systematic approach?

To summarize the existing knowledge from previous literature, a two-part systematic literature review was conducted in the research areas of DDBMs and BMR. The connection between these two research areas should lead to a comprehensive overview of the current knowledge about DDBMR in research and achieve RG_1.
It is important to understand the current state of research before conducting studies to advance knowledge. As a next step in this research, a study focused on practical DDBMR experiences from incumbent companies and their responsible working experts was conducted. These insights are important to achieve RG_2. Thus, RQ_2 was divided into three parts. First, existing

DDBMR cases in incumbent companies were summarized ($RQ_{2.1}$). Second, how companies structure this process was determined ($RQ_{2.2}$). Third, the differences between the results from practice and those in the literature were identified ($RQ_{2.3}$).

$RQ_{2.1}$: Which DDBMR cases are currently realized by incumbent companies and which types of DDBMR exist?

$RQ_{2.2}$: How is the process of DDBMR by incumbent companies structured?

$RQ_{2.3}$: Which differences can be observed between the process of DDBMR in the literature and in the cases from our study?

To answer these RQs, an empirical qualitative study based on data from semi-structured interviews was conducted. This research design allowed speaking with multiple experts from practice to identify the required periods and actions through DDBMR. By comparing the findings with those reported in the existing DDBM literature, more open-ended questions and understandings could be identified.

The identification of DDBMR cases and periods provided a better understanding of the structured DDBMR process. However, to understand what companies explicitly need to obtain the right DDBMR capabilities, an analysis was performed to identify the resources that enabled the companies to realize their DDBMs ($RQ_{3.1}$). The resources used within the DDBMR process provided additional knowledge about how a DDBM idea was executed in incumbent companies. The combination of DDBMR periods and resources allowed for the identification of key challenges and enablers for resource utilization, which helped in achieving RG_3.

$RQ_{3.1}$: How do incumbent companies realize their DDBMs and which resources do they need?

$RQ_{3.2}$: Which challenges and enablers shape resource utilization in the DDBMR process?

With a focus on RG_4, the RBV was applied as a theoretical lens to identify the challenges and enablers of the DDBMR process. The RBV is well established in information systems research, where resources from “traditional” management areas are connected to the use of IT resources to create value. On the basis of the DDBMR resources connected to the DDBMR periods, challenges, and enablers identified with the empirical study, this thesis provides a solid foundation for achieving RGs.

Many interviewed experts mentioned missing guidance through a method or tool, which helps them validate actions and decisions through the realization process. Previous research has not offered such guidance. RG_4 seeks to develop a method or a tool to help DDBMR teams execute their business cases and support their decision-making processes under uncertainty. To reach this goal, $RQ_{4.1}$ and $RQ_{4.2}$ were formulated, focusing on two things: first, to classify the key elements that must be validated through DDBMR periods and, second, to build a DDBMR artifact, which can be used as a validation tool by practitioners through the realization process.

$RQ_{4.1}$: Which are the key elements a decision maker should validate through the periods of DDBM realization?

$RQ_{4.2}$: How should an artifact be designed to help decision makers identify required actions in the DDBMR process?

To develop such a DDBMR artifact, this research applied a DSR approach. The systematic literature review revealed that iterative experts' interviews were conducted in two steps. The results provided a fundament for developing the "DDBM realization board." The feedback of the experts who delivered multiple DDBMR cases provided valuable input for developing this artifact. The resulting artifact provided a condensed overview of the DDBMR elements and periods for validating and advancing planning in the DDBMR project.

By answering the previous RQs, this thesis improved the understanding of how incumbent companies realize DDBM in a structured way. An important learning through this research was the use of independent DDBVs for realization. However, how incumbent companies create DDBVs in their organizations remains unclear. Hence, this work explored the capabilities and activities required to realize a DDBV in an incumbent company.

RQ_5: Which capabilities and activities do incumbent companies use for realizing data-driven business ventures?

On the basis of the RBV and responses to the semi-structured interviews, this work could identify and structure multiple DDBV capabilities and activities. With this first-time link between DDBMR and digital venture research, the understanding of information systems research was improved and underlines the large demand of DDBVs to realize DDBMR cases for practice. With these insights, RG_5 can be achieved and a good starting point can be identified for formulating further research questions in the field of DDBVs.

Overall, this work could break the five research goals down into five publications with ten research questions (Table 1):

Research Goals	RQ_1	$RQ_{2.1}$	$RQ_{2.2}$	$RQ_{2.3}$	$RQ_{3.1}$	$RQ_{3.2}$	$RQ_{4.1}$	$RQ_{4.2}$	RQ_5
RG_1: Identify knowledge about DDBMR in existing literature	●						●	●	
RG_2: Understand how incumbent companies realize DDBMs and compare it to recent research	●	●	●	●	●	●			
RG_3: Identify challenges and enablers of DDBMR in the execution process				●	●	●	●		●
RG_4: Acquire design knowledge for a guidance tool within the DDBMR process							●	●	
RG_5: Improve the understanding how digital ventures support DDBMR in incumbent companies		●							●

Table 1: Research goals (RG) and connected research questions (RQ) of the thesis

1.4 Structure

This cumulative thesis is structured into thirteen chapters. Chapter 1 provides an overview of the research topic, the motivation of this research, and the problem statement. It defines the RGs and RQs. The second chapter focuses on the theoretical background of this work by outlining the existing research on traditional BM research, RBV, DDBMs, DDBMR, and digital ventures. The third chapter provides an overview of the overall research strategy and describes the applied research methods.

Chapter 4 presents an overview of the five articles included in this paper, the RQs they addressed, the methodology applied, the contributions provided, and the outlets published in/submitted to. Chapter 5 discusses the results of the studies, focusing on their theoretical and practical contributions and research goals. In Chapter 6, the limitations of the studies are described, followed by further research opportunities in Chapter 7. Chapter 8 presents the literature used in Chapters 1 to 7. The published articles are included in this order, from Chapters 9 to 13.

Beginning with literature-based research, the first publication in Chapter 9 presents the current state of research by focusing on DDBMs and BMR. Chapter 10 follows with a description of an empirical study among practitioners from multiple companies and industries to understand the DDBMR process in practice. In Chapter 11, the RBV was used to identify required resources, capabilities, and activities from empirical results and classify key challenges and enablers of DDBMR. In Chapter 12, the DSR publication presents the “DDBM realization board,” a helpful tool for the DDBMR process. Finally, the article in Chapter 13 connects the research on digital innovation and ventures with the realization of DDBMs in incumbent companies.

2 Theoretical Foundations

2.1 Data-Driven Business Models

Business model research has been a well-established field in management research for many years. It is an important element to not only analyze the business strategy and operations of companies but also create new business opportunities in a structured way. Over time, multiple publications have analyzed manifold aspects of business models and how they can be used for innovation (Baden-Fuller and Morgan 2010; Chesbrough 2010; Johnson et al. 2008). Osterwalder and Pigneur's (2010) business model canvas had a strong influence on the following research and is today still the business model framework benchmark in practice. In general, the business model research is not focused on a specific industry or technology; rather, it investigates all types of business models. However, further business model researchers divide this topic into several subareas to examine more specific business model characteristics such as high usage of digital technologies, specific resources, or goals (Baden-Fuller and Haefliger 2013; Wirtz et al. 2016; Zott et al. 2011).

Besides the use of digital technologies, data use in companies has become an important element of business strategy, which has led to the research field of DDBMs (Brownlow et al. 2015; Bulger et al. 2014; Hartmann et al. 2016). In particular, the “data-driven business-model framework” with its elements (Figure 1) from Hartmann et al. (2016) is an important foundation for DDBM research and this thesis. As one of the first researchers, Hartmann et al. (2016) revealed that DDBMs do not just consist of selling customer data but that they need many more models, resources, processes, and elements for a successful data-driven business. The results are based on a study of DDBMs of start-up companies but can also provide incumbent companies with insights into how new DDBM ideas are developed. Many elements are also required in incumbent companies that try to build new DDBMs or transform their existing BM.

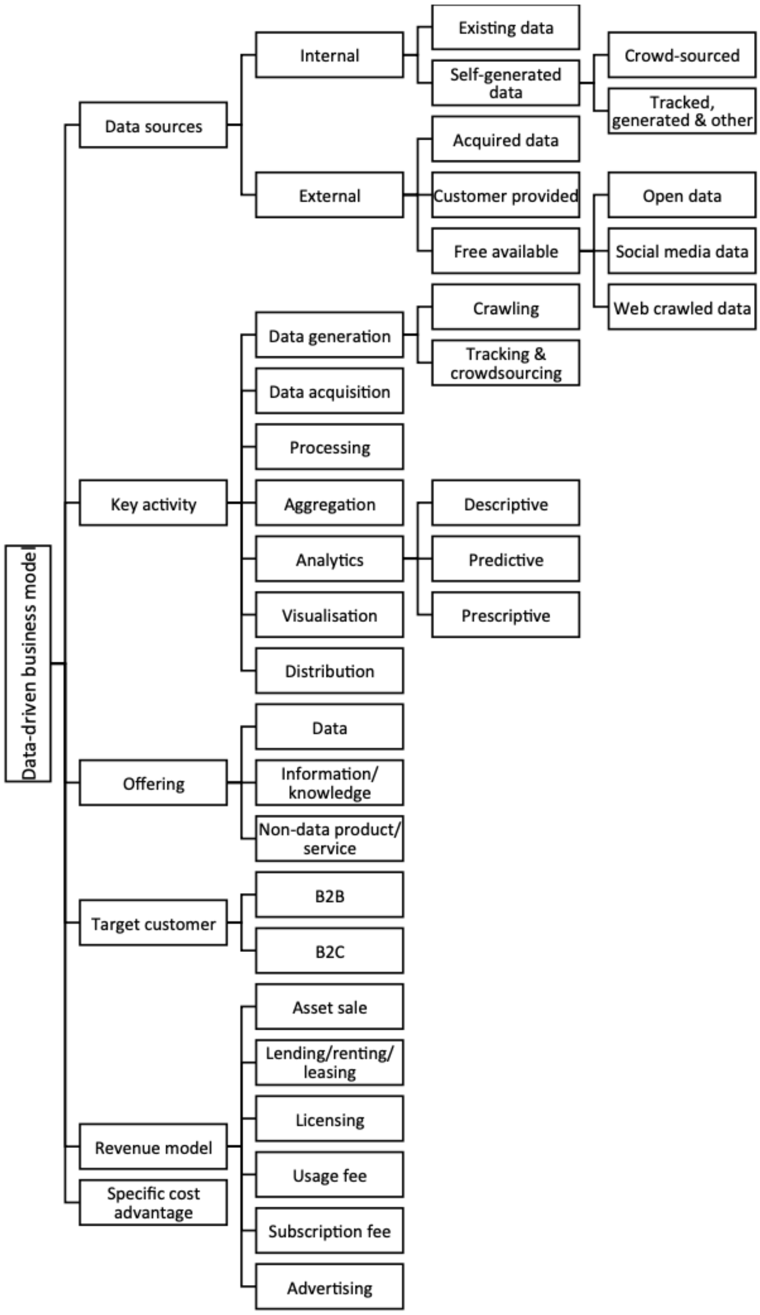

Figure 1: The data-driven business-model framework (DDBM) (Hartmann et al. 2016)

This study identified that no generally accepted definition of DDBMs exists. Throughout the years, many researchers have described DDBMs as a business model where data are the key resource or fundament for business (Brownlow et al. 2015; Bulger et al. 2014; Hartmann et al. 2016). However, recent studies have clearly shown that not only data are a key resource for a DDBM (Kayser et al. 2021; Kühne and Böhmann 2019; Wiener et al. 2020). More resources, capabilities, and activities are required to design a DDBM for the market and customers. To cover this understanding, the business model definition of Teece (2010) was used and adapted for DDBMs in this study: “A data-driven business model defines how a company creates and delivers value from data to customers and extracts value from these activities.”

Through their use of digital products and services for customers, DDBMs are mostly part of companies' digital innovation strategies (Fichman et al. 2014; Nambisan 2017). Therefore, they have a strong connection not only to digital business models but also to their roots in technology and data as key resources for value generation. Manifold frameworks and taxonomies were developed to describe the necessary elements of a DDBM for a company (Dehnert et al. 2021; Engelbrecht et al. 2016; Kühne and Böhmann 2019). All this research is useful for understanding the design of manifold types of DDBMs. Despite the importance of DDBM design, it is only a small part of the complex process of DDBMR. The process of realizing DDBM ideas in a company remains an under-researched area compared with the relevance of this topic in practice and the related investments made by companies.

2.2 Realization of Data-Driven Business Models

A missing key element in DDBM literature is the question of how companies implement DDBM ideas and concepts and how they create and implement an operating model for a sustainable data-driven business (Davenport and Malone 2021; Günther, Mehrizi, et al. 2017; Wiener et al. 2020). DDBMs are not static elements that are just created once in the beginning; they are dynamic and changing throughout the realization process with the help of digital technologies over time (Vial 2019; Wessel et al. 2021). In previous research, companies have been analyzed on the basis of their DDBM business strategy, operations, and projects in their approaches to realizing DDBMs (Alfaro et al. 2019; Chen et al. 2017; Günther, Hosein, et al. 2017). Owing to the focus on real-life cases, the authors described the use case of DDBMs in practice and with which company initiatives they tried to realize DDBM elements in practice. They reflect the first understanding of important elements of DDBMR in companies. The results of these studies helped to understand companies' DDBM ideation as an essential part of the comprehensive realization process. However, the authors provided no structured guidance concerning the challenges and required capabilities through DDBMR.

A first approach for a structured process model to realize DDBMs was developed by Hunke et al. (2017). They developed a literature-based “DDBM innovation process,” which presents a first overview of the complex execution process of DDBMR projects. In line with traditional project management, the authors see the execution as a traditional process layout, with the starting point “Initiation,” followed by “Ideation,” “Integration,” and “Realization” as the end point. In this process, companies are asked to perform manifold activities such as “BM analysis,” “data assessment,” or “risk evaluation,” which are required for a successful realization. This process provides an initial idea about the general execution, but it remains on an abstract level. With the authors' perspective on seeing realization as part of an innovation process project, it does not reflect the complex realization steps from practice.

Some articles published during the research process of this thesis also presented initial ideas about DDBMR. Hirschlein and Dremel (2021) focused on the realization of business value from BDA capabilities. Business value realization is an important element of DDBMR. With their artifact and design principles, they present new knowledge about how business value can be derived from data. These concepts are also useful for DDBMR research, but data analytics is only one small part of the comprehensive picture of DDBMR. Ermakova et al. (2021) applied a different view of research and tried to understand why data-driven projects are failing. They argued that while data-driven business projects have been a big hype in recent years, many organizations have struggled with practical execution. The results show the many challenges and reasons why projects fail. However, these studies do not offer guidance or recommendations on how to solve these problems. This supports the need for the present research because previous publications missed this highly required perspective from research and practice. Rashed et al. (2022) created a “DDBM innovation reference model” based on seven DDBM innovation design principles. This model offers structured guidance for a general DDBMR approach with a combination of agile and top-down management elements. Nevertheless, the recently published research mainly focused on the strategic management level and less on operational execution in business divisions. To support DDBMR on an operational level, additional research is required to support decisions through realization and a better understanding of the organizational resources required for DDBMR.

2.3 Resource-based View

The RBV of a firm is a leading theoretical framework for describing the use of resources for value creation by companies. It is an important viewpoint to understand how organizations use manifold resources and develop capabilities and thereby create business value for the company. The original concept was developed in business management research and based on the idea that company accomplishment is rooted in the forms of resources under control by the company (Barney 1991; Hart 1995; Wernerfelt 1984). Figure 2 shows Hart's (1995) comprehensive overview of the RBV elements.

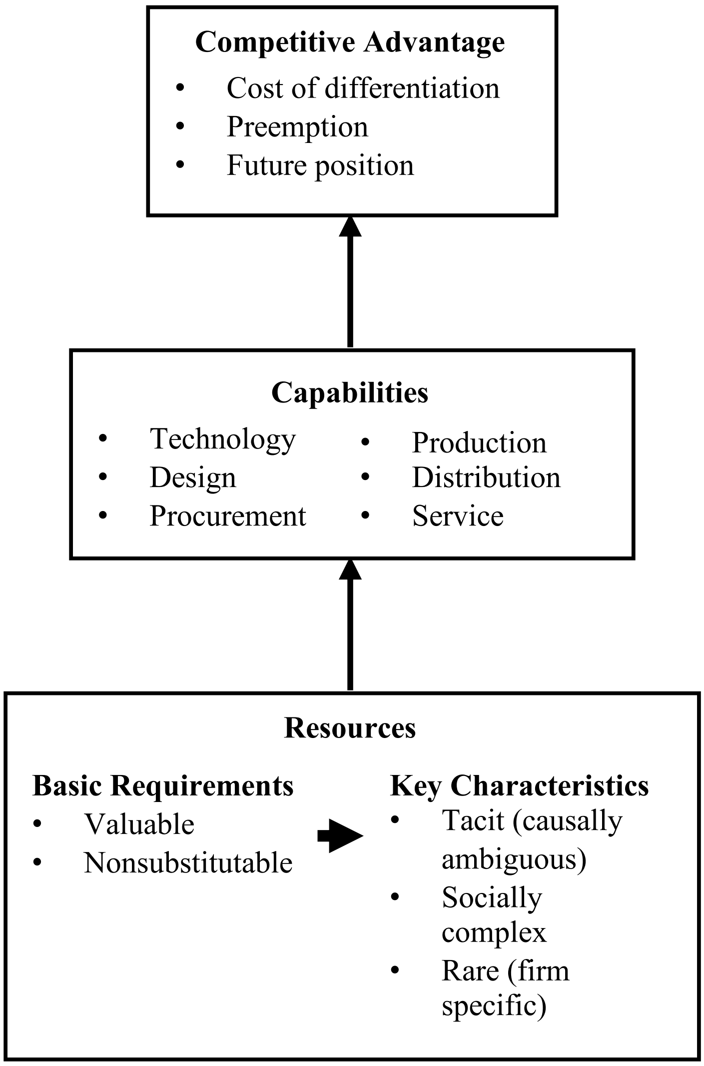

Figure 2: The resource-based view (Hart 1995)

On the basis of this concept from business management research, not all resources create the same value for a company, which depends on multiple influencing factors. The combination of different rare resources to form capabilities is essential for creating business value and can lead to a competitive advantage in the market and generate income. The resources can be differentiated into three types: tangible resources (e.g., budget and core resources), human skills (e.g., know-how and management), and intangible resources (e.g., company culture and ownership), which is a classification this thesis followed (Barney 1991; Grant 1991). A company that is using its resources in the best way will outperform its competitors and be successful in the market. The connection between the resources used and firm performance is mostly established in business management. Until today, the RBV remains one of the most important pillars of current business management research.

The idea of the use of resources and their relation to company success was also adapted as an important theoretical concept in information systems research (Bharadwaj 2000; Wade and Hulland 2004). The RBV in business management research has a general perspective on resources and does not concentrate on specific resources, capabilities, or processes to create value. In information systems research, the focus especially lies on the use of information technology resources and the required complementary resources from “traditional” business areas to create business value. In the context of this thesis, data are an important key resource for creating a data-driven business, in combination with other company resources.

With a focus on a data-driven business value approach and the connected required capabilities, Gupta and George (2016) conducted a two-part quantitative study of BDA capabilities. They identified seven big data resources based on existing research, which they segmented into established resource types from the RBV (Figure 3).

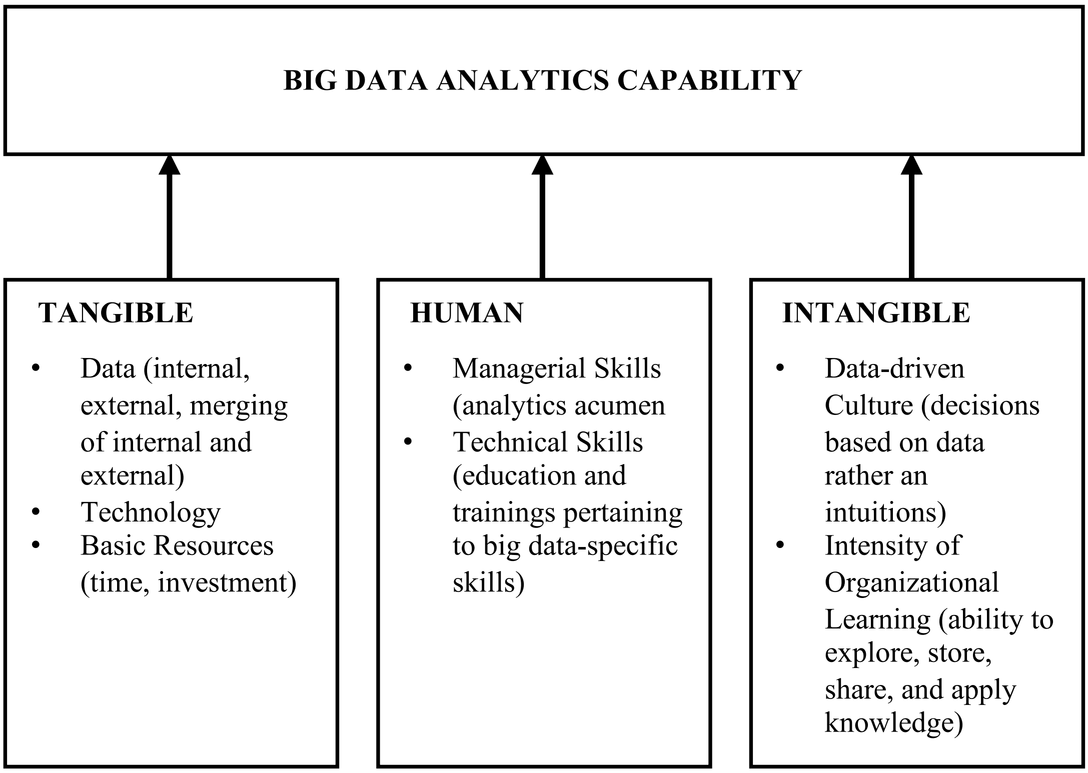

Figure 3: Classification of big data resources (Gupta and George 2016)

By using surveys, they verified their seven resources for big data capabilities but remained on an abstract and quantitative level, which delivered few implications for practical adoption in organizations. To improve these practical understandings, Wamba et al. (2017) conducted another study that focused on BDA capabilities and firm performance based on case studies from Chinese companies. Their results showed a strong correlation between big data dynamic capabilities and the financial performance of the companies. These findings demonstrate the usefulness of data for the creation of business value. However, the authors did not provide precise guidance on which activities were required by companies to do this. Mikalef et al. (2020) also showed a relationship between BDA capabilities and competitive advantage. Their research model builds on previous research findings by adding more capabilities that positively influence competitive performance. The insights provided a good overview of the required resources for BDA and proved a positive effect of data use and company performance. However, the focus also remains on big data capabilities instead of looking at the performance of a DDBM. It also provided no guidance based on the RBV about which capabilities and resources are essential for the realization of DDBMs.

2.4 Digital Ventures

DDBMR for the market and customers requires appropriate organizational structures to execute these ideas. Previous studies have tried to understand how incumbent companies can be transformed into data-driven organizations (Berndtsson et al. 2018; Hupperz et al. 2021). Some ideas for these steps can be adopted for DDBMR research, but the results of these studies have shown that a data-driven transformation of an organization is a complex task aligned with too many risks for the incumbent successful business model.

A way that is more common to realize DDBM ideas is by creating new digital units or ventures alongside traditional business operations (Lorson et al. 2022; Raabe et al. 2020). Digital ventures can be defined as independent organizational units that execute business model ideas with the help of digital technologies (Huang et al. 2017; Nambisan and Baron 2019). In general, these digital ventures are part of the digital entrepreneurship initiatives of incumbent companies (Berger et al. 2021; von Briel et al. 2021; Steininger 2019). In these initiatives, DDBMR is one part of the digital business model portfolio development (i.e., e-commerce, marketplaces, or platform) that focuses on data-driven business development. The use of ventures with DDBMR cases allows for an independent organization environment, which can focus on the main challenges of the DDBM business and is not restricted by old systems, cultures, or processes.

Huang et al. (2017) identified an important key element of these digital ventures: they target scale the business as fast as possible to reach a critical number of customers, which leads to scalable revenue streams. Figure 4 shows the dependencies between venture actions and business growth.

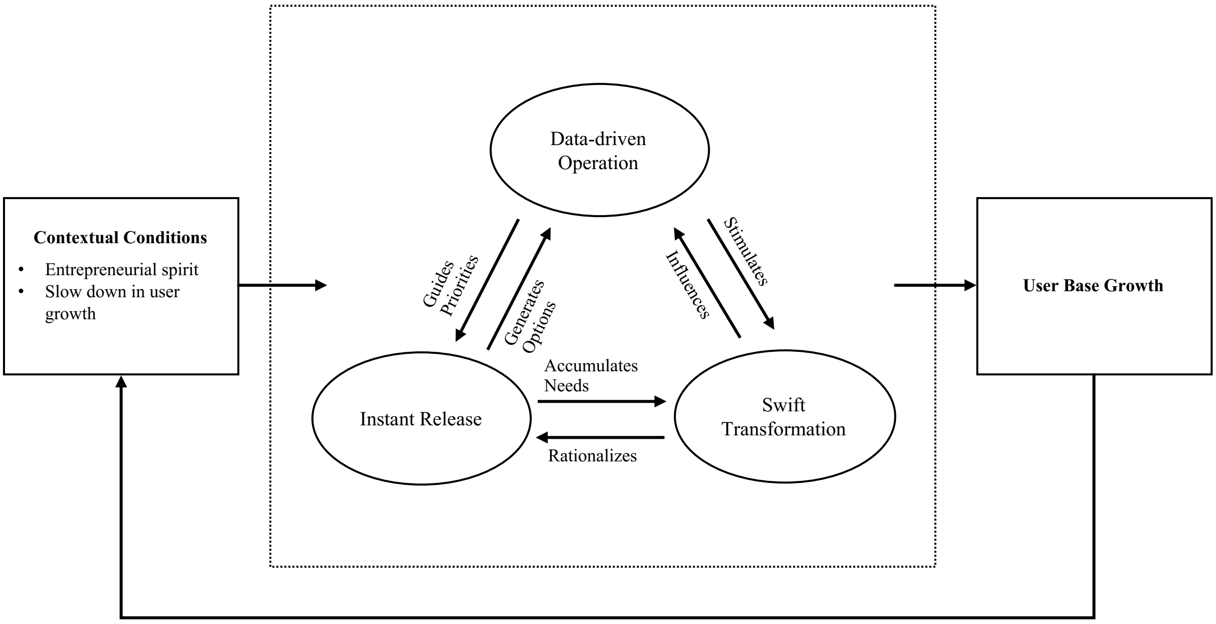

Figure 4: Mechanism of rapid scaling through digital innovation (Huang et al. 2017)

Many successful DDBM approaches started as digital ventures and developed into new business areas or independent companies over time (Alfaro et al. 2019; Nambisan et al. 2017). The connection of a digital venture with a DDBM to a DDBV is a highly complex task, which needs multiple resources, capabilities, and activities during the realization process (von Briel et al. 2018; Sultana et al. 2022; Ullah et al. 2021).

In the beginning, companies are challenged by the task of creating the right teams from multiple talents and acquiring the right technological abilities. With these two elements, it is possible to follow DDBV ideas and start business experiments. The company must understand that most of these ideas will fail. Thus, it is important to invest in and execute multiple DDBV ideas to reduce risk and try a scalable business idea. If some DDBVs have a successful approach, the company must establish structures to build products and services that can be delivered and offered to the customer without negotiating the established business (Lehmann and Recker 2022; Lehmann et al. 2022). An important element is that these data-driven digital products are mostly not “complete.” They need continuous development to bring more features to customers, which leads to additional revenue.

The digital venture setup allows companies to establish DDBVs in addition to the ongoing business and grants freedom for new DDBM experiments, hiring young talents and protecting the market competitiveness of the company by additional data-driven product offerings. Previous studies have not focused on linking DDBMs and digital ventures in incumbent companies. However, the successful execution of DDMB ideas requires a connection between these disciplines and an understanding of the capabilities and activities required for DDBV throughout the execution periods.

3 Research Design

3.1 Research Strategy

This thesis addresses five research goals, as outlined in Chapter 2. The research goals $RG_{1–5}$ take the lack of knowledge about DDBMR as a starting point. To reach these RGs and answer the RQs, this research chose a multiple-method approach consisting of a systematic literature review, qualitative empirical research, and a DSR approach.

In the first step, a literature review was conducted, which was required to identify the existing relevant literature. To identify relevant research from the disciplines of DDBM and BMR research, a two-part system literature review was conducted by following the guidance of Webster and Watson (2002) and vom Brocke et al. (2009), who published works on this systematic approach. This literature-based groundwork enables the development of the next research steps for this thesis. By an incremental extension of the initial literature review with additional research areas and topics over time, this stayed updated by recent research and publications.

On the basis of the literature knowledge fundament, this work conducted a qualitative-empirical study. The RGs of this thesis contain open topics that have not been explored by research until now. For a better understanding of this topic, DDBMR experts need insights from practice (Bogner et al. 2009). The specific focus was to interview experts from incumbent companies who knew the elements of DDBMR in an established environment. Qualitative expert interviews were identified as the best-fitting method to obtain activities from practice about this new phenomenon (Mayring 2007; Myers 1997). For the interviews, a semi-structured interview guide was designed (Myers and Newman 2007). This interview design allowed us to address relevant topics based on the literature analysis but additionally provided an open atmosphere to discuss DDBMR experiences and collect useful information from practice.

Finally, a DDBMR artifact was constructed for researchers and practitioners on the basis of the DSR approach, the findings from the literature, and the results from the expert interviews (Gregor and Hevner 2013; Peffers et al. 2007). The current research literature shows that tools for DDBMR execution, unlike the DDBM design, do not exist so far. Thus, to provide experts

with a tool that they can apply to better understand DDBMR cases, the "DDBM realization board" was created. On the basis of the general idea of a business framework, it offers a structured validation tool for decision makers regarding the next steps of DDBMR.
In the following sections, the research methods and their application in this thesis are described. It starts with a systematic literature review to understand the current state of the literature. This is followed by semi-structured interviews to gather depictions of DDBMR cases in practice. Finally, the DSR approach is described, which was applied to create the DDBMR artifact.

3.2 Research Methods

3.2.1 Literature Review

To understand the current state of the DDBM and BMR research literature, an initial two-part systematic literature review was conducted (vom Brocke et al. 2009; Webster and Watson 2002). Owing to the lack of knowledge about the connection between the two research streams, the review was divided into two parts: DDBMs and BMR (see Figure 5).

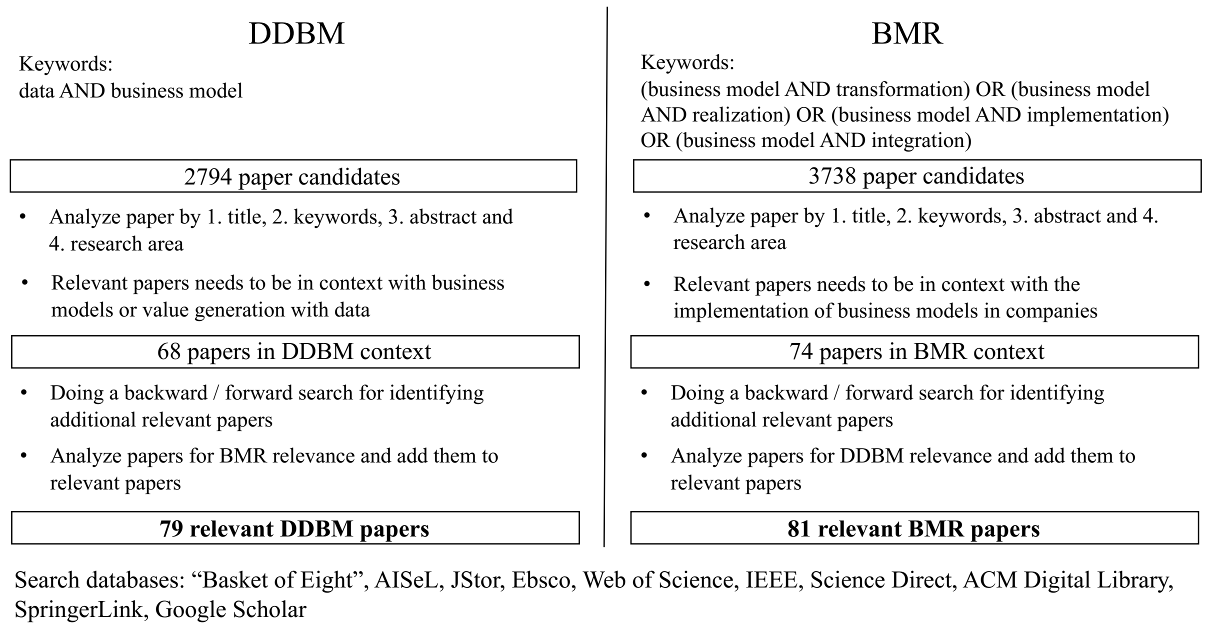

Figure 5: Systematic literature search and analysis (Lange and Drews 2020)

Owing to the international audience of this research, only English literature was included in the research process. Before the start of the study, a heuristic search using Google Scholar and multiple search terms was conducted to find the essential search terms for the literature review. An iterative exploration approach revealed (data AND business model) as the best matching search terms for relevant DDBM literature. For the BMR stream, the search terms (business model AND transformation) OR (business model AND realization) OR (business model AND implementation) OR (business model AND integration) were used.

To reflect a wide range of relevant research papers from information systems and business management research, the “Basket of Eight” and the libraries AISeL, JStor, Ebsco, Web of Science, IEEE, Science Direct, ACM Digital Library, SpringerLink, and Google Scholar were investigated. No range has been defined regarding the year of publication. For the “Basket of Eight,” AISeL, and JStor, this work searched for titles, abstracts, and keywords of papers. On Ebsco, Web of Science, IEEE, Science Direct, ACM Digital Library, SpringerLink, and Google Scholar, a huge number of results were displayed, so the search was limited to the title. Defining more specific search terms would not have led to better results, and relevant papers would have been excluded.

In total, 2794 papers on DDBM and 3738 papers in the BMR context were found. In the first step, all papers were analyzed by 1) title, 2) keywords, 3) abstract, and 4) research area. For the DDBM stream, papers that addressed business models or value generation with data were selected. For BMR, the focus was on the implementation of business models in the company. Owing to the lack of papers on the intersection of DDBMs and BMR, all relevant papers related to BMR for the literature review were selected, including those not focused on DDBMs. Papers that did not fit these criteria were excluded. Duplicates were removed. A backward and forward search was then conducted to identify additional relevant papers (Webster and Watson 2002). DDBM papers for BMR were also considered for review if they contained aspects of BMR (and vice versa).

After the identification of the relevant literature, paper contents were analyzed for a better understanding of the current research status. Overall, 79 papers on DDBMs and 81 papers on BMR were considered for further analysis and conceptualization. For the literature review, the DDBM papers were analyzed on the basis of the “data-driven business-model framework” of Hartmann et al. (2016). For the BMR literature review, 13 relevant approaches were identified that formed the basis for a general understanding for the realization of business models in companies. As mentioned before, this literature review was extended with more recent publications and relevant keywords so that the most recent research knowledge can be used for the publications. The results of the literature review were also the basis for Chapters 12 and 13 because many elements can be used as fundament for this research approach.

3.2.2 Qualitative Research

On the basis of the results of the systematic literature review, a qualitative expert interview approach was used (Bogner et al. 2009; Myers and Newman 2007). Multiple experts with multiple DDBMR business or realization experiences in their companies were interviewed. The focus was on experts from the fields of data science, information systems, or digital business who know which resources and capabilities are required for DDBMR. The experts were selected from multiple companies of different industries and sizes to collect data from several perspectives. The selected companies were incumbent companies operating globally with their businesses. All companies had launched initiatives for DDBMR in their organizations and/or offered advice to their customers about how to do so. Table 2 shows a list of the interviewed experts.

Company	Interview	Role	Industry	Company size
1	A and B	Lead Data Scientist and Managing Partner	Software	<500
2	C	Director Digital Lab	Engineering	500–9,999
3	D	Data Scientist	Energy	500–9,999
4	E	Project Manager	Automotive	10,000–99,999
5	F	Product Owner Data Intelligence	Transport	>100,000
6	G	R&D Manager	Automotive	>100,000
7	H	Data Scientist	Shipbuilding	500–9,999
8	I	IoT Engineer	Software	500–9,999
9	J	Product Owner Data Platform	Insurance	10,000–99,999
10	K	Head of Data Science	Mobility	500–9,999
11	L	Information Security Officer	Aviation	10,000–99,999
12	M	Head of AI & Data Analytics	IT Consulting	500–9,999
13	N	CEO	IT Services	<500
14	O	Senior Expert	Automotive	>100,000
15	P	Advisor Corporate Strategy	Automotive	>100,000
16	Q	Head of Technology Marketing	Public Sector	500–9,999
17	R	Head of Customer Insights	Retail	>100,000
18	S	Tribe Lead AI	Communication	>100,000

Table 2: Interviewed experts

For the interviews, semi-structured interview guides were designed (Myers and Newman 2007). The guide for interviews A–L focused on general DDBMR and the project level. The interview guide for the interviews M–S had a deeper focus on the realization of data monetization and was acquired with the help of researchers from the Karlsruhe Institute of Technology. These two perspectives present a wide-ranging overview of manifold cases, projects, and tasks

through DDBMR. Interviews A, B, and D were personal interviews; interviews C and E–S were conducted by phone or online conference tool (Skype, Google Hangouts, and Zoom).
This first qualitative study is based on interviews with 19 experts from 18 companies. All interviews were recorded and fully transcribed. The experts received the interview transcripts for review and approval. The duration of the interviews ranged from 24 to 63 minutes, with an average duration of 44 minutes. All interviews were fully transcribed, and the transcriptions were analyzed by conducting a qualitative content analysis to obtain relevant knowledge (Mayring 2000, 2007). An open coding approach was applied. The interviews were analyzed for statements from DDBMR cases in practice about resources and procedures through realization. The mentioned statements were segmented according to the RBV into DDBMR capabilities, resources, and periods. The resources were segmented into three resource types, which were later connected to the required DDBMR capabilities (Barney 1991; Hart 1995). The identified periods were revised multiple times during the research process. The classified DDBMR cases, periods, and capabilities allowed for the identification of key challenges and enablers for each period from the interviews. For this, the transcripts were analyzed for statements of DDBMR challenges/enablers for resource utilization, and the results were segmented into a period/capability matrix. The experts described manifold cases, which were supplemented by the mentioned Internet sources. In total, 45 DDBMR cases from the interviews (Table 3) were examined for this study, which is the important empirical qualitative fundament to answer the RQs and achieve the RGs. The insights from these DDBMR cases were also used as a foundation to build the initial artifact in the DSR approach.

