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Leveraging Enterprise Architecture for Data-Driven Business Model Innovation

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Zürich, März 2021 Faisal Rashed

Abstract

Motivation: Maximizing the value from data has become a key challenge for companies as it helps improve operations and decision making, enhances products and services, and, ultimately, leads to new business models. The latter two have been investigated by scholars as part of an emerging research field on data-driven business model innovation. While enterprise architecture (EA) management and modeling have proven their value for IT-related projects, the support of enterprise architecture for data-driven business models (DDBMs) is a rather new and unexplored field. We argue that the current understanding of the intersection of data-driven business model innovation and enterprise architecture is incomplete because of five challenges that have not been addressed in existing research: (1) lack of knowledge of how companies design and realize data-driven business models from a process perspective, (2) lack of knowledge on the implementation phase of data-driven business models, (3) lack of knowledge on the potential support enterprise architecture modeling and management can provide to data-driven business model endeavors, (4) lack of knowledge on how enterprise architecture modeling and management support data-driven business model design and realization in practice, (5) lack of knowledge on how to deploy data-driven business models. We address these challenges by examining how enterprise architecture modeling and management can benefit data-driven business model innovation.

Research Approach: Addressing the challenges mentioned above, the mixed-method approach of this thesis draws on a systematic literature review, qualitative empirical research as well as the design science research paradigm. We conducted a systematic literature search on data-driven business models and enterprise architecture. Considering the novelty of data-driven business models for academia and practice, we conducted explorative qualitative research to explain "why" and "how" companies embark on realizing data-driven business models. Throughout these studies, the primary data source was semi-structured interviews. In order to provide an artifact for DDBM innovation, we developed a theory for design and action. The data-driven business model innovation artifact was inductively developed in two design iterations based on the design science paradigm and the design science research framework.

Contribution: This thesis provides several contributions to theory and practice. We identified a clear gap in previous research efforts and derived 42 data-driven business model-related EA concerns. In order to address the identified literature gap, we provide empirical evidence for data-driven business model innovation. Four pathways of data-driven business model design and realization were identified. Along these pathways, an overview of EA application areas was derived from the empirical and theoretical findings. With the aim of supporting practitioners in data-driven business model innovation, this thesis was concerned with the development of a reference model. The reference model for data-driven business model innovation provides a broad view and applies enterprise architecture, where appropriate. This thesis provides five recommendations for practitioners realizing data-

driven business models that address the demand for support in data-driven business model innovation.

Limitations: Several limitations must be considered. We acknowledge the threat to validity based on the fact that the thesis was written over the span of two years. As DDBMs are an emerging phenomenon in the literature, our thoughts on the underlying concepts have also evolved. Our ideas evolved to include a wider range of literature, different terminology, and a broader empirical foundation. We have gathered and analyzed the extended literature on EA and DDBM interconnectivity. However, the selection of keywords restricts the set of results. The data stem from a limited number of organizations and industries; thus, our conceptual developments need further testing to ensure generalizability.

Future Research: This thesis suggests several fruitful research avenues. Complementing the current concepts with additional data and quantitative research methods could address the existing threats to validity. A deeper understanding of data-driven business model innovation pathways, in the light of the detailed methods per pathway, would enhance the knowledge on this topic. Future research could focus on conducting additional design cycles for the data-driven business model innovation reference model. It would be interesting to enrich the findings of this thesis with quantitative data on correlations in data-driven business model innovation and enterprise architecture support. Furthermore, investigating a single case study and exploring new application fields of enterprise architecture in the data-driven business model innovation context would benefit research and practice would benefit.

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List of Abbreviations

ADM	Architecture Development Method
AI	Artificial Intelligence
BDA	Big Data Analytics
BM	Business Model
BMC	Business Model Canvas
BMI	Business Model Innovation
CRM	Customer Relationship Management
DDBM	Data-Driven Business Model
EA	Enterprise Architecture
EAM	Enterprise Architecture Management
ERP	Enterprise Resource Planning
GDPR	General Data Privacy Regulation
IS	Information Systems
IoT	Internet of Things
MVP	Minimum Viable Product
RQ	Research Question
SCM	Supply Chain Management
TOGAF	The Open Group Architectural Framework
UC	Use Case
WST	Work System Theory

1 Introduction

1.1 Motivation

"Data is the new oil" Clive Humby in (Arthur, 2013)