Case	**Area**	**Target Industry**	**Status/Stage**	**Focus**	**Interview**
1	Solar Panel Maintenance	Energy	Live/MMP	B2B	A
2	Product Simplification	Manufacturing	Development/ Experiment	B2B	C
3	Smart Power Grids	Energy	Live/MMP	B2C	D
4	Grid Planning Tool	Engineering	Live/MMP	B2B	D
5	Property Assessment	Real Estate	Live/MMP	B2B	D
6	Solar Panel Recognition	Energy	Development/ Experiment	B2B	D
7	Sensor Data Selling	Automotive	Development/ Experiment	B2B	E
8	Sensor Data Platform	Automotive	Development/ Experiment	B2B	E
9	Weather Data	Automotive	Live/MMP	B2B	E
10	Car Data Marketplace	Automotive	Live/Scaling	B2B	E
11	Smart Fleet Maintenance	Transport	Live/MMP	B2B	F
12	Car Data Marketplace	Automotive	Live/Scaling	B2B	G
13	Data Insights Platform	Automotive	Live/MMP	B2B	G
14	Traffic Data	Automotive	Live/Scaling	B2B/B2G	G

15	In-Car Entertainment Platform	Automotive	Live/MMP	B2C	G
16	Use-Based Car Features	Automotive	Development/ Experiment	B2B/B2C	G
17	Predictive Repair Service	Automotive	Development/ Experiment	B2C	G
18	In-Car Advertisement	Automotive	Development/Experiment	B2B/B2C	G
19	Project Transparency	Shipbuilding	Live/Scaling	B2B/B2C	H
20	Smart Metering Services	Energy	Development/MVP	B2B	I
21	Predictive Wind Power Maintenance	Energy	Live/Scaling	B2B	I
22	Predictive Component Replacement	Manufacturing	Development/ Experiment	B2B	I
23	Predictive Escalator Maintenance	Manufacturing	Live/Scaling	B2B	I
24	Device Data Hub	Software	Live/Scaling	B2B	I
25	Product Evolution	Insurance	Development/MVP	B2B/B2C	J
26	Usage-based Insurance Service	Insurance	Development/MVP	B2B	J
27	Smart Investments	Insurance	Development/ Experiment	B2B/B2C	J
28	Transportation Platform	Mobility	Live/Scaling	B2C	K
29	Plane Data Platform	Aviation	Live/Scaling	B2B	L
30	Flight Data Selling	Aviation	Live/Scaling	B2B	L
31	Personalized Flight Services	Aviation	Development/Experiment	B2B/B2C	M
32	Predictive Plane Maintenance	Aviation	Live/MMP	B2B	M
33	Car Data Marketplace	Automotive	Live/Scaling	B2B	O
34	Car Repair Knowledge Base	Automotive	Live/Scaling	B2B	O
35	Car Data Selling	Automotive	Live/Scaling	B2B	P
36	Car Data Marketplace	Automotive	Live/Scaling	B2B	P
37	Car Data Ecosystem	Automotive	Live/Scaling	B2B	P
38	Smart Insurance	Insurance	Development/MVP	B2B	P
39	Satellite Data Selling	Public Sector	Live/Scaling	B2B	Q
40	Ship Detection Service	Public Sector	Live/Scaling	B2G	Q
41	Shopping Data Selling	Retail	Live/Scaling	B2B	R
42	Shopping Insights Hub	Retail	Development/MVP	B2B	R
43	Smart Assortment Platform	Retail	Live/Scaling	B2B	R
44	Location Data Service	Communication	Live/Scaling	B2B	S
45	Data Insights Platform	Communication	Live/MMP	B2B	S

Table 3: DDBMR cases

3.2.3 Design Science Research

From the literature analysis and the empirical research, this study shows that DDBMR is a complex plan for incumbent companies and that companies are asking for guidance from research that supports them in making key decisions through the realization process. Research has not yet developed prescriptive methods or tools for guiding the validation of DDBMR activities. To provide researchers and practitioners with a helpful guidance tool, a DSR approach was conducted to create a new and innovative DDBMR artifact that helps to solve a real-world problem (Gregor and Hevner 2013; Peffers et al. 2007). For this, the iterative DSRM process of Peffers et al. (2007) was followed, which consists of six phases: (1) problem identification and motivation, (2) objectives of a solution, (3) design and development, (4) demonstration, (5) evaluation, and (6) communication. This process was adapted in a more iterative version for a modified DSR approach (Figure 6):

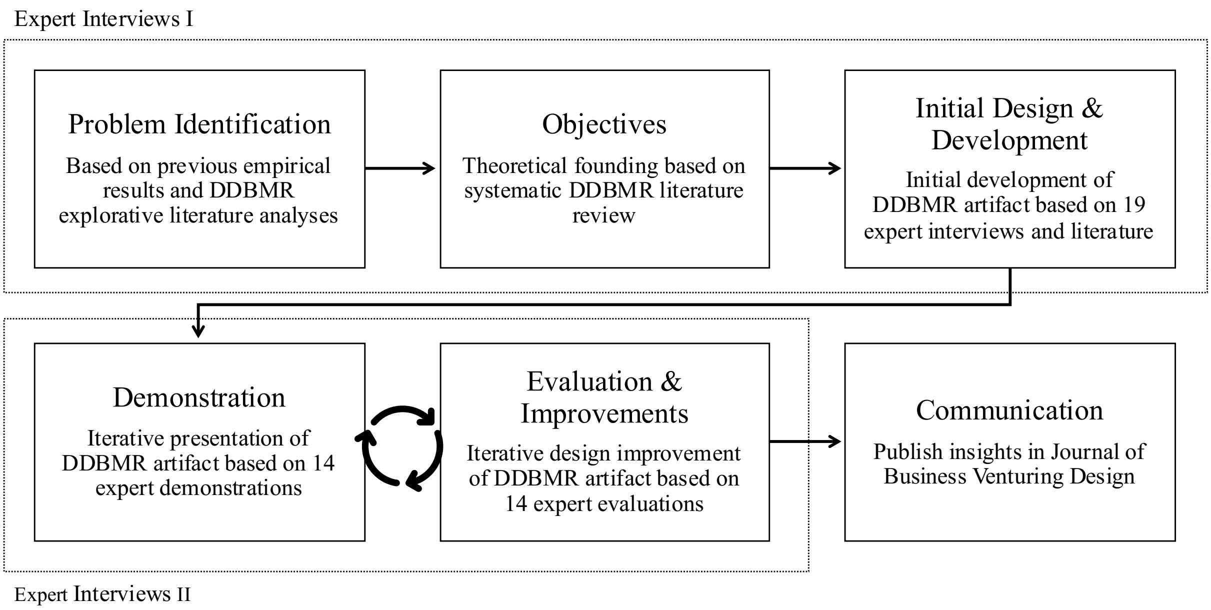

Figure 6: Design science research approach (adapted from Peffers et al. 2007)

The problem-centered approach was chosen as the entry point because it was an important goal to solve a relevant real-world problem with the artifact. The literature analysis and previous empirical studies revealed that it was understandable that decision makers and researchers need an artifact for DDBMR validation. The motivation was to build a practical-oriented tool for researchers and practitioners, which helped to understand and execute the DDBMR process in an incumbent company. This employed an iterative research approach with a literature review, interviews with multiple experts, and validation cycles with potential users to improve the new artifact (Venable et al. 2016). To find the relevant objectives for a solution and first artifact design elements, the results from the systematic literature review were updated with recent publications. Overall, 37 relevant papers were identified, which were analyzed using a content analysis (Mayring 2000).

To build the initial DDBMR artifact, the contents of the qualitative interviews with the 19 experts and the described 45 DDBMR cases were analyzed. On the basis of the initial DDBMR artifact design, the artifact was presented in a further step to 14 experts to validate and improve it. In the first iteration, seven experts participated in the first interview series. In the second iteration, the artifact was validated with new experts from new companies who provided new insights for the artifact design (Table 4). New experts are marked with *, and experts with new roles in the first interview series are marked with **. The artifact was demonstrated via an online conference tool (Google Meet).

Number	Expert	Iteration	Role	Industry	Company size
1	A	I	Lead Data Scientist	Software	<500
2	D	I	Data Scientist	Energy	500–9,999
3	J	I	IT Security Manager**	Insurance	10,000–99,999
4	K	I	Head of Data Science	Mobility	500–9,999
5	I	I	IoT Engineer	Software	500–9,999
6	G	I	Product Owner**	Automotive	>100,000
7	F	I	Product Owner Data Intelli-gence	Mobility	>100,000
8*	S	II	Product Owner	Finance	500–9,999
9*	T	II	Business Intelligence Ana-lyst	Energy	<500
10*	U	II	Managing Director	IT Consulting	<500
11*	V	II	Project Manager Digitaliza-tion	Commerce	500–9,999
12*	W	II	User Experience Expert	Finance	500–9,999
13*	X	II	Product Manager	Automotive	>100,000
14*	Y	II	Agile Project Manager	Software	<500

Table 4: Experts for iterative DDBMR artifact demonstration and evaluation

The artifact was presented to the experts using a digital whiteboard and screen sharing. In this presentation, the elements were discussed and connected to usage regarding practical decision making in the DDBMR process. The evaluation of the experts allowed us to follow an iterative design process to develop the artifact by ensuring the significance and applicability of the resulting artifact. It took multiple pivots of the artifact through the evaluation and development cycles. Finally, the results are planned to be published in a scientific journal.

4 Publications

Publications P1–P5, which were included in this thesis, are outlined in Table 5. They are attached in the same order in Chapters 9 to 13.

No.	Authors	Title	Outlet	Type	Status
P1	Hergen Eilert Lange, Paul Drews	From Ideation to Realization: Essential Steps and Activities for Realizing Data-Driven Business Models	IEEE 22nd Conference on Business Informatics (CBI 2020)	Conference	Published
P2	Hergen Eilert Lange, Paul Drews, Markus Höft	"Ideation is Fine, but Execution is Key": How Incumbent Companies Realize Data-Driven Business Models	IEEE 23rd Conference on Business Informatics (CBI 2021)	Conference	Published
P3	Hergen Eilert Lange, Paul Drews, Markus Höft	Realization of Data-Driven Business Models in Incumbent Companies: An Exploratory Study Based on the Resource-Based View	Proceedings of the 42nd International Conference on Information Systems (ICIS 2021)	Conference	Published
P4	Hergen Eilert Lange, Paul Drews	Guiding the Iterative Realization of Data-Driven Business Models - An Artifact for decision-making support	Journal	Journal	Under Review
P5	Hergen Eilert Lange, Paul Drews	Capabilities and Activities for Realizing Data-Driven Business Ventures in Incumbent Companies	Journal	Journal	Under Review

Table 5: Embedded publications

5 Contributions

On the basis of the results of the five included studies, this thesis contributes relevant findings for research and practice. In Table 6, the most important contributions are listed with their descriptions of how they influenced current research and their impacts on company management.

No.	Contributions
RG_1	• Summarized current state of literature of DDBM and BMR research streams • Connected existing DDBM and BMR research streams to the research field DDBMR • Identified knowledge gap and need of research about the realization of DDBMs in theory and practice
RG_2	• Enabled first knowledge for DDBMR on an operational level in incumbent companies • Identified 45 DDBMR cases and four periods from practice, which provides important empirical knowledge fundament for research • Compared the current DDBMR literature with results from practice, to show multiple literature vs. practice gaps
RG_3	• Applied the RBV as theoretical fundament for required DDBMR resources and capabilities in incumbent companies • Connected the RBV and DDBMR cases which led to the identification of four DDBMR key capabilities and 25 connected resources • Based on these capabilities and resources, 16 key DDBMR challenges and enablers were identified for research
RG_4	• Used the DSR approach to get design knowledge for structured guidance through the realization process • Developed and evaluated the “DDBM realization board”, a comprehensive template for DDBMR validation and decision making • Showed that a permanent validation and experimentation through DDBMR is an important element for a successful realization
RG_5	• Gained first knowledge how DDBMR can be realized in an incumbent organization structure • Developed an initial understanding of DDBV based on the RBV by identifying nine key resources and 108 activities • Compared DDBVs to the research field of digital ventures, to show similarities and differences

Table 6: Key contributions of this thesis

5.1 Theoretical Contributions

By achieving $RG_{1–5}$, this thesis seeks to advance knowledge about the realization of DDBMs in incumbent companies for information systems research. With the systematic literature review in P1, this thesis analyzed the existing literature on DDBMR to fulfill RG_1. Previous literature reviews focused on the ideation of DDBMs but had less focus on the realization part or missed connecting with realization approaches from traditional BM literature. On the basis of the analyzed existing literature, the “DDBM realization process approach” was developed, which is a useful foundation for further research and validity of the following studies. The results of the literature review showed that empirical evidence of how DDBMR is conducted in practice is very limited. Empirical studies on the execution of DDBM ideas are fairly scarce. First, approaches for a structured DDBMR execution exist but have not been validated by experts actually executing DDBMR projects in practice (Anand et al. 2016b; Hartmann et al. 2016; Hunke et al. 2017).

To improve the empirical knowledge about this phenomenon, in P2, an initial accomplished qualitative study based on expert interviews, where the interviewer spoke with 19 experts from multiple incumbent companies about experiences in their DDBMR cases, was conducted. This work is the first important step in gaining knowledge from practice and transferring this to research. The identified 45 DDBMR cases show an overview of the multiple characteristics of the DDBMR cases. By connecting the results of the study with the recent research identified in the literature, RG_2 was achieved. The identified results provide a much better understanding of research gaps between theory and practice. The classified four DDBMR periods, case types, and activities provide additional awareness about the complex and challenging setting through the realization process.

In P3, important expertise could be gained about the challenges and potential enablers of DDBMR in companies through the realization process, which followed RG_3. Previous research has mostly focused on general failures or potential tasks of the process but has no specific focus on the manifold capabilities that are required to utilize resources in DDBMR (Ermakova et al. 2021). This thesis presents the first empirical-based outline of four DDBMR capabilities and their 25 connected resources. With these capabilities, 16 key challenges and potential key enablers were identified for successfully conducting DDBMR. Realizing digital or data-driven projects remains a complex task, but this research can provide better knowledge of what is really important and which elements must be discussed in further investigations.

Through study P4, this work addressed RG_4 by creating a useful DDBM realization tool based on DSR to provide a better structured understanding through DDBMR. With this, this study seeks to shift the focus from DDBM design tools to DDBM realization and validation tools (Brownlow et al. 2015; Kühne and Böhmann 2019). With the "DDBM realization board," this thesis constructed a first artifact, which provides guidance to researchers and practitioners through DDBMR in an agile environment.

The results show that a permanent validation of the DDBM element throughout its realization is key for success. Artifacts from traditional business model validation research can help to understand these requirements but cannot include all aspects of a dynamic DDBMR process transformation through its lifetime (Dellermann et al. 2019; Linde et al. 2021). By understanding the DDBMR process, the required capabilities and validation tools contribute a lot of knowledge for research on how companies realize their cases.

Another important subject is the right organization entity, which is required to successfully execute DDBMR in the incumbent organization. To achieve this, this work connected the research field of DDBMR with the topic of digital ventures in P5. Digital ventures such as DDBMs are part of the digital transformation initiatives, but previous publications did not link these research streams. To achieve RG_5, this thesis presented the need for DDBVs to execute data-driven business ideas (von Briel et al. 2018; Steininger 2019). On the basis of manifold DDBV cases and the RBV, this thesis presents a view of the required capabilities and activities involved in a DDBV setup. The identified nine capabilities and 108 activities are the first approach to extending the knowledge for research about the required actions for DDBV realization. The activities are not complete but provide a first approach on which further research can evolve the required connection of DDBMs and venture development. Also, the first-time comparison of DDBV with general digital venture realization shows important specifics for DDBVs as digital venture type.

5.2 Practical Contributions

The results of this thesis are of high relevance for practice, as they are strongly connected to empirical evidence stemming from DDBMR projects in companies. The RGs were defined to create value for theoretical research and application in practical execution.

Following RG_1, in P1, knowledge about DDBMR in the existing literature could be identified. The systematic literature review offers practice a first overview of the existing DDBM approaches and tools. For example, the "Data Insight Generator" or "DDBM framework" presents structured ideas on how to design and construct DDBM ideas (Hartmann et al. 2016; Kühne and Böhmann 2019). Moreover, existing case studies have reported useful best practices regarding which kind of DDBMs are working, which elements are needed, and which can have a strong influence on the DDBM designs for companies' practices (Alfaro et al. 2019; Chen, Kazman, Schütz, et al. 2017).

Nevertheless, an important learning from this literature review is that the existing papers take a static or ideation-focused view. They do not represent the real-life complex and challenging realization process, so they could be identified as a big knowledge gap between theory and practice in realizing DDBMs. The development of the “DDBM realization process approach” was a first attempt based on knowledge from the literature but provides low empirical evidence. To solve this gap and support practice with theoretical knowledge based on empirical research, RG_2 was followed and how incumbent companies realize DDBMs was analyzed in P2. The empirical results from this work in comparison with previous research publications show that theory still mostly emphasizes traditional waterfall-like project approaches. In practice, companies are much more agile in the DDBMR context and try to execute their ideas as quickly as possible through small teams and scaling. The identified four DDBMR periods from practice (development/experimentation, development/MVP, live/MMP, and live/scaling) reflect these insights and offer guidance for companies and practitioners on which steps are required to realize a DDBM idea. This allows more companies to get a general configuration for their own DDBMR cases.

Through these DDBMR processes, multiple challenges occur that require possible enablers to solve them. For this, following RG_3, this research identified P3 challenges and enablers of DDBMR based on the analysis of 45 DDBMR cases. With these results, this research supports the execution of DDBMR in companies based on the identified capabilities, resources, challenges, and enablers. Many incumbent companies do not have any experience with the use of data for business. They are focused on traditional asset sales such as machines, cars, ships, planes, or services. DDBMR is different from the existing business practices, but companies already understand that it is important to use data to stay competitive in the market and have already started manifold DDBM experiments. The research results and discussions support these companies by describing the key challenges and providing possible enablers to solve them.

In addition, in P4, with the “DDBM realization board,” a new tool to guide companies through DDBMR cases was developed, which follows RG_4. The results show that permanent validation of the DDBM is essential to realize a successful business. The board offers support through DDBMR projects, which were missed by many experts before, as the interviews have shown. Especially in agile project execution under high uncertainty, this structure helps identify the next steps in the decision-making process. The tool can be applied by companies in workshops, board meetings, or project teams who are executing the ideas in reality. By building this board on frameworks already known in the management world, incumbent companies should be able to use this kind of tool more easily in their DDBMR cases.

In line with the developed capabilities, resources, and tools, the aim of this thesis was to go one step further by showing a possible entity for DDBMR. By targeting RG_5, the aim of this research was to provide incumbent companies with guidance and show how they can realize their DDBMR cases with the support of digital ventures. In P5, this work connected existing digital venture research and DDBMR knowledge to provide the concept of DDBVs. Many experts mentioned that an incumbent company has huge challenges in implementing a digital or DDBV. Most companies do not have any experience in such kind of business because they sell hard goods or have a traditional company culture and processes. The developed DDBVs, including the nine capabilities and 108 activities, offer important guidance on what companies and managers need to do through the DDBV realization process. Realizing DDBVs in companies is a complex task, but this research provides help for companies to both build the required capabilities and successful ventures.

6 Limitations

This thesis and the five studies included make multiple contributions to theory and practice. However, the results of these studies have some limitations. First, the systematic literature review focused on publications in the field of business management and information systems research. The literature review was limited to the most important search databases in this research field but did not guarantee that all published DDBM were included. In addition, the initial literature review was conducted in 2020 but was extended by iterative literature research through the years. Through later stages of the research process, the entrepreneurship and innovation literature was identified to be an important source for the realization of DDBMs in companies. This is especially true from an experimental-oriented perspective to realize a business model instead of strictly planning it from the beginning. For conducting more research in this field, it would be useful to extend the literature review by including entrepreneurship research and entrepreneurship-specific search terms to connect the research disciplines.

Second, in the qualitative study, only the employees from German-based incumbent companies operating in international markets were interviewed. This regional restriction might bear cultural or region-specific limitations due to, for example, the high relevance of data protection in Europe. To obtain initial knowledge about DDBMR, this focus on German companies was sufficient, but for further research, it would be valuable to speak with experts from companies from various countries and continents to see if diverse cultural settings would lead to different results. In addition, the interviewed experts were mostly from an operational level, which corresponded to the focus on realization in the execution team rather than on the design on higher company management levels. This provides relevant insights into operational actions in the DDBMR cases but misses the strategic decisions of DDBM development on a management level. In further studies, it would be useful to connect experts from different hierarchical levels to get a better picture of the connection between required DDBMR management strategy and execution team activities.

Third, with the DSR, this thesis created a structured artifact with many DDBMR elements based on the statement's multiple experts, cases, and companies. However, these elements can still be very subjective, based on the experts' and companies' experiences in their industry. The DDBMR artifact is only based on existing empirical knowledge but was not tested in the environment of a real DDBMR case. With the first validation cycles (Table 4) of the artifact by the interview experts from multiple companies, a first empirical validation was made. However, further validation is needed through additional studies in which the gained insights, tools, and activities are related to company success. In addition, the developed DDBV approach and its influence on possible business success need more input from practice. Through this validation, more improvements and insights can be expected, which will lead to better guidance for DDBMR cases.

7 Future Research

For future research, on the basis of the contributions of this thesis, three areas offer interesting avenues for further research. First, the focus on the agile execution of DDBMR cases should have a stronger focus in future research. The empirical results of the studies show that DDBMR projects are realized like digital projects, based on information technology, software development, and digital skills. Traditional project management with concrete milestones is not working for such a complex and iterative DDBMR project. Many studies about agile methodologies, lean start-ups, and go-to-market of an MVP already exist (Abrahamsson et al. 2002; Eisenmann et al. 2012; Schwaber and Sutherland 2011). Upcoming studies could build a stronger connection between DDBM research, digital entrepreneurship, and agile software development to improve the understanding of how scalable data-driven businesses are established and how they grow (Becker et al. 2020; Huang et al. 2017). The identified DDBMR execution periods offer a first understanding of how the realization of business model elements fits together, but a deeper investigation on this topic is needed. The business scaling of a DDBMR case and the required scaling of resources and capabilities are an important topic for a successful realization. Second, besides the general approach of DDBMR through execution periods, another important research area for future research might comprise additional studies on DDBVs. Digital ventures are an established concept in research that focuses on the development of internal or external businesses based on digital technology and products (Lehmann and Recker 2022; Proksch et al. 2021). The expert interviews revealed the difficulties in realizing a DDBMR case. A DDBV can be a good approach for incumbent companies to avoid problems such as a clash of cultures, outdated technology, or missing skills. In a DDBV as the organizational setting, ideas, skills, and talent can grow to build a new data-driven business for the company portfolio with manifold options of growth. Research on DDBVs is just beginning, but the results of nine capabilities and 108 activities provide a good foundation for future research and studies.

Third, the insights of this thesis are the result of combined input from 27 experts and 45 DDBMR cases. To validate these results in the best way possible, it would be an important next step to focus on an in-depth longitudinal single case study in which the delivered ideas, concepts, tools, and activities are getting into action. First, one-case studies exist but do not use all the aspects and knowledge found in this research (Michalik et al. 2018; Otto and Aier 2013). By observing a full DDBMR case study from the beginning of DDBM ideation, building of first prototypes, gaining first customers, and scaling the business by time would be perfect validators for our previous research. For sure, many new elements can be identified, and research on this work could be extended by new DDBMR capabilities, resources, or activities.

With the results of this thesis, a solid foundation for DDBMR and DDBV was built, on which future research can be developed to provide more valuable insights for experts from research and business. This will help them to better understand the complex but fascinating nature of DDBMR.

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9 From Ideation to Realization: Essential Steps and Activities for Realizing Data-Driven Business Models

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Abstract. Data have become a key resource for competition in several industries. As a response to this challenge, companies seek to create and realize data-driven business models (DDBMs). Although the ideation of DDBMs has been the subject of research, the realization of DDBMs remains an under-researched area. In this paper, we present a four-step process for guiding the realization of DDBMs. This process is grounded in a two-step literature review of research related to DDBMs and business model realization (BMR). By drawing on the four steps of BMR and six dimensions of DDBMs, the process locates 54 activities for realizing DDBMs. Furthermore, we cluster the activities to develop a consolidated model and demonstrate the application of the process by applying it to three case studies from the literature. The process is a starting point for further research on the realization of DDBMs and helps companies structure their activities for realizing a DDBM.

Keywords. business models, data-driven, data monetization, realization

8.1 Introduction

How to create value from data is a current and highly relevant topic for practice as well as for research. Through the massive commercial success of data-driven giants from Silicon Valley, this topic has become increasingly relevant for incumbent companies of many industries. Chen et al. [1] showed how Lufthansa connected data about the customer relationship system with external social media data to deliver a personalized customer experience and increase passenger turnover. Alfaro et al. [2] described how the Spanish bank BBVA successfully developed a data monetization portfolio by investing in different projects over time. Similar to Lufthansa and BBVA, many other companies are trying to capitalize on big data and advanced data analysis approach-es. Although consulting and IT firms offer support for companies interested in becoming a “data-driven company,” it is still perceived as one of the greatest challenges in the digital transformation journey.

Research has taken up this challenge from practice and seeks to provide knowledge grounded in empirical studies, new approaches and methods for guiding the transformation activities. Thus far, these approaches and methods mainly focus on the ideation of business models as one of the key challenges. Data-driven business model (DDBM) frame-works were developed based on well-known models from general business model research, including the work of Osterwalder and Pigneur [3] and Johnson et al. [4]. However, these DDBM frameworks mainly focus on ideation, while omitting the challenges related to the implementation of DDBMs.

Thus, in this research, we tackle the following research question: Which activities are required to realize a DDBM, and how can they be integrated and structured in a systematic approach? To answer this question, we conducted a two-part literature review. First, we extracted the specific characteristics of DDBMs from the literature. Second, we re-viewed and compared existing approaches for realizing business models. Based on the results of these two reviews, we developed a four-step DDBM realization process. The process provides a structured approach and highlights key activities for guiding the realization of DDBMs. This extends the existing research in two ways. First, compared to existing approaches focusing on the ideation of DDBMs, the process addresses the broader challenges related to realizing the business model, including the activities for implementation and review. Second, the results highlight the specific activities related to DDBMs compared to general approaches for business model realization (BMR). The results are also relevant for practice as the process can be used as a blueprint for projects in practice.

The paper is structured as follows: In section II, we pre-sent a short summary of related research for the field of DDBMs and business model realization. In section III, we describe the methodological approach. In section IV, we summarize the results of the two-part literature review, followed by the DDBM realization process. The paper closes with a discussion and conclusion in section V.

8.2 Related Research

In this research, we seek to integrate two, thus far, mostly separated streams of research. The first stream is related to data-driven business models. The second stream is related to the realization of business models. After briefly introducing both streams, we emphasize the weak link between the two streams.

Business model research is a well-established field in management research. Teece [5] provided a short definition of the term business model: “In short, a business model defines how the enterprise creates and delivers value to customers, and then converts payments received to profits.” Several authors developed frameworks to structure the different elements of a business model during the ideation process and to provide an integrated overview of these elements [3], [4], [6]–[8].

A recent sub-field of research on business models is concerned with data-driven business models. The topic of lever-aging data as a key driver for business models is increasingly important for research and practice. Chen et al. [9] per-formed the first step to connect big data and business models, followed by Hartmann et al. [10] who developed a DDBM framework based on Osterwalder and Pigneur’s [3] business model canvas. A widely accepted definition of DDBMs does not exist. For this paper, we extend Teece’s definition [5] and define a DDBM in the following way: A data-driven business model defines how a company creates and delivers value from data to customers and extracts value from these activities.

Existing business model frameworks emphasize activities related to the ideation and design of new business models while providing less or no guidance on the implementation and execution. The literature on business model realization is —according to the limited number of publications—still in an early stage [11], [12]. Casadesus-Masanell and Ricart [13] connected the abstract strategic form of a business model with concrete tactics that can be used for planning and realizing business operations. These tactics can lead to concrete activities to evolve the business model in the company. De Reuver et al. [14] drew on the product roadmap approach and adjusted it for the implementation of business models. Baden-Fuller and Haeflinger [15] developed a technical-oriented approach by connecting the focal technology innovation to the development of business models. Focusing on data, Anand et al. [16] developed several scenarios for extracting business value from data. However, the authors did not provide a concrete implementation approach, and their research was only loosely linked to established business model frameworks. The contributions de-scribed above highlight different façades of BMR and lack a common or established understanding and conceptualization. In line with previous research, in this paper we define business model realization as the structured analysis, de-sign, implementation and review of a business model in a company.

The research streams of DDBM and BMR have not been integrated. McAfee and Brynjolfsson [17] provided the first idea for how to make use of big data in enterprises, but they did not provide a structured approach for this challenge. Fichman et al. [18] developed a framework with stages for realizing digital innovations. This framework is a structured approach for implementing digital products, but it merely considers the business model. Hunke et al.'s [19] process model is a multipart overview of data-driven business mod-el innovation, but does not describe concrete activities for its realization. Therefore, the current literature does not provide an approach that structures the activities that are necessary to realize a DDBM in a company. In this paper, we seek to take the first step to close this gap by integrating existing knowledge on DDBMs and BMR in a structured DDBM realization process.

8.3 Method

To gather and summarize the status quo of the research literature on data-driven business models and the realization of business models, we conducted a two-part systematic literature review based on Webster and Watson's [20] and vom Brocke et al.'s [21] work. Due to the lack of articles about the intersection of the two topics, we split the review into two parts dedicated to the topics DDBMs and BMR (see Figure 7). Because an international audience is the target for the study, only literature published in English was included in the research process.

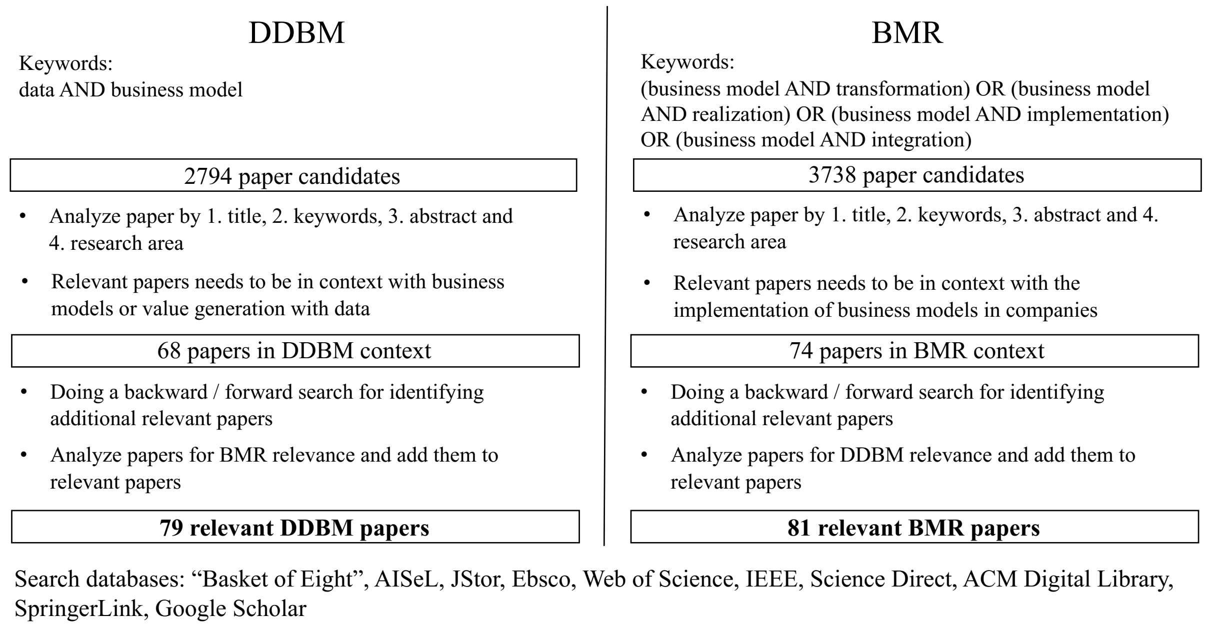

Figure 7: Systematic literature search and analysis

A. Search Terms

Before we started with the systematic search, we con-ducted a heuristic search by using Google Scholar and a variety of word combinations to find the essential search terms for the literature review. We started with the most common search terms, such as "data driven" and "business model," and pursued an iterative process to develop the best-matching search terms. Based on these results, we chose the keywords for the DDBM search (data AND business model). We received a high number of hits for this general search term. However, it was necessary to avoid excluding too many relevant papers in the beginning of the research. For the topic business model realization, we used the search terms (business model AND transformation) OR (business model AND realization) OR (business model AND implementation) OR (business model AND integration).

B. Find Relevant Databases

To consider a wide range of relevant research papers from information systems and business management research, we searched in the “Basket of Eight” as well as in the libraries AISeL, JStor, Ebsco, Web of Science, IEEE, Science Direct, ACM Digital Library, SpringerLink and Google Scholar. There was no range of published years. For the “Basket of Eight,” AISeL and JStor we searched for title, abstract and keywords of the papers. At Ebsco, Web of Science, IEEE, Science Direct, ACM Digital Library, SpringerLink and Google Scholar, we got a huge number of results, so we limited the search to the title. Defining more specific search terms would not have led to better results, and relevant papers would have been excluded.

C. Analyze the Papers

In total, we found 2794 papers for the DDBM topic and 3738 paper in the BMR context. In the first step, all papers were analyzed by 1) title, 2) keywords, 3) abstract and 4) research area. For the DDBM area, we selected papers that addressed business models or value generation with data. For the realization of business models, we focused on the description or models for implementation in the company. Due to the lack of papers on the intersection of DDBMs and BMR, we considered all relevant papers related to BMR, including those without a focus on DDBMs. We excluded papers that did not fit these criteria. Duplicates were re-moved. Following Webster and Watson [20], we conducted a backward and forward search to identify additional relevant papers. We also considered DDBM papers for the BMR review if they contained aspects of BMR (and vice versa).

D. Document the Results

After selecting the relevant literature, we started a deep content analysis of the paper to get insights into the research status. Overall, 79 papers on DDBMs and 81 papers on BMR were considered for further analysis and conceptualization. For the literature review related to DDBMs, we ana-lyzed the papers based on Hartmann et al.’s [10] “data-driven business-model framework”. The framework was built based on the results of start-up companies, but the key dimensions of this framework also apply to incumbent companies. For the BMR literature review, we identified 13 relevant approaches, which formed the basis for structuring the BMR process in four steps: analysis, design, implementation and review. These steps are based on the approaches of de Reuver et al. [14] and Frishammar and Parida [22].

E. Connect the Research Streams

To develop the DDBM realization process, we took the four steps of BMR as the first element of the structure and used the dimensions of Hartmann et al.'s DDBM framework as an orthogonal dimension. Next, we derived necessary activities from the DDBM and BMR literature. These essential activities were structured by the four steps of BMR and the dimensions of Hartmann et al.'s framework.

F. Validate the Process

The process was validated by practitioners from the IT industry. We conducted short interviews with three IT experts from the areas of software architecture, IT management and digital sales at a leading German digital agency who deal with different aspects of realizing DDBMs. We started with individual interviews (45 minutes) which were separated into three parts: 1) a presentation of the found DDBM realization activities from Table 8, 2) a quantitative assessment with six five-point Likert-scale questions and 3) a qualitative assessment with six open questions (e.g., "Is the DDBM realization process complete? Did you omit further steps or activities?"). After the interviews, we held a group discussion (60 minutes) in which we discussed the DDBM realization process to find missing process elements. All experts had eight or more years of professional experience in IT or digital units and provided additional feedback for the process from a practical view, which helped to check and refine the process. To provide additional case-oriented vali-dation, we demonstrate how the DDBM realization process can be applied to analyze three literature-based DDBM case studies at the end of this paper.

G. Structure the Process

To structure the DDBM realization process, we divided the approach into the four BMR steps, and we grouped the results shown in Figure 8 into 16 clusters with four dimensions (data assets and architecture, data operations and skills, data ecosystem and data monetization). Each cluster summarizes similar activities, which are essential to realize a DDBM. For example, we clustered the activities "identify existing internal and external data sources," "understand data quality, coherences and condition" and "evaluate existing organizational data-related resources; IT systems, data skills, workforce" into "analyze data resources." Overlapping activities can be part of two clusters.

8.4 Results

In the first part of the results, we present the findings of the literature review of the DDBM research. In the second part, we compare existing BMR approaches and outline the four steps of BMR. In the third part, we present a structured DDBM realization process with essential steps and activities which is based on the literature on DDBMs and BMR.

A. Characteristics of Data-Driven Business Models

For developing a BMR process that is specific for data-driven business models, we need to understand their key characteristics. During the last few years, authors such as Hartmann et al. [10] and Brownlow et al. [23] developed, mostly based on Osterwalder and Pigneurs's [3] business model canvas, specific DDBM frameworks. For this paper, we analyzed DDBM-related papers of the literature search and structured the key characteristics according to the dimensions of Hartmann et al.'s [10] framework.

1) Key resources: For a business model to be successful, it is essential to have the required resources available. Data are a key asset for a DDBM. In general, it is possible to divide data assets into two types: internal and external [24], [25]. Internal data include sources the company owns or has direct access to it (e.g., enterprise resource planning or customer relationship management systems). Such internal data could lead to new opportunities but often are not yet used for improving existing business models or for creating new ones [10], [26], [27]. External data are data that are not produced or generated by the company, but which can be acquired from data providers or collected from the company's products for use as a resource to generate value [23], [25], [28], [29]. Furthermore, additional data can be provided by partner companies to generate co-value [2], [30]–[32]. Access to a powerful IT infrastructure to store these data is essential for a DDBM [1], [2]. In addition, human re-sources, such as skilled data scientists or software engineers, are essential elements [33].

2) Key activities: To transform the data resources into valuable assets, companies must execute activities to use the data. The basic and mandatory activities for any DDBM are data generation and data collection [10], [33]. This includes building the capabilities for processing the data in useful IT systems, such as a data warehouse or data platforms [25], [34], [35]. This step, called data consolidation, aims at making data available as a useful resource pool for all other activities of the DDBM [36], [37]. Part of this activity is also to acquire required external data sources for increasing the value of the company's data if necessary [10], [38]. Furthermore, data structuring is necessary to contextualize the data, to select the relevant data from the data pool to avoid overhead and to secure the data quality [1], [27], [28]. The data quality is an

essential requirement for the offering, potential customer segments and revenue model and requires a lot of strategy planning and data science skillsets [24], [28], [38].

3) Offering/Value proposition: With the activities and data resources, companies are able to offer a value proposition for potential customers [34], [39]. The classic approach of data business is to collect and analyze data and sell them to a customer as a “data provider” [10], [25], [33]. Another area of value proposition is the development of products based on the analysis and interpretation of the company’s data. This can lead to new or additional non-digital or digital product offerings such as “Analytics-as-a-Service” or “Predictive Maintenance” [24], [31], [39]–[42]. In addition to the development of new or additional product offerings, improvement in the company’s performance or competitive advantages strengthens the company’s performance [17], [19], [25], [35], [41], [43]. To support the development and implementation of DDBMs, consulting services and tool provider offerings exist, which support incumbent companies [28], [36], [44].