Data have traditionally been perceived as a crucial component of business operations, strategic decision making, and new business development (Brynjolfsson and McAfee, 2012; Chen et al., 2012). Advancements in information technology, especially big data, the Internet of things (IoT), cloud computing, and machine learning, have further accelerated the increasing importance of data for progress and innovation. Accumulating evidence on the benefits associated with big data analytics provides legitimacy that it "will revolutionize many fields" (Chen et al., 2012, p. 1). Gathering and analyzing a tremendous amount of data in real-time enables managers to improve decision-making and performance. New datasets open business opportunities that might have stayed untapped (Günther et al., 2017). Brynjolfsson and McAfee (2012, p. 7) claim "that almost no sphere of business activity will remain untouched by this movement" toward data exploitation. Additionally, their study revealed that data-driven businesses are, on average, more productive and profitable. Data have been acknowledged as a pivotal driver for many disciplines and have received considerable attention, especially from the information systems discipline (Abbasi et al., 2016; Baesens et al., 2016; Chen et al., 2012; Günther et al., 2017; Sharma et al., 2014). Data exploitation has been investigated under several terms in research, ranging from business intelligence, business analytics, and big data to big data analytics (Chen et al., 2012). Scholars have advanced the research on big data analytics from only a technological perspective, defined by the four characteristics—volume, variety, velocity, and veracity—toward a multisided socio-economic phenomenon (Abbasi et al., 2016; Dremel and Wulf, 2017; Wiener et al., 2020). Researchers have examined the potential value of data in three major areas: improved decision making, enhanced products and services, and new business models (Engelbrecht et al., 2016).

"Data is just like crude. It's valuable, but if unrefined, it cannot really be used. It has to be changed into gas, plastic, chemicals, etc., to create a valuable entity that drives profitable activity." Michael Palmer in (Arthur, 2013)

Elaborating on the view of "data as crude oil" that needs refinement emphasizes the essential ties between value creation and value capture in the deployment of big data analytics. While the perceived value from data depends on an organization's strategic goals (Günther et al., 2017), value creation is accomplished during data refinement, encompassing data cleansing, analysis, and the reintegration of insights into the business context. However, these efforts only lead to competitive advantage and sustainable traits if the generated value is captured by 'driving profitable activities.' Without mechanisms to capture the value generated from the adoption of big data, analytics, and machine learning, the prospected benefits will not be gained. Fruhwirth et al. (2020) noted that research avenues had adapted accordingly in the past five years, giving rise to the phenomenon of data-driven business models (DDBMs). "Trying to exploit the strategic business potential embedded in big data, many organizations have started to renovate their business models or develop new ones" (Wiener et al., 2020, p. 1). DDBMs are either realized by improving traditional business models or implementing new business models (Parvinen et al., 2020). DDBMs rely on data as a critical resource (Hartmann et al., 2014) and/or have data processing as a crucial activity (Rashed and Drews, 2021), which makes data essential for value propositions (Schuritz and Satzger, 2016). Considering the high dependency on big data analytics, DDBM innovation orchestrates information systems design and implementation, which requires alternative support in the design and realization compared to offline BM innovation (Fruhwirth et al., 2020).

"But the failure rates of big data projects, in general, and artificial intelligence (AI) projects, in particular, remain disturbingly high. And despite the hype (e.g., "data is the new oil"), companies have yet to cite the contributions of data science to their bottom lines." (Redman, 2019, p. 1)

Realizing DDBMs has become a key challenge for organizations. Especially, incumbent companies are expected to rest on huge amounts of unused data "treasure," facing several challenges in DDBM innovation and seizing new business opportunities (Fruhwirth et al., 2020). Research on DDBMs is still in its infancy, with most contributions emerging in the past five years (Fruhwirth et al., 2020; Wiener et al., 2020). Many business leaders do not consider data as synonymous with profits (Bulger et al., 2014). It is naïve to believe that optimistic data gathering will prove profitable (Günther et al., 2017). Organizations have to transform their business and operating models as well as their enterprise architecture in order to capitalize on data or insights gained from analyzing data.

Challenges in DDBM innovation deal with data privacy, new capabilities, and organizational transformation (Günther et al., 2017). With the General Data Privacy Regulation (GDPR) effective since May 2018, data privacy has become increasingly important (Parvinen et al., 2020). Companies must comply with strict regulations in processing the data of European citizens. This law takes one step in the right direction toward sensitizing companies to the moral and ethical responsibility of personal data usage.

Transforming an organization to integrate a DDBM with the required analytical and technical capabilities could be viewed as the most challenging hurdle. Prevailing roles, processes, and technologies and their interplay must be well understood for sensitive transformational interventions to succeed (Günther et al., 2017). Practitioners face several challenges in DDBM innovation (Günther et al., 2017; Redman, 2019), from identifying relevant opportunities and conducting an evaluation to, ultimately, implementing the DDBM (Fruhwirth et al., 2020; Parvinen et al., 2020). Additionally, due to the novelty of this topic in academia and practice, most efforts have concentrated on understanding the nature of the phenomenon (Wiener et al., 2020). In particular, details for designing and implementing

DDBMs as socio-technical systems from method, process, and tool perspectives have received little attention (Fruhwirth et al., 2020; Kühne and Böhmann, 2019; Rashed and Drews, 2021; Wiener et al., 2020). Two recent literature review journal articles identified DDBM deployment (Wiener et al., 2020) and DDBM innovation methods (Fruhwirth et al., 2020) as future research avenues, highlighting the lack of support for practitioners realizing DDBMs. Furthermore, Fruhwirth et al. (2020) revealed a stronger focus of the current literature on DDBM design rather than implementation and emphasized the benefits of connecting related fields to contribute to DDBM innovation research. Parvinen et al. (2020, p. 2) argue that, particularly, incumbent companies planning to engage in DDBM innovation face questions like, "What options do we have?" and "What routes should we take?" due to the novelty of DDBMs.