4) Customer segments: Brownlow et al. [23] separated the potential customer segments into three parts: business-to-business (B2B), business-to-consumer (B2C) or consumer-to-consumer (C2C). The typical customers are from the B2B segment, such as data scientists or business people who are trying to improve their value creation process with data [31], [38]. Important success factors are easy access and a superior customer experience, because most users are not IT specialists. The second important actor in the B2B segment is the company’s partners. Through exchange of data co-working, companies can create more value out of the combined data set [25], [30]. This leads to possible revenue growth for both partners and strengthens partnerships.

5) Revenue model: Due to the intangible nature of data, a wide range of different types of revenue models is possible [3], [10], [45]. The classic approach is to sell the asset “da-ta” for a fixed price (= asset sale) [25], [43]. Another possibility is to offer the customer a rental or subscription mod-el. In this model, the offered product or service can be used for a fixed or usage-based price [10], [19], [31], [44]. It is also possible not to sell the data to customers, but to create a service such as online advertising to improve the company’s revenue [25]. In the consulting business, it is common to sell the customer personnel-days for project support for data-driven consulting [28]. If the business model relies on working with partners, co-creation and cross-selling of partner products are a relevant revenue income stream for companies that use DDBMs [44], [46].

6) Cost structure: During the creation of a DDBM, it is crucial to monitor and plan the cost factors. Analytics tools, IT infrastructure technology or data interfaces need large

investments to stay competitive in the market [25], [33], [34], [47], [48]. This includes the costs of protecting the data, because most data can be personalized or have sensitive information which can lead to high damage for the provider or users [28], [36], [37]. To use this technology, and to gain value from the data, a broad set of skills is necessary [17], [27], [37]. During operation, the cost of the technical infrastructure, human resources or data fees has a permanent effect on the company's profitability [25], [44], [48]. In the process of creating a DDBM, soft factors like internal politics and stakeholder management are important in the change process [28], [34], [49].

	Analysis	*Design*	*Implementation*	*Review*	*Context*
Adrodegari et al. [51]		●	●		Industrial Innovation
Batocchio et al. [54]			●		General
Broekhuizen et al. [12]			●	●	General
Doll and Eisert [50]	●	●		●	General
Hunke et al. [19]	●	●	●		Business Model Innovation
Fichman et al. [18]	●	●	●	●	Digital Innovation
Frishammer and Parida [22]	●	●	●	●	Sustainability
Geissdoerfer et al. [53]	●	●	●		General
McAfee and Brynjolfsson [17]		●	●		Big Data
de Reuver et al. [14]		●	●	●	General
Schaller et al. [55]	●	●	●	●	General
Schallmo et al. [52]	●	●	●		Digital Transformation
Teece [5]	●	●	●	●	General

Table 7: Four steps of business model realization

B. Business Model Realization Approaches

As stated in section III, the literature review emphasized a lack of research about BMR in the data-driven context. Thus, the search process was expanded to include general BMR approaches. Through the search, we identified 13 BMR approaches (see Table 7) from different contexts de-scribing activities, which we classified according to the four steps of BMR.

1) Analysis: To start the BMR process, it is necessary to conduct an analysis of the status quo of the company's current business model. This can be done by applying conceptual tools like Osterwalder and Pigneur's [3] business model canvas or other frameworks we mentioned in the related research section. The benefit is a structured approach for analyzing the shortcomings or opportunities of concrete business model characteristics [22]. This could be the better

value proposition of a competitor, the possibility of realizing scale effects through acquiring new partnerships or in-venting new products or resources that are not yet integrated in the business model [14], [50]. This step is mostly a minor topic in the BMR papers, but is important to plan the right steps for the design phase.

2) Design: As the second step, the creation process starts with the idea generation of a new or evolved business model approach [51]. Based on the analysis results, but also by adopting competitors' successful elements, the company needs to develop the characteristics of prospective business models [19], [22], [52], [53]. These include the view on technological, organizational or financial resources and capabilities that are needed to change the BM elements [14]. Activities for this phase are targeting the right customer segments in the market and creating an appropriate value proposition or mechanisms to capture value from customers and block imitation by others [5], [18]. Adrodegari et al. [51] described the final step with a comparison of the status quo and the prospective business model to find the existing gaps and necessary activities for the implementation phase.

3) Implementation: After the conceptual design of the targeted business model, the most important step is the implementation in the company. The implementation starts with small-scale pilot testing, which affects only a small company business unit or internal start-ups to learn from the feedback [12], [53]. In this pilot, modifications, such as cultural changes, new roles, technology, needed skills or access to new resources, can be implemented [17], [18]. In particular, finding the right team for the pilot is a critical element, because it must fit the characteristics of the new business model [19], [54]. In the IT context, pilots are often developed as a minimum viable product (MVP). The number of pilots is not limited, so it is possible for companies to test different approaches at the same time. If a business model pilot is successful, it can be scaled by applying it to other units or by increasing the workforce or budget for the mass market [22].

4) Review: Many BMR approaches simply stop after implementation in the company. The BMR approach has a one-time technical deployment character which ends after execution. Authors such as Broekhuizen et al. [12] and Schaller et al. [55] emphasized that it is necessary to continuously review and reconfigure the implemented business model. This includes changes in business model characteristics, cultural changes, competition or new technologies. Revenue growth and cost structure can be analyzed to identify opportunities and achieve them through agile structures [18]. The results of the review should lead to concrete tasks which are sorted into critical and most effective activities for company success [14].

Although the phase-based structure might be associated with a waterfall-like structure, the BMR process is not de-scribed as a linear project. Instead, the process is a continuous cycle of analysis, idea generation, execution and assessment to deliver a consistent creation of value for the company. Nevertheless, events such as “start with the implementation” or “business model is implemented” mark important gates in the process between design, implementation and review.

C. DDBM Realization Process

With the literature review, we conducted a literature-based analysis of the status quo of DDBM research and insights for BMR approaches. The results emphasized the lack of knowledge about how to realize DDBMs. To fill this gap, we connect the results of the two reviews to create a DDBM realization process and link the four steps of BMR with Hartmann et al.’s DDBM dimensions to structure necessary activities (see Table 8). The activities are numbered in each step to identify them in the evaluation and DDBM realization process approach.

	Step 1: Analysis	***Step 2: Design***	***Step 3: Implementation***	***Step 4: Review***
Objective	Analysis of the current data-related business elements	Design of the DDBM approach	Implementation of the designed DDBM in the company	Continuously review DDBM after implementation
Key Resources	1 - Identify existing internal and external data sources [10], [26], [38] 2 - Understand data quality, coherences and condition [19], [23], [24] 3 - Evaluate existing organizational data-related resources; IT systems, data skills, manpower [17], [19], [24]	13 - Identify necessary existing and new data resources [10], [23], [36] 14 - Construct information systems architecture and data model [1], [18] 15 - Frame needed skillset and resources [33], [46] 16 - Get senior management support for DDBM realization [1], [34]	30 - Implement data processing systems/structures (BI-tools, middleware, data warehouse) [1], [2], [25] 31 - Recruit or educate skills and human resources for data processing [2], [16], [17]	42 - Monitor and extend data sources [16], [53] 43 - Observe technology developments [18], [46] 44 - Adjust data skills and resources [1], [46]
Key Activities	4 - Analyze existing data use and processes [19], [34], [47] 5 - Identify shortcomings in data use [22], [24] 6 - Categorize data ecosystem interactions (stakeholders, partners, etc.) [19], [25]	17 - Link existing and new data use [10], [23], [47] 18 - Plan necessary processes and activities for DDBM implementation [14], [23] 19 - Design data partner ecosystem [19], [25] 20 - Evaluate data privacy compliance and security [19], [27]	32 - Implement a DDBM pilot [17], [22], [57] 33 - Choose internal or external execution [2], [12], [54] 34 - Scale business through data ecosystem [1], [22], [46] 35 - Establish company data culture [1], [17], [46]	45 - Improve activities, processes and roles [11], [12], [17] 46 - Growth the data ecosystem [17], [53] 47 - Secure the data and maintain data compliance [27], [42]

Offering/ Value Proposition	7 - Explore the connections between data and own business offerings [2], [57] 8 - Scan for trends of data offerings on the market [22], [44]	21 - Development of new data business opportunities [17], [26], [46] 22 - Extend existing product offerings by data [1], [2], [33] 23 - Focus on customer experience [27], [38], [52] 24 - Imitate successful DDBM approaches [22], [44]	36 - Deliver the product/data to the customer [19], [43] 37 - Create co-value through the partner ecosystem [25], [46]	48 - Establish a continuous data offering improvement [17], [27] 49 - Continuous assessment of the DDBM offering and partner ecosystem [19], [44], [46]
Customer Segments	9 - Analyze existing and new potential DDBM customer segments [22], [23]	25 - Define target customers for data monetization [23], [36] 26 - Use customer data for co-creation [1], [38]	38 - Capture value from customer segments [27], [43]	50 - Learn and improve from a loyal customer base [12], [53] 51 - Scale data business to other industries/branches [32], [46]
Revenue Model	10 - Analyze existing company revenue strategies [2], [19], [22] 11 - Explore data pricing opportunities on the market [22], [33], [44]	27 - Design the new or evolved pricing model for data monetization [10], [23], [25]	39 - Integrate the different data pricing models in the company [23], [45]	52 - Recalibrate and extend the data pricing model [44], [53]
Cost Structure	12 - Analyze costs for DDBM development and management [27], [48]	28 - Evaluate the existing and new cost elements [22], [48] 29 - Define the investment budget for DDBM [34]	40 - Execute the planned investments for DDBM offering [2], [14] 41 - Growth of DDBM running data, technical or analytical costs [25], [53]	53 - Control the cost structure and growth cost efficiency [22], [23], [48] 54 - Transfer analytical cost to partners [25]
Step Outcome	Understanding of the current data business in the company, selection of a conceptual tool for the DDBM design	Finalized DDBM concept, defined activities for implementing the DDBM step-by-step in the company	DDBM is implemented in the company; customers are using the services provided by the DDBM	Ideas for improving the DDBM and necessary steps for its transformation

Table 8: Steps of the DDBM realization process structured by Hartmann et al.'s DDBM dimensions

Step 1 - Analysis: To start the realization process, a status quo analysis of the current dealing with internal and external data in the company business must be conducted. In many cases, the company does not know which data are accessible or have been used. The evaluation of the data landscape, information systems and accessible skillsets provides a good understanding of which capabilities for data business exist. Further, the company must evaluate their data and the connection to the company's products, process-es and pricing. This includes the interactions with the partner ecosystem. Based on the findings of the data analysis, it is possible to find unused data with potential value or business opportunities that can be a starting point for a DDBM. In addition, it is important to search for data-related trends in the market, technical breakthrough or scientific discoveries, which can help the company's data business grow, and explore existing data monetization approaches. Furthermore, studying existing customer interactions or potential custom-er segments is valuable, to understand possible needs for data-related offerings. The analysis is essential to collect all possible data-related sources and understanding of the company's activities. This analysis is the toolbox that will be used in the following design step.

Step 2 - Design: The focus in the design phase is how the use of data can improve the company's business value. It is possible to use Hartmann et al.'s [10] framework to design a reliable concept. The evaluation of the status quo analysis and data business opportunities are the origin for the targeted DDBM. To make the data valuable, processes, activities and roles must be designed to set up a useful data ecosystem. This includes the information system architecture, data processing skills and required human resources. Designing partner interactions with the data ecosystem and considering data privacy compliance are additional activities that are essential for a successful design. Based on the identified data business opportunities or best practices, the company's value proposition can be created. These offerings are connected to applicable customer segments and revenue models that exceed the costs and investment budgets. The newly designed DDBM is the origin for changing the company's business model completely or adding data business to the company portfolio [2]. The gaps between the existing and new planned company offerings are the activities that must be executed in the implementation step.

Step 3 - Implementation: The most complex part in the realization process is the execution of the designed business models and planned activities. Handling with data as a key resource is a completely new field for many companies and can differ substantially from the existing business model. To reduce the complexity, it is good to start with a small business unit that is developing new business for the company. The unit can be built as an internal business unit or as an external but company-related start-up. In this independent unit, it is possible to try multiple strategies to create value from data. Concepts such as lean start-up can be used to acquire early feedback and evaluation for DDBM ideas. In pilot projects, the teams can experiment with the designed data processing systems and data sources in a secure environment. In addition, it is easier to start with the right skilled people (such as data scientists, solution engineers or digital managers) and a flat organizational structure in a smaller environment than in a highly structured incumbent company. Hilbig et al. [56] showed by analyzing start-ups in Berlin numerous approaches for creating a digital product offering based on the understanding of data. The use of pilots does not trans-form the complete company business immediately. The new business approaches should not offend the established business success. If the DDBM is successful, incumbent companies can scale pilots to more units and areas to remain competitive in the market. After the successful start of DDBM units, the offerings must be communicated to the customer segments. Through the use of partner data, co-value creation is possible. Acquiring the first customers is important to fix the pricing model and to implement an applicable delivery method for the offered data product. The connection to customers and partners is necessary to implement a data ecosystem. This data platform will give the company the possibility of developing more data business opportunities over time.

Step 4 - Review: The DDBM realization process is not a one-time business implementation. Many resources, activities or market environments change over time. The permanent company-owned data resources and use typically grow and must be monitored. New data sources become available, old ones get lost; new technology allows much better data use. Through the customer interactions, the company is able to establish continuous learning from the data which allows the companies to evolve their data ecosystems. These changes can require new skills and technology to refine the implemented DDBM to the next level. Other companies can adapt their own DDBM and create a competitive offering. This list is not complete, because numerous events can have a strong influence on the business model. A continuous review process of the executed DDBM is necessary to change the business model characteristics with required activities. It is useful to connect a business model and data road mapping to build a permanent pipeline of DDBM pilots that are available for go-to-market.

If it is not possible to adjust the existing DDBM with economic useful activities, or it is foreseeable that the concept will not work in the future, the company starts with a new status quo analysis and restarts the realization process. The process is ongoing. With the combination of a structured approach, but with an agile mindset during the execution, it is possible to successfully realize an ongoing DDBM.

For demonstrating the use of the DDBM realization process, we applied it to case studies from the literature. We mapped the described activities in the cases to the activities of the process listed in Table 8. With this step, we demonstrate that essential activities of DDBM realization are covered and structured by this process. Furthermore, the demonstration shows that a broad range of other activities from this process were not described in the cases. Thus, the process could also guide a deeper analysis of the cases by looking for activities which that were not described.

Günther et al. [38] described in their case study LogiCo a European postal service provider that developed a DDBM for business clients. LogiCo analyzed existing internal customer data and data available from public data partners to understand the firm's data asset opportunities (1). The strategy was to combine multiple internal and external data sources to get a better understanding of household properties (2). This data-driven information product was designed for a B2B ecosystem, which wanted to use the product for marketing campaigns (25). LogiCo first implemented a self-service data platform, where clients could select data and buy them via a website (32). This ecosystem was extended over time with more data (34). After the successful implementation, the company reviewed its data monetization strategy. The company changed different DDBM characteristics and transformed the self-service into an analytic service model (50). In addition, the data offering was limited to structured customer profiles to give a better customer experience and a better purchase process for the client.

In a case study of Lufthansa, Chen et al. [1] provided in-sights into how the airline company used their data for business model renovation. Lufthansa used a top-down innovation process "Value Discovery" in which existing data were analyzed and clustered into different possible company use cases (4). Through the design step, the use cases were selected and prioritized to choose the best approaches for data-driven value creation (21). The company implemented four DDBM pilots in different areas of the company, including customer relationships, airport organization, flight logistics and aircraft maintenance (32). Lufthansa implemented a company-wide data architecture and ecosystem, which supported all DDBM pilots with the necessary data resources and operations (34). The DDBM pilots were refined over time and provided the possibility of offering new services to customers and improving aircraft performance (45). The setup as a company-wide data ecosystem allowed Lufthansa to scale the pilots to more business units and develop more DDBM or data-driven services in the future (51).

The activities of the Spanish BBVA data journey were published by Alfaro et al. [2]. As one of Europe's leading financial groups, BBVA made many attempts to create value with data. During the start of the BBVA data initiative, they analyzed the data resources with a small team of data scientists (1). This core team started with different DDBM approaches and designed an ecosystem with data and research partners (19). BBVA understood that skills and resources are elementary for a successful DDBM and hiring and educating data experts early (31). The first pilots were scaled to company-wide data science of excellence, which supported different business units by implementing a DDBM. Data were monetized by selling information solutions to customers, improve existing business processes and combining existing products with data services (38). By the end of 2017, a portfolio of 17 DDBM projects had been successfully launched and created value for BBVA (51).

Evaluation: The evaluation with the experts showed that the proposed DDBM realization process is seen as a useful tool for practitioners. In the quantitative assessment, participants agreed that the process is understandable, relevant, useful, correct and applicable. In the qualitative assessment part, the practitioners provided feedback for which types of companies the DDBM realization process can be useful. The experts commented that the structured approach is a good blueprint for inexperienced companies in the field of data-driven business. In addition, the process should be interesting for start-ups that are trying to create new data-driven companies. The practitioners commented that the static process did not replace iterative activities in each step. In addition, the process was seen as a loop, not as a one-time integration process. In a further development of the process, this "loop" characteristic should be a more important element. The experts also requested an example or use case, in which this process is executed to get better practical knowledge for DDBM realization. This would prove the literature-based process and give a practical best-practice guideline.

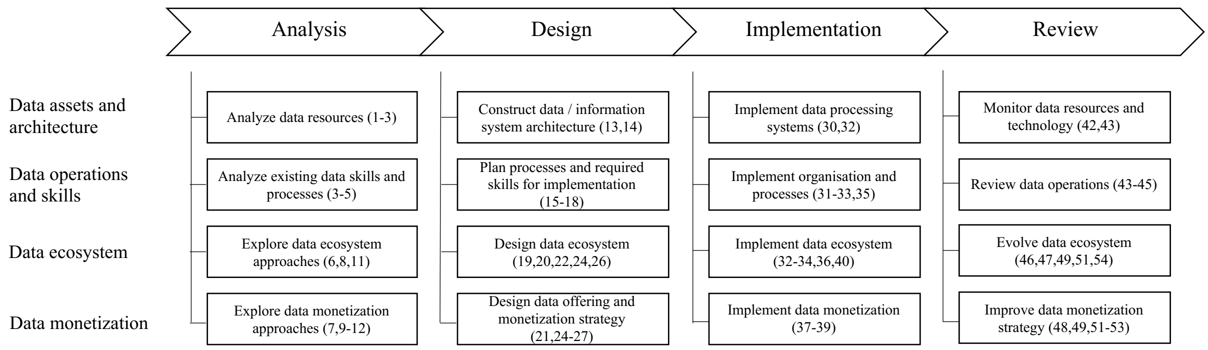

Figure 8: DDBM realization process approach

To create a more compact approach, we took the results from Table 8 and grouped them into different clusters in Figure 8. Each cluster summarizes the activities per step. In this revised structure, we replaced Hartmann et al.'s DDBM dimensions with four dimensions (data assets and architecture, data operations and skills, data ecosystem and data monetization) that we developed bottom up from the activities.

8.5 Discussion and Conclusion

Through the literature review, we learned that several studies addressed the challenge of ideating and designing DDBMs. Several frameworks and characteristics of DDBMs have been developed, which help to understand how we can create ideas for DDBMs. However, this ideation is only one part of the realization process. We argue for taking a broader perspective on DDBMs that includes the implementation and review. Furthermore, it is necessary to connect the activities through the different steps of BMR. The existing approaches support this argument and show that the problem of a lack of integration between the different steps is already well-known. However, the existing approaches turned out be limited in supporting the deduction of concrete activities for DDBMs. Data as a resource, the delivery channels or the transformation speed can differ significantly from traditional business models. Specifically, missing characteristics such as “partners” or “customer relationships,” in Hartmann et al.’s framework must be analyzed, because of the big opportunities for companies in using data ecosystems. The realization of a DDBM is strongly driven by information technology, as the model requires specific activities, such as providing a powerful IT infrastructure and data processing tools during the full data lifecycle or establishing data protection management to gain customer trust. This allows companies to create more advanced offerings than just selling and shipping their collected data.

The DDBM realization process presented in this paper provides a new perspective on the activities required to realize DDBMs. Existing papers take a static or ideation-focused view. The DDBM realization process provides a more comprehensive blueprint of the steps and activities that are needed to realize a DDBM. Nevertheless, a complementary “agile” mindset is useful to allow DDBM teams to quickly respond to new requirements, opportunities or feedback during the DDBM realization process. The approach presented in this paper is not without limitations. This DDBM realization process is a first step toward a better understanding of this challenge. For now, this process is mainly grounded in the existing literature and has been evaluated by only three experts. This paper can be the starting point for conducting more research in the field of DDBM realization. The most important activities must be identified in detail. This is important to understand the main enablers and barriers for adoption and realization by a company. The literature findings provide the first idea, but the realization process must be verified with additional practical experiences, and the first use cases should be realized.

Realizing data-driven business models is a complex and challenging task. Data are a highly important resource for every modern company, which tries to stay competitive in the market. In this paper, we addressed the gap of a lack of integration of BMR and DDBM research. Based on a structured literature review, we summarized key articles on both topics and deductively integrated them to outline a DDBM realization process. This process extends DDBM research as it goes beyond the challenge of ideating DDBM, and the process extends BMR research as it considers DDBM-specific activities. However, the process was developed based only on existing literature and lacks empirical validation beyond the evaluation on a larger scale. As next steps for future research, qualitative-empirical studies of DDBM realization projects should be conducted, and additional experts should evaluate the present findings.

8.6 References

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10 “Ideation is Fine, but Execution is Key”: How Incumbent Companies Realize Data-Driven Business Models

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Abstract. Realizing innovative ways of data usage and monetization are considered to be important for companies in many industries today. Hence, companies are developing multiple approaches for developing and realizing data-driven business models (DDBM). Current research provides the first methods to support the design of DDBM. However, empirically grounded knowledge on how incumbent companies realize DDBM is scarce. To close this gap, we interviewed experts from multiple industries to learn from their experiences. Based on 45 cases, we developed four DDBM realization case types. Grounded on the case analysis, we identified four execution periods that companies pass through during DDBM realization. Finally, we compared the findings from this study to a DDBM realization process, which was developed based on the synthesis of literature. The results contribute to a better understanding of DDBM realization by drawing on a rich set of cases.

Keywords. data-driven, business models, realization, cases

9.1 Introduction

The growth of data is increasing worldwide from year to year. Companies collect data from manifold sources and store it in their on-premise or cloud-based data storages. For several years, incumbent companies in multiple industries have strived to realize value from this data. Research tries to support companies by developing tools like data-driven business model (DDBM) frameworks, which guide the creation of necessary organizational and technological design [1], [2]. Research has already captured some DDBM cases in case studies, which provide useful insights into which data monetization strategies companies developed and tried to execute in the market [3], [4]. These case studies reflect and structure practices carried out for the ideation and design of DDBM. However, these results from previous studies do not provide support for companies that seek to realize their DDBM ideas. While DDBM research has focused on DDBM ideation, studies on DDBM realization (DDBMR) are scarce or mainly grounded in reviewing existing literature. Hence, in our paper, we are addressing the following research questions (RQ): RQ1: Which DDBMR cases are currently realized by incumbent companies and which types of DDBMR exist? RQ2: How is the process of DDBMR by incumbent companies structured? RQ3: Which differences can be observed between the process of DDBMR in the literature and in the cases from our study?

To answer these questions, we conducted 19 expert interviews with managers and data specialists working in DDBMR projects. They work on realizing DDBM ideas and allowed us to reflect on their practical experience in these projects. Most companies for which the interviewees in our study are not companies that mainly focus on data. Instead, they are incumbent companies from traditional industries and try to transform their business through DDBMR. We analyzed the interviews and identified 45 DDBMR cases from different industries, company sizes, and customer focus. The interviews allow us to learn how companies realize DDBMs and which challenges they face from start to execution and scaling. We identified four periods that companies go through for successfully realizing a DDBMR. With this, we are extending the existing research by adding an empirically grounded understanding of DDBMR compared to previous, mainly literature-based approaches. In each of the periods, we were able to identify significant differences between the literature and practice, which also provides a starting point for future research. In practice, the results can help companies to learn from previous cases and to check whether their DDBMR approach includes important activities.

The paper is structured as follows: In the following section, we present the related research for the field of DDBM and business model realization (BMR). In the next section, we show the methodological approach. Subsequently, we present our results and close with a discussion and a conclusion in the final section.

9.2 Related Research

Business model research is a long-established research field with a wide variety of publications. A much newer subfield is the research area of DDBMs. This area has become increasingly important as data is the focus of action in many companies seeking to develop their business model further or to develop a new business model. Based on Teece's [5] definition, a DDBM defines how a company creates and delivers value from data to customers and extracts value from these activities.

The first steps to describe data as a key driver for business value generation were made by LaValle et al. [6] and Chen et al. [7], who described the usage of data analytics as an important tool to create a value proposition. Hartmann et al. [1] extended these ideas and formed a DDBM framework based on the business models of start-up firms. Brownlow et al. [2] developed the DDBM innovation blueprint by synthesizing insights from start-ups and established businesses into one framework. Both DDBM frameworks focus mainly on the design part and are intended to be helpful in creating business strategies for DDBMs. Hunke et al. [8] went one step further and created a process layout for DDBM to show the necessary elements during the integration process in the company. To focus on the different aspects in this integration process, following DDBM research focused on learning from use cases in companies. Günther et al. [9] provide insights on how to realize value from data by studying a European postal service organization and its way of creating a DDBM. Chen et al. [4] and Alfaro et al. [10] examined big incumbent companies (Lufthansa and BBVA) to identify the challenges and potentials of DDBMs.
Both cases show that data science represents an important ability that companies should employ to create DDBMs. With the growing importance of DDBM, the role of data scientists is becoming increasingly important. Data science provides companies guidance on how to make their data tangible for business processes and models. Meierhofer and Meier [11] connected the areas of data science and value creation in their service design process. Frameworks like CRISP-DM or ASUM-DM provide a structured process model that helps to execute data science projects [12], [13]. CRISP-DM is an open-standard and established process tool for companies seeking to structure their projects, but it was originally made for data mining. ASUM-DM was developed by IBM and extends the CRISP-DM approach. Recently, researchers challenged the use of traditional project management approaches and drew on agile approaches for supporting data science projects. For example, Baijens et al. [14] show how Scrum can be applied in data science projects and create a connection between data science and the current move toward applying agile methods in business and IT projects.
In the literature, the general discussion about DDBM is dominated by publications focusing on ideation and design [1], [15], [16]. But there are also the initial research approaches that focus on the more complex realization process. De Reuver et al. [17] developed the "business model roadmapping" method, which supports companies in planning their BM lifecycles and structuring a BM creation process. The authors showed the necessary element of continuous enhancement of the BM. They present novel ideas for activities to execute the BM in the company. Berends et al. [18] highlighted that a scheduled realization process is a complex learning and adaption process that leads to the targeted BM over time. Broekhuizen et al. [19] focused on

the challenges that occur during the implementation of a BM in an existing company. In the context of data and value generation, McAfee and Brynjolfson [20] recommended starting with a prototype process with a small team, which can grow and adjust over time. Schüritz and Satzger [21] identified different patterns of DDBM innovation in companies and also highlighted the need to conduct further studies of the implementation process of DDBMs in practice. Wiener et al. [22] mentioned the lack of knowledge about DDBM implementation and argued for further research in this area. To close this research gap, Lange and Drews [23] did a two-step literature review for DDBMR to connect the research streams of DDBM and BMR. This study analyzed DDBMR purely from a literature perspective. Thus, the gap in empirical knowledge about DDBMR remains unclosed. Rashed and Drews [24] provided the first empirically grounded study to analyze DDBM design and realization strategies at the enterprise level. For this, they interviewed 16 senior management experts from consulting firms who specialized in enterprise DDBM strategy consulting. The study delivers the first insights into the DDBMR pathways. However, they mainly capture the strategic perspective, and the study does not provide knowledge about the technological and operational issues related to DDBMR. As a better understanding of DDBMR should also include this perspective, we used this gap as the starting point for our research. While research lacks knowledge about the operational perspective of DDBMR, it could also inform practitioners in incumbent companies and support them in conducting their DDBMR projects.

9.3 Method

For our research, we employed qualitative expert interviews as the best fitting method to obtain useful insights from practice. We followed the qualitative content analysis approach of Mayring (2007) to analyze the interview data.

Our target was to interview people who are realizing data-driven business ideas in their companies. We wanted to speak with people who are involved on the operating level and know how to build and combine the resources, processes, and tools required for DDBMR. We, therefore, concentrated on experts in the field of data science, information systems, or digital business. We searched for people with multi-year business or project experience in data-driven business from different management levels. We included companies from different industries and sizes to collect data from multiple perspectives. All companies are operating in international markets. Table 9 shows an overview of all interviews we did with different experts.

All companies are incumbent companies, which are exploring ways of DDBMR in their own company or execute DDBMR projects for customers. The interviewed companies are based in

Germany, but operating in worldwide markets. For the interviews, we designed a semi-structured interview guide (Myers and Newman 2007). This interview design allowed us to address topics that we considered relevant based on the literature analysis, but it additionally provided the possibility to create an open atmosphere and to discuss interesting aspects of their experience in the data-driven business.

Company	*Interview*	*Role*	*Industry*	*Company size*	*Duration (in minutes)*
1	A and B	Lead Data Scientist and Managing Partner	Software	40	63
2	C	Director Digital Lab	Engineering	4,000	40
3	D	Data Scientist	Energy	9,000	57
4	E	Project Manager	Automotive	38,500	47
5	F	Product Owner Data Intelligence	Transport	315,000	56
6	G	R&D Manager	Automotive	300,000	48
7	H	Data Scientist	Shipping	2,700	35
8	I	IoT Engineer	Software	4,800	47
9	J	Product Owner Data Platform	Insurance	21,000	52
10	K	Head of Data Science	Mobility	2,200	58
11	L	Information Security Officer	Aviation	10,000	56

Table 9: Interviewed experts I

The interview guide comprises 31 questions and consists of two parts. The first part addresses general DDBMR knowledge, while the second part specifically aims at DDBMR project experience. In the first part, we focused on the elements of DDBMR and how they are represented in the company. In the second part, we wanted to understand which steps and actions are necessary to realize a DDBMR project. Interviews A and B were personal interviews, and interviews C through L were held by phone.

Additionally, we collected data in a second interview series with seven interviews for a deeper focus on data monetization realization. The duration of the interviews M-S was between 24 and 52 minutes, and they were conducted by using an online conference tool.

Company	Interview	Role	Industry	Company size
12	M	Head of AI & Data Analytics	IT Consulting	500 – 9,999
13	N	CEO	IT Services	<500
14	O	Senior Expert	Automotive	>100,000
15	P	Advisor Corporate Strategy	Automotive	>100,000
16	Q	Head of Techno-logy Marketing	Public Sector	500 – 9,999
17	R	Head of Customer Insights	Retail	>100.000
18	S	Tribe Lead AI	Communication	>100.000

Table 10: Interviewed experts II

In total we interviewed 19 experts. All interviews were recorded and fully transcribed. The transcripts were used as the dataset for a qualitative content analysis aimed at filtering the relevant interview information [25], [26]. The open coding was made with the goal of identifying the key elements and processes in data-driven business projects. We analyzed the answers based on each interview question to identify relevant statements. The interview statements were supplemented by Internet sources the experts gave us. In a further step, we grouped the statements into codes and clusters to identify important DDBMR cases and insights.

Through the interviews, the experts described different cases, which gave a wide overview of different approaches in the companies. In total, we identified 45 DDBMR cases from the interviews (Table 11). Interview N mentioned no clear case, so no DDBMR case was classified for our study. Based on existing literature we identified four DDBMR types from the clusters, which are described in the results section [22], [27]. The companies target through their cases customers in their own or foreign industries. Fifteen cases are still in development, while 30 are already launched to the market. In combination with the stage, this shows the progress of DDBM realization, which we also outline in more detail in the results section. Most cases focus on business-to-business (B2B) customers and only a few target business-to-consumer (B2C)/ business-to-government (B2G) markets. Hence, for most of the cases, DDBMR is a new field that is still in an evolutionary process. The scope of the DDBMR cases can be separated into three segments: 1) Transform Business: Company is transforming a traditional BM into DDBM in the same industry, 2) Extend Business: Company is extending a traditional BM by developing a new DDBM in the same industry and 3) New Business: Company is creating a new DDBM in a different industry.

9.4 Results

In the following, we present our results in two parts. In the first part, we show how the cases can be structured into case types based on their degree of innovativeness and the role of data for the DDBM. In the second part, we present our findings regarding the sequential structure of the DDBMR process while also considering activities in each period as well as the agile approach within each period.

Case	**Area**	**Type**	**Target Industry**	**Status/Stage**	**Focus**	**Scope**	**Interview**
1	Solar Panel Maintenance	Data Product	Energy	Live/MMP	B2B	New Business	A
2	Product Simplification	Business Improvement	Manufacturing	Development/ Experiment	B2B	New Business	C
3	Smart Power Grids	Data Product	Energy	Live/MMP	B2C	Extend Business	D
4	Grid Planning Tool	Data Product	Engineering	Live/MMP	B2B	New Business	D
5	Property Assessment	Data Product	Real Estate	Live/MMP	B2B	New Business	D
6	Solar Panel Recognition	Data Product	Energy	Development/ Experiment	B2B	Extend Business	D
7	Sensor Data Selling	Data Selling	Automotive	Development/ Experiment	B2B	Transform Business	E
8	Sensor Data Platform	Data Platform	Automotive	Development/ Experiment	B2B	Transform Business	E
9	Weather Data	Data Product	Automotive	Live/MMP	B2B	Extend Business	E
10	Car Data Marketplace	Data Platform	Automotive	Live/Scaling	B2B	Extend Business	E
11	Smart Fleet Maintenance	Data Product	Transport	Live/MMP	B2B	Transform Business	F
12	Car Data Marketplace	Data Platform	Automotive	Live/Scaling	B2B	Extend Business	G
13	Data Insights Platform	Data Platform	Automotive	Live/MMP	B2B	Extend Business	G
14	Traffic Data	Data Product	Automotive	Live/Scaling	B2B/B2G	Extend Business	G
15	In-Car Entertainment Platform	Data Platform	Automotive	Live/MMP	B2C	Extend Business	G
16	Use-Based Car Features	Data Product	Automotive	Development/ Experiment	B2B/B2C	Extend Business	G
17	Predictive Repair Service	Data Product	Automotive	Development/ Experiment	B2C	Extend Business	G

18	In-Car Advertisement	Data Product	Automotive	Development/ Experiment	B2B/B2C	Extend Business	G
19	Project Transparency	Business Improvement	Shipbuilding	Live/Scaling	B2B/B2C	Transform Business	H
20	Smart Metering Services	Business Improvement	Energy	Development/MVP	B2B	Transform Business	I
21	Predictive Wind Power Maintenance	Data Product	Energy	Live/Scaling	B2B	Transform Business	I
22	Predictive Component Replacement	Data Product	Manufacturing	Development/ Experiment	B2B	New Business	I
23	Predictive Escalator Maintenance	Data Product	Manufacturing	Live/Scaling	B2B	New Business	I
24	Device Data Hub	Business Improvement	Software	Live/Scaling	B2B	Extend Business	I
25	Product Evolution	Business Improvement	Insurance	Development/MVP	B2B/B2C	Transform Business	J
26	Usage-based Insurance Service	Data Product	Insurance	Development/MVP	B2B	Extend Business	J
27	Smart Investments	Business Improvement	Insurance	Development/ Experiment	B2B/B2C	Transform Business	J
28	Transportation Platform	Data Platform	Mobility	Live/Scaling	B2C	Transform Business	K
29	Plane Data Platform	Data Platform	Aviation	Live/Scaling	B2B	Extend Business	L
30	Flight Data Selling	Data Selling	Aviation	Live/Scaling	B2B	Extend Business	L
31	Personalized Flight Services	Business Improvement	Aviation	Development/ Experiment	B2B/B2C	Transform Business	M
32	Predictive Plane Maintenance	Business Improvement	Aviation	Live/MMP	B2B	Transform Business	M
33	Car Data Marketplace	Data Platform	Automotive	Live/Scaling	B2B	Extend Business	O
34	Car Repair Knowledge Base	Data Product	Automotive	Live/Scaling	B2B	Transform Business	O
35	Car Data Selling	Data Selling	Automotive	Live/Scaling	B2B	Extend Business	P
36	Car Data Marketplace	Data Selling	Automotive	Live/Scaling	B2B	Extend Business	P
37	Car Data Ecosystem	Data Platform	Automotive	Live/Scaling	B2B	Extend Business	P
38	Smart Insurance	Data Product	Insurance	Development/MVP	B2B	New Business	P
39	Satellite Data Selling	Data Selling	Public Sector	Live/Scaling	B2B	Extend Business	Q
40	Ship Detection Service	Data Product	Public Sector	Live/Scaling	B2G	Extend Business	Q
41	Shopping Data Selling	Data Selling	Retail	Live/Scaling	B2B	Extend Business	R
42	Shopping Insights Hub	Data Product	Retail	Development/MVP	B2B	Extend Business	R
43	Smart Assortment Platform	Data Platform	Retail	Live/Scaling	B2B	Transform Business	R

44	Location Data Service	Data Product	Communication	Live/Scaling	B2B	Extend Business	S
45	Data Insights Platform	Data Platform	Communication	Live/MMP	B2B	Extend Business	S

Table 11: Case list

A. Case Types

The different industries, foreknowledge or culture give each company another starting point for DDBMR. The identified cases can be classified into four DDBMR case types (Figure 9). The classification in the matrix is based on the focus on data trading and the case business innovation scope. The dimension of data trading shows the company monetization focus on core data trading and delivering to third parties. More data exchange and trading with third parties' results in a higher position in Figure 9. Business innovation shows the DDBMR innovative characteristic concept from traditional companies' BMs. A higher degree of innovativeness leads to a higher score in our DDBMR case type matrix. For example, in case 2, the manufacturing company is improving its BM by using its own data, but it is only involved to a limited degree in trading core data with third parties. The pure improvement is only a limited innovation compared to the firm's traditional BM. Hence, the case type of case 2 is "Business Improvement". In case 8, the automotive company is developing a sensor data platform where data trading between multiple stakeholders is an essential part of the DDBM. It is also a totally new business innovation approach that shifts its BM from being a hardware manufacturer toward being a DDBM platform provider. The type of this case is "data platform".

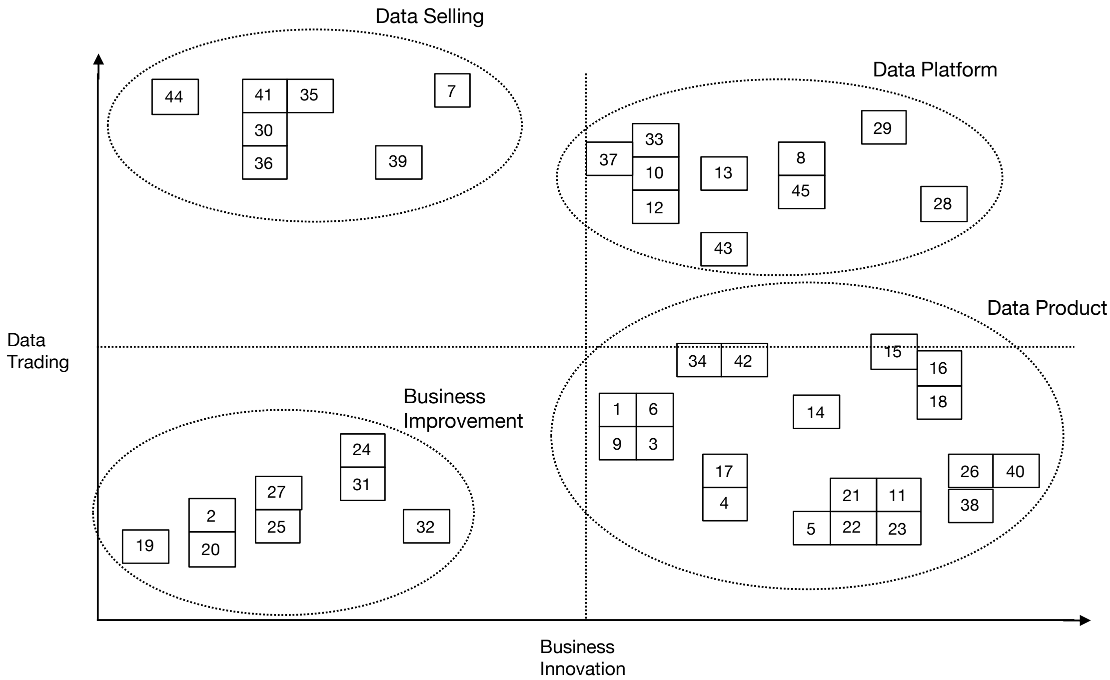

Figure 9: DDBMR case types

1) Business Improvement: The DDBMR cases in this type are characterized by their focus on improving their existing business through new data-based features or technology. We identified eight cases that add data-based improvements to their existing business for DDBMR execution. Mostly, these companies are in the very early stage of data-based business innovation and are challenged by the market to find additional income streams, process improvements, or cost reductions. They are experimenting with different data processing tools and invest in the first data monetization approaches. Nevertheless, the companies still have limited organization and technological resources for a strong data business. For example, in case 19, the company uses data for processes. We chose to include this type of DDBMR, though it has a limited focus on transformation. The pure improvement of existing business can lead to revenue increasement, but it is mostly not leading to a scalable ship-building business.

2) Data Selling: Another type of DDBMR is to sell data as an asset. Selling data is the most-discussed data monetization case type in the literature, and many authors only refer to data selling when they are doing research related to DDBM. With the right data, this type of technology and customers' business models can be realized to create a highly profitable and independent BM. The examples of the American technology companies and their highly scalable DDBMs are proving this. However, we identified only seven cases that follow this DDBMR type. Especially in cases in the automotive industry, which is known for owning extensive data processing capabilities and high IT investment budgets, data is sold to independent DDBM. project transparency to improve their marketplaces like AutoMat, Caruso, Databroker, or Otonomo and provides companies with additional income streams. In general, realizing this type of DDBM can be very challenging for incumbent companies to follow, as they are facing barriers like bad data quality, low data processing skills, or data privacy concerns. *"The data quality is, related to master data, mostly not existent or abysmal."* (Interview C)

3) Data Product: An opportunity with much more business opportunities for companies is summarized in the DDBMR case type data product. In these cases, data is not simply sold to other companies, but it stays in the company. The companies realize cases of this type create data products, which can deliver insights, features, or services by app/website directly to the customer. For companies, these offerings are very attractive because of a wide variety of pricing opportunities, customer segments, and scaling abilities. We identified 20 cases in which companies created data products through their DDBMR. In these cases, we identified two sub-types: 1) *data hybrid product* and 2) *data service product*. Data hybrid products are connected hardware and software components that create a useful DDBM customer value proposition. For example, the offering of predictive wind power maintenance (Case 21) needs the fitting smart wind turbines (power units) that are able to process the data. Additionally, it needs fitting IoT software, which connects and controls the data from the wind power stations. Based on the hardware and software components, the company offers data-based predictive maintenance services.

Pure data service products are DDBMR, which are similar to the offerings of the software-oriented digital economy and are created without additional hardware components in most cases. The services are distributed by website or APIs where the customer gets useful insights or digital features for their business, which they can use for their own value generation. For example, the ship detection service offers a web portal where the customer can identify all ships that are operating in the north-sea (Case 40) or the shopping insights hub, where food manufacturers can get customer insights by self-service (Case 42).

4) Data Platform: The most complex, but also the DDBMR approach with most-valuable business opportunities aims at creating a digital data platform and ecosystem. We identified ten cases that followed a DDBMR data platform approach. Through the data platform, the companies want to create a DDBM not only for selling assets but for delivering products. They want to create a data-based offering, mostly based on a flexible cloud architecture, where they can build a closed ecosystem for their insights, product, and service offerings. In this ecosystem, suppliers, partners, customers, and the vendor are connected, can exchange their data, and use vendor offerings. This connection opens the possibilities for active value co-creation and a long-lasting value network. To realize such a complex DDBM, a high number of skills, time, resources, and budgets is necessary. However, this can lead to a scalable concept with high revenues and margins. In case 29, a plane manufacturer created a plane data platform, where all customers, suppliers, and service partners can buy and exchange data insights to their planes. Another example is a car manufacturer that created its own car data marketplace, which grows with more data, apps, and users by time (Case 12).

The different case types show that there are multiple monetization opportunities for DDBMR. The improvement of only a few parts of the business can increase the business performance only on a low level in most cases. The selling of data can be a solid additional income stream, but its implementation can become complex due to data privacy and compliance issues. The companies in our study mostly try to realize data products or platforms while also ensuring their data ownership and monetization experience to create DDBM offerings for long-term company success.

B. DDBMR in Practice: Agile approach with distinct decision gates

Based on the DDBMR elements analysis, design, implementation, and review from the literature, we interviewed the experts about their experiences in realizing DDBM in practice. Our data points to a gap between the understanding of phase-oriented realization in literature and DDBMR and a build-measure-learn approach in practice. Figure 10 shows the four periods in which companies try to realize their DDBM in an iterative way. They start with prototyping and build, iterate, and test the new ideas in small teams. Through different "stop-or-go-gates," the companies are deciding if they want to invest more digital and human resources or if the approach will be stopped.

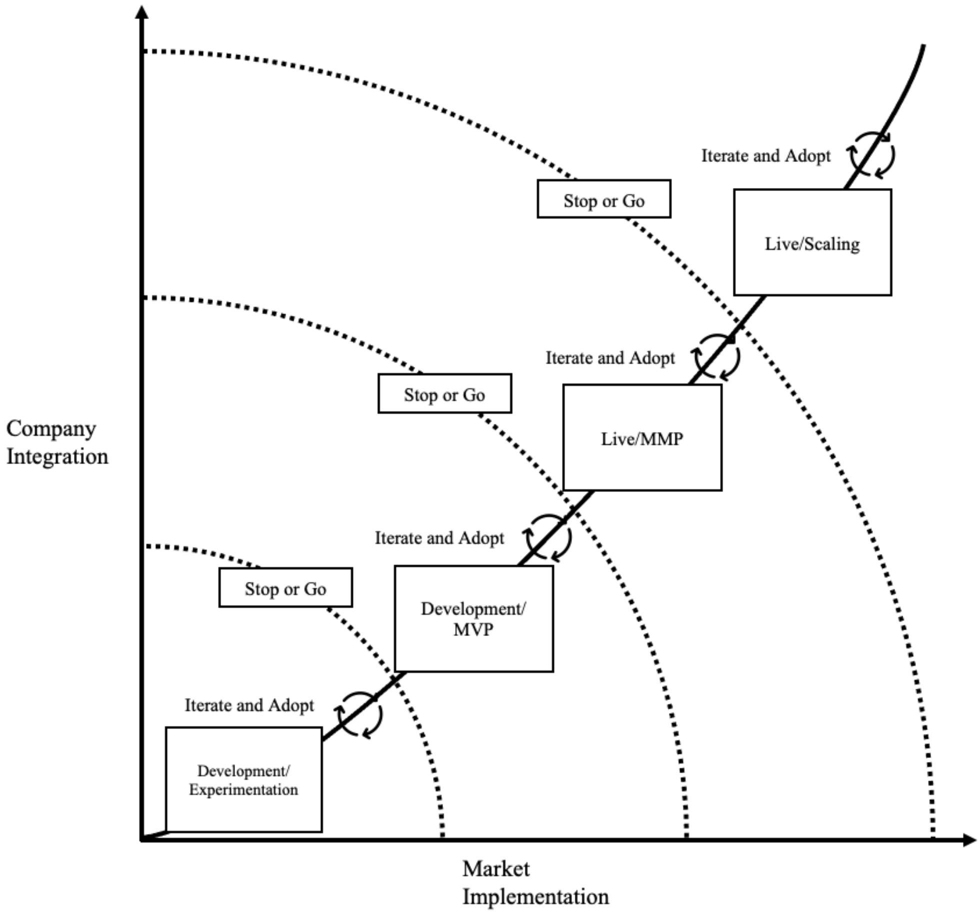

Figure 10: DDBMR periods in practice

1) Development / Experimentation: Companies are developing their first ideas for potential DDBM through experiments in a short period. For this, the companies start by finding real-world problems that can be solved with company skills, data resources, and potential market demand. These ideas do not need to be revolutionary and can be a DDBMR case just by improving the existing business or selling data. In many cases, the companies are observing

best practices in their own or foreign branches. Some seek to benefit from being a "first mover" with new case ideas for data products or platforms and accept a higher investment risk.

The experts' experience showed that long analysis phases without monetization focus are not leading to successful DDBMR cases, but often expend significant financial resources. A finalized DDBM design is fine, but it needs to be realized in a realistic amount of budget and time. The companies are investigating manifold ideas that they are analyzing in small effective teams that can provide feedback in a short period, if the idea and insights are useful. This includes a short validation for feasibility, data availability, timing, monetization, and alignment to the company strategy. "There are always issues which are very interesting and can be satisfied for people. Issues where you should have a deeper look. For us it is always a part of the equation: How big is the potential that we can retrieve money for the enterprise or other dimensions" (Interview D). Elements of the "lean startup" concept have a big impact on this approach and influence other areas of DDBMR [28]. The big impact of this approach is fast feedback and smarter decision making for developing products and services for DDBMs. Through experimentation, the development managers understand if there is an DDBM opportunity to follow or if the resources should be transferred to other DDBMR cases.

This is a distinctive approach to existing DDBM literature, which still proclaims a very phased-oriented idea of realization and which sees data selling as a key monetization approach for DDBM success. In practice, the companies see data as an important resource for much more than just selling. They are experimenting with their data and trying to find ways to solve market problems with business improvements and customer-oriented solutions. Interviewees rated it problematic to have a look at data resources and try to see possible business opportunities: "The way to look at data and try to build business models from it, is a forlorn approach" (Interview K).

2) Development / MVP: After the first idea validation through experimentation is done, the companies go further and start to create concepts and decide which DDBMR cases should be targeted. Through this period, teams are founded, which are doing DDBM design and requirement engineering as the starting point for further activities in the DDBMR process. The teams are doing workshops with design science elements in mostly a special open-minded environment. This approach is very open-structured and gives the teams the ability to discuss and generate multiple ideas before going into a more detailed concept. The teams consist of three or four people and are mostly organized in separate units (labs, innovation hubs, R&D departments) to work independently from daily business. With team size limitations and separate departments, companies can limit the needed budget, create lean structures, and pursue multiple

approaches at the same time. In practice, the DDBM design in the beginning is only a short creation step and is not focused on DDBMR. Execution and implementation in an iterate way are much more important for DDBM success than a long planning period.

After the DDBM design activities, it is important for the companies to develop a minimum-viable-product (MVP) as fast as possible. This is necessary to understand if their approach is realistic, technically viable, and could potentially be accepted by the customers. The experts noted that 12 weeks was the optimal period for the MVP development to get a first impression of the DDBM approach. This includes understanding the relevant data, connecting the necessary stakeholders, and developing first data usage concepts. This MVP can give the company an initial understanding of whether the approach has the opportunity to grow to a valuable DDBM for the company or if the approach should be terminated. The team needs to answer important questions: Can we offer it as a data product or service? Can we earn money with it? How can we create value for other companies? The MVP project can be terminated earlier if the team understands that this way does not make any progress: “We are focusing on the ‘fail-cheap-fail-early’ approach. We do not want to work for 12 weeks only to see that the approach is not working for us. But we have built the option that we can terminate the project earlier. After four weeks we do a first review, that is the natural breaking point to end the project, if for example the data quality is not acceptable or the business value for the company is too low” (Interview D).

All the experts in our interviews referred to an agile project management approach. The level of agile integration in the company organization differs, as well as the usage of Scrum or Kanban elements. In general, many elements of modern software development projects have been described by the experts. Most experts see the DDBMR process in iterative periods. Agile teams, with cross-functional team members, usually have the Scrum roles of Scrum master, product owner, and development team. The development team includes data scientists, innovation managers, user experience experts, or technical experts, who are co-working with people from the traditional business units for guidance in market demands, marketing, target groups, and pricing strategies. This input is necessary for development of user stories in the product backlog: “Of course, there is the product owner of the project, who gets new requirements from the department. It will be put in the backlog and be considered or not” (Interview F). The items of the product backlog need to be prioritized, conceptualized, developed, and tested over time. The teams are working in sprints with sprint goals that are oriented toward the project goals. In each iteration, new features with user benefit are delivered or the product is improved.

3) Live / MMP: In practice, the development of the MVP is the technical fundament for further steps in an iterative DDBMR case. It already has a focus on customer requirements and software development elements, but it is still a first prototype with limited features or services. So mostly, the MVP is not ready for the market. Sometimes, a pilot customer is helping the company through development and testing the DDBMR case, but it is not ready to be sold to a wide range of customers. Depending on the DDBMR case type, the MVP needs to be tested, and elements can change many times through the development process. In business improvement cases, this can be much simpler than in complex data products or platforms cases.
A big step for the companies is the DDBM "go-live". This means that the offering of a minimum-marketable-product (MMP) is available to the market and successfully adopted by the first customers. For this, the developed DDBM has minimum-marketable features (MMF), which leads to customer value and willingness to pay. The MMF can be improvements, features, services, or insights for the customer. The MMP gets developed with more MMF over time through iterative implementation of more DDBM elements and sources toward an independent DDBM. Similar to the MVP development, a long-lasting analysis or market entry planning is not considered appropriate by the companies. They prefer a bottom-up approach of execution, test the case in the market, and adopt successful DDBM elements. The MMF needs a continuous iterative review process. It needs to be necessary to add new data sources, IT resources, partners, and customers: "We do not have one model, where we say: This is complete" (Interview K).
After the market MMP launch, most companies restructure their previous organizations and evolve the existing small teams to their own departments or start-ups. Through development/MVP it is mostly still a very tech-focused realization part, but with the market launch, the business perspective and monetization become much more important. Through live/MMP it needs to be proved if the DDBMR case can be delivered to the market and can generate cash flows. The development of fitting sales, marketing, operations, and leadership structures is necessary. Also, it opens up the possibility for third-party investments, faster decisions, or sale of the DDBM-operating company. Another important point is the acquisition of the right digital and human capabilities, which are able to improve the started business over time. Advanced processing of data is a highly complex field. Hence, the recruiting of data scientists and developers is a crucial success factor for DDBMR.

4) Live / Scaling: Despite an iterative DDBMR approach and fast market launch, the realization can be a long and expensive challenge before the company has a solid DDBM offering. In general, a DDBMR case for business improvement can be done easier than a complex

data platform case, but it has limited scaling opportunities. If a MMP is successfully launched to the market, the companies try to create a durable DDBM on the market to earn money from their investments. The companies want to scale their DDBM over time to more customers and extend their ecosystem. To leverage this possibility, companies mostly build DDBMs based on scalable IT architecture and pricing models, which they can offer a wide range of customers. For this, most companies draw on a scalable cloud infrastructure for their DDBM offerings. It allows a flexible infrastructure for experimentation, MVP, and MMP and can be scaled to a bigger business by time: "[…] every company that does it the right way will do it in the cloud, otherwise you will have too many costs for server farms maintenance. That is non-sense. You are operating it on the cloud, creating a solid security concept and data encryption so that foreign people will not have access to it. The cloud is the best way for cost efficacy and scalability" (Interview K). A differentiation where the MMP ends and the scaling begins depends on the individual case, and the step is not always explicitly visible due to the iterative development process.

The business target is to deliver the offering to multiple customers, with low additional costs for the company in the long term. This approach is typically known from software or cloud offerings and is successfully done by numerous software companies, which many experts see as their role models for modern DDBMs. To establish the DDBM for long-term success, it is important to establish a data ecosystem. The experts argued that it is the main goal for each company to create its own data ecosystem where they can connect with customers, suppliers, and other stakeholders of the company. Thus, they need to build a solid infrastructure, where they develop customer relationships, digital products, and new pricing approaches to implement new DDBMs or evolve existing business approaches. For example, company C is developing data science solutions for their own enterprise processes and analysis. If the software product is working well and there is market demand, the software is sold as data-science-as-a-service (DSaaS) to other energy companies through a cloud platform offering. For the company's success, it is important to scale and invest in the right DDBM MMPs to complement the company business model portfolio and gain the investment resources for the execution of new DDBM ideas.

9.5 Discussion & Conclusion

In our results, we described how incumbent companies execute DDBMR in their own company. We learned that DDBMR and the field of data monetization are still seen as important and relevant topics by the interviewed experts. Data is seen as a key resource for today's business opportunities and results in multiple DDBMR projects in the companies.

To answer our RQ1, which DDBMR cases are currently realized and which types of DDBMR exist, we identified 45 DDBMR cases. The identified cases show a wide variety of approaches the companies follow. The DDBMR approaches shown in the companies are very software and information technology oriented. Pricing models, growth strategies, project method, key resources, or team roles are analogous to agile software companies and are inspired by Silicon Valley BMs and organizations. Nevertheless, we could identify four DDBMR case types, which can be categorized by dimensions of data trading and business innovation. Business improvement can be viewed skeptical if it is a part of DDBMR, but the experts are describing it as part of their data monetization strategy. Data selling is the classic way of data monetization, but it also gets more and more complicated to just sell the data through privacy concerns. Besides this, the companies understand which worthful asset they are giving away. Data product cases are the most named cases from our experts. The focus is to create digital products, instead of focusing on core data processing or selling. With this focus, the companies are able to use existing information skills and knowhow for multiple DDBMs. This enables much more resources than just data scientists or processing systems and net product opportunities. Data platforms are the supreme DDBMR cases. They are mostly very complex, need a high investment of resources, and have a high number of stakeholders. However, if the DDBMR is successful, the realized business can be highly profitable and secure the company's earnings for years.

Based on our cases and expert interviews, we can answer RQ2, which is related to the periods companies need to pass through for DDBMR. We recognized four important periods that the companies need to fulfill for a successful DDBMR case by time: development/experimentation, development/MVP, live/MMP and live/scaling. Through the development/experimentation period the companies do the most research for market demands, business opportunities, and DDBM design. The DDBM literature so far has a significant focus on this period, but in practice it is only one element, before the company proceeds toward the more complex implementation. In the development/MVP period, the companies tried to execute many ideas with limited resources to create useful DDBM prototypes. This experimentation can be done in digital innovation units with their own resources and data processing technology, following a bimodal IT setup [29], [30]. A key question the companies seek to answer with the MVP is whether the company can earn money with the DDBM. The strategies can be manifold, but depend on the resources of the company [31]. To avoid wasting resources, failed DDBM experiments are terminated and the resources reused for other ideas.

	Literature	Practice	Gaps
Development/ Experimentation	• Intense period of analysis [1], [2], [15] • Detailed status-quo analysis of resources, skills, architecture, and processes [8], [20] • Company analyses capabilities before DDBM design [15], [23], [24]	• Short analysis of resources and capabilities • Fast move forward to DDBM experimentation and MVP • Continuous requirement analysis through DDBMR	• Pre-realization analysis short in practice • Focus lies on execution, less planning • Analysis does not stop after ideation, but is conducted continuously
Development/MVP	• Strong focus on DDBM design with creation tools and frameworks [1], [22], [35] • Finalized DDBM concept before implementation [1], [8], [24] • Definition of activities for DDBMR in the company [8], [36]	• DDBM design as a short period to target real-world business needs • Fast transformation of DDBM ideas into MVP • Necessary DDBMR activities are detected through experimentation	• Design is only a small part of DDBMR practice • Focus on prototyping, less conceptual work • Learning-by-doing instead of complex requirement catalogues
Live/MMP	• Top-down approach of execution [37], [38] • DDBM design gets executed step-by-step through project into company [4], [8], [10] • Starting with DDBM pilots and growth over time [4], [21]	• Bottom-up approach of execution • MMP development through agile adoption of MMF • Starting with MMPs and scale through ecosystem	• Iterative DDBMR in practice instead of linear project execution • Focus on fast going-to-market, less integrity • Scaling approach in literature and practice similar
Live/Scaling	• Strong project view of DDBMR [10], [23], [39] • DDBM readiness after project execution [4], [19] • Improvement/adjustment of DDBM elements by time [9], [18]	• Long-term business view of DDBMR • Scaling as an important success factor • Continuous iteration and adoption of DDBM MMF	• Long-term DDBMR success view instead closed project-thinking • Focus on scaling, less completion • Continuous DDBMR development

Table 12: DDBMR literature vs. practice

Divergent from a traditional business perspective, the abortion of the DDBMR is not considered as failure but as learning. It is desired to stop the pointless execution as fast as possible and to use the resources to follow a new idea and adopt the learnings in the new DDBM approach. The market launch in the live/MMP periods marks the most important step in every DDBMR. At this moment, the DDBM needs to prove whether it can be a solid element of the company's business. The DDBM is still in an early stage, but with customer feedback and business bug fixing, the business perspectives become more visible. If the idea is working, the company tries to scale in the live/scaling period to more business and customer segments. The basic goal of scaling is the growth of the DDBM, aiming for an increase in revenues, but also lowering the necessary resources. The complexity of scaling manifests in various challenges, such as poor data quality, data silos, IT infrastructure, company cultures, and privacy concerns. These challenges need to be solved over time and enable the company to integrate the DDBM with elements from the modern software IT industry (usage-based pricing, cloud architecture, fast prototyping) in the existing BM portfolio and organization structures.

An important success factor for this is to create a company data ecosystem, which can be the platform for sustainable DDBM scalability [32]–[34]. Without a solid structure of data partners, suppliers, and infrastructure, the most interviewed companies would struggle to realize a useful DDBM, which can also lead to a discussion of data ownership and data value sharing. For companies, DDBMR is a long-term challenging process, through the fast changes in IT technologies, regulations, and trends, to refine their product and DDBM. It is interesting to note that none of the analyzed companies are interested in doing short-term data selling. They want to create and improve digital products that can be sold to customers based on their own long-term data ecosystem.

To answer RQ3, which differences can be observed between DDBMR in the literature and in our cases, we compared in Table 12 the insights from our four DDBMR periods with previous literature-based research. It summarizes gaps between the literature and the practice as described by the interviewees. Previous publications still have a dominant focus on traditional, waterfall-like project approaches. In practice, companies are much more agile in the DDBM context than expected, and they seek to step from ideation toward execution as fast as possible. Within development/experimentation the pre-realization analysis is short, and the companies focus on executing DDBMR cases from the DDBM ideas. In the development/MVP period the described DDBM design from the literature is only a small element in practice. DDBMR is made by fast prototyping and practical learning instead of long requirement catalogues. Through the live/MMP period the companies aim for a fast go-to-market and add MMF by time, instead of a complete feature plan from the beginning. If the market entry is successful, the company's focus in the live/scaling period is on continuous market success and DDBM scalability, instead of a fast project plan completion.

Nevertheless, our results have some limitations. We only interviewed German-based companies, which is a limitation, because it is possible that in North America, Europe, or Asia other DDBMR approaches exist. Nevertheless, all interviewed companies are operating in international business, so they are not limited to the German market. To get the initial knowledge, our focus on German companies was sufficient, but for further research it would be good to speak with companies from different countries and sizes. Our interviewed experts were mostly from the operating level, which gives a good view of practical doings, but mostly excluded the strategic enterprise management level, which are mostly deciding about strategic business models for the companies. We only spoke with experts from companies that already have data specialists. Hence, there was already knowledge about advanced data processing in the companies, which might lead to different approaches compared to other incumbent companies that do not have experience or experts in this field.

Our findings contribute to the research of DDBMR with the first insights from practice. Based on the practical experiences of DDBMR experts, we developed an initial idea of how companies address the realization path. Further research should investigate the four periods of the DDBMR lifecycle in more detail. Additionally, the investigation of single DDBM projects, in the form of case studies, would create deep knowledge about the executed activities.

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11 Realization of Data-Driven Business Models in Incumbent Companies: An Exploratory Study Based on the Resource-Based View

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Abstract. The generation of value from data is a key issue for many incumbent companies in our modern economy. While they are stuck in traditional business environments, they seek to develop and realize data-driven business models (DDBMs). Previous research aimed at analyzing and supporting the DDBM ideation process. In this study, we focus on developing an improved understanding of the process of realizing DDBMs and required capabilities and resources. It is grounded on interviews with 19 experts from multiple industries. By leveraging the resource-based (RBV) view as a theoretical lens, we analyzed 45 DDBM realization cases. We identified four execution periods, four capabilities, and 25 resources to characterize the process of DDBM realization. The results contribute to the field of DDBM research by theorizing the process of DDBM realization with a focus on challenges and enablers of resource utilization.

Keywords. data-driven, business models, realization, resource-based view

10.1 Introduction

Data as a business fundament became an essential resource for establishing a successful long-term business model. Over the last decades, research on big data and data analytics has taken a huge step forward. But researchers and business leaders are still struggling to overcome the challenge to realize the promised benefits (Davenport and Malone 2021; Dremel et al. 2020; Klee et al. 2021). Especially incumbent companies struggle with the challenges of establishing a comprehensive data monetization strategy. Previous research started to explore valuable data monetization approaches, but the results stayed on a very abstract level and had only a weak

connection to business models (Lavalle et al. 2011; Najjar and Kettinger 2014; Woerner and Wixom 2015). A starting point for understanding the development and realization of data-driven business strategies was set by Hartmann et al. (2016), who highlighted the role of startups in the development of data-driven business models (DDBM). More authors followed this perspective and conducted case studies focusing on the process of how companies innovate and develop DDBMs (Alfaro et al. 2019; Brownlow et al. 2015; Chen et al. 2017). However, these studies focused mostly on the ideation phase of the DDBM process and did not consider the challenges and strategies in the realization process. Studies on DDBM realization (DDBMR) are very scarce so far and do not yet provide insights into challenges occurring in the realization process. To stay competitive in the market, incumbent companies need the appropriate resources and capabilities for successfully completing the DDBMR process. Based on this research gap, we seek to answer the following research questions (RQ) in our paper: RQ1: How do incumbent companies realize their DDBMs, and which resources do they need? and RQ2: Which challenges and enablers shape resource utilization in the DDBMR process?
To answer these research questions, we conducted 19 expert interviews with managers and data specialists from 18 companies. The interviews were guided by the results of a systematic literature review of research related to DDBM(R). The interviewees are all working in DDBMR projects and conduct international business. These companies work on realizing DDBM ideas, and this allowed us to investigate the practical experience made in these projects. Furthermore, the companies are mainly incumbent companies from traditional industries which are on their way to developing and realizing DDBM. We analyzed the interviews and identified 45 DDBMR cases at different levels in the realization progress as well as with varying industries, company sizes, and customer focuses. The interviews allowed us to understand how companies realize DDBMs and which resources are necessary for successfully realizing a DDBM case. By applying a resource-based view (RBV) in our investigation, we identified four periods, four capabilities, and 25 resources which structure and constitute the DDMBR process. With this, we are extending the existing research by adding an empirically grounded understanding of DDBMR compared with the previous literature. In each of the periods, we identified challenges and enablers of DDBMR based on capability and resource perspectives. In practice, the results can help companies to learn from previous cases and to realize successful DDBMs. The paper is structured as follows. In the following section, we present the RBV and the realization of data-driven business models as the theoretical foundation and related research. In the next section, we present the methodological approach. Finally, we describe our research results and close with a discussion and a conclusion in the final section.

10.2 Theoretical Foundations

10.2.1 The RBV and its Application in Information Systems Research

The RBV of the firm is one of the leading theoretical frameworks to describe the role of appointed resources for the creation of value. The original concept was developed in business management researchers and is grounded in the idea that company success is based on the types of resources the company have under control (Barney 1991; Hart 1995; Wernerfelt 1984). According to this concept, not all resources can create the same value and a combination of different resources is required to create business value. The resources can be differentiated into three types: tangible (e.g., budget and core resources), human skills (e.g., know-how and management), and intangible resources (e.g., company culture and ownership), which is a classification we followed in our research (Barney 1991; Grant 1991). The main hypothesis is that the company which is using its resources in the best way will outperform its competitors and be successful in the market (Sirmon et al. 2011). The relations between company resources and firm performance are an important and accepted factor in management research (Hitt et al. 2001; Kunc and Morecroft 2010; Lin and Wu 2014).

The idea to analyze resources and company success was also adapted as a very important theoretical lens in information systems research (Bharadwaj 2000; Wade and Hulland 2004). In information systems research, the focus lies especially on the usage of IT resources and necessary additional resources from "traditional" management areas to create value. Melville et al. (2004) created a model based on the RBV which describes the association between information technology and organizational performance. This model is a useful blueprint for research, but it needs more empirical validation due to its literature-based approach. Gupta and George (2016) conducted a two-part quantitative study for big data analytics capabilities. They identified seven resources based on literature research which they segmented into the three resource types. Through surveys, they verified their resources for big data capabilities, but their very static view of resources ultimately produced very few implications for practical adoption in the companies. Wamba et al. (2017) created a research model with a focus on big data analytics capabilities and firm performance based on data from Chinese companies. The results showed a strong mediating effect between process-oriented dynamic capabilities and firm performance. This influence underlines that management needs to provide these capabilities for big data analytics success, but is not clear as to how they should do this. Mikalef et al. (2020) identified resources of big data capabilities and segmented three types of resource clusters in a model. They extended their research model by adding more capabilities which positively influence competitive performance. The results provided a good overview about required resources for big data analytics, but previous research has provided no guidance about which capabilities and resources are necessary for the realization of data business and DDBMs.

10.2.2 Realization of DDBMs

To identify relevant research for the realization of DDBMs, we conducted a systematic literature review (Vom Brocke et al. 2009). Based on a first heuristic search, we chose the keywords for the search (data AND business model), (analytics AND business model), (business model AND transformation) OR (business model AND realization) OR (business model AND implementation) OR (business model AND integration) to find relevant papers. We searched in the following libraries: (1) AISeL, (2) JSTOR, (3) EBSCO, (4) Web of Science, (5) IEEE, (6) Science Direct, (7) ACM Digital Library, (8) SpringerLink, and (9) Google Scholar. There was no range of published years. For AISeL and JSTOR, we searched for title, abstract, and keywords. For EBSCO, Web of Science, IEEE, Science Direct, ACM Digital Library, SpringerLink, and Google Scholar, we limited the search to the title due to the high number of results. Irrelevant, duplicate, and non-peer-reviewed results were excluded. Only literature published in English was included in the research process. All papers were analyzed by title, keywords, abstract and research area. Papers were selected as relevant for our research if they are meeting the following criteria: (1) Realization of DDBMs or data monetization in focus of the paper, (2) the paper provides insights of necessary resources and capabilities for the realization process or (3) the paper offers insights of challenges and enablers for the DDBM realization process. We conducted a backward and forward search to identify additional relevant papers (Webster and Watson 2002). Overall, we identified 45 relevant papers which we analyzed based on a content analysis (Mayring 2000). In the first step, we conducted a content analysis and searched for terms like "resources", "capabilities", "challenges", and "enablers". In a second step, we read the papers and extracted the main statements related to DDBMR. The target of this review was to summarize the existing literature and to develop a knowledge fundament for the interview guidelines.

Through our review we identified that a generally accepted definition of DDBMs is not existing. For this paper, we draw on the business model definition of Teece (2010) an adopt it for DDBMs: A data-driven business model defines how a company creates and delivers value from data to customers and extracts value from these activities. DDBMs are part of the digital innovation processes of companies (Fichman et al. 2014; Kohli and Melville 2019; Nambisan et al. 2017). DDBMs are not static strategies, but they are dynamic and changing through the realization process. DDBMs can be new business approaches, but also traditional business models can be transformed to DDBMs with the help of digital technologies over time (Vial 2019; Wessel et al. 2021).

In general DDBM research, the previous focus was less about the practical realization of such business, but more about the ideation and design. Manifold frameworks and tools were developed to describe the necessary elements of a DDBM for a company based on traditional business model research (Brownlow et al. 2015; Hartmann et al. 2016; Kühne and Böhmann 2019). A missing key element in these publications is the question of how companies implement these elements and how they create the operating model of a DDBM (Davenport and Malone 2021; Günther, Mehrizi, et al. 2017; Wiener et al. 2020). In previous research, companies were analyzed by their DDBM business strategy, operations, and projects (Alfaro et al. 2019; Chen et al. 2017; Günther, Hosein, et al. 2017). The results of these studies helped to understand companies' DDBM ideation as an essential part of the comprehensive realization process. However, the authors provided no structured guidance concerning the challenges and required capabilities through DDBMR.

Anand et al. (2016) developed one of the first approaches for realizing value of digital data streams. The process has four steps which describe the general strategy for data value realization. The ideas are useful for further research, but are too limited to comprehensively describe relevant DDBMR elements. Hunke et al. (2017) went one step further and developed a literature-based DDBM innovation process, which offers a general overview of the complex execution process of DDBMR projects. Still, this process is very static and has limited empirical grounding. In a qualitative study, Rashed and Drews (2021) provided an analysis of DDBM design and realization strategies at the enterprise level. They mainly interviewed senior management experts from consulting firms and delivered some of the first insights into how DDBMR pathways unfold. However, the study was mainly based on the external perspective of consultants, and it did not provide further details about the challenges and necessary capabilities or resources related to DDBMR.

10.2.3 Challenges and Enablers for DDBMR

The RBV and the realization of DDBMs are the theoretical fundaments of our study. Information systems research has made great progress in the field of big data analytics capabilities, but the perspective of data monetization and value creation is only covered in a minor part of the studies. From the existing DDBMR research, we already have gained insights into DDBM design and use case development, but it has not yet covered the required execution and realization steps. Due to the nature of the research questions of our study, we needed a more comprehensive overview about challenges and enablers of DDBMR to understand and explain which capabilities companies need to realize DDBMs.

An initial overview of the challenges of company transformation through big data and analytics was made by Baesens et al. (2016). The authors highlighted the dramatic shift that can occur in company organization structures and the key challenges presented by data storage and usage. The source of these insights is not clear; thus, the empirical validation is unclear. Jensen et al. (2019) explored the challenges of realizing value from big data analytics projects in a qualitative study. They interviewed different experts from a Danish wind turbine manufacturer and analyzed their experiences of project challenges. However, as the focus was on just one company and its big data analytics, the generalizability of their study is limited. In the study of Ermakova et al. (2021), the authors conducted a survey of impact factors for the failing of data-driven projects. The challenges can be partly related to DDBMR projects and are a good starting point for further research, especially because this highlights the need for finding answers about how to avoid failings by consequently addressing them.

Research about enablers of DDBMR is also very limited. The existing research has mostly focused on the design of data-driven organizations. Schüritz et al. (2017) described the construction and enablers of analytics competency centers (ACCs) in companies. Some organizational ACC elements can also be used to describe DDBMR units, but the results are limited to an internal data analytics focus, instead of a company- and organization-wide perspective. Berndtsson et al. (2018) published their initial idea about how companies can transform towards becoming data-driven organizations (DDOs) by identifying enabling factors for data-driven culture and maturity levels of analytics capabilities. Their research is still in progress and has a limited impact due to their primary focus on the company organization structures rather than on the connection to the DDBMR business view. Hagen and Hess (2020) also analyzed the needed design parameters for DDOs. They conducted a case study with five companies and developed a taxonomy with ten design parameters for DDOs. The results were focused on DDOs, so they were not able to answer questions about specific enablers of DDBMR and data monetization.

Our review of the existing literature revealed that there is a lack of knowledge about the operational perspective of DDBMR as well as about the encountering of challenges and necessary enablers for realization. With our qualitative expert interview focus, we will offer a different perspective to previous publications and develop a better understanding of the expert knowledge in this field. This knowledge will be very helpful for researchers and practitioners to better understand and shape value generation through DDBMR projects and to avoid failure.

10.3 Research Method

To answer our research questions, we employed a qualitative expert interviews approach (Bogner et al. 2009; Gläser and Laudel 2004). Based on the interview transcriptions, we conducted a qualitative content analysis to analyze the interview data (Mayring 2007; Myers 1997). We searched for experts with multi-year business or project experience in realizing data-driven business ideas in their companies. We focused on experts from the fields of data science, information systems, or digital business who know which resources and tools are necessary for DDBMR. The experts were selected from companies of different industries and sizes in order to collect data from multiple perspectives. We recruited the experts through our professional network and LinkedIn searches. The selected companies are incumbent companies which are active in international markets. All these companies have launched initiatives for DDBMR in their organizations and/or give advice to their customers about how to do so. Table 13 shows a list of all interviewed experts. For the interviews, we designed semi-structured interview guidelines (Myers and Newman 2007). The A–L portion of the interview guide had a focus on general DDBMR and the project level, and the M–S portion had a deeper focus on the realization of data monetization. This allowed us to get relevant insights about DDBMR challenges and the necessary resources for DDBMR as well as about how the companies have tried to generate a return on their investments. Through the open questions and atmosphere, it was possible to focus on different aspects of their data-driven business experience with each expert based on their perspective. Interviews A and B were personal interviews, interviews C–S were held by phone or with an online conference tool (Skype, Google Hangouts, and Zoom).

Company	Interview	Role	Industry	Company size
1	A and B	Lead Data Scientist and Managing Partner	Software	<500
2	C	Director Digital Lab	Engineering	500–9,999
3	D	Data Scientist	Energy	500–9,999
4	E	Project Manager	Automotive	10,000–99,999
5	F	Product Owner Data Intelligence	Transport	>100,000
6	G	R&D Manager	Automotive	>100,000
7	H	Data Scientist	Shipbuilding	500–9,999
8	I	IoT Engineer	Software	500–9,999
9	J	Product Owner Data Platform	Insurance	10,000–99,999
10	K	Head of Data Science	Mobility	500–9,999

11	L	Information Security Officer	Aviation	10,000–99,999
12	M	Head of AI & Data Analytics	IT Consulting	500–9,999
13	N	CEO	IT Services	<500
14	O	Senior Expert	Automotive	>100,000
15	P	Advisor Corporate Strategy	Automotive	>100,000
16	Q	Head of Technology Marketing	Public Sector	500–9,999
17	R	Head of Customer Insights	Retail	>100,000
18	S	Tribe Lead AI	Communication	>100,000

Table 13: Interviewed experts

In total, we interviewed 19 experts from 18 companies. All interviews were recorded and fully transcribed. The experts received the interview transcripts for review and approval. The duration of the interviews was from 24–63 minutes with an average duration of 44 minutes. The transcribed data were used for qualitative content analysis to receive relevant insights. We applied an open coding approach in two steps. First, we analyzed the interview statements for DDBMR cases from practice. The experts described manifold cases, which were supplemented by mentioned internet sources. Based on the cases and further statements of the experts we could identify four periods which structure the realization of DDBMs (Figure 11). The identified periods were revised multiple times during the research process. Second, we identified key resources, challenges, and enablers based on the interview statements (Table 15). The resources were segmented into three resource types (Barney 1991; Grant 1991). We segmented the used resources into four DDBMR capabilities. The classified DDBMR cases, periods and capabilities allowed us to identify key challenges and enablers for each period and capability from the interviews. For this, we analyzed the interviews for statements of DDBMR challenges/enablers for resource utilization and segmented the results into a periods/capability matrix. The essential key challenges and enablers for resource utilization are shown in Table 16. For example, the statement "The data quality is, related to master data, mostly not existent or abysmal" (Interview C) was segmented into data capabilities as intangible data resource. The poor data quality was perceived as a big challenge for developing an MVP, so it was segmented as key challenge in the Development/MVP period. In total, we included 45 DDBMR cases from the interviews (Table 14) in our analysis. We identified four DDBMR case types: (1) business improvement: improving existing business by data-based features or technology, (2) data selling: selling data as an asset, (3) data product: creating data products which are connected to physical products or company services, and (4) data platform: creating a digital data platform and ecosystem. Fifteen cases are still in development, and 30 are already live on the market. In combination with the stage, this shows the case level of DDBM realization. We will describe this further in the results section. Most cases focused on business-to-business (B2B) customers, and only a few targeted business-to-consumer (B2C) or business-to-government (B2G) customers. The case scope can be divided into three segments: (1) transform business: company is transforming a traditional BM into DDBM in the same industry, (2) extend business: company is extending a traditional BM by developing a new DDBM in the same industry, and (3) new business: company is creating a new DDBM in a different industry.

Case	Area	Type	Target Industry	Status	Stage	Focus	Scope	Interview
1	Solar Panel Maintenance	Data Product	Energy	Live	MMP	B2B	New Business	A
2	Product Simplification	Business Improvement	Manufacturing	Development	Experiment	B2B	New Business	C
3	Smart Power Grids	Data Product	Energy	Live	MMP	B2C	Extend Business	D
4	Grid Planning Tool	Data Product	Engineering	Live	MMP	B2B	New Business	D
5	Property Assessment	Data Product	Real Estate	Live	MMP	B2B	New Business	D
6	Solar Panel Recognition	Data Product	Energy	Development	Experiment	B2B	Extend Business	D
7	Sensor Data Selling	Data Selling	Automotive	Development	Experiment	B2B	Transform Business	E
8	Sensor Data Platform	Data Platform	Automotive	Development	Experiment	B2B	Transform Business	E
9	Weather Data	Data Product	Automotive	Live	MMP	B2B	Extend Business	E
10	Car Data Marketplace	Data Platform	Automotive	Live	Scaling	B2B	Extend Business	E
11	Smart Fleet Maintenance	Data Product	Transport	Live	MMP	B2B	Transform Business	F
12	Car Data Marketplace	Data Platform	Automotive	Live	Scaling	B2B	Extend Business	G
13	Data Insights Platform	Data Platform	Automotive	Live	MMP	B2B	Extend Business	G
14	Traffic Data	Data Product	Automotive	Live	Scaling	B2B/B2G	Extend Business	G
15	In-Car Entertainment Platform	Data Platform	Automotive	Live	MMP	B2C	Extend Business	G
16	Use-Based Car Features	Data Product	Automotive	Development	Experiment	B2B/B2C	Extend Business	G
17	Predictive Repair Service	Data Product	Automotive	Development	Experiment	B2C	Extend Business	G
18	In-Car Advertisement	Data Product	Automotive	Development	Experiment	B2B/B2C	Extend Business	G
19	Project Transparency	Business Improvement	Shipbuilding	Live	Scaling	B2B/B2C	Transform Business	H
20	Smart Metering Services	Business Improvement	Energy	Development	MVP	B2B	Transform Business	I
21	Predictive Wind Power Maintenance	Data Product	Energy	Live	Scaling	B2B	Transform Business	I
22	Predictive Component Replacement	Data Product	Manufacturing	Development	Experiment	B2B	New Business	I
23	Predictive Escalator Maintenance	Data Product	Manufacturing	Live	Scaling	B2B	New Business	I
24	Device Data Hub	Business Improvement	Software	Live	Scaling	B2B	Extend Business	I

25	Product Evolution	Business Improvement	Insurance	Development	MVP	B2B/B2C	Transform Business	J
26	Usage-based Insurance Service	Data Product	Insurance	Development	MVP	B2B	Extend Business	J
27	Smart Investments	Business Improvement	Insurance	Development	Experiment	B2B/B2C	Transform Business	J
28	Transportation Platform	Data Platform	Mobility	Live	Scaling	B2C	Transform Business	K
29	Plane Data Platform	Data Platform	Aviation	Live	Scaling	B2B	Extend Business	L
30	Flight Data Selling	Data Selling	Aviation	Live	Scaling	B2B	Extend Business	L
31	Personalized Flight Services	Business Improvement	Aviation	Development	Experiment	B2B/B2C	Transform Business	M
32	Predictive Plane Maintenance	Business Improvement	Aviation	Live	MMP	B2B	Transform Business	M
33	Car Data Marketplace	Data Platform	Automotive	Live	Scaling	B2B	Extend Business	O
34	Car Repair Knowledge Base	Data Product	Automotive	Live	Scaling	B2B	Transform Business	O
35	Car Data Selling	Data Selling	Automotive	Live	Scaling	B2B	Extend Business	P
36	Car Data Marketplace	Data Selling	Automotive	Live	Scaling	B2B	Extend Business	P
37	Car Data Ecosystem	Data Platform	Automotive	Live	Scaling	B2B	Extend Business	P
38	Smart Insurance	Data Product	Insurance	Development	MVP	B2B	New Business	P
39	Satellite Data Selling	Data Selling	Public Sector	Live	Scaling	B2B/B2G	Extend Business	Q
40	Ship Detection Service	Data Product	Public Sector	Live	Scaling	B2G	Extend Business	Q
41	Shopping Data Selling	Data Selling	Retail	Live	Scaling	B2B	Extend Business	R
42	Shopping Insights Hub	Data Product	Retail	Development	MVP	B2B	Extend Business	R
43	Smart Assortment Platform	Data Platform	Retail	Live	Scaling	B2B	Transform Business	R
44	Location Data Service	Data Product	Communication	Live	Scaling	B2B	Extend Business	S
45	Data Insights Platform	Data Platform	Communication	Live	MMP	B2B	Extend Business	S

Table 14: DDBMR cases

10.4 Results

Grounded on the insights from the literature, we interviewed the experts about their experiences in realizing a DDBM in practice. In determining our results, we focused on the DDBMR process with the necessary capabilities and required resources for its execution. Based on these two elements, we identified multiple challenges and enablers for resource utilization which occur through the DDBMR process.

10.4.1 DDBMR Periods, Capabilities, and Resources

The data analysis led to an understanding of DDBMR as an iterative build-measure-learn approach with a few defined decision points that mark important phases of the project. The companies start with slight and fast prototyping in small teams for experimentation. Through success-based "stop-or-go-gates," the management decides if they want to invest more and develop additional capabilities or if the project will be terminated. Figure 11 shows the four periods in which companies execute their DDBMR cases:

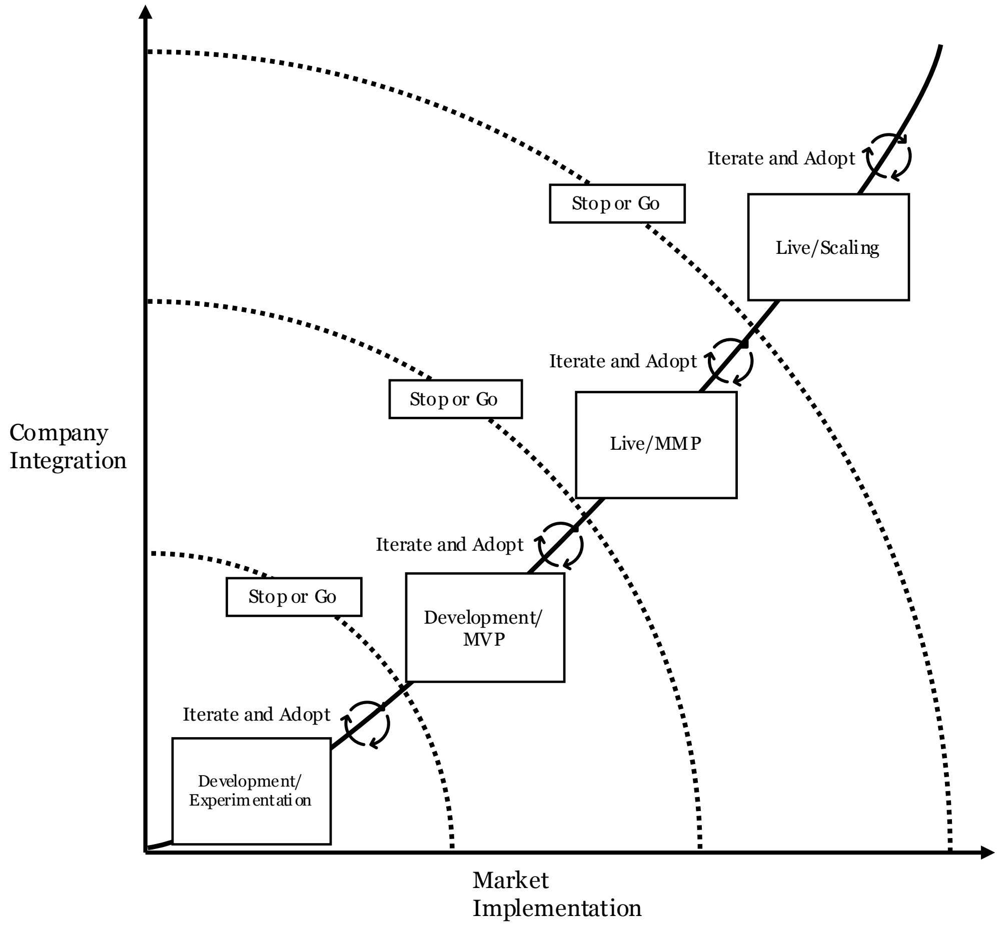

Figure 11: DDBMR periods in practice

(1) Development/Experimentation: The companies investigate manifold ideas based on real-world problems through small and often changing teams. Through fast feedback in a short period of time, these teams analyze if the ideas are useful or not. This validation depends on the necessary budget, time, feasibility, and capabilities as well as on the monetization potential and the strategic fit for the company.

(2) Development/MVP: After the first validation through experimentation, the companies decide which DDBMR cases are to be targeted. They form interdisciplinary fixed teams

which develop a DDBM Minimum-Viable-Product (MVP) through an agile approach as fast as possible. This MVP is important for understanding if the DDBM approach is realistic, technically viable, and could potentially be accepted by customers.

(3) Live/MMP: The development of the MVP is the technical fundament, but it still not ready for the market. This means that, after internal tests, the DDBM needs to be converted to a Minimum-Marketable-Product (MMP) and will then be ready to do "go live" in the market and prove their value to the first customers. After a successful launch, most companies restructure their DDBM organization and evolve the existing small teams to the point where they own departments or start-ups.

(4) Live/Scaling: If a DDBM is successfully launched to the market, the companies try to make it durable on the market for long-term success. The target is to scale the DDBM over time to multiple customers and extend the ecosystem. The successful DDBMs also provide the investment capital for the execution of further DDBM ideas in the future.

The periods are an important element for company success because most more traditional and waterfall-like project execution methods do not work in the complex DDBMR field. Through the periods, the companies rely on their DDBMR capabilities and on their iterative adjustment. In previous publications, companies were mainly analyzed by their data analytics capabilities (Gupta and George 2016; Mikalef et al. 2020; Wamba et al. 2017). This is still an important capability; however, for DDBMR, we need a more business-oriented and company-wide capabilities view. Based on the previous literature and the expert interviews, we identified four required DDBMR capabilities and 25 resources (Table 15):

DDBMR capabilities	**DDBMR resource type**	**DDBMR resources**	**Description**
Data capabilities	Tangible	• Data availability • Data storage	Provision of data assets
	Human skills	• Data management • Data processing	Handling of data assets and processes
	Intangible	• Data ownership • Data quality • Data security	Governance of data assets and processes
Technology capabilities	Tangible	• IT architecture • Scalable IT infrastructure • Software tools	Provision of technological fundament
	Human skills	• IT management	Administration of technological fundament
	Intangible	• IT security	Protection of technological fundament

Organization capabilities	Tangible	• Manpower	Provision of workforce
	Human skills	• Business operations • Skills and know-how • Talent development	Operation of organization assets and processes
	Intangible	• Company culture • Organization structures • Partner relationships	Structure of organization environment
Monetization capabilities	Tangible	• Investment budget • Target customers	Provision of financial budgets
	Human skills	• Finance management	Handling of financial budgets
	Intangible	• Market research • Monetization strategy • Pricing models	Generation of financial income

Table 15: DDBMR capabilities and resources in practice

(1) Data capabilities are the companies' ability to capture and handle data resources for their DDBMR cases. The companies need to provide, enrich, analyze, and select data as a core resource for DDBMR insights and execution.

(2) Technology capabilities are the companies' ability to build a fitting technological infrastructure for their DDBMR cases. The companies need to provide the right technology and processing fundament for DDBMR execution.

(3) Organization capabilities are the companies' ability which allow them to change and structure their organization for DDBMR cases. Companies need to create and calibrate firm-wide processes, roles, skills, relationships, and structures to provide DDBMR execution conditions.

(4) Monetization capabilities are the companies' ability to return their investments from DDBMR cases. The companies need to find, with the help of market research, marketing, and sales, the right data monetization concepts for long-term company success and competitive performance.

10.4.2 DDBMR Key Challenges and Enablers of Resource Utilization per Period

The successful realization of a DDBM in practice with fitting capabilities and resources can be a very complex task. Companies do have many challenges to overcome when attempting to utilize their resources efficiently. When advancing through the DDBMR periods, these challenges are more or less important in each period. Thus, the companies need to find and choose the right enablers for achieving a successful realization. Table 16 provides a first overview of the key challenges and enables of resource utilization for DDBMR.

Development/Experimentation		
Capability	**Key challenges of resource utilization**	**Key enablers of resource utilization**
Data	• Low data sources knowledge	• Select core data
Technology	• Missing tools	• Introduce independent tools
Organization	• Traditional company culture	• Form independent teams
Monetization	• No data-based use cases	• Use DDBMR best practices
Development/MVP		
Data	• Poor data quality	• Enrich relevant data
Technology	• Complex IT system landscape	• Setup bimodal IT architecture
Organization	• Missing know-how and manpower	• Build DDBMR units and operations
Monetization	• Unclear realization costs	• Focus on “low hanging fruit”
Live/MMP		
Data	• Unclear data ownership	• Clarify usage rights
Technology	• Redundant IT systems	• Develop cloud first strategy
Organization	• Missing data ecosystem	• Acquire DDBM data partners
Monetization	• Unclear monetization approach	• Focus on high revenue MMPs
Live/Scaling		
Data	• Missing data governance	• Establish data quality standards
Technology	• Non-scalable IT systems	• Target cloud-based IT landscape
Organization	• Missing reintegration	• Plan DDBMR unit reintegration
Monetization	• Early realization resignation	• Establish long-term business view

Table 16: DDBMR key challenges and enablers of resource utilization

Development/Experimentation

In the beginning of a DDBMR project, many companies start to focus on their data, as many of them see it as “raw gold” which only needs to be mined with the right tools. For the interviewed companies, data is a worthful resource, but they often do not really know what data exists in the IT system landscape and who works with it. Multiple data sources from different IT systems with diverse data models are very difficult to handle. This unstructured data is mostly of very bad quality and needs to be edited to create a data monetization opportunity. As one participant stated, “The companies do not need artificial intelligence or data science in the beginning. They would get much further with simpler things. We see that many companies did not do their homework. The data quality is not existing or very bad, the core data, very adventurous” (Interviewee C). For companies who want to realize DDBMs, it is important not to get lost in their “data jungle,” but to analyze their company’s landscape and to start experimenting with selected core data sources. It is not helpful at this point to start with a large amount of data cleaning because the data value opportunity is unclear.

Other challenges in the beginning of a DDBMR case for incumbent companies is a data processing-ready technical fundament. The companies are mostly not from the software industry and do have an IT architecture which is not built for DDBMR projects. Problems can be limited access to data origin systems, law restrictions, manifold systems variety, and missing interfaces between these systems. Especially in enterprise companies, it is very difficult to have an overview about which systems are existing and who owns the data of these systems. To consolidate all these sources in the beginning is impossible: “A unified enterprise-wide master data management is unrealistic” (Interviewee F). Further, the companies do not have the right tools for data analytics and first data model development. A useful approach to solve these challenges is to create an independent technology structure for fundamental DDBMR experimentation. The companies can deploy independent data hubs where the selected core data is imported. With this independency, they are able to avoid interfaces in existing IT legacy systems in order to be much more flexible in exploring DDBMR experiments.

Comparable with the missing technical fundament, it can be a major challenge for incumbent companies to create the proper organization form for a DDBMR case. Traditional company’s organizations are typically very complex through manifold organization responsibilities, multiple hierarchy levels, and company politics. This can make it very difficult to give the right persons the ability to access relevant data and create business ideas from them. Moreover, a traditional non-technology-driven company culture can make it very difficult to gain supporters for DDBM cases and budget. New business approaches need to be understood over time and can lead to conflicts in the organization. Thus, for experimentation, it is important to stay mostly independent of these legacy structures and create small interdisciplinary teams, which can operate unconventionally and generate useful DDBM ideas. As one participant noted, “We have very agile cross-functional teams. You need always identify the correct people for the topic . . . to follow the idea of co-creation with sales, business development, software engineers and more” (Interviewee G). Additionally, it is useful to coach employees from business departments for cooperation through the ideation process.

For companies from traditional industries, it can be difficult to identify and understand real-world problems which can be solved with data. Most businesses in our study have a physical product in focus, which they are selling. Through these business operations, they generate and store a great deal of data. Sometimes, they also analyze it for data-based business improvements, but they do not generate ideas and use cases about how to monetize the data itself. In fact, one participant stated, “The way to look at data and try to build business models from it, is a forlorn approach” (Interviewee K). To accelerate data monetization concepts in incumbent companies, the DDBMR teams and experts conduct evaluation workshops to accelerate use case and idea development from different business areas. These concepts do not need to be revolutionary. In many DDBMR cases, the companies take a look at best practices in their own or foreign branches. An alternative way, seen in our DDBMR cases, is to hire specialized consultants from Accenture, Fraunhofer, or Palantir, who support the company in its realization process.

Development/MVP

Through the validation of the DDBMR ideas in the experimentation period, the data sources become a major resource. In many cases, the companies had to solve the challenge of bad data quality from existing databases. The problems related to data quality can be many and various. Data can be obsolete, missed, or redundant, so that it is difficult to use it. The data needs to be analyzed to determine if it can be enriched for DDBMR or not. If it is not useful, there needs to be an immediate decision to move on other more valuable data sources: "For example, we had a project with an interesting business question and monetization opportunity. But, the data source was missing sensor data, which was not measured. If you want to train a data science model on this kind of data source, it will require many months or years. The data was simply not existent, and then we needed to say that it was not possible" (Interviewee D). Another recurring challenge is data privacy and security. This is an important challenge through the whole DDBMR process, but especially in the MVP period as it needs to be validated if the development teams are allowed to build data-based products with the core data. If this challenge cannot be addressed in this period, it will make a developing DDBM very hard to assure data sensibility and security processes. Data is a valuable asset for the companies, which needs to be protected from hackers and other third parties, and its use has to be compliant with multiple laws. Also, the companies are very sensitive about the use of personalized data, which can have negative influence on public relations with potential public scandals.

For building the MVP, the companies face the challenge of providing their software engineers, data analysts, and business managers with the tools they need for DDBMR development. The existing IT landscape is often of high complexity with multiple interfaces and data transfer standards. This often hinders a modern agile DDBMR development. Through experimentation, the teams test and apply their data tools, which allows them to generate first ideas. For the creation of the MVP, it is necessary to extend this technological fundament to provide software tools for the teams and their agile and collaborative project work. The experts described the main enabler as a way to build a bimodal IT setup where the DDBM units build their own IT architecture and centralized data processing systems to have all tools in one place: "If I reach the step where I have central access to data and do not need to merge it from different systems, then I can start to ask concrete questions and start with new business models" (Interviewee F). In most DDBMR cases, the teams do this in a cloud environment to be prepared for scaling and analytics abilities in further periods: "It is more and more obvious, that all what we need for data analysis is going to the cloud" (Interviewee D).

The connection between the traditional organizations and the agile teams was described as a challenge for all interviewed companies. The agile approaches often do not fit in the traditional business organizations, which also makes bimodal organization structures necessary. Through experimentation, the teams are formed loosely from different departments and business areas for ideation. Through MVP development, the previously loose teams need to be organized in long-term organizational units, who can develop and operate the DDBMR case. The companies structure independent units, which create an agile and data-driven environments for DDBMR. These cross-functional teams are highly flexible in their structure. They exist to build an original prototype and validate the DDBM market potential. If they are not successful, they get terminated and follow new paths: "We are focusing on the 'fail-cheap-fail-early' approach. We do not want to work for 12 weeks only to see that the approach is not working for us. But we have built in the option that we can terminate the project earlier. After four weeks, we do a first review, which is the natural breaking point to end the project, if for example, the data quality is not acceptable or the business value for the company is too low" (Interviewee D). For incumbent companies, it can be very hard to provide the necessary skills and manpower for such DDBMR units because they often require totally different skills than in their traditional business. For this, it is important to establish active external recruiting and internal mentoring programs to achieve a sustainable long-term DDBMR development.

The interviewed experts often mentioned the fear of high realization costs. Bad experiences with IT or big data projects from the past had shown a need for large investment budgets for these projects, which often provided limited impact for the company value. MVP development is the enabler to avoid long and costly analysis and project phases involved in traditional IT projects without monetization focus. They most often do not lead to successful business models, but still require a large amount of money. The experts noted that previous big data projects had a strong focus on data generation, storage, and processing. These are important technical enablers for DDBMR projects. But it is of little importance which data the company has; it is more important how the company can earn money with it. It needs data-driven market research and sales to understand the customer needs through the co-creation of business and product development in the agile teams: "We tested it in the market, calculated a business case, did market research and more. It was only after that we had the feeling that it makes sense and the potential partner was interested" (Interviewee G). Without sufficient market knowledge, a successful MVP that can go live is hard to realize and will likely fail.

Live/MMP

Through experimentation and MVP development, the company acquires the ability to develop and change many components, but when going live, the real world gets directly connected to the project. Many essential challenges occur through this launch of the DDBM in the market. One important issue in this period is the question of data ownership. Most of the interviewed companies not only use their own data in their data hubs, warehouses, lakes, or platforms, but also draw on and process a lot of customer and partner data. The usage of this data for business is complicated, and the experts need to address such questions as: Who owns this data?, Which data can be used?, and Who needs to participate? The enabler for companies is to create contracts, agreements, and consent to connect to the data providers and set a legal fundament for usage rights: "We work on our customers' data in most cases, and here we are back to the ownership issue. We can't necessarily use that unless the customer gives us permission" (Interviewee M). For the DDBM to achieve success, this is very important because, otherwise, the company can get into serious trouble with the law, press, partners, or customers. After the DDBM launch, another challenge occurs involving the enrichment of data sources over time. Because of the large amount of data, it is difficult to choose the right data to enable the growth of the value provided by the DDBMR. It often requires significant effort to connect the existing DDBM processing with new data in hopes of developing a better business.

The bimodal IT setup leads in many DDBMR cases to the challenge of redundant IT systems. The independent mostly cloud-based IT architectures are necessary for the MVP development and a scalable launch to market. The experts stated that it requires strategic guidance to unify the IT architecture over time in order to enable access to all company data sources and systems over the long term. A DDBMR case is a useful project to start a cloud first strategy, but can also result in complex company challenges: "Not all data can be stored in the cloud through law restrictions or company compliance rules. Then there is the question: can the data be stored in the cloud? Maybe it needs to be an on-premise solution. Can the software be run at the customer or in the one's own server farm? How do we get the data in the development environments? That is a big topic" (Interviewee B). To limit this complexity, the experts mentioned that it is necessary, especially in cloud environments, to minimize the number of software vendors. For the DDBMR operations, it is more valuable to use a unified technology platform of one vendor than to connect multiple tools and vendors through multiple interfaces. This only limits the system opportunities and leads to more challenges.

Connected to the question of data ownership is the important goal for DDBMR to build and to establish a data ecosystem. Most of the interviewed companies do have connections with a wide range of stakeholders, with whom they interact through business actions and data exchange. It is necessary to analyze these relations, select useful partners, suppliers, and other stakeholders, and to connect them to the company through partner programs and platforms. For DDBMR, a data platform is not mandatory, but it makes it simpler to handle all data in one place: "We have the idea to get to this platform idea, but it is not mandatory for a product or service to have this platform" (Interviewee G). The companies build a solid infrastructure, where they develop customer relationships, data products, and new pricing approaches to implement new DDBMs or evolve existing business approaches. The strong connection to multiple partners through DDBMR can also help to handle the challenge of limited resources in the companies' own organization. As mentioned previously, recruiting and finding the right experts from the market are challenging activities. The outsourcing of DDBM elements and use of co-creation are established enablers in many DDBMR cases.

The launch of the MMP is the proof-of-concept to determine if the created DDBM can work in the market. In many cases, it is necessary to revalidate the data monetization strategy after a certain time. The challenges can be many: missing pilot customers, non-acceptance of pricing models, or changed customer requirements. These challenges are not perceived as failing per se, but they require actions to be taken and an adjustment of the monetization model. Through validation, the companies analyze which MMP cases do have the highest revenue potential and try to adjust the DDBM in an iterative way for business success. This can be a hard task for incumbent companies, who normally do have another market approach. "If you bring a premium car to the market, then you know the forecasts, sales plan, and indicators. Fine. But it is hard to have the breath to build ten digital business models. Maybe one of them is succeeding, maybe after three years, and sometimes it needs additional investments. This is hard for an enterprise company" (Interviewee G). The tools applied during the monetization iterations are various and include co-creation benefits for pilot customers as well as switching from established fix price models to annual subscription models.

Live/Scaling

Going to market with an MMP is an important step, but for long-term DDBM success, it is important to be capable of scaling it. If the DDBM had initial success, the companies have to decide if they want to add more resources to scale up the business opportunities and revenue or not. In general, with the scaling of the DDBM, the amount of data is scaled as well. Data of more partners and suppliers gets acquired and more meta-data is generated. The excessive scaling of data volume can lead to high costs, while the amount of unstructured data grows and revenues decline. So, it is important to limit the data growth, especially based on its utility, and to establish data quality through data governance standards. With the data and partner growth through scaling, the risk of hacks or data breaches also increases. More stakeholders acting in the data ecosystem makes it more sensitive to security issues. To enable a secure data fundament for DDBMR, it is important to establish data agreements and processes company-wide as well as with partners.

Bimodal IT architecture is a successful enabler for DDBMR success, but it also has its limits in the business scaling period. The planned reintegration of data and IT systems needs to be executed in this period of a DDBMR. The systems and processes built to that point need to be integrated into the company's IT legacy landscape to establish long-term DDBM operations. Reintegration is not easy because of the numerous technical dependencies and attributes that need to be investigated. However, it is necessary for a long-term scalable fundament. Only this enables the scaling of the DDBM potential to more business areas, reduces redundant IT resources, and establishes a company-wide IT security concept. The experts agree that the most common way is establish a cloud first strategy for a company IT landscape and try to transfer concepts such as private, hybrid, and public cloud environments for the whole company: ". . . every company that does it the right way will do it in the cloud; otherwise, you will have too many costs for server farms maintenance. . . . The cloud is the best way for cost efficacy and scalability" (Interviewee K).

In addition to the technical systems' reintegration or evolution, the company needs to decide upon the long-term character of the DDBMR unit. Depending on the organization's character, it is useful to discuss the reintegration or a later unit spin-off for DDBMR success: "These are, at the moment, employees of our innovation department. But it is in internal startup, which acts very independently in the market with its own brand and customers. For now, it is not an independent spin-off, but this can be happen" (Interviewee D). Independent units can create their own innovative culture and skills, but have to deal with limited budgets and resources. For a successful DDBM scaling, it is necessary to increase the budget, skills, and resources. This can be enabled by selling or acquisition of the unit. The complete reintegration can be an option, if the company has the ability to scale and operate the business in its own structures. Due to the independent unit cultures of traditional and data business, this can lead to a clash of the organization cultures. Thus, it requires good planning and iterative change management to reconnect the established and new business areas to benefit the entire company.

Scaling is required to transform the DDBMR project into a cash cow. However, to gain this status, companies have to address additional challenges. Limited stamina is a major factor in the scaling period, as a traditional company culture requires rapid successes and strict project success targets. Managers and employees often strive for achieving quick results, instead of having a long-term success mindset. Many DDBMR projects are terminated before they develop their full scaling potential. The companies need to enable a long-term business view, instead of fast cash flows. The success of DDBMR scaling can take years, but if it turns out to be successful, the company can generate a lot of money for further DDBMR cases. Therefore, success uncertainty for many companies causes them to struggle in their decision-making about whether or not to engage in more DDBM investments. The enabler is a DDBM life cycle portfolio development, where all DDBMR cases are observed by business management, making it more plannable as to which cases are useful for establishing a long-term DDBMR roadmap.

10.5 Discussion and Conclusion

With our results, we generated useful insights about how incumbents' companies try to realize their DDBMs. The 19 interviewed experts described 45 DDBMR cases which served as a solid basis for answering our research questions.

To answer RQ1 concerning how incumbent companies realize their DDBMs and which resources they need, we identified an iterative realization approach through four DDBMR periods: Development/Experimentation, Development/MVP, Live/MMP, and Live/Scaling. DDBMR, as part of digital business, is a complicated topic for many incumbent companies, which operate outside their traditional business field (Nambisan et al. 2019; Svahn et al. 2017). The iterative realization approach offers the companies the ability to experiment with the new DDBMR cases using only limited resources in the beginning. If the DDBM idea works and a market demand exists, the company is able to add more DDBMR resources over time to scale the business for long-term success. This concept has proven to be very successful in many industries, and it can be adapted for DDBMR guidance (Alfaro et al. 2019; Huang et al. 2017). The four core capabilities, based on DDBMR resources, are main assets that every company needs to work on if they want to establish a successful DDBM. With data capabilities, the company gets the ability to provide, secure, analyze, and select the right data resources. The data needs to be processed through an appropriate technological process for all DDBMR operations. With their organization's capabilities, the companies structure their organization through firm-wide processes and roles to create the required DDBMR management framework. To be able to invest and scale their DDBMR cases, the companies need to establish monetization capabilities for sustainable business success.

Based on the insights from the interviews, we can also answer RQ2 which addresses the challenges and enablers that shape resource utilization in the DDBMR process. It is a complex task to establish the explained DDBMR periods and capabilities in incumbent companies. We described the different challenges and possible enablers of resource utilization in our results section, which we consolidated through an overview of the key challenges and enablers of resource utilization, as shown in Table 16. In the beginning of DDBMR development, it is a big challenge for incumbent companies to take the first step in the data business. The companies need to research their existing data sources, explore necessary tools, and generate data monetization ideas. A huge challenge in companies from traditional industries is the company culture. A company culture which has been successfully developed for a traditional business is difficult to adapt to software-based DDBMs (Warner and Wäger 2019). It is useful to start in small independent teams, which are allowed to select their own tools and core data. This enables the teams to generate ideas from valuable data sources and use best practices from the digital economy, which can lead to successful DDBMR cases. After the teams generate their first ideas, the companies need to move forward by building an MVP, which provides the core functions of the DDBM. In this period, it is important to validate the existing company environment and identify factors which might lead to failure. This can be poor data quality from the complex IT system landscape, missing know-how, or a missing budget needed to build the first DDBM prototype. For the MVP realization, the key enablers are the construction IT architecture and business units, which can operate independently from the company's core business and which are able to execute the DDBMR cases (Haffke et al. 2017; Teece 2018). This agility provides the necessary competency to enable an MVP to MMP transformation and focus on valuable business approaches (Leonhardt et al. 2017). The MMP mostly marks the DDBMR's going live in the market with customers. This means that all activities from that point are not only limited to the company, but they affect and need to be negotiated with multiple stakeholders in the economy for business growth. This challenge occurs in this period along with other challenges such as unclear data ownership, missing monetization, redundant IT systems, or failing ecosystems. At that point, the need of management capabilities which accompany the technical capabilities become obvious. This also requires key resources which can build the structures to transform the DDBM from a prototype to a scalable business concept. The companies need to acquire partners in their data ecosystem, clarify the usage rights of the transferred data, adjust pricing concepts, and focus on high revenue MMPs for scaling. Through the DDBMR scaling, the resources grow and the capabilities become more important for the company strategy. Otherwise, the growing of the business also leads to a growth of data, which means a greater effort in establishing a data governance. The companies also need to make a long-term plan for a scalable organizational and technical reintegration of the DDBM business and operations. Only this allows the companies to scale all company data and business areas and make them relevant parts of the company income streams.

Our contribution to theory pertains to three specific areas. First, previous DDBM research focused mostly on the ideation of DDBMs and did not cover the realization activities which are required to create and scale the operating model (Brownlow et al. 2015; Bulger et al. 2014; Hartmann et al. 2016). First approaches for a structured DDBM implementation were published, but stayed theoretical and had no validation from experts who were really executing the DDBMR projects (Anand et al. 2016; Hunke et al. 2017; Rashed and Drews 2021). With our qualitative study, we have provided first insights on how incumbent companies realize DDBMs and presented a structured four-period approach which can also serve as a starting point for further research. Second, we have presented a complete view on the necessary capabilities involved in DDBMR. In previous publications, the researchers focused mainly on the technical aspects of data analytics capabilities, but our results indicated that it also requires strong management capabilities to cover all parts of the DDBMR (Gupta and George 2016; Mikalef et al. 2020; Wamba et al. 2017). Third, with our research, we have identified important insights about the occurring challenges and potential enablers of DDBMR in companies. Researchers have many times mentioned the major obstacles to execution, but have not given suggestions for research as to how to overcome them (Ermakova et al. 2021; Jensen et al. 2019). Realizing digital concepts in companies remains a difficult task, and research can provide knowledge about essential enablers which can help companies to address this and to avoid failure (May et al. 2020; Metzler and Muntermann 2020). For practice, we support the execution of DDBMR in companies with our findings on the periods, capabilities, resources, challenges and enablers. The experts we interviewed repeatedly mentioned the high uncertainty which exists in the companies relating to data-driven projects. Most incumbent companies do not have any experience with the processing and selection of data for value generation. They are predominantly concerned with selling machines, cars, ships, planes, or services. Realization of a DDBM is different from their existing business practices, but the companies understand that it is very important to use data to stay competitive in the market. With our research, we thus support these companies with a structured realization process and enablers.

Our study is not without limitations. Though all expert interviews were held with people working in companies with an international business focus, the companies and interview partners were all located in Germany. This regional focus might bear cultural or region-specific limitations, for example, due to the high relevance of data protection in Europe. For further research, it would be valuable to see if different cultural settings would lead to different results. With the qualitative research approach, we identified many DDBMR elements mentioned by the experts. However, these elements can still be very subjective and therefore need further validation through additional studies in which the identified enablers are related to company success. The interviewed experts were mostly from the operational and project team levels, which corresponded to our focus on realization, less than on ideation occurring on higher company management levels. For further research, it would be useful to connect experts from different hierarchical levels as well as from external views to develop a richer picture of DDBM strategy and execution in practice.

With our paper, we provide first-time insights on how companies realize their DDBM in practice from an operational perspective. Based on the experiences of DDBMR experts, we identified periods, capabilities, and resources for DDBMR and connected them with occurring challenges and possible key enablers. These understandings represent a useful basis for further research and provide practical guidance for companies who want to reach DDBMR success.

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12 Guiding the Iterative Realization of Data-Driven Business Models - An Artifact for decision-making support

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Abstract. The usage and processing of data are key elements of the digital innovation activities of incumbent companies. Coming from traditional industries and businesses, they try to leverage their data assets and develop data-driven business models (DDBMs) to create new business ventures. Previous research focuses on the ideation and design of DDBMs, but it does not provide structured guidance on how incumbent companies can iteratively realize them. In this paper, we focus on developing an artifact that supports the iterative realization of DDBMs. Our study is grounded on interviews with 26 experts from multiple industries. By following a design science research approach, we iteratively created an artifact based on the expert interviews and the literature. The developed artifact, the "DDBM realization board," addresses the challenge of evaluating the intermediate states of a DDBM for decision makers. The results contribute to the field of business research by providing prescriptive knowledge for the realization of DDBMs. Practitioners can apply this knowledge to steer their DDBM development activities.

Keywords. data-driven, business models, realization, validation, decision making

12.1 Introduction

The usage and processing of data are topics that are becoming more and more important in today's economy and business ecosystems. Companies are trying to find ways to utilize and monetize their data, to stay competitive in the market, and to realize new business ventures and support their digital transformation (Bitzer et al. 2021; Lehmann et al. 2022; Nambisan 2017; Proksch et al. 2021). However, researchers and businesses are still trying to understand how to realize especially in incumbent companies a valuable data business in practice (Davenport and Malone 2021; Hirschlein and Dremel 2021). Data-driven business models (DDBMs) are an important element of data value generation as they are often leveraged to guide the creation of data-grounded business ventures (Ullah et al. 2021). Previously developed DDBM frameworks offer support for designing a data-driven business, but they do not consider the realization and execution of the business model (Brownlow et al. 2015; Fruhwirth et al. 2020; Hartmann et al. 2016). To address this shortcoming, some studies have provided guidance for the realization of DDBMs and developed structured approaches to their execution (Anand et al. 2016; Günther et al. 2017; Hunke et al. 2017; Lange et al. 2021). These structured approaches provide phase-oriented overviews of the execution process of data-driven business model realization (DDBMR). However, they do not provide guidance for decision makers to evaluate the progress of a DDBMR process. A method which is able to support managers in analyzing the complex aspects of DDBMR, in examining the current state of a process, and in deciding on the next steps to be taken could summarize valuable prescriptive knowledge. Assessing and validating the development of DDBMR could help practitioners to decide which ventures they should invest in and which they should not continue with or begin. This would allow them to invest in the DDBM with the highest business value opportunities. To address this lack of prescriptive knowledge on DDBM validation, we seek to answer the following research questions: (RQ1) Which are the key elements a decision maker should validate through the periods of DDBM realization? (RQ2) How should an artifact be designed to help decision makers identify required actions in the DDBMR process?

To answer these questions, we employ a design science research (DSR) approach to create a new DDBMR artifact that helps to validate the subsequent actions to be taken throughout the realization process. To design the artifact, we conducted a literature review of the existing DDBMR research to draw on this body of knowledge. In a further step, we conducted 19 expert interviews with digital managers, information technology specialists, and data experts to develop a grounded understanding of the challenges faced and strategies implemented. The interviews experts were working on realizing DDBM cases in their companies. Hence, they offered us valuable practical experience based on their project experiences. Grounded on the insights from the interviews and the knowledge stemming from the literature, we designed an initial artifact. We evaluated the artifact with seven experts from the first interview series and seven new experts. The feedback was iterative and used for validating intermediate states of the artifact and improving it in the following periods. The resulting artifact contributes to the research as it offers prescriptive knowledge for validating DDBMR projects across different periods. In practice, the tool can help companies to inform and structure decisions made regarding DDBMR projects.

The paper is structured as follows: In the second section, we present research related to our study, mainly stemming from the field of data-driven business models. In section three, we present the methodological DSR approach. Finally, we describe the results of the DSR approach and close with the discussion and conclusion in the final section.

12.2 Related Research

Through the last decades business model research became an important field in business and management science. Starting from the first concepts to describe important business components, to the development of business models as important value concept of business innovation and company strategy (Chesbrough and Rosenbloom 2002; Teece 2010; Zott et al. 2011). Especially business models' frameworks became popular as important tool for business innovation, the most well-known "business model canvas" from Osterwalder and Pigneur (2010), which had a big influence on research and practice. Through ongoing research in recent years, it became clear that there is not one type of business model and canvas, but there is a wide variety of types. Digital business models (DBM) are one type of them, who have their foundation in the usage of technologies and digital product offerings for customers (Al-Debei et al. 2008; Keen and Williams 2013; Lehmann et al. 2022). Beside the research to DBMs the field of DDBMs has become increasingly relevant in recent years (Brownlow et al. 2015; Hartmann et al. 2016; Wiener et al. 2020). We see DDBMs as a special category of DBMs, who are part of the digital entrepreneurship and transformation processes of businesses, in which companies try to grow and transform their existing businesses with the help of especially data-driven offerings and business activities (Fichman et al. 2014; Lehmann and Recker 2022; Vial 2019). A widely accepted definition of DDBMs also does not exist in the literature. A hard separation from DBMs is difficult, because of their strong relationship to each other. But it is important to subdivide these two types, because the strong dependence on data assets, processing and analytics makes DDBMs special and leads to more specific business model requirements. For this paper, we draw on the business model definition of Teece (2010) and adapt it for DDBMs: A data-driven business model defines how a company creates and delivers value from data to customers and extracts value from these activities.

Previous research has acknowledged the high relevance of business opportunities stemming from opportunities for data monetization and provides knowledge that supports DDBM creation, mainly in the ideation phase. Existing literature mainly describes how DDBMs can be structured by employing frameworks or tools to design a new business field (Brownlow et al. 2015; Dehnert et al. 2021; Hartmann et al. 2016; Kühne and Böhmann 2019). This design-focused approach conceptualizes the necessary elements of a DDBM and is helpful during the first ideation period of a new data-driven business. However, ideating and planning a DDBM are only the first steps toward its realization. Its realization requires concrete actions to operationalize the DDBM ideas in the real-world environment of a company. To provide more insights into such actions, researchers started analyzing the execution of companies' data-driven business strategies, operations, and projects in practice (Alfaro et al. 2019; Baesens et al. 2016; Günther et al. 2017). The insights from multiple company case studies show that realization is a complex task and that guidance regarding the structured and iterative execution of the DDBMR process is needed. These publications explored very useful aspects in their DDBM research but only at the abstract level of the business model, with a limited focus on realization periods, capabilities, and resources. In the research area of big data analytics, some authors have started to perform research into the capabilities required to successfully adopt data analytics in practice (Mikalef et al. 2020; Wamba et al. 2017). The results from these studies help in realizing some elements of DDBMR, but they do not offer advice on how to validate key dimensions of a DDBM in the intermediate stages of its realization.

The general business model literature comprises approaches to supporting the realization of business models (BMR). De Reuver et al. (2013) developed "business model roadmapping" for BMR, which offers an orientation for setting it up at the operational level. The authors focused on providing an overview of the realization of business models by following a "waterfall"-like project approach. They include business model validation and changes as important elements of the realization process, but they do not offer further guidance about how the necessary changes are validated during the realization. In their exploratory study, Heikkilä et al. (2017) identified three BMR paths for companies aiming to realize a business model: profitability, growth, and new business. Especially with regard to the "new business" path, the authors identified two "test and iterate" periods during its realization. Unfortunately, the authors also use a very classical top-down execution scheme and do not provide any tools for testing and developing it iteratively. A comprehensive framework for BMR was developed by Frishammar and Parida (2019). The authors structured a full phase-based process from the ideation to the scaling of a circular business model. While the results of this study offer useful insights, and some elements might also be useful for DDBM, they do not account for DDBM-specific issues, the described process is also very top-down oriented, and the revision process throughout the actual realization is poorly described.

Like mentioned before we see a strong connection from DDBM to digital entrepreneurship literature. Nambisan (2017) showed the importance of digital technologies in the field of entrepreneurship. The author presented a research agenda for digital entrepreneurship and also outlined that digital or data-driven business models needs more guidance through the high uncertainty in their development. Developing business models in an uncertain environment was also presented by more entrepreneurship researchers, who try do understand the development process (Andries et al. 2013; Bocken and Snihur 2020; McDonald and Eisenhardt 2020). They showed manifold challenges that new business ventures have in their business model creation. The design of business models cannot or hardly be "planned" from the start. The progress and challenges are unclear and it needs an experiment-oriented approach to improve the business model development over time. This iterative approach is a first important fundament for the realization of business models. But the authors stay focused on the development of the business model design and do not give guidance through tools or frameworks with which resources the companies realize the business model in the company. With the "lean startup framework" Shepherd and Gruber (2021) made an important further step to adapt insights of business model development from practice to entrepreneurship research. Their five building blocks gives a good structure for research, which elements are important for the companies to execute their business ideas. But the framework it still is only an overview and not a useful tool which helps trough operative execution. Also, with a view of other publications in entrepreneurship research, we only see approaches to support the business model design process through tools and frameworks, but for realization such a tool or framework is still missing to give guidance to companies through business model experiments (Allweins et al. 2021; Osterwalder and Pigneur 2010; Täuscher and Abdelkafi 2017).

Due to the missing DDBMR context in previous research, authors started to search for answers as to how companies realize their DDBMs in practice. Hunke et al. (2017) developed a literature-based DDBM innovation process, which offers an overview of the complex execution process of DDBMR projects. While this process is rather static, it offers a first complete overview of the necessary actions and elements of DDBMs, which need to be realized over time. Nevertheless, these results need a better empirical fundament to acquire a superior understanding based on practice. In a qualitative study, Lange et al. (2021) analyzed DDBM realization cases in practice. The authors showed multiple periods and identified resources and capabilities required during the complex DDBMR process. Their results show that a top-down planned DDBM execution is unrealistic. Instead, companies follow a more iterative realization approach through experiments (Figure 12). While the study identifies validation, including the stop or go decision and the subsequent adjustments, as essential activities in the DDBMR process, it does not provide insights into how companies are validating their DDBMR activities.

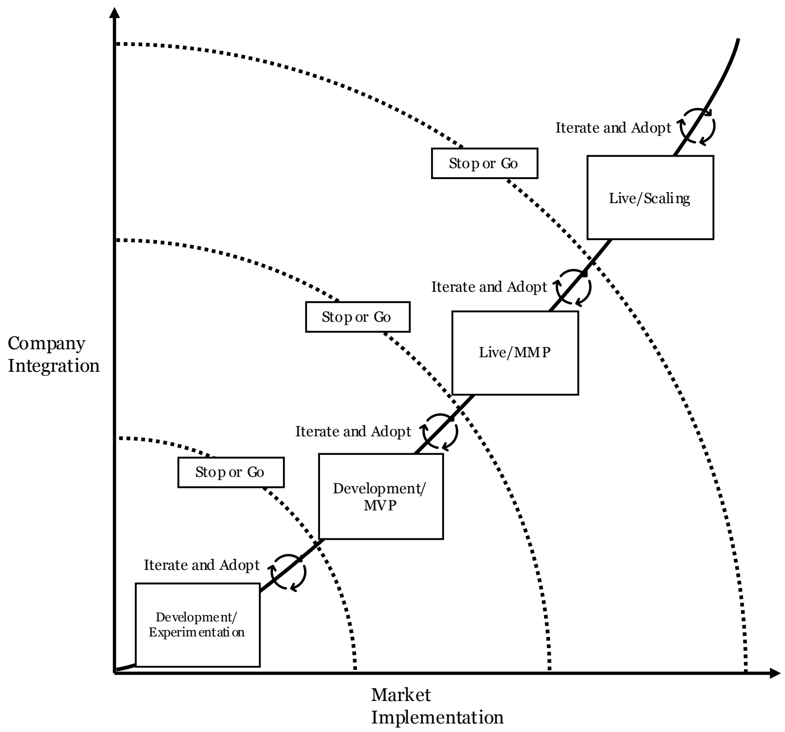

Figure 12: DDBMR periods in practice (Lange et al. 2021)

In the general business model context, some authors have already developed first approaches to how companies can validate whether their business models are on successful pathways or not. Haaker et al. (2017) constructed a business model stress test as a tool for identifying necessary improvements based on the business model canvas (Osterwalder and Pigneur 2010). The tool describes a business model test process with six steps for identifying risks and opportunities. This test offers a general validation of a business model, but it does not include action items to improve it in the next development iteration. Dellermann et al. (2019) developed decision design principles for the validation of business models and constructed a software tool for a “business model check.” This is also a useful tool for general validation, but it does not suggest actions for solving problems or weaknesses. The best support for DDBMR is provided by Linde et al. with regard to “digitalization traps” (2021). In the context of business model evaluation, they interviewed multiple industry experts regarding business model traps. Based on their insights from this study, they developed a framework for evaluating digital business model opportunities. The evaluation is carried out in three phases: Phase A focuses on assessing customer value, in phase B the operational feasibility and risks are validated, and phase C aims at creating potential financial opportunities for the company. Some elements of this evaluation can also be adopted for DDBMR, but still, the validation method should include all the elements of a DDBM.

Summarized we see that there is a big understanding in previous research, that DDBMR is a complex topic. Through experimentation and iterative approaches, the companies try to realize their DDBMR cases in their organization. Previous research gave manifold tools/frameworks for BM design, but a tool which gives guidance through the challenging DDBMR process with manifold experimentation and validation is still missing. With our research, we seek to provide a first comprehensive DDBMR tool for supporting research and practice in analyzing DDBMR activities and supporting the subsequent decisions made by practitioners based on such analysis.

12.3 Method

From the literature analysis, we learned that some literature already exists with regard to the DDBMR process, but research has not yet developed prescriptive methods or tools for guiding the validation of DDBM activities. To advance the research in this field, we followed a design science research (DSR) approach to create a new and innovative DDBMR artifact that helps to solve a real-world problem (Gregor and Hevner 2013; Peffers et al. 2007). We followed in general the iterative DSRM process of Peffers et al. (2007) which consists of six phases (Figure 13): (1) problem identification and motivation, (2) objectives of a solution, (3) design and development, (4) demonstration, (5) evaluation, and (6) communication. We adapted these for our DSR approach by developing our artifact in a more iterative way, than the original more static DSRM process.

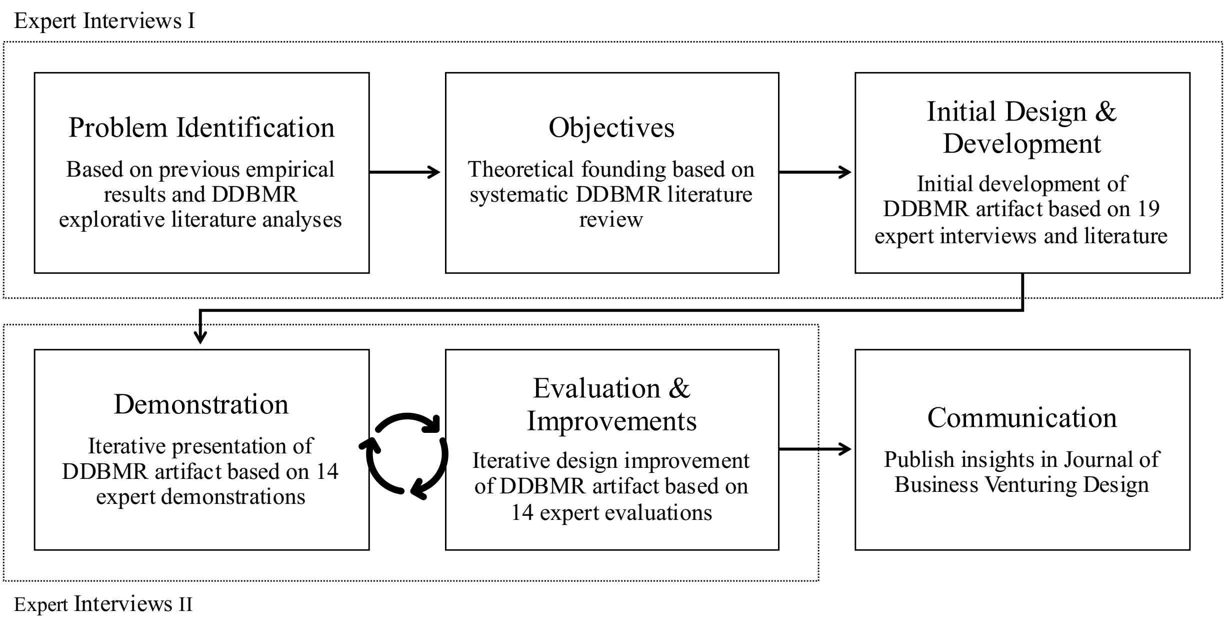

Figure 13: Design science research approach (adapted from (Peffers et al. 2007)).

We chose a problem-centered approach as our entry point, because we want to solve a relevant real-world problem with our artifact. Grounded on the literature analysis and previous empirical insights, we understand that no framework exists to help decision makers and researchers validate business value and decide on the next steps to be taken during a DDBMR project. Our motivation was to build a practical tool for researchers and managers to help them understand and execute the DDBMR process. We employed an iterative research approach by using a literature review, multiple expert interviews, and validation cycles with potential users to improve the artifact (Venable et al. 2016). To find the relevant objectives of a solution and the first artifact design elements, we conducted a systematic literature review (Webster and Watson 2002). Based on a heuristic search, we chose the keywords for our search to find relevant papers: (data AND business model) OR (business model AND transformation) OR (business model AND realization) OR (business model AND implementation) OR (business model AND integration). We searched in the following libraries: (1) AISeL, (2) JSTOR, (3) EBSCO, (4) the Web of Science, (5) IEEE, (6) Science Direct, (7) the ACM Digital Library, (8) SpringerLink, and (9) Google Scholar. No range was established with regard to the publication years. In AISeL and JSTOR, we searched titles, abstracts, and keywords. For EBSCO, the Web of Science, IEEE, Science Direct, the ACM Digital Library, SpringerLink, and Google Scholar, we limited the search to titles due to the high number of results. Irrelevant, duplicate, and non-peer-reviewed results were excluded. Only literature published in English was included in the research process. All the papers were analyzed by (1) title, (2) keywords, (3) abstract, and (4) research area. We selected papers that focused on the DDBMR process and gave guidance regarding a DDBM validation artifact. We conducted a backward and forward approach to finding additional relevant papers. Overall, we identified 37 relevant papers, which we analyzed based on a content analysis (Mayring 2000).

To build our initial DDBMR artifact, we additionally conducted qualitative interviews with 19 experts from 18 companies (Table 17) in the field of DDBMR (Bogner et al. 2009; Myers 1997). The experts had multi-year business or project experience in realizing DDBMs in their companies and came from the fields of data science, information systems, and digital business. The selected companies were incumbent ones, which were active in international markets and had already begun DDBMR activities. The experts were selected from companies from distinct industries and of different sizes to acquire insights from multiple perspectives. We recruited the experts through our professional network and LinkedIn requests. We used a semi-structured interview guideline for our interviews (Myers and Newman 2007). Interviews A–L had a focus on general DDBMR at the project level (Appendix A). Interviews M–S were held by external researchers from the Karlsruhe Institute of Technology and focused more on data monetization (Appendix B). The interviews lasted between 24 and 63 minutes with an average duration of 44 minutes. Interviews A and B were personal interviews, and interviews C–S were conducted by phone or with an online conference tool (Skype, Google Hangouts, or Zoom). All the interviews were recorded and fully transcribed. The transcribed data were used for qualitative content analysis to extract relevant insights. The experts described 45 DDBMR cases and also stated internet sources related to those cases, which were used to supplement the interview data. We applied an open coding approach to identify key elements for our initial research artifact design.

Number	Expert(s)	Role	Industry	Company size
1	A and B	Lead Data Scientist and Managing Partner	Software	<500
2	C	Digital Lab Director	Engineering	500–9,999
3	D	Data Scientist	Energy	500–9,999
4	E	Project Manager	Automotive	10,000–99,999
5	F	Product Owner Data Intelligence	Mobility	>100,000
6	G	R&D Manager	Automotive	>100,000
7	H	Data Scientist	Shipping	500–9,999
8	I	IoT Engineer	Software	500–9,999
9	J	Product Owner Data Platform	Insurance	10,000–99,999
10	K	Head of Data Science	Mobility	500–9,999
11	L	Information Security Officer	Aviation	10,000–99,999
12	M	Head of AI & Data Analytics	IT Consulting	500–9,999
13	N	CEO	IT Services	<500
14	O	Senior Expert	Automotive	>100,000
15	P	Corporate Strategy Advisor	Automotive	>100,000
16	Q	Head of Technology Marketing	Public Sector	500–9,999
17	R	Head of Customer Insights	Retail	>100,000
18	S	Tribe Lead AI	Telecommunication	>100,000

Table 17: Interviewed experts for initial artifact design and development

We presented our initial DDBMR artifact design to 14 experts for validation and improvement. Seven of the experts involved in the evaluation had previously participated in the first interview series, and seven were newly acquired experts, who provided new insights for the artifact design (Table 18). The new experts are marked with *, and the experts with changed roles compared to in the first interview series are identified with **. The demonstration was conducted via an online conference tool (Google Meet). We presented the artifact to the experts and discussed the elements and usage of it regarding practical decision making in the DDBMR process. The evaluations of the experts allowed us to follow an iterative design process to develop the artifact toward a “DDBM realization board” while ensuring the significance and applicability of the resulting artifact. This required multiple pivots of the board throughout the evaluation and improvement cycles. An alternative process-oriented concept of the realization board was rejected during the development process. Finally, we have chosen to communicate our results through their publication in this article.

Number	Expert	Iteration	Role	Industry	Company size
1	A	I	Lead Data Scientist	Software	<500
2	D	I	Data Scientist	Energy	500–9,999
3	J	I	IT Security Manager**	Insurance	10,000–99,999
4	K	I	Head of Data Science	Mobility	500–9,999
5	I	I	IoT Engineer	Software	500–9,999
6	G	I	Product Owner**	Automotive	>100,000
7	F	I	Product Owner Data Intelligence	Mobility	>100,000
8*	S	II	Product Owner	Finance	500–9,999
9*	T	II	Business Intelligence Analyst	Energy	<500
10*	U	II	Managing Director	IT Consulting	<500
11*	V	II	Digitalization Project Manager	Commerce	500–9,999
12*	W	II	User Experience Expert	Finance	500–9,999
13*	X	II	Product Manager	Automotive	>100,000
14*	Y	II	Agile Project Manager	Software	<500

Table 18: Experts for iterative DDBMR artifact demonstration and evaluation

12.4 Results

Based on our insights from the qualitative expert validation and iterative development process, we developed a “DDBM realization board” as the resulting artifact. It is a one-page visualization of all the key elements to be considered when implementing a DDBMR case. The board is inspired by the idea of visual planning tools, such as the business model canvas, data insight generator, and platform canvas (Allweins et al. 2021; Kühne and Böhmann 2019; Osterwalder and Pigneur 2010). Instead of an ideation view, our board has a stronger focus on the comprehensive realization process and how it is connected to key elements. It is a tool for decision makers and practitioners who are realizing a DDBM in their company and need to validate it. The result of the validation influences decisions, such as whether the company should invest more in the business idea, adjust the DDBM elements, or abandon the realization process. As observed in previous research, a DDBMR team faces multiple decision gates where it needs to assess the current project status and plan the subsequent actions to be taken (Hirschlein and Dremel 2021; Lange et al. 2021). These decisions have a high impact on a company's resources, strategy, and revenue. The DDBM realization board offers fundamental decision metrics to reach a conclusion and bring transparency to the manifold DDBMR opportunities available.

	KEY QUESTIONS	STATUS	TARGET	IMPACT	RISKS	ACTIONS
CUSTOMERS	• Do we have enough existing DDBM customers? • Do we have a worthy DDBM addressable market potential?					
MONETIZATION	• Do we have a pricing model that realizes DDBM revenue? • Do we make profit through our DDBM growth?					
STRATEGY	• Do we have DDBM alignment with our company strategy? • Do we establish the DDBM as business pillar in company strategy?					
TECHNOLOGY	• Do we have suitable IT architecture and systems as DDBM fundament? • Do we have the right tools for further DDBM data and product development?					
DATA	• Do we have the right DDBM data assets, quality, and partners? • Do we have fitting DDBM data analytics and processing workflows?					
PRODUCT	• Do we have the right DDBM product for our customers? • Do we have marketable features in backlog for further DDBM product development?					
FUNDING	• Do we have a big enough budget for DDBM execution? • Do we have a DDBM concept how to return our investments by time?					
ORGANIZATION	• Do we have a fitting organization form, structures and culture for DDBM setting? • Do we have the right skills in the DDBM organization?					
LEGAL	• Do we satisfy with DDBM data privacy and partner contracts? • Do we have legal and compliance permission for our DDBM?					

Figure 14: DDBM realization board

The DDBM realization board is a matrix that consists of vertical and horizontal elements. The usage and completion of this tool can lead to decision makers being able to reach a conclusion about the subsequent actions to take in a DDBM project. The vertical columns consist of nine elements:

1. **Customers:** The customer-centric view is a key consideration at the beginning of the validation activities. The (potential and also, later, the existing) customer base is the starting

point for the validation process. Despite a company being successful with regard to all the other DDBMR elements on the board, the business will fail without a market and customer demand. It is important to analyze the total addressable market (TAM) to identify a potential customer base for a successful DDBM offering. If a sufficient market is accessible, the typical growth of DDBM customers is very similar in most successful cases. The DDBM customer is not an anonym but has specific needs which need to be fulfilled throughout the realization process. At the beginning of the realization period, only a few co-creation customers exist for data-driven prototype projects, and they provide very useful insights for further development. It is important to recruit these key customers and try to build a customer-centric business model and a DDBM product that fits a huge number of use cases. If the company builds a specific data-driven business for only a few customers, it will be impossible scale the business over time. If the decision makers understand from the customer validation that the customer base is not growing or declining, it is time to adjust the DDBM or abandon it to make way for other business opportunities.

2. **Monetization:** The expert interviews showed that many DDBMR cases have very limited earnings and high investments in the beginning. Revenue generation and making a profit are essential factors of every business model that is looking to generate returns on its investment. Alongside the search for potential customers, it is much more important to acquire customers who are willing to pay for the DDBM product or service on offer. To be able to reach a wide range of potential paying customers, manifold pricing models are possible (subscription models, pay-per-use, licensing, one-time payments). These need to be tested in the market and can be changed or mixed multiple times throughout the different DDBMR periods. For example, pricing can be a combination of a fixed installation fee with additional usage-based pricing. Many of the observed DDBMR cases prefer a usage-based pricing model and try to implement it in the market through realization. It is one of the best scalable pricing opportunities because with the growing customer base of the DDBM, revenue will increase and make highly profitable regular revenue streams possible.

   For such companies, it is important to observe the monetization status through realization. This needs to be validated in terms of how the company can generate money from the DDBM and support the long-term business growth of the whole organization. If the DDBM is not expected to generate a useful income return over time, it is better to terminate the realization process because the company will just be burning money.

3. **Strategy:** Beside the several mentions of customers and monetization, the experts talked about the fit of the DDBM with the comprehensive company strategy as an important

element of DDBMR. Companies have visions and strategies they want to achieve with their businesses, which they communicate to their stakeholders, especially when they are publicly traded. Most incumbent companies are known for having specific visions, images, and stakeholder values. These values help stakeholders place their trust in the company, resulting in a fragile relationship that should not be damaged.

Strategic fundamentals provide guidance to management and are the groundwork for company operations. In most cases, a company's digital innovation and roadmaps are part of its vision and strategies. The monetization of data is a sensitive topic and needs to be an available option in terms of the company's digital strategy. Sometimes, there is no motivation from top management or shareholders to sell data or build data-based products for the market. The reasons behind this can be manifold but can strongly influence DDBMR. If there are too many problems, the execution of a DDBMR case is not recommended, because it will quickly fail as a result of the company governance or management structures.

To avoid these conflicts, it is important to validate the strategic fit of the DDBM with the company vision and strategy by using our artifact throughout the realization process. DDBMs can be a huge business opportunity for incumbent companies, so top management needs to be aware of these important decisions when developing data and digital strategies. Additional strategic management tools, such as SWOT analysis, are used by the interviewed experts to get a better understanding of the required strategy adjustments (Hill and Westbrook 2000).

4. **Technology:** A DDBM, as part of the digital business model family, needs technology to deliver value to the customer. The requirements regarding technology in a DDBMR case are manifold and constantly changing: For DDBMR, it is important to find an IT architecture that fits with the different realization periods. In the beginning, the company needs to have a flexible and fast setup, which allows it to experiment with few data assets and build the first data-driven prototype. This can be a cloud platform, which integrates data sources, tools, and interfaces.

   Bi-modal IT setups are a useful method for establishing this type of flexible system in an incumbent company, without having the restrictions of the existing legacy of the IT system landscape. Over time, in most DDBMR cases, it is necessary to connect the newly built IT architecture to the existing IT landscape to be able to scale the DDBM elements to match the regular incumbent business operations. Beyond this, it is also crucial to automate as many operation processes as possible. This avoids extra costs resulting from repetitive tasks and helps the employees focus on improving the DDBM elements. To prevent the DDBM from attacks or data breaches, the IT systems need to be protected by effective security systems.

Additionally, throughout the realization periods, different tools need to be added to this core technology to, for example, process the data assets or develop the DDBM products. This tool landscape can be manifold: It needs project management software for agile development and data analysis software to process the data, as well as sales/marketing software to deliver the product to the market. The software tool landscape will change over time because the requirements will change depending on the scaling process in the company. The permanent validation of these tools is important in terms of focusing on the right instruments based on the realization progress. If certain tools are not needed anymore, they need to be discarded to avoid new legacy systems in the company.

5. **Data:** Data provision is key to the execution of a DDBM. Incumbent companies have a lot of data sources, and a huge challenge is taking the first step toward finding a good DDBM idea. The experts explained that having a huge number of data assets is not as essential as having the right data assets. Based on these data assets it is important to make a DDBM more valuable based on the company's actions and operations in the DDBMR process. In our observed typical DDBMR case, the companies start with a small selected core data set, which is analyzed and enriched by their own or third-party data over time. Throughout the realization, the companies need to validate their used data and plan adjustments to or acquisitions of data for their DDBMs. To have a useful data assets fundament, companies try to establish data ecosystems, which help them to grow their own businesses but can also generate co-valuation with business and technical partners.

   One technical aspect is that the data need to be technologically available, which is the basis for all data-driven operations in a DDBM. Ongoing data sourcing, processing, and analysis by data experts is required. The data quality, in particular, is an essential DDBM element and is based on the data's accuracy, consistency, and relevance. If the data quality is no longer sufficient, all the other activities involved in the DDBM realization become very hard to execute because the results will be unsatisfactory. Especially in the later DDBMR scaling steps, it is useful to establish strict data governance standards, which secure the data as a valuable asset. Otherwise, incomplete, duplicate, or missing data will cause the DDBM to quickly fail because it will be impossible to deliver a valuable offering to customers.

6. **Product:** As in a traditional business model, an important element of a DDBM is the offering of a digital product or service to the customer. This offering needs to be valuable to the customer and needs a willing to pay to use it. In DDBMs, these offerings are mostly

software applications, sometimes added by hardware devices, which need to be developed through the DDBMR process and distributed to customers mostly via the internet. The variation in these digital products is diverse and includes elevator maintenance services for buildings, smart insurance for car owners, and data marketplaces for multiple industries. In most described DDBMR cases, the company's digital product development approach starts with prototyping. This means the development team builds a minimum viable product (MVP). The MVP is the technical working fundament, which is improved over time and becomes a customer-ready minimum marketable product (MMP). This product is enhanced with minimum marketable features (MMFs) and additional data assets to provide a better product offering for the customer. This development approach through DDBMR is similar to many existing digital or software business projects. Through an agile environment, the features are mostly conceived as part of a backlog before being developed. To decide which features are added to the product, tools such as "story mapping" or the "RICE model" are used (Kukhnavets 2018; Patton and Economy 2014). These tools are already established in many modern digital companies that are making digital offerings to customers. It is important to focus on the right features with the highest value for the DDBM, to use the company's efforts efficiently, to deliver valuable new features to the customer, and to be able to monetize the DDBM offering in the best possible way.

7. **Funding:** In line with most kinds of business projects, DDBMR needs solid funding throughout its realization. For this, company sponsors from top management are needed, who are able to deliver a concrete budget that can be invested in manifold DDBM ideas and prototypes. In the beginning, the approved budget in a typical DDBMR case is small because, first, a proof of concept of the DDBM ideas is required. If the team and management are pleased by the initial results, additional investments in resources, people, and knowhow are required to be able to scale the DDBM over time.

   The experts explained that in incumbent companies it is very important to educate top management regarding the fact that the realization of a DDBMR case is related with high uncertainty but also high reward opportunities. Depending on the goals of management, this can be a complicated task because short-term manager goals can conflict with long-term company business opportunities. To reduce the business risk for a company, it is important to invest in a wide DDBM portfolio, similar to the usage of venture capital in other startups. As in traditional company venture building or startup investments, many of the DDBMR cases that are initiated will fail. Only some of them will generate serious business for the incumbent company, but, in the best case, these will be able to make returns on their investments through their scalable business models.

8. **Organization:** Many of the experts described how incumbent companies generally have a very traditional company hierarchy with many multiple management levels, decision makers, and processes. In many cases, this system has worked for decades and still continues to be the most popular choice.

   For the realization of a DDBM, this traditional organizational type is often not the best option because such a business model needs a more flexible structure to make fast decisions and adjustments through DDBMR. In the beginning, DDBMR development needs flexible, interdisciplinary, and agile teams, which can start working independently based on the existing legacy structures. For this reason, many incumbent companies build their own "labs" or "factories" to create an independent creative environment for data and digital experts, who perform multiple experiments with DDBM ideas. If some of these DDBM experiments are auspicious, the agile teams develop their own business ventures, which gradually involve more employees, structures, and stakeholders. For the company-wide scaling of a DDBM, it is mostly necessary to reintegrate the unit into the company structures. Another option can be outsourcing the DDBMR unit to an independent company, which allows a more flexible development or venture exit. It is important to validate and challenge these DDBMR units throughout the realization because they will have a significant impact on the probability of the company's long-term DDBM success.

   Besides the organizational structure, many experts mentioned that it is essential to have the right skills and talents for DDBMR. Incumbent companies mostly do not have the right skills for data analysis, software development, or agile project management. Many companies need to recruit knowhow from external sources. They require specialists, such as data scientists, developers, and digital project managers, to explore the existing data assets, build the first data-driven prototypes, and bring the new DDBM to the market. The scaling of a DDBMR venture needs additional management talent, such as sales managers, marketing experts, and account managers, to establish the DDBM in the market.

9. **Legal:** As mentioned previously, the usage of data in a monetization context is a sensitive task for a company, its reputation, and its customers. Many of the experts described the legal aspect as one of the main reasons behind the failure of a DDBM, so it is important for companies to be legally saved when using data for DDBMR. Two aspects are especially important: First, the data ownership needs to be clarified. The company needs answers if it is to legally use the data assets. The clarification of the usage of own data assets is mostly

handleable, but it becomes more complex if the DDBM gets enriched with external data assets through DDBMR. Third-party contracts or the licensing information of partners in the data ecosystem need to be investigated by legal advisors to provide a solid fundament for data business operations.

Second, in the case that customer or personal data are used, they need to be employed in line with data privacy norms, governance, and customer trust. The use of internal or technical data may not be as critical in relation to privacy concerns. However, the situation is often more complicated with regard to customer or other sensitive data, which can have high reputational or penalty risks. Norms, such as the GDPR in Europe, give strict guidelines for the usage of customer data and can lead to high financial penalties. Customers mostly need to actively allow companies to use their private information and are often very protective of their own data; non-allowed data usage can cause big reputational problems and strongly influence trust in companies if it is made public. A permanent legal validation through DDBMR can be exhausting but is mandatory to guarantee the successful scaling of a DDBM and to make long-term business success possible.

The elements are organized in a specific order. A DDBM realization board user should start on the left and validate the elements by progressing through the other horizontal columns to the right. If the user of the board understands, based on the validation, that one of the DDBM elements in the DDBMR process is not present and cannot be used to work toward a successful business in the future and that the DDBM in question is not adjustable, the validation process can be aborted.

The vertical columns should be used to validate the most important questions regarding each DDBMR element and plan the next steps for its realization. The horizontal column consists of five rows:

1. **Status:** When beginning to validate each element, it is necessary to identify the status quo of the DDBMR component. What is the maturity level of the element? What are its key foundations? Quantitative metrics can be used, but it is more useful to focus on qualitative analysis, which allows a more concrete examination for further DDBMR development.
2. **Target:** To make a useful contribution to DDBMR, the users need to identify a target that should be achieved in the next realization step. This is necessary to guide the teams and managers throughout the realization periods. Otherwise, manpower and resources can be used in the wrong or an inefficient way. Based on the status and the identified target, the teams are able to identify the gap between the existing and targeted levels of the DDBMR element, which influences the subsequent actions.

3. **Impact:** Based on the target, it is important to specify the impact that the subsequent actions should have on DDBM development. The possible business impact that can be achieved by improving the DDBMR element needs to be identified. This can be a quantitative number but also a qualitative improvement of the DDBMR case itself. By understanding the possible impact or benefits, the user is able to validate the potential value for the company.
4. **Risks:** The realization of new features or improvements regarding the DDBM can lead to multiple risks. For each element, it is necessary to analyze these specific risks, which can occur through realization and have an impact on the DDBM or the company itself. Understanding these risks as early as possible can help the company take the right actions to lower the risks or eliminate them.
5. **Actions:** After the intensive validation of the DDBMR elements, subsequent concrete actions need to be scheduled. It is mandatory to define concrete action points to be performed in the next DDBMR period. The actions points are translated into concrete tasks to start initiatives or make adjustments in the company. The progress of these tasks needs to be measured to control their success in the next DDBMR period. The tasks need to be viable and useful, reach their targets, and have an impact on business value.

After completing the DDBM realization board, the decision makers have a solid fundament for drawing conclusions about the next steps and actions to be taken on their DDBMR path. It gives a comprehensive overview of all the important DDBMR elements, the targeted impact, and the actions that need to be executed. In the end, the potential value for the company and the necessary investment needs to be considered when deciding on the non-execution or further execution of the DDBMR case.

12.5 Discussion and Conclusion

Our paper provides a useful insight for researchers and decision makers who want to execute their DDBMR projects. We learned that the realization of a DDBMR case is a very complex task, with many uncertainties which are occurring through DDBM experimentation. But with the help of our developed artifact, we hope to improve the success rate. The DSR approach, the 26 experts interviewed, and the DDBMR elements identified provide a solid fundament for answering our research questions.

To answer the first research question concerning the key elements a decision maker should validate throughout the DDBMR realization process (RQ1), we need to examine our results section. We identified nine key elements that need to be observed. If we look at previous research on digital business or DDBMs, many authors focus on data and technology (Fruhwirth et al. 2020; Klee et al. 2021; Wiener et al. 2020). For sure, these are an important part of any digital business model, but, based on our insights from the experts, they are not the starting point for the validation of DDBMR progress in practice.

Previous publications show that customer-centric business models with good user experiences are key for most successful businesses in terms of digital transformation (Ismail et al. 2017; Shah et al. 2006). In recent DDBM research, customers are an essential element, but they are less in focus than in traditional business model research (Hartmann et al. 2016; Kühne and Böhmann 2019; Osterwalder and Pigneur 2010). Our results show that at the beginning of the DDBM validation in each realization period, it is essential to focus on the customers and, based on this, the connected potential of the TAM for a data-driven product offering.

If a group of potential customers is identified, these customers also need to be willing to pay for the data-driven product or service on offer. Existing DDBM literature has already identified monetization as an important element in creating revenue from DDBM operations (Baecker et al. 2020; Dehnert et al. 2021). Also, our results from the experts show that this topic is very important for validating the business potential of a DDBMR case. In the beginning, the number of DDBM customers is mostly small, but it is important to scale this through realization. Without the foreseeable fulfillment of customer numbers and monetization throughout the DDBMR periods, it will be very hard to scale a successful DDBM in the market (Huang et al. 2017).

An important factor to consider when it comes to monetizing customers is how the DDBM fits with the company strategy. Current research shows that it is common for nearly every company to use its data to create a DDBM and make money from it (Engelbrecht et al. 2016; Kühne and Böhmann 2019; McAfee and Brynjolfsson 2012). Our insights do not lead us to this understanding because the situation is much more complex. Every incumbent company has a brand, products, or services that the company is known for and its customers trust (Bendixen et al. 2004). Based on this, it is important to understand which DDBMs will be accepted by the customers and which will not. Also, it is important to understand whether the company stakeholders will support the DDBM case or if they are skeptical with regard to data-related business operations. Some of the experts described failed DDBMR projects because the potential customers experienced a lack of trust in the companies' skills concerning such a data-driven offering or top management did not recognize the value of such a model in terms of the company's strategy.

As shown in our results section, data assets play a key role in any DDBMR case. Some authors talk a lot about big data as the new "oil." The argument put forward often involves acquiring as much data as possible to store in a data lake/warehouse to earn more money (Himmi et al. 2017; McAfee and Brynjolfsson 2012; Woerner and Wixom 2015). Our insights from the expert interviews do not support this argument. At the beginning of the realization process, it is critical to experiment with a small data set and try to solve a real-world problem, which, in the best case, comes from an existing pilot customer. Recent research has shown the big problems associated with and the complexity of big data projects for companies (Dremel et al. 2020; Jensen et al. 2019). Most incumbent companies have large amounts of unstructured data, which are not useful when starting a DDBMR process. Without the right and good quality data, which are fundamental in terms of the MVP, successful monetization is impossible because the value proposition for the customer will be very bad or useless.

To be able to use data for DDBM operations, it is necessary to provide the right technologies throughout the DDBMR periods. Many publications mostly focus on big data analytic capabilities and see technology as a requirement that needs to be fulfilled (Mikalef et al. 2020; Wamba et al. 2017). However, our results show that many incumbent companies have hundreds or thousands of legacy systems and programs with manifold interfaces, data, and permission structures. This makes it very difficult for them to implement a modern technological fundament for a DDBMR project. Most of the experts interviewed preferred a bi-modal IT setup to connect existing system landscapes with modern software tools (Horlach et al. 2016). For project teams, it is much easier to start with modern, mostly cloud-based tools, which can gradually be customized and scaled. It is important to give the software engineers, data scientists, and product owners functional development and management tools to build an agile development environment. The experts described multiple project management, deployment, coding, and analytic tools as essential to their businesses.

These tools give the ability to build the right digital product, which is normally the core offering of a DDBM. Previous research often highlights the selling of data as the main revenue driver for companies (Loebbecke and Picot 2015; Vial 2019), but our insights from practice provide another perspective. An incumbent company not only wants to sell its raw data, but also tries to ennoble these data with its company capabilities, which are delivered by a digital product, service, or platform (Lehmann and Recker 2022; Nambisan et al. 2017; Nylén and Holmström 2015). This can be a website, app, or API services. The customer gains value from the insights delivered and not from the data assets themselves.

Being able to create such data-driven products with the right technology and data requires funding (Dubey et al. 2020; Zolnowski et al. 2017). This aspect is mostly missing in existing DDBM literature because it is a “given” in the analysis of DDBMs (Hartmann et al. 2016; Kühne and

Böhmann 2019). However, this element is not as obvious as it seems. Many of the experts mentioned that it can be very hard to obtain adequate budgets for their DDBMR projects if they cannot prove the possible future revenue opportunities. Especially at the beginning of the DDBMR process, the value realization is influenced by high uncertainty, and it needs strong support from top management or company managers regarding initial investment. One option involves creating independent startups or cooperating with other companies with more digital-driven strategies and reputations that can better reach certain customer segments (Kollmann et al. 2021).

As mentioned in our results, in the beginning, an organization needs small, flexible, but also high-skilled, agile teams. Previous research has understood these requirements, but it has also shown the huge challenge facing incumbent companies because they do not have the right skills and people for DDBMR inside their established organizations (Bitzer et al. 2021; Gerster et al. 2020; Lange et al. 2021). Our experts described how it is often necessary to recruit external experts and form a mix of incumbent and new employees. This helps transfer the specialist knowledge to more company members and is an important resource scale factor throughout the DDBMR process (Huang et al. 2017).

Finally, a sometimes underestimated but very important aspect is the legal perspective of DDBMs. Many DDBMR cases are very data- or technology-driven projects, and sometimes essential legal aspects are forgotten. Previous research has identified the ownership and privacy of the data assets used as key considerations (Fadler and Legner 2022). This is not always easy in practice because the usage of data can be very complex. If a company uses its own internal data, the ownership can be more easily clarified. However, if the company also uses partner data from a data ecosystem, the situation becomes more complex. In particular, the breaching of data privacy laws concerning sensitive customer data can lead to high penalty charges. The experts described this legal aspect as a key element for the success or failure of DDBMR cases, so it is an important validation element throughout the realization periods (Hunke et al. 2017).

The identification of the nine key elements of DDBMR gives us the ability to answer our second research question (RQ2) regarding the type of DDBMR artifact that helps decision makers identify required actions in the realization process. If we have a look at previous publications, we can observe a lot of artifacts for the ideation and design of business models. Osterwalder and Pigneur's (2010) well-known BMC provides business people with an important overview of the elements required when establishing a new business, but it gives no guidance as to how to fulfill these requirements in company organizations, nor does it focus on DDBMs. The "data insight generator" of Kühne and Böhmann (2019) does have this DDBM focus and is built on empirical knowledge from practice. The authors understood the required validation of the DDBM elements, but also focused ideation, less realization. Allweins et al.'s (2021) "platform canvas" has no data focus, but it extended the ideas of the BMC and also shows the dynamics that occur through the many elements of a multifaceted business model. This connection to the DDBM literature shows the complexity experienced throughout realization.

In our "DDBM realization board" (Figure 14), we can see a first structured overview of all the important elements to consider throughout the DDBMR periods.

In our interviews, the experts mentioned a lot of the elements of the board, but a widely accepted standard for realization does not exist. The experts frequently spoke about management decisions, business venturing, and pitches, but companies do not have a standardized tool to validate DDBMR progress or the adjustments that are required. Because of the high uncertainties the companies do have through the DDBMR, they need guidance how to decide on important "stop-or-go" steps in their experiments (Andries et al. 2013; Standing and Mattsson 2018).

Similar to the existing artifacts described in previous research, we want to give researchers and decision makers a one-sided overview deck, which they can use as a comprehensive approach to validation through the DDBMR process (vom Brocke et al. 2021; Kühne and Böhmann 2020; Osterwalder and Pigneur 2010). The vertical column provides decision makers with a fundamental validation structure they can use to analyze DDBMR from left to right. For a successful DDBMR case, it is important to analyze the manifold elements and not only focus on technology or data. The order of the elements was refined through the artifact creation and validation process and reflects the experts' priorities. The horizontal columns give a structured approach to validating each DDBMR element in terms of the most important aspects. The user starts with the status quo and describes the target that should be reached, the possible impact in terms of the business, and the possible risks with regard to the next step. This analysis leads to required action items, which should be executed during the subsequent period to make the DDBM more successful. If the validation of one element shows that the realization is going in the wrong direction or failing, the DDBM needs to be adjusted or even abandoned to ensure the efficient use of the company's resource investments. The "DDBM realization board" is the first comprehensive tool to be developed that can be used to realize a DDBM in practice and that can also help researchers understand how DDBMR is executed in a real-world business venture environment.

Our contribution to the research is threefold. First, our results strengthen the DDBM literature to move the focus away from just DDBM design toward execution and permanent validation. Most previous literature has addressed ideation but not the realization activities (Brownlow et al. 2015; Hartmann et al. 2016; Kühne and Böhmann 2019). How companies validate their DDBMs and decide on the next realization steps remains unclear (Baecker et al. 2021; Hunke et al. 2017; Lange et al. 2021). With our DDBMR artifact, we provide a first comprehensive approach that encompasses all the necessary DDBMR elements based on a qualitative study with experts who realize DDBMs in practice. This is a good starting point for further research and more case studies.

Second, we link the traditional BMR element with DDBMR and show the connections between these disciplines (Frishammar and Parida 2019; de Reuver et al. 2013). The results show that it is correct to have a digital/technology focus throughout the realization of a DDBM. It is also very important to analyze the more management-oriented elements, such as customer value and funding. Our results show that a permanent validation of the DDBM elements throughout the realization process is key success factor. A dynamic DDBM experiences a lot of changes throughout its lifetime as a venture concept (Berends et al. 2021). Traditional business model validation tools can help, but a more comprehensive view of DDBMR is needed to be able to react in an agile environment and make the right decisions (Dellermann et al. 2019; Linde et al. 2021). Our DDBM realization board gives such an overview and is a good starting point for further research, especially that connected to business ventures.

Third, we are giving support to digital entrepreneurship research by giving an important and useful tool to validate the realization process of DDBMs. The entrepreneurship perspective of seeing the development of new business models through experiments is in line with our empirical findings and makes it more comprehensible that top-down execution of business models is not working (Andries et al. 2013; McDonald and Eisenhardt 2020; Sarasvathy 2021). For business model experimentation companies needs tools like a canvas or frameworks to get guidance through the realization process (Shepherd and Gruber 2021). The creation of a canvas to realize business models is an innovative research field. Our "DDBM realization board" can be a starting point for further research to adapt also for DBM or other types of business models.

In practice, the DDBM realization board is a complete tool that can be used during the execution of DDBM projects. The board gives the guidance many experts are missing and provides an overview of all the necessary aspects. The tool can be used in workshops, management meetings, and operating teams as an important form of orientation throughout realization. Many incumbent companies do not have much experience in the field of digital or data-driven business. They mostly exist in traditional industries, their employees are not digital natives, and their existing structures are designed with traditional businesses in mind. However, such companies understand the importance of using data to stay competitive in the market. Based on our research, the structured DDBM realization board can be used to support these companies and decision makers.

Our results are not without limitations. All the expert interviews were conducted with people working in companies with an international business focus, but the organizations and interview partners were all from Germany, and this regional focus might present country-specific limitations. Factors such as the high importance of data protection or lower technological levels of these companies compared to, for example, US companies could be an important limitation. In further research, a good improvement would be to acquire insights from multiple countries to see whether different cultural settings give different expert insights. Using the DSR approach, we identified the elements of our DDBM realization board based on aspects mentioned by the experts. These elements are still very subjective, and, thus far, the artifact has not been tested in practice. For its practical validation, it would be useful to include the artifact in a company's DDBMR project to see whether it is helpful for the users or if more improvements are needed. The experts interviewed were mostly from the company operational level in order to focus on the day-to-day execution of such processes, rather than on top management strategic planning. However, our artifact is not only useful at the operational level, but also helpful for management when deciding on DDBMR investments and strategies. In further research, it would be practical to mix experts from different hierarchical levels to observe the practical usage of the artifact in companies. This would allow the observation of whether the artifact is useful for all levels of business or if a different artifact is needed for higher management.

With our paper, we provide, for the first time, a comprehensive DDBMR tool, which companies can use to overcome challenges and uncertainties in their practices. Based on DDBMR expert experience, we constructed our DDBM realization board, which is a tool that can be used throughout the different DDBMR execution periods. These understandings represent a useful basis for further research and provide practical guidance for companies who want to successfully execute their DDBMR projects.

12.6 Appendix

Appendix A: Interview guideline I

(1) Introduction

- Please introduce yourself and your role in the company.
- please briefly describe your company and what is the connection to the topic of digitization and data?

(2) Digitization / Transition of DDBMs

- What does the topic of digitization mean to you?
- How does data play a crucial role in this? Do you deal with topics such as Big Data / Data Science / Data-driven products?
- How has this impacted your product offering? Are there any changes to the business model?

(3) Idea generation

- How have you developed ideas for creating value with data? Have you used specific tools/frameworks to generate ideas for new data-driven business models? If yes, what were they? (e.g., Business Model Canvas / Google Design Sprints).
- Are these ideas aimed at evolving the existing business model or creating a completely new digital business model?
- Do the new ideas pursue a platform concept?
- Which practical examples did you use to develop your own business model?
- Was there external support (e.g., from consulting firms) in generating these ideas?

(4) Realization process

- How did you implement your ideas in practice? Did you use a specific process model / framework for realizing the business model? If yes, which models did you use?
- Was an agile approach used for the realization of the business model? What experiences did you have with it?
- How did you analyze the data available to you? How did you identify the relevant data?
- Were there any problems with the data quality? How could these be solved?
- What data from partners, external service providers or freely available sources "Open Data" were used? What were the challenges and how did you overcome them?

(5) Project experience

- which specific project has your company carried out in the area of data-driven business models (or products)?
- What data or sources were used in this project?
- What technologies were used?
- What new products were developed or added for the customer?
- What steps did you take during the implementation process?

- How was the business environment / ecosystem involved in the development or how did it change?
- Which persons (roles) were involved in the realization?
- In what form was the data-driven business model integrated into your company? (Pilot/company-wide/startup)
- How was the data-driven business model extended into other areas of the company?

(6) Further development

- Which divisions/positions are tasked with coordinating/operating the business model?
- How do you continue to develop the data-driven business model (or digital products)?
- Overall, looking back at the business model development process, what were the biggest challenges and how were they overcome?
- What would have helped you to plan and execute the process of realization even better?

(7) End

- What are your plans for further projects based on data-driven business models in your own company?
- What are your expectations about the future impact of data-driven business models on your industry?

Appendix B: Interview guideline II

(1) Welcome and explanation of the background of the study.

(2) Obtaining permission to record the interview

(3) Background and introductory questions

- Could you give me a brief description of your position within the company?
- What is the significance and importance of data to your company?
  - Would you describe your company as data-driven?
  - Does your company treat data as a strategic asset? If so, how does this manifest itself?
  - What does "data monetization" entail for you?
  - d. Could you briefly outline the history of your data monetization strategy?
- What prompted you to start monetizing data? Was there a specific trigger?
- How has your "data monetization" strategy evolved or changed over time?
- What is the importance of "Data Monetization" to your organization? Is "Data monetization" necessary to remain competitive in the long term?

(4) Questions about the business model

- Are your data products/services proprietary products that can be delivered independently of the core product?
- What does your typical data customer look like? (industry, size, etc.)
- How is relevant data for monetization identified in your organization?
  - Why do you think your data is valuable to other organizations? How is this value confirmed for other organizations?
  - What type of data is most suitable for monetization?
- Who in your company is responsible for collecting and preparing the data? What do the organizational structures look like in concrete terms? (Keyword: "data governance/stewardship").
- How does your internal data become marketable data products/services?
  - Could you briefly describe the process of creating the raw data into marketable data products/services?
  - Are strategic business partners involved in the process of creating the raw data into marketable data products/services?

- How do you make money from your data?
  - How do you price your data products/services?
  - What "revenue model" have you implemented for your data products/services business?
- How do you deliver your data products or services to your customers?
  - What mechanisms do you use for the delivery of data products/services?
  - Are third parties involved in the data delivery process? (e.g., data marketplaces)
- How do you sell your data products/services?
  - What marketing tools do you use to market your data products/services?
  - Do you actively approach potential customers? If yes, how do you identify these customers?
- What contractual provisions are in place regarding the use and liability of your data? Are these negotiated individually with each customer or are there general terms and conditions?

(5) Questions about performance and barriers

- How do you rate your "data monetization" performance compared to other companies?
  - In your industry?
  - Overall?
- Could you once briefly explain what challenges you faced in monetizing your data? How did you overcome these challenges?
- Why do you think other companies have difficulty monetizing data?

(6) Questions about success factors and future plans

- What factors have helped you successfully monetize data?
- What are the most important lessons you have learned about monetizing data?
- What are your future plans regarding your "data monetization" strategy? Are there any strategic partnerships planned with other companies?

(7) Other

- Can you think of anything else that might be of interest to me that was not addressed in this interview?

Would you like certain details just discussed not to appear in the interview transcript? Would you like certain details to be added?

Appendix C: DDBMR case list

Case	Area	Type	Target Industry	Status	Stage	Focus	Scope	Interview
1	Solar Panel Maintenance	Data Product	Energy	Live	MMP	B2B	New Business	A
2	Product Simplification	Business Improvement	Manufacturing	Development	Experiment	B2B	New Business	C
3	Smart Power Grids	Data Product	Energy	Live	MMP	B2C	Extend Business	D
4	Grid Planning Tool	Data Product	Engineering	Live	MMP	B2B	New Business	D
5	Property Assessment	Data Product	Real Estate	Live	MMP	B2B	New Business	D
6	Solar Panel Recognition	Data Product	Energy	Development	Experiment	B2B	Extend Business	D
7	Sensor Data Selling	Data Selling	Automotive	Development	Experiment	B2B	Transform Business	E
8	Sensor Data Platform	Data Platform	Automotive	Development	Experiment	B2B	Transform Business	E
9	Weather Data	Data Product	Automotive	Live	MMP	B2B	Extend Business	E
10	Car Data Marketplace	Data Platform	Automotive	Live	Scaling	B2B	Extend Business	E
11	Smart Fleet Maintenance	Data Product	Transport	Live	MMP	B2B	Transform Business	F
12	Car Data Marketplace	Data Platform	Automotive	Live	Scaling	B2B	Extend Business	G
13	Data Insights Platform	Data Platform	Automotive	Live	MMP	B2B	Extend Business	G
14	Traffic Data	Data Product	Automotive	Live	Scaling	B2B/B2G	Extend Business	G
15	In-Car Entertainment Platform	Data Platform	Automotive	Live	MMP	B2C	Extend Business	G
16	Use-Based Car Features	Data Product	Automotive	Development	Experiment	B2B/B2C	Extend Business	G
17	Predictive Repair Service	Data Product	Automotive	Development	Experiment	B2C	Extend Business	G
18	In-Car Advertisement	Data Product	Automotive	Development	Experiment	B2B/B2C	Extend Business	G
19	Project Transparency	Business Improvement	Shipbuilding	Live	Scaling	B2B/B2C	Transform Business	H
20	Smart Metering Services	Business Improvement	Energy	Development	MVP	B2B	Transform Business	I
21	Predictive Wind Power Maintenance	Data Product	Energy	Live	Scaling	B2B	Transform Business	I
22	Predictive Component Replacement	Data Product	Manufacturing	Development	Experiment	B2B	New Business	I
23	Predictive Escalator Maintenance	Data Product	Manufacturing	Live	Scaling	B2B	New Business	I

24	Device Data Hub	Business Improvement	Software	Live	Scaling	B2B	Extend Business	I
25	Product Evolution	Business Improvement	Insurance	Development	MVP	B2B/B2C	Transform Business	J
26	Usage-based Insurance Service	Data Product	Insurance	Development	MVP	B2B	Extend Business	J
27	Smart Investments	Business Improvement	Insurance	Development	Experiment	B2B/B2C	Transform Business	J
28	Transportation Platform	Data Platform	Mobility	Live	Scaling	B2C	Transform Business	K
29	Plane Data Platform	Data Platform	Aviation	Live	Scaling	B2B	Extend Business	L
30	Flight Data Selling	Data Selling	Aviation	Live	Scaling	B2B	Extend Business	L
31	Personalized Flight Services	Business Improvement	Aviation	Development	Experiment	B2B/B2C	Transform Business	M
32	Predictive Plane Maintenance	Business Improvement	Aviation	Live	MMP	B2B	Transform Business	M
33	Car Data Marketplace	Data Platform	Automotive	Live	Scaling	B2B	Extend Business	O
34	Car Repair Knowledge Base	Data Product	Automotive	Live	Scaling	B2B	Transform Business	O
35	Car Data Selling	Data Selling	Automotive	Live	Scaling	B2B	Extend Business	P
36	Car Data Marketplace	Data Selling	Automotive	Live	Scaling	B2B	Extend Business	P
37	Car Data Ecosystem	Data Platform	Automotive	Live	Scaling	B2B	Extend Business	P
38	Smart Insurance	Data Product	Insurance	Development	MVP	B2B	New Business	P
39	Satellite Data Selling	Data Selling	Public Sector	Live	Scaling	B2B/B2G	Extend Business	Q
40	Ship Detection Service	Data Product	Public Sector	Live	Scaling	B2G	Extend Business	Q
41	Shopping Data Selling	Data Selling	Retail	Live	Scaling	B2B	Extend Business	R
42	Shopping Insights Hub	Data Product	Retail	Development	MVP	B2B	Extend Business	R
43	Smart Assortment Platform	Data Platform	Retail	Live	Scaling	B2B	Transform Business	R
44	Location Data Service	Data Product	Communication	Live	Scaling	B2B	Extend Business	S
45	Data Insights Platform	Data Platform	Communication	Live	MMP	B2B	Extend Business	S

Appendix D: DDBM realization board development stages

Pivot 0:

	Data Assets	Data Quality	IT Architecture	Tools	Skills	Organization	Monetization	Customers
	Do we have the necessary data assets?	Is our data quality good enough?	Is the IT architecture fitting?	Do we have the right tools for analytics and operations?	Do we have the right skills for analytics and operations?	Do we have the right structures for operations	Can we create value from our operations?	Do we have enough existing or potential customers?
Status								
Target								
Input								
Potential								
Risks								
Conclusion								

Pivot 8:

	Customers	Monetization	Technology	Data Assets	Organization	Governance	Strategy
	Can we reach enough existing or potential customers?	Can we create value from our operations?	Do we have fitting IT architecture, systems and tools?	Do we have the necessary data assets and quality?	Do we have the right structures, resources and skills?	Can we use our data?	Do the business fit into our company strategy?
Status							
Actions							
Potential							
Risks							

Pivot 14:

	CUSTOMERS	MONETIZATION	STRATEGY	TECHNOLOGY	DATA	PRODUCT	FUNDING	ORGANIZATION	LEGAL
	Do we have enough existing or potential customers?	Do we have a pricing model that realizes revenue?	Do we have compatibility with our company strategy?	Do we have suitable IT architecture, systems, and tools?	Do we have the right data assets, quality, and partners?	Do we have the right product for our customers?	Do we have a big enough budget for execution?	Do we have the right structures, culture and skills?	Do we have legal and compliance permissions for execution?
STATUS									
TARGET									
IMPACT									
RISKS									
ACTIONS									

Alternative realization board process concept (discarded):

	KEY QUESTION	PIVOT 0	PIVOT I	PIVOT II	PIVOT III	PIVOT IV
CUSTOMERS	Do we have enough existing or potential customers?					
MONETIZATION	Do we have a pricing model which realize revenue?					
STRATEGY	Do we align with our company strategy and management?					
FUNDING	Do we have enough budget for execution?					
TECHNOLOGY	Do we have fitting IT architecture, systems and tools?					
DATA	Do we have fitting IT architecture, systems and tools?					
ORGANIZATION	Do we have the right structures, resources and skills?					
GOVERNANCE	Do we have ownership or permission to use the data?					
RESULT	Stop or Go?					

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13 Capabilities and Activities for Realizing Data-Driven Business Ventures in Incumbent Companies

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Abstract. Leveraging data as an important resource for business success is an enormous challenge for incumbent companies. Previous research has focused on how companies design or realize data-driven business models (DDBMs), but not on how companies establish the relevant organization, capabilities, and resources for data-driven business ventures (DDBVs). By leveraging the resource-based view (RBV) as a theoretical lens for our analysis, we identify nine key capabilities and 108 activities for DDBV realization. Finally, we compared the DDBV findings to general digital venture realization. The results contribute to the field of information systems research by theorizing DDBM realization through company ventures.

Keywords. data-driven, ventures, business models, realization, incumbent companies

13.1 Introduction

The use of data assets has become an important requirement for business success. Initially, mostly internet or start-up companies tried to leverage data for their digital business models and products. Today, incumbent companies have also discovered the importance of data for business development. However, business managers and researchers are still struggling to find appropriate pathways to realize the benefits of data (Hirschlein and Dremel 2021; Klee et al. 2021; Sebastian et al. 2017). To help companies with their data monetization operations, Hartmann et al. (2016) developed a taxonomy of data-driven business models (DDBM) of start-up companies. Subsequent authors followed these approaches by conducting additional research for DDBM design and case studies (e.g., Alfaro et al. 2019; Brownlow et al. 2015; Kühne and Böhmann 2019). The missing assistance for how companies realize DDBM in practice was supplemented in a later stage to understand the required steps and activities for data-driven business model realization (DDBMR) (Baecker et al. 2021; Hirschlein and Dremel 2021; Hunke et al. 2017; Lange et al. 2021). Based on the results of these studies, the importance of

DDBMR to incumbent companies who are transforming their businesses for the digital business age has become more understood (Nambisan et al. 2019). However, incumbent companies find it extremely challenging to perform this transformation in their current processes and organizations (Svahn et al. 2017).

To solve these problems, incumbent companies have started to create data-driven business ventures (DDBV) in which they are developing and launching their own data-driven business activities. Realizing a DDBV is a very challenging and complex task for incumbent companies. The core business of incumbent companies mostly does not provide the right capabilities and skills for a DDBV, so it needs support how to do a successful realization. Otherwise, the DDBV will mostly fail. However, previous research has provided insights for elements of DDBMR, but not for the required capabilities and activities to realize these DDBVs in practice. Based on this research gap, we address the following research question (RQ): Which capabilities and activities do incumbent companies use for realizing data-driven business ventures?

To answer this research question, we analyzed interviews with 26 business managers, data specialists, or information technology engineers from 25 companies. The interviewees all work on data-driven business projects, and their firms conduct international business operations. Most of the interviewees are from incumbent companies in the process of developing and realizing DDBVs. The interviews allowed us to understand how these companies realize DDBVs and which capabilities and activities are necessary for successful realization. We identified nine key capabilities and 108 activities structured on the Lange et al. (2021) DDBMR execution periods: Development/Experimentation, Development/Minimum-Viable-Product (MVP), Live/Minimum-Marketable-Product (MMP) and Live/Scaling (Figure 15). Our research extends the existing research by adding an empirically grounded understanding of the realization of DDBMs through DDBVs. In practice, the results will help companies successfully realize DDBVs by focusing on the correct capabilities.

This paper is structured as follows: In the following section, we present the theoretical foundation and related research on the realization of DDBMs and digital ventures. In Section 3, we present the methodological approach. In the final section, we describe our empirical research results and close with a discussion and conclusion.

13.2 Theoretical Background

13.2.1 Resource-based view and information systems research

The resource-based view (RBV) of a firm is one of the most important theoretical lenses for the analysis of utilized resources for business value generation in companies. Various management researchers developed the theory over time, and it is grounded in the idea that company success is based on a company's own resources and capabilities (Hart 1995; Wernerfelt 1984). Based on the RBV, most single resources cannot create unlimited value; a combination of different resources is required to create a company's business capabilities (Barney 1991; Grant 1991). Resources can be segmented into capabilities that the company uses to determine the best way to outperform its competitors and be successful in its business. This is an accepted hypothesis in management research, and we will follow this classification in the current study (Hitt et al. 2001; Kunc and Morecroft 2010; Sirmon et al. 2011). This approach to analyzing resources or capabilities in relation to company success has also been adopted in information systems research (Bharadwaj 2000; Melville et al. 2004; Wade and Hulland 2004), focusing on the connection of IT capabilities and the required additional capabilities from company business areas to create business value. This also includes the capabilities for data analytics, which are becoming an essential requirement for creating business value out of data assets. Gupta and George (2016) conducted a quantitative study of the required resources and capabilities for big data analytics, and their results are a good starting point for understanding the required capabilities; however, few implications for practical adoption were provided. To offer more insights from practice, Wamba et al. (2017) created a research model focused on big data analytics capabilities and firm performance, which analyzed data from multiple Asian companies. The results showed a strong coherence between data analytics capabilities and firm performance. The authors recommended that companies build data analytics capabilities for long-term company success; but they do not provide guidance on how to execute it. Mikalef et al. (2020) extended this research approach by identifying additional capabilities that positively influence company performance. The results provided a comprehensive overview of the required capabilities for data analytics; however, once again, little guidance was given for how to execute it in practice. Thus, while the existing research has applied the RBV to understand necessary data analytics capabilities, it remains unclear which activities are performed to create these capabilities in practice. Furthermore, the connection to DDBMs for a more comprehensive management view and the realization of DDBMs in data-driven business ventures (DDBVs) is still missing.

13.2.2 Realization of data-driven business models

Through our literature research, we identified that a generally accepted definition of DDBMs does not exist. For this paper, we draw on the business model definition of Teece (2010) and adopt it for DDBMs: *A data-driven business model defines how a company creates and delivers value from data to customers and extracts value from these activities*. Through their strong connection to technology and management, DDBMs are mostly part of companies' digital innovation processes (Fichman et al. 2014; Kohli and Melville 2019; Nambisan et al. 2017). DDBMs are not static models; they are dynamic and change throughout the realization process. No DDBM works from the beginning. In most cases, multiple elements must be changed throughout the realization process because of new requirements for a successful digital data-driven business (Vial 2019). DDBMs can be either new business approaches or traditional business models that have been transformed to DDBMs with the help of digital technologies over time (Wessel et al. 2021).

In general, previous DDBM research has focused less on the practical realization of such a business and more on ideation and design (Dehnert et al. 2021; Lange and Drews 2020; Wiener et al. 2020). Multiple frameworks and tools were developed based on traditional business model research to describe the necessary elements of a company's DDBM (Brownlow et al. 2015; Hartmann et al. 2016; Kühne and Böhmann 2019). A missing key element in these publications is the question of how companies execute these elements and how they create an operating model for a successful DDBM (Davenport and Malone 2021; Günther et al. 2017; Wiener et al. 2020). In previous research, companies have been analyzed by their DDBM business strategy, operations, and projects (Alfaro et al. 2019; Baesens et al. 2016; Chen et al. 2017). The results of these studies helped to understand companies' ideation as an essential part of a comprehensive DDBMR process.

Anand et al. (2016) developed one of the first approaches for realizing the value of digital data streams. The process has four steps that describe the general strategy for data value realization. Although useful for further research, the ideas are too limited to a pure data monetization perspective. Hunke et al. (2017) tried to understand the required activities for DDBM innovation and developed a literature-based DDBM innovation process that offers a general overview of the implementation process. These insights are important to initially recognizing the complexity and challenges of realization; however, the described process is static and has limited empirical grounding. Based on multiple empirical cases, Lange et al. (2021) developed the following four periods of DDBMR:

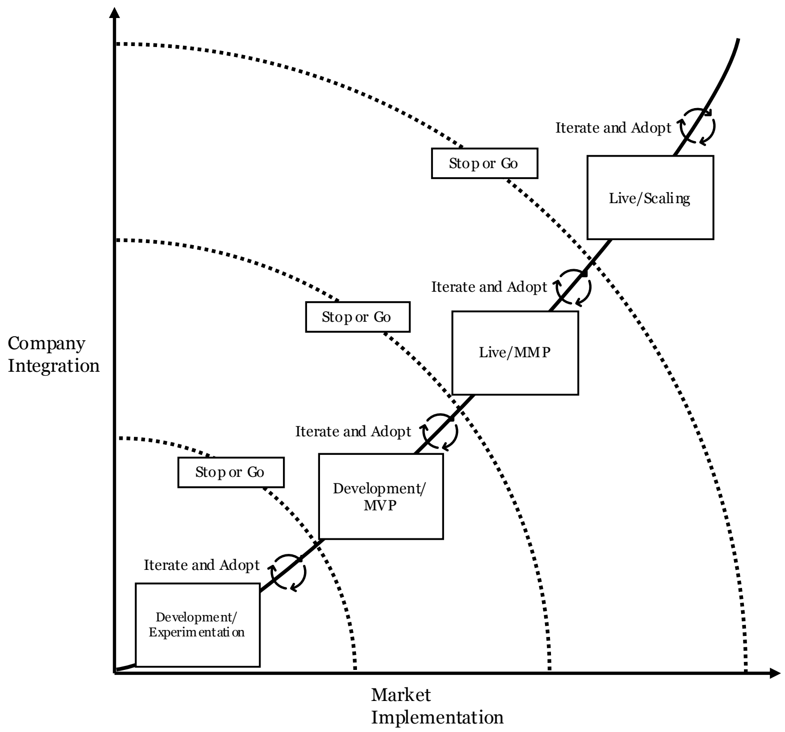

Figure 15: DDBMR periods in practice (Lange et al. 2021)

Development/Experimentation: Generate initial ideas, build first prototypes; Development/Minimum-Viable-Product (MVP): Build initial data-driven product or services; Live/Minimum-Marketable-Product (MMP): Launch DDBM offering to first pilot customers; and Live/Scaling: Scale the business to more business areas/segments. We will use these periods as a process template for our research. This approach demonstrates how companies try to solve the complexity of DDBMR by starting with selected capabilities and activities through business growth over time.

13.2.3 Digital ventures

To be able to implement and scale a DDBM in the market, companies must build a fitting organizational environment (Yoo et al. 2012). Previous research has tried to explain how an incumbent company can be transformed into a data-driven organization (Berndtsson et al. 2018; Hagen and Hess 2020; Hupperz et al. 2021). In many cases, these steps for DDBMR are way too complex in the existing organizational structures and aligned with too many risks of damaging existing business operations. A more established way is to create new digital ventures (DV) alongside traditional business operations. DVs can be defined as independent organizational units that execute business model ideas with the help of digital technologies (Huang et al. 2017; Lehmann et al. 2022; Nambisan and Baron 2019). In these DVs, DDBMR is executed as part of the digital entrepreneurship initiatives of incumbent companies (Berger et al. 2021; von Briel et al. 2021; Steininger 2019). Many successful businesses started as DVs and developed into their own business areas or independent companies over time (Alfaro et al. 2019; Nambisan et al. 2017). This allows companies to experiment with DDBMR cases in an independent organizational environment and adopt new ideas while still being independent from established business operations and their important income streams. The creation of a DV as a DDBV is a highly complex task, requiring multiple resources, capabilities, and activities throughout the realization process (von Briel et al. 2018; Schymanietz et al. 2022; Sultana et al. 2022; Ullah et al. 2021).

At the beginning of the process, it is challenging to connect the right people, data, and technology to develop initial DDBV ideas and start business experiments. In this early stage, the ventures are mostly simple because of low organizational complexity and small teams. If the DDBVs become more significant, it is necessary to establish structures to build products and services that can be delivered to the customer without negotiating the established business (Lehmann and Recker 2022). The goal of companies is to scale these DVs by time and generate new income streams (Huang et al. 2017). This setup allows companies to establish DDBVs beside their ongoing businesses and provides the freedom for performing new company culture experiments, hiring good talents, and securing market competitiveness by data-driven offerings. Previous literature has not connected DDBMs and DVs in incumbent companies. However, for DDBMR success, it is essential to connect these disciplines and understand the required capabilities and activities for DDBV throughout the execution periods. In the following sections, we will extend previous research and provide answers for how to realize DDBVs.

13.3 Methods

To answer our research question, we conducted qualitative interviews and discussions with multiple experts (Bogner et al. 2009). We designed semi-structured interview guidelines (Myers and Newman 2007). Based on a qualitative content analysis, we analyzed the interview data for required resources and capabilities throughout the DDBMR periods (Myers 1997; Myers and Newman 2007). The DDBMR periods can be adopted for the realization of a DDBV in company organizational structures. We recruited experts with multi-year business or project experience in realizing data-driven projects in their companies.

We focused on experts from the fields of data analytics, data science, or digital business who are working more on an operational working level and less on a strategic level. This allowed us to obtain knowledge on the necessary capabilities, activities, and tools for establishing a

DDBMR in a DV. The experts were selected from companies of different industries and sizes to collect data from multiple perspectives. We recruited experts through our personal or professional networks and LinkedIn requests. The selected experts were from incumbent companies that are active in international markets (meaning that they are normally operating in non-data-focused industries) and came from the fields of data science or information systems. Most of these companies have successfully launched DDBVs in their organizations and/or provide advice to their customers about how to do so. Table 19 shows a list of all the interviewed experts. The valuable insights from these experts can be used as best practices for other companies DDBV initiatives.

Number	**Expert**	**Role**	**Industry**	**Company size**
1	A and B	Lead Data Scientist and Managing Partner	Software	< 500
2	C	Director Digital Lab	Engineering	500–9,999
3	D	Data Scientist	Energy	500–9,999
4	E	Project Manager	Automotive	10,000–99,999
5	F	Product Owner Data Intelligence	Mobility	> 100,000
6	G	Research & Development Manager	Automotive	> 100,000
7	H	Data Scientist	Shipping	500–9,999
8	I	Internet of Things Engineer	Software	500–9,999
9	J	Product Owner Data Platform	Insurance	10,000–99,999
10	K	Head of Data Science	Mobility	500–9,999
11	L	Information Security Officer	Aviation	10,000–99,999
12	M	Head of Artificial Intelligence & Data Analytics	IT Consulting	500–9,999
13	N	Chief Executive Officer	IT Services	< 500
14	O	Senior Expert	Automotive	> 100,000
15	P	Advisor Corporate Strategy	Automotive	> 100,000
16	Q	Head of Technology Marketing	Public Sector	500–9,999
17	R	Head of Customer Insights	Retail	> 100,000
18	S	Tribe Lead Artificial Intelligence	Telecommunication	> 100,000
19	T	Product Owner	Finance	500–9,999
20	U	Business Intelligence Analyst	Energy	< 500
21	V	Managing Director	IT Consulting	< 500
22	W	Project Manager Digitalization	Commerce	500–9,999
23	X	User Experience Expert	Finance	500–9,999
24	Y	Product Manager	Automotive	> 100,000
25	Z	Agile Project Manager	Software	< 500

Table 19: Interviewed experts

Interviews A–L focused on general DDBMR and the project level, which provided useful insights about the necessary capabilities and activities for DDBMR throughout the venture establishment process. Interviews M–S were conducted with external researchers from the Karlsruhe Institute of Technology and had a deeper focus on the realization of data monetization to understand how the companies have tried to generate a return on their investments. Through the open questions and atmosphere, it was possible to focus on different aspects of data-driven business experience with each expert based on their perspectives. Interviews T–Z were discussions conducted with the help of a digital whiteboard on the previously found resources and capabilities to build a DDBV to validate the results and gain additional knowledge from a more interactive perspective. The experts described multiple DDBV cases, which were supplemented by the mentioned internet sources. We applied an open coding approach. We segmented our results into nine DDBV capabilities. The classified DDBV activities were segmented into four execution periods. For this, we analyzed the interviews for statements of required DDBV capabilities/activities and segmented the results into a capability/period matrix. Our identified DDBV activities are shown in Table 2. For example, the statement *"[…] every company that does it the right way will do it in the cloud; otherwise, you will have too many costs for server farms maintenance. […] The cloud is the best way for cost efficiency and scalability"* (I10) was segmented as an activity of technology capability throughout all periods because it is an important activity to build a scalable technology fundamental to a DDBV.
Interviews A–C were in-person interviews, while interviews D–Z were held by phone or with an online conference tool (Skype, Google Hangouts, or Zoom). In total, 26 experts from 25 companies were interviewed. Experts A–S received the interview transcripts for review and approval. Experts T–Z received the discussion whiteboard deck. The interview durations ranged from 24–63 minutes.

13.4 Results

Based on the insights from our interviews, we identified nine required capabilities how companies realize a DDBV: Customers, Monetization, Strategy, Technology, Data, Product, Funding, Organization, and Governance. Each of these capabilities requires multiple activities, which are shown in Table 20. In total we identified DDBV 108 activities. The companies performed these activities throughout the stated DDBMR execution periods (Figure 15), which we adapted for DDBVs: Development/Experimentation, Development/Minimum-Viable-Venture (MVV), Live/Minimum-Marketable-Venture (MMV), and Live/Scaling (Figure 16). The companies start with slight and fast prototyping in small DDBVs for experimentation and add capabilities and activities by time. Through success-based "stop-or-go-gates," the management decides if they want to invest more or if the DDBV will be terminated. Also, after a successful DDBV market launch and scaling the companies still need to maintain their data-driven business which can lead to new development/experimentation periods and DDBVs.

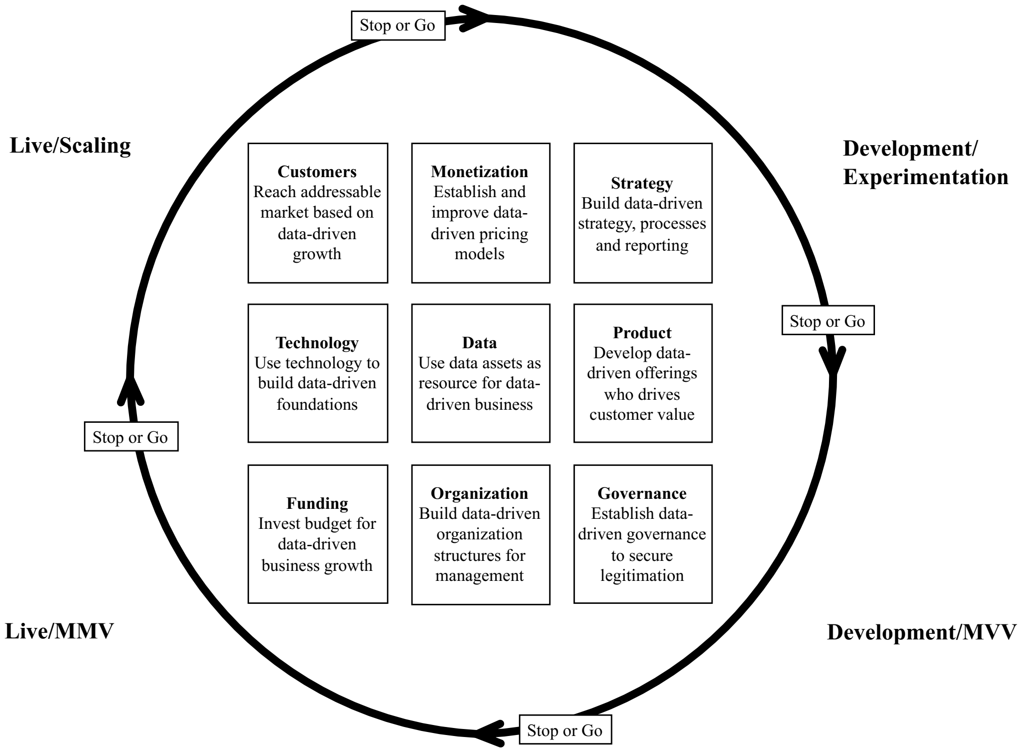

Figure 16: DDBV capabilities and periods through realization

Customers: Before a company structures departments or invests budgets into ideas, it takes a two-sided data- and customer-centric view throughout the first experiments. The teams need to identify a general market demand and potential target customer groups who can have interest in using a data-driven product or service to solve a real-world problem: *"The challenges are to find the right customers, who have a use case for our offering"* (I15). The companies mostly learn from existing customer data and lessons from the past to identify and solve relevant pain points. The company can have fantastic data assets, but with no demand from customers, the business will nevertheless fail and investments will be lost. If such relevant customers and a relevant total addressable market (TAM) opportunity for a data-driven product can be identified, the teams start to build initial prototypes with a strong focus on customer requirements based on company data resources (e.g., which data/insights are needed or how do customers get the product/service): *"We try to identify from a customer perspective, which are business opportunities with potential, try to understand the pain point of this business opportunity and try to analyze how a data product could be possible"* (I16). The integration of the initial customer feedback data in this stage of the DDBV development process is important for early idea validation, helping avoid sunk cost or non-working offerings in the future and much more expensive realization steps. If the prototype setup of the data-driven products or services is working for the first customer groups, the company can analyze the success and possible trust at the customer level. Data-driven offerings always have a sensible relationship, which requires extensive trust between business partners. If trust exists and the offering is working at the customer level, the companies are able to scale the business data-driven to more markets and industries for a rapidly growing customer base. Based on customer and market data potential this can be new customers who are acquired by sales and marketing campaigns or existing customers scaled through product or service upselling opportunities. Continuous customer feedback data is important throughout the scaling process for the long-term development of DDBV elements and business success.

	Development/ Experimentation	**Development/ MVV**	**Live/MMV**	**Live/Scaling**
Customers	• Take data and customer-centric view as fundamental for initial experiments. • Identify general demand from customer and market data • Use existing lessons learned from previous customer data for DDBV setup	• Build initial data-driven prototypes with strong potential customer value • Try to quantify total addressable market (TAM) based on market and customer data • Integrate pilot customers for early feedback data	• Launch DDBV core products or services to initial customer segments • Identify significant customer clusters based on early customer data • Use customer feedback data for further data-driven development of DDBV elements	• Scale DDBV operations to more markets and industries based on market data • Analyze key customer segments from customer data for up-/cross-selling opportunities • Continuous adjustment of DDBV elements based on customer feedback, trust, and market data
Monetization	• Understand potential for paying customers of the DDBV offering • Benchmark pricing models in the market data and try to learn from benchmarks for own offering • Focus on long-term monetization targets instead of fast revenue gains	• Focus on “low hanging fruits” with clear data-driven customer problems • Validate multiple pricing models based on first customer data • Build prototypes with potential data-driven monetization and scaling ability	• Improve the DDBV products/services with revenue-growing features • Transform pricing model to a scalable subscription model for long-term revenue growth • Prove DDBV monetization opportunities based on market data	• Scale DDBV revenue by data-driven growth of customer base and market expansion • Grow customer revenue with additional paid services and price adjustments • Use earnings as investments fundamental for data-driven DDBV pipelines and roadmaps

Strategy	• Develop DDBV as part of the company digital strategy • Obtain support from top management for data as a business opportunity • Align data business experiments with company image, values, and reputation	• Establish DDBV as part of company digital transformation initiatives • Present data-driven prototype products to higher management for support and feedback data • Use data as a critical source for business growth	• Integrate DDBV market launches into the company strategy and processes • Observe DDBV effects in connection with traditional business areas • Validate data-driven operations based on acceptance/reputation/image in the market	• Establish DDBV as a significant part of company business strategy • Recalibrate company strategy and management, based data-driven success indicators • Gain DDBV reputation and trust to launch more DDBVs in the market
Technology	• Use digital technology as an essential element for DDBV development • Use flexible and standardized data tools for initial DDBV approaches • Use standard software for first data analysis experiments and validations	• Build scalable cloud technology fundamental for DDBV operations • Set up bi-modal IT architecture to work independently from incumbent systems • Use cloud platforms with integrated analytic tools, interfaces, and data storages	• Extend technology fundamental to making offerings scalable to customers • Improve IT architecture by time for data-driven product features, system security, or process automation • Enhance data analysis and systems to adapt more insights/value for the customer	• Scale technology depending on customer data and DDBV requirements • Re-integrate systems in existing IT architecture for scaling and data-driven company transformation • Scale data analysis capacities to improve user and product experience
Data	• Acquire data assets as an essential key resource for DDBV setup • Analyze data assets for valuable business opportunities and availability in the company ecosystem • Use a small amount of data assets in the beginning for efficient focus	• Use data assets as a resource for development of initial DDBV prototypes and offerings • Validate data assets for use cases, technical challenges, and business potential • Modify data assets and add new or existing data sources	• Deliver insights and value from data assets as digital offerings to customers • Analyze pilot customers for additional data requirements and feedback • Establish data cooperation or a data ecosystem to grow data assets over time	• Secure data assets as a key resource for scalable long-term business • Adjust used data assets over time based on DDBV customer and operations requirements • Scale the data ecosystem with valuable partners, stakeholders, and customers
Product	• Develop data-driven product or service ideas as offerings of the DDBV • Start with low resources on multiple data-driven product experiments • Use methods like design sprints, product canvases, or wireframes to visualize first product ideas	• Develop an initial usable data-driven product prototype with focus on scalability • Prove technical usability and value for the customer with limited resources and time • Establish an agile product management develop data-driven features	• Launch a scalable data-driven product in the market as fast as possible • Improve first products by real-life customer feedback to increase customer value, satisfaction, and success • Create data-driven product development roadmaps to deliver fast improvements and features in the market	• Scale the data-driven product in the market • Learn from growing customer feedback data for more valuable features and services over time • Data-driven validation of feature value with tools, such as story mapping or the RICE model

Funding	• Understand the potential required budget for execution based on company data • Obtain financial sponsorship from top management for DDBV development • Use investment budgets for experiments to determine DDBV opportunities	• Validate DDBV investment into the correct resources for efficient budget use • Secure the financial support of management by performing data-driven key indicators • Understand long-term DDBV potential and required future investments	• Increase budget to improve DDBV elements for data-driven market scalability • Establish data-driven reporting of customer growth and revenue for decision makers • Use first customers as additional funding for DDBV elements	• Shift DDBV funding from external budget to independent funding over time • Establish DDBV as an important source for data-driven revenue, growth, and profit • Use the growing revenue as budget for DDBV pipeline
Organization	• Establish independent teams as a source for data-driven innovation • Create small interdisciplinary groups with data skills, talents, and backgrounds • Focus on data-driven analysis and business development for fast DDBV idea validation	• Build agile teams who can deliver an initial product and organization prototype in a limited amount of time • Structure business units for the DDBVs to allow data-driven operations from incumbent processes and structures • Change focus through prototyping on software skills to deliver a data-driven prototype	• Modify the agile teams by data-driven requirements, scaling or reducing the team over time • Extend the DDBV teams to their own venture units after launch to add sales, marketing, and other operations • Enhance the organization with more management skills to run business operations	• Scale the organization by structuring teams into scaling organization types • Develop a strategy to make the DDBV unit an independent company or business area • Extend human resources and skills by growing customer feedback data and operations functions

Table 20: Capabilities and activities through the DDBV realization periods

Monetization: To focus on the customer as a core user is important; however, understanding customers' willingness to pay for a data-driven offering is critical. While many offerings can be useful, a customer must wish to pay for the benefit to make it a successful DDBV business for the company: *"There are always issues which are very interesting and can be satisfied for people. Issues where you should have a deeper look. For us, it is always a part of the equation: How big is the potential that we can retrieve money for the enterprise or other dimensions"* (I4). Through experimentation, the companies observe the market for similar offerings to understand which business concept is working and what is not. Pricing models for similar offerings in the market also are observed. For sustainable success, these early stages focus on long-term monetization and not fast revenue gains. Ideas are validated for "low hanging fruits," in which clear customer problems exist in the market that the company's technology, data, and organization is able to address by quickly building a scalable product prototype: *"You can say, you should earn the low hanging fruits first, with a clear focus on adding value, before you are moving to more complex topics […]"* (I8). This also includes validating multiple pricing models through the acquisition of initial test customers (e.g., subscription model, pay-per-use, licensing, one-time payment): *"To develop pricing models is a very difficult topic, because it is also* *a very complex topic. But normally we are working with consumption- or subscription-based pricing models"* (I13). With the launch of the DDBV prototype and its products/services into the market, monetization starts to grow. It is an important part to add this core offering by providing more revenue-growing features over time. The pricing model can change multiple times throughout realization periods. The pricing needs to prove the monetization opportunity in the market. In the end, the DDBV target is to transform the pricing model into a scalable subscription model for long-term revenue growth in the customer base and market, such as in many Software-as-a-Service (SaaS) offerings. Besides the growth with new customers, the DDBVs try to extend the business with existing customers through upselling with additional paid services or price adjustments. The income gained from monetization is a solid fundamental component for the investment in other DDBVs and the company's long-term success. If the DDBV does not earn a useful income return over time, the companies start to terminate the realization process instead of burning money.

Strategy: Building a DDBV is a highly complex, expensive, and challenging task for a company. To have the necessary strategic and organizational resources, the development of DDBVs is mostly part of the company's digital strategy: *"Our unit's name is digital products, data strategy and strategic cooperation's. This is the specific unit in the company strategy department. We do have there a specific project in data strategy which focus on the evaluation of data-driven business models."* (I14) Thus, DDBVs need top management support for data experiments as a business opportunity. In many companies, data monetization can create a significant internal political debate because of privacy, reputation, or security issues: *"If you bring a premium car to the market, then you know experiments need to align with company image, values, and reputation. If the business ideas are clearly not working with this, it is better to move to another business opportunity. To be in line with company strategy, the DDBV prototypes should be integrated as part of the company's digital transformation roadmaps. The forecasts, sales plan, and indicators. Fine. But it is hard to have the breath to build ten digital business models. Maybe one of them is succeeding, maybe after three years, and sometimes it needs additional investments. This is hard for an enterprise company"* (I6). Regular presentations of the DDBV prototypes to higher management are essential to obtain top management support and attention for these topics. Throughout the prototyping process, the public does not know about the company actions or target; however, when the DDBV launches in the market, the message is mostly communicated in line with a comprehensive company strategy and processes. The company observes the effects of DDBV launches in connection with traditional business areas and notice acceptance/reputation/image in the market. Data-driven offerings can have a significant influence on a company if the data get out of control or systems get hacked. Markets may not accept offerings if the company is not trusted or not known for such offerings. If the market accepts the new DDBV offerings and a fundamental customer scalability is accessible, the business is most times integrated as a significant element of the company's strategy. Through the exceptional flexibility of data-driven businesses, the strategy based on DDBV scale success will change over time. With successful data-driven business offerings in a market, a company gains a reputation and trust from customers, which enables launching more DDBVs and becoming a data-driven business leader in the market.

Technology: In nearly all digital business approaches, the use of digital technology is an essential part of DDBV building. Experimentation requires flexible and non-complex IT tools, such as digital creation tools (e.g., Miro and Figma) or project management tools (e.g., Asana, Trello, and Jira). For initial data analysis, the use of standard software is sufficient to understand data relations, opportunities, and quality determined through experiments (e g. Qlik, Splunk or Tableau). If the experiments show significant potential for a scalable DDBV, the companies try to find a fundamental technology through prototyping. The technology must be able to deliver a scalable, data-driven offering to customers by using sustainable technology standards. The alignment to technology standards is required to stay compatible to customer and developers' technology from the market. In most observed cases from our interviews, a bi-modal IT setup is preferred by the companies to create digital business on a scalable cloud-software infrastructure, without the limitation of existing legacy systems (e. g. Snowflake, AWS, Google Cloud, Microsoft Azure): *"It is more and more obvious, that all what we need for data analysis is going to the cloud"* (I4). Based on these cloud platforms, the companies mostly use the integrated analytic tools, interfaces and data storages to easily scale it by time. *"[...] every company that does it the right way will do it in the cloud; otherwise, you will have too many costs for server farms maintenance. [...] The cloud is the best way for cost efficiency and scalability"* (I10). With the launch of a DDBV into a market and continuous customer onboardings, it is time to extend the fundamental technology to make it "customer ready." The DDBV products, services, or platforms are improved over time through, for example, more requested features, system security requirements, or process automation optimization. In this period, the company learns a lot about technical requirements through feedback from customers. The technology provides the infrastructure for all customer interactions and is adapted over time according to business requirements. This includes the enhancement of data analysis and systems to adapt more insights or value for customer and data monetization opportunities. After the first lessons in the market and business success, the technology and data analysis capacities get scaled, depending on customer and DDBV requirements. If possible, the company mostly initiate the re-integration or adoption of the DDBV systems in the existing IT architecture for scaling it in the incumbent company and moving on to the data-driven company transformation.

Data: The key resource for a DDBV approach is data, which are used—along with the appropriate processes, capabilities, and other resources—to create useful offerings for customers. Acquiring data assets is essential for DDBV building in an incumbent company. The data must be available for experiments. It is not mandatory to use own company data in the beginning; however, own data is easier to handle than external data. These data assets are analyzed for business opportunities and further availability in the company's ecosystem: *"[...] data are strategic assets for us. With this data assets we want to generate a gross margin based on the data-driven business models"* (I14). In the beginning, the DDBV focus on a small amount of data assets to be able to understand the data relations and business approaches. It is not required to have big data; however, it is essential having the right data assets on a central workplace (cloud platform), which becomes more valuable through company actions and operations in the realization process: *"If I reach the step where I have central access to data and do not need to merge it from different systems, then I can start to ask concrete questions and start with new business models"* (I5). Through prototyping, these data assets are transformed with the help of software tools and coding to initial technical prototypes and digital product offerings. In connection with the product prototypes, the data assets are further analyzed for customer use cases, technical challenges, and business potential. The agile development of these prototypes leads to the modification of used data assets over time and requires adding new or existing company data sources. This is part of the flexible realization process of a DDBV. After launching the DDBV offering into the market, the companies start to deliver data-driven insights and value from the used data assets as digital offerings to customers. The company analyzes pilot customers for additional data requirements and more use cases. As more insights from owned data assets can be delivered, more customer success can be achieved in the market. To evolve DDBV possibilities, the companies establish data cooperation and create a data ecosystem to enrich data asset catalogues over time: *"There are short term goals, to create short possibilities to earn money. But we are sure, that it is important to establish long-term scalable solutions. Without cooperation's it will not be working. We need to create a data ecosystem with strategic partners"* (I14). With the success and scaling of the DDBV, the business becomes increasingly important to the company's monetization strategies. The companies try to secure data assets as a key resource for a scalable, long-term business by acquisition or licensing and contracts. Through scaling, the requirements for customer value will grow; thus, the DDBV is adjusting its used data assets over time. This includes the scaling of a closed data ecosystem with more partners, stakeholders, and customers. This ecosystem allows for having a long-term perspective on the DDBV in the market and building entry barriers for competitors.

Product: An important part of building a DDBV is creating a product or service for the customer. Without this, there is no offering to monetize the data assets. The companies normally start with low resources on multiple product experiments through ideation. Many companies intend to target a data platform business from the beginning, which may be too complicated for a first prototype: *"We have the idea to get to this platform idea, but it is not mandatory for a product or service to have this platform."* (I6). To validate product ideas, methods like design sprints, business validation, or wireframes are used to visualize initial business product ideas: *"We are using multiple models. We are doing a lot of value proposition design, business model canvas and design thinking, to get first ideas"* (I2). After validating these first ideas for technical realization and potential customer value, the companies develop a first usable technical product from initial product experiments and insights. This product needs to prove its technical usability for the customer and be developed with fixed resources and a limited amount of time. For subsequent development, agile product management establishes a prioritization of product features. To validate whether the product is useful for customer needs and a scalable approach, the product must be launched in the market as quickly as possible: *"It is useful, if it is possible, to test it not with all customer, but first with a selected group of customers"* (I10). With the help of real-life customer feedback, the product can be improved to increase customer value and satisfaction. In the long term, the companies create a product development roadmap to deliver fast improvements in the market and provide customers a clear vision about further features. Scaling the product in the market is essential for long-term DDBV success and monetization. *"Exactly, the scalability is a big topic. The question is how can we scale the product to the customer without having big manpower increase in this process."* (I6) The growing customer base creates more requirements for features and services over time. The requirements are validated by the companies with tools, such as story mapping or more business value-oriented calculations, to understand which features will bring the most value for customers, thus creating product monetization.

Funding: Realizing a DDBV requires understanding potential budgets. The practical execution of funding is an investment of the company in future revenues and strategies without fast income from the venture itself. Top management needs support DDBV development through their realization. In the beginning, the investment budgets are used by the companies for experiments to find interesting DDBV opportunities. Based on the budget, the venture invests in the first resources to realize initial prototypes: *"Without solid funding, you will not be able to execute your ideas. So, this is an important part of the realization process"* (I21). During the prototyping process, the companies try to understand and validate long-term DDBV business potential and required investments. This can be for example the analysis of the TAM, the expected growth margin or competitive analysis in the market. To secure financial support and obtain additional budget, delivering regular progress reporting to top management is necessary. This can also be done in the form of internal venture pitches, in which teams present their progress for further funding. If management is supporting the venture, after the prototype development and business opportunity, it is time for the DDBV to improve the elements for successful market scalability. Market launches require enormous resources for marketing, sales, and operations in the beginning; thus, it is necessary to establish continuous reporting of customer growth and revenue for decision markers. With a growing customer base, the DDBV earns larger income streams, which can then be used as additional funding. The funding of a venture can take many years before the profits return. However, in the end, the funding of the venture must transform from external sources to own business sources to establish it as an important source for the company's profit and growth. The growing revenue from successful DDBVs can be used by the companies to create more DDBVs over time to establish a venture pipeline that brings permanent new data-driven business opportunities into the market.

Organization: For incumbent companies, it is a challenging task to create new business models and approaches in the established organization. The processes, resources, and culture are created for the incumbent business operations, which secures the company revenues. To create space for creation and new ideas, most companies establish independent teams as sources for data-driven business innovation. These teams are small interdisciplinary groups with different skills and backgrounds, providing input for business ideas from different perspectives: *"We have very agile cross-functional teams. You always need to identify the correct people for the topic [...] to follow the idea of co-creation with sales, business development, software engineers, and more"* (I6). In the first data-driven experiments, the focus is on data analysis and business development for fast idea validation and next steps in a limited amount of time: *"We are focusing on the 'fail-cheap-fail-early' approach. We do not want to work for 12 weeks only to see that the approach is not working for us. But we have built in the option that we can terminate the project earlier. After four weeks, we do a first review, which is the natural breaking point [...]* (I3). If a business idea has potential, the ideation teams are normally transformed by adding mostly more technical roles into agile teams who can deliver a first product prototype. Based on the previously created teams, it is then time to structure business units for the

DDBV to allow independent operations from incumbent processes, cultures, and structures: *"These are, at the moment, employees of our innovation department. But it is in an internal startup, which acts very independently in the market with its own brand and customers. For now, it is not an independent spin-off, but this can happen."* (I3). Throughout the prototyping process, the focus changes from a business to a more technical perspective. Software development and data architecture skills are required to deliver a functional prototype as fast as possible. With the market launch, teams are required to remain flexible and changeable. Agile team resources are provided by the companies based on business requirements and technical scalability. If the number of teams and people grow, the companies are extending their own venture units after launch to add sales, marketing, and operations. During this market launch period, the development of a venture has many options and challenges, which require a permanent transformation of the organization by more management skills to run the business. New people and skills are onboarded quickly, which requires scaling organization types, operations, and management levels. For this growing organization the company needs to develop a long-term strategy for the DDBV unit as an independent company or as a business within the incumbent company's structure.

Governance: If a company starts experimenting with data sources for business opportunities, it analyzes which data the company owns and can be legally used. This includes possible data privacy concerns, particularly when using private-customer or sensitive internal company data: *"We work on our customers' data in most cases, and here we are back to the ownership issue. We can't necessarily use that unless the customer gives us permission"* (I12). Initial data quality for further maintenance and quality assurance is an important factor in subsequent development steps. Through the identification of useful data assets by the DDBV, it is time to clarify legal ownership or identify contract opportunities with third-party owners. Without usability for future business, a DDBV can quickly fail. Many companies also have governance rules and legal restrictions. The company's DDBV prototypes need to be align with these rules to be launched in the market. Prototyping is providing a clearer picture of the inherent complexity by connecting multiple data assets to build a valuable product for customers. The teams also analyze further maintenance efforts and create strategies to assure data quality: *"We see that many companies did not do their homework. The data quality is not existing or very bad, the core data, very adventurous"* (I2). By the start of DDBV operations in the market it is important factor for long-term business success to secure legal use of data assets and contract agreements with third-party suppliers. Licensing of technology or more data assets can become an important factor throughout ongoing DDBV development. By operating with data in the market, the teams are observing new legal privacy rules, such as the General Data Protection Regulation (GDPR), to avoid reputation problems and financial penalties from legal administrations. To secure the usefulness of used and new data assets, a DDBV establish an ongoing quality assessment process of data assets, products, and services: *“Data quality was a big challenge. It starts with processes, who are most times not designed to guarantee data quality. Properly speaking you need to start with the data processes, and adjust them to improve the data quality”* (I5). Using more data sources can lower data quality, which can be a major reason for business failures because the customer receives a bad user experience. If the DDBV can solve all the challenges for a working data-driven business, scaling the task secures the business by extending data ownership through third-party legal agreements or acquisitions. The growth of the DDBV leads to increased publicity, which also leads to more observers of data privacy and regulations. Adhering to legal restrictions when scaling is an important factor in preventing business failures: *“Depending on the contract work we are getting supported by legal department, but it is also possible to have legal counsel in the team”* (I3) New product features/services are validated for these risks to secure ongoing scaling. Furthermore, the protection of data quality by strong data governance through scaling remains critical. Only structured and useful data will save DDBV revenue streams and make long-term business operations possible.

13.5 Discussion and Conclusion

Our results generated useful insights into how incumbent companies try to realize their DDBVs. The 26 experts interviewed shared valuable perspectives that served as the basis for answering our research question.

To determine which capabilities and activities incumbent companies use in the implementation of a DDBV, we identified nine capabilities and 108 activities based on the four execution periods (Lange et al. 2021). Incumbent companies face numerous challenges when trying to establish the correct capabilities, starting with determining the necessary activities for realizing the DDBM in a DDBV (Metzler and Muntermann 2020; Teece 2018).

	Data-Driven Business Ventures	Digital Ventures	Comparison
Development/ Experimentation	• DDBV market opportunities are explored through two-sided experimentation (data- and customer-centric). • Data assets are fundamental components for initiating ventures and developing DDBV offerings. • Ensuring data ownership, quality, and privacy as key element during DDBV experiments.	• The identification of market opportunities for DVs primarily focuses on a customer-centric perspective. • A wide range of potential business foundations exist for DV market offerings. • DV experiments typically do not have a restricted focus on specific elements/resources.	• DDBVs derive their ideas from a dual perspective, leveraging both owned data assets and customer demand, while DVs are mostly customer-centric. • Data assets are the key drivers behind DDBV experiments. DVs find their key resources through experimentation.
Development/MVV	• There is a strong focus on providing the customer with a data-driven value proposition. • Cloud-based data analytics technologies form the foundation for data-driven product development. • Data experts and skills are key functions within DDBV organizations.	• DVs mostly focus on the value proposition of digital products for the customer. • DV digital product development can be supported by multiple core technologies. • Flexible teams are formed based on the specific requirements and design of the DV.	• DDBVs place a strong emphasis on building a data-driven value proposition, as opposed to a more general offering, as in the case of DVs. • DDBVs mostly focus on data-driven prototyping, while DVs typically focus on digital product prototyping.
Live/MMV	• The launch of DDBVs primarily relies on structured and analyzed customer/market feedback data. • The development of a data ecosystem is an important element in ensuring long-term success in DDBVs. • Continuous data governance is mandatory for a successful DDBV market launch.	• The launch of a DV is based on initial customer feedback data. • A partner ecosystem is established to support DV product development and business growth. • Governance in DVs is typically a minor requirement for market launches.	• DDBVs are launched to market based on established data structures. DVs also employ data structures, albeit with less rigidity. • Data ecosystems and governance are crucial for DDBV success. However, governance and ecosystems are not mandatory for rapid growth in DVs.
Live/Scaling	• Scaling is a critical success factor for DDBVs to leverage their data assets effectively. • The data ecosystem is an important element in DDBV scaling. • Cultivating an agile and data-driven culture is important for DDBV scaling opportunities.	• Scaling is a critical success factor for most DVs that sell digital products. • There are manifold options for DV scaling, primarily driven by customer product adoption and growth. • Fostering an agile organizational culture is an essential part of DV scaling.	• Both DDBVs and DVs need to scale to achieve business success. DDBVs leverage economies of scale to maximize the value of their data assets. • Cultivating an agile organization is an important part of DDBV and DV realization. Additionally, fostering a data-driven culture is an important element of DDBV realization.

Table 21: Comparison of DDBV vs. DV realization through the periods

This is particularly true for companies from incumbent industries with little connection to digital business models, such as energy, automotive, or insurance (Nambisan et al. 2019; Oberländer et al. 2021; Svahn et al. 2017). As described in the results section, companies start with small teams to explore initial DDBM ideas, considering customer requirements and market best practices. Ideas are often created using the tools/methods derived from digital entrepreneurship research, such as design sprints or lean startups (Eisenmann et al. 2012). A strong connection exists between DDBMs and their realization through DVs. DVs allow incumbent companies to build capabilities and execute activities to realize business models with fewer limits from traditional organizational structures (Lorson et al. 2022; Svahn et al. 2017). Previous research has primarily focused on processes or products, failing to identify the essential connection between DDBMs and DVs in executing DDBM ideas in the real world, instead focusing on processes or products (Alfaro et al. 2019; Hunke et al. 2017). DDBVs represent a logical progression in the complex field of realizing DDBMs. DDBVs have multiple similarities to DVs, such as their iterative approach, customer-centricity, or prototyping, but also very specific data-driven attributes, which makes them a subcategory of DVs. We compared these two types of ventures in Table 21.

In addition to their customer-centric view, DDBVs derive ideas for experiments/prototyping from the company's data assets, which serve as the key resource for DDBV experiments. There is no single way of creating DDBV ideas; however, it is useful to initially embrace simplicity when formulating the concept for realization (von Briel et al. 2018). For execution, it is important to identify relevant DDBV ideas that have the potential of becoming long-term monetization opportunities, have a relevant total addressable market (TAM), and have the chance to be realized through capabilities and activities in the company's environment as a DDBV. In addition, the DDBV IT systems, people, and data assets must be connected to build an MVV, which can be fundamental for a company's scalable data-driven business (Huang et al. 2017). The DDBV goal is to create a digital data-driven offering (platform, product, or service) that can deliver data-driven value to customers. By building an IT architecture for the DDBV, the venture can be developed independently of technical or business limitations (Haffke et al. 2017; Horlach et al. 2016; Zysman and Kenney 2018). One distinguishing characteristic, similar to general digital offerings in DVs, is the ongoing development of more activities and features to enhance customer value and drive monetization (Lehmann and Recker 2022; Oberländer et al. 2021). The launch of DDBVs primarily relies on a solid foundation of structured data, especially customer data, which become a valuable decision-making tool for subsequent steps. While DVs also leverage structured data, they may place less emphasis on this asset—especially in the early stages of development—or incorporate structured data analysis at a later stage in the venture. A special characteristic of DDBVs is the usage and critical importance of data ecosystems. DDBVs need an ecosystem in which they can obtain additional data assets, partners, and distribution channels to improve their data-driven offerings. In particular, feedback data play a major role in identifying the requirements for new capabilities and activities that can significantly improve the scalability of a business. The range of possible activities is limitless, assuming the necessary adjustments are made to meet the required data assets, pricing models, or technology components (Nambisan and Baron 2019; Ullah et al. 2021). DVs do not necessarily need such a data ecosystem for business growth; rather, it depends on the concrete digital market offering. For scaling DDBVs and DVs, both venture types follow the same concept. Both are trying to use economies of scale by growing their customer base with their digital or data-driven products as quickly as possible. DDBVs accomplish this primarily through a data-driven approach due to their early focus on developing data analytics capabilities. The transition from a DDBV to a scaling business is a challenging task; however, it is a necessary step to ensure the long-term success of an incumbent company (Huang et al. 2017). Both DDBVs and DVs start by experimenting with agile teams and organizations, and as they progress, they often require the introduction of additional organizational structures and hierarchies. A notable feature of the DDBV is its distinct data-driven culture, which remains important even as it scales to run and improve operations. With the money and knowledge gained from previous DDBVs, a company can build a DDBV roadmap to react to incumbent business life cycles and develop further business opportunities (Anderson and Zeithaml 1984; Drover et al. 2017; de Reuver et al. 2013).

Our contribution to theory pertains to three specific areas. First, previous research has mostly focused on the ideation of DDBMs with design tools but not on how companies realize these ideas in an established organizational environment or venture (Brownlow et al. 2015; Hartmann et al. 2016; Kühne and Böhmann 2019). While DDBM design is important, realizing it through a DDBV is an entirely different task. The initial approaches to realizing DDBMs focused on their elements but overlooked the essential capabilities necessary for a comprehensive realization (Anand et al. 2016; Hunke et al. 2017; Lange et al. 2021). Second, we connected the DDBMR research field to the topic of DVs. DVs, similar to DDBMs, are part of digital transformation initiatives; however, previous research failed to connect these topics with the realization of DDBMs (von Briel et al. 2021; Steininger 2019). DDBVs serve as the necessary vehicle and unit to make DDBMR possible within the company as part of digital transformation and strategy initiatives (Nylén and Holmström 2015). By comparing multiple elements of DDBVs and DVs throughout the realization stages, we showed for the first time that it is necessary to understand these two types of ventures separately. Third, we presented a complete view of the essential capabilities and activities involved in DDBV success. Previous research studies have understood the challenges and potential capabilities associated with DDBV success but have failed to define concrete activities (von Briel et al. 2018; Sultana et al. 2022; Ullah et al. 2021). In contrast, we identified 108 activities in this study, providing a novel approach to expanding the research knowledge of the required activities in the realization of a DDBM. Our study is the first to offer insights into how incumbent companies realize DDBVs and what sets them apart from DVs, establishing a solid starting point for further qualitative or quantitative studies in this research area.

From a practical standpoint, our findings regarding capabilities and activities support the realization of DDBVs in companies. In our interviews, many experts mentioned the significant challenges an incumbent company may face in implementing a digital or DDBV. Such companies have no experience with this kind of business model because they mostly sell hard goods or have traditional selling processes. However, they understand that it is important to use their data assets to stay competitive in the market and to obtain new business opportunities. Incumbent companies need guidance about which activities they must perform and which capabilities they need to develop through the realization process. Given that realizing DDBVs in companies remains a difficult task, our research provides knowledge about the essential activities that can help companies address this need and mitigate the risk of failure.

Our study is not without limitations. Although all expert interviews were conducted with people working in companies with an international business focus, the companies and interview partners were all located in Germany. This regional focus might have cultural or region-specific limitations, for example, due to the high relevance of data protection in Europe. For further research, it would be valuable to conduct an enhanced empirical study to speak with people from companies in other countries to determine any differences or new insights. Using the qualitative research approach, we identified many activities mentioned by the experts through our result analysis. However, activities can still be highly subjective through our open coding approach. Therefore, it needs further validation through additional studies in which the activities are tested on practical projects through case studies. The interviewed experts were mostly working on operational levels, which corresponded to our focus on DDBV realization, and less on strategic decisions at higher company management levels. For further research, it would be useful to speak with experts on DDBV from higher management levels to add a strategic perspective for realization.

In our paper, we provide first-time insights regarding which activities and capabilities companies need to realize their DDBVs in practice from an operational perspective. Based on the experiences of multiple experts, we identified nine key capabilities and 108 activities for realizing DDBVs. These understandings represent a useful basis for further research and provide practical guidance for companies that want to achieve long-term success with DDBVs.

13.6 Appendix

Appendix A: Interview guideline I

(1) Introduction

- Please introduce yourself and your role in the company.
- please briefly describe your company and what is the connection to the topic of digitization and data?

(2) Digitization / Transition of DDBMs

- What does the topic of digitization mean to you?
- How does data play a crucial role in this? Do you deal with topics such as Big Data / Data Science / Data-driven products?
- How has this impacted your product offering? Are there any changes to the business model?

(3) Idea generation

- How have you developed ideas for creating value with data? Have you used specific tools/frameworks to generate ideas for new data-driven business models? If yes, what were they? (e.g., Business Model Canvas / Google Design Sprints).
- Are these ideas aimed at evolving the existing business model or creating a completely new digital business model?
- Do the new ideas pursue a platform concept?
- Which practical examples did you use to develop your own business model?
- Was there external support (e.g., from consulting firms) in generating these ideas?

(4) Realization process

- How did you implement your ideas in practice? Did you use a specific process model / framework for realizing the business model? If yes, which models did you use?
- Was an agile approach used for the realization of the business model? What experiences did you have with it?
- How did you analyze the data available to you? How did you identify the relevant data?
- Were there any problems with the data quality? How could these be solved?
- What data from partners, external service providers or freely available sources "Open Data" were used? What were the challenges and how did you overcome them?

(5) Project experience

- which specific project has your company carried out in the area of data-driven business models (or products)?
- What data or sources were used in this project?
- What technologies were used?
- What new products were developed or added for the customer?
- What steps did you take during the implementation process?
- How was the business environment / ecosystem involved in the development or how did it change?
- Which persons (roles) were involved in the realization?
- In what form was the data-driven business model integrated into your company? (Pilot/company-wide/startup)
- How was the data-driven business model extended into other areas of the company?

(6) Further development

- Which divisions/positions are tasked with coordinating/operating the business model?
- How do you continue to develop the data-driven business model (or digital products)?
- Overall, looking back at the business model development process, what were the biggest challenges and how were they overcome?
- What would have helped you to plan and execute the process of realization even better?

(7) End

- What are your plans for further projects based on data-driven business models in your own company?
- What are your expectations about the future impact of data-driven business models on your industry?

Appendix B: Interview guideline II

(1) Welcome and explanation of the background of the study.

(2) Obtaining permission to record the interview

(3) Background and introductory questions

- Could you give me a brief description of your position within the company?

- What is the significance and importance of data to your company?
    - Would you describe your company as data-driven?
    - Does your company treat data as a strategic asset? If so, how does this manifest itself?
    - What does "data monetization" entail for you?
    - d. Could you briefly outline the history of your data monetization strategy?
- What prompted you to start monetizing data? Was there a specific trigger?
- How has your "data monetization" strategy evolved or changed over time?
- What is the importance of "Data Monetization" to your organization? Is "Data monetization" necessary to remain competitive in the long term?

(4) Questions about the business model

- Are your data products/services proprietary products that can be delivered independently of the core product?
- What does your typical data customer look like? (industry, size, etc.)
- How is relevant data for monetization identified in your organization?
    - Why do you think your data is valuable to other organizations? How is this value confirmed for other organizations?
    - What type of data is most suitable for monetization?
- Who in your company is responsible for collecting and preparing the data? What do the organizational structures look like in concrete terms? (Keyword: "data governance/stewardship").
- How does your internal data become marketable data products/services?
    - Could you briefly describe the process of creating the raw data into marketable data products/services?
    - Are strategic business partners involved in the process of creating the raw data into marketable data products/services?
- How do you make money from your data?
    - How do you price your data products/services?
    - What "revenue model" have you implemented for your data products/services business?
- How do you deliver your data products or services to your customers?

    - What mechanisms do you use for the delivery of data products/services?
    - Are third parties involved in the data delivery process? (e.g. data marketplaces)
- How do you sell your data products/services?
    - What marketing tools do you use to market your data products/services?
    - Do you actively approach potential customers? If yes, how do you identify these customers?
- What contractual provisions are in place regarding the use and liability of your data? Are these negotiated individually with each customer or are there general terms and conditions?

(5) Questions about performance and barriers

- How do you rate your "data monetization" performance compared to other companies?
    - In your industry?
    - Overall?
- Could you once briefly explain what challenges you faced in monetizing your data? How did you overcome these challenges?
- Why do you think other companies have difficulty monetizing data?

(6) Questions about success factors and future plans

- What factors have helped you successfully monetize data?
- What are the most important lessons you have learned about monetizing data?
- What are your future plans regarding your "data monetization" strategy? Are there any strategic partnerships planned with other companies?

(7) Other

- Can you think of anything else that might be of interest to me that was not addressed in this interview?
- Would you like certain details just discussed not to appear in the interview transcript? Would you like certain details to be added?

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