Introducing a new DDBM requires decisive intervention in the entire organizational structure. The current (as-is) architecture must be well understood, and the desired target (to-be) architecture, embedding the DDBM, must be crucially planned. Enterprise architecture (EA) practice addresses related challenges concerned with designing and implementing socio-technical systems. EA is associated with the information systems body of knowledge and a key concept for developing and, specifically, implementing socio-technical systems (Aier and Winter, 2011). It is concerned with the establishment, maintenance, and purposeful development of the organizational architecture (Aier and Winter, 2011). Furthermore, EA has proven its potential in improving information systems' efficiency and effectiveness and is also a critical component of strategic planning, top management decision making, and project management (Aier and Winter, 2011).

In order to support the evolution of an organization towards a target state, EA provides artifacts, such as metamodels, frameworks, tools, guiding principles, and management methods (Weiss et al., 2013). Many organizations have established an enterprise architecture management (EAM) function concerned with the aforementioned goal. The key components of an organization and their interdependencies are represented in EA models (Winter and Fischer, 2007). The models built based on these metamodels are concerned with either the current (*as-is*) or desired (*to-be*) enterprise state. Thus, the EAM function supports the transition from the as-is to the to-be state through several intermediate architecture stages (Aier et al., 2011; Rashed and Drews, 2020). For the big data analytics context, companies need to document big data-related influences on the EA layers of their organization in order to plan, coordinate, and guide continuous transformation driven by big data analytics (Burmeister et al., 2018). This applies to big data as well as to narrowed value data sets processed via advanced analytics technology. EA can provide a common taxonomy for information objects and their privacy treatment with clear data maps.

Designing reusable artifacts for the DDBM innovation context requires modeling techniques. Reference models have proven their potential for knowledge accumulation and as a source of descriptive and prescriptive design knowledge in related fields such as data management (Legner et al., 2020). They serve as abstract representations of socio-technical systems (Schermann et al., 2009) to support practitioners in developing company-specific solutions (Fettke and Loos, 2007; Frank et al., 2014). Reference models are design boundary objects and elevate research as it matures over time. Knowledge from various disciplines is explicated and integrated to contribute to their respective fields in the form of reference models (Legner et al., 2020). As the problem space changes over time, reference models survive through adjustment and transfer design knowledge to new reference model versions. However, reference models have not been proposed by the literature for the DDBM innovation context.

Despite the vast potential applications of EA modeling and management concepts for DDBM design and realization, their utilization in practice is unknown. Research at the intersection of DDBM and EA is emerging in the literature, bearing in mind the innovativeness of DDBMs (Vanauer et al., 2015; Wiener et al., 2020). To date, only one article has directly addressed this highly relevant topic: Vanauer et al. (2015) proposed a methodology for DDBM deployment by combining business modeling techniques with EA concepts. However, their contribution examined the intersection from a conceptual standpoint. The literature still lacks empirical research on this intersection at this juncture.

Motivated by this research gap and the lack of empirical findings in DDBM innovation design knowledge and the potential value from enterprise architecture, this thesis aims to examine how enterprise architecture modeling and management can support the design and realization of data-driven business models in practice.

1.2 Problem Statement

Despite its importance for practice, little is known about DDBM design and realization (Fruhwirth et al., 2020; Parvinen et al., 2020; Wiener et al., 2020). Recent literature reviews of DDBMs revealed numerous publications since 2014 in this thriving research field (Fruhwirth et al., 2020; Wiener et al., 2020). However, Wiener et al. (2020) argued that most studies describe the nature of the DDBM (author uses acronym BDBM for big data business model) phenomenon, with little emphasis on empirical research. Markedly, the "dynamic aspects of BDBM deployments (process perspectives)" have received very little attention (Wiener et al., 2020, p. 75). They highlighted the demand for research capturing stakeholder views and broadening the current focus on Western worldviews to incorporate international viewpoints. Additionally, the authors emphasized the value of research on design and realization challenges for practitioners from almost every industry facing the journey to DDBM realization.

Literature also does not provide enough details on how data-driven business model innovation is conducted in practice. Fruhwirth et al. (2020) emphasized the benefits of connecting related fields such as business modeling, big data, and enterprise architecture to contribute to DDBM innovation research. The support of enterprise architecture modeling and management has only been briefly described in the past. The following five challenges provide an overview of the current shortcomings in literature on DDBMs and EA management and modeling support, which will be particularly addressed in this thesis:

Challenge 1: Lack of knowledge of how companies design and realize DDBMs from a process perspective.

The literature on DDBMs is still quite scarce, i.e., a limited number of articles address this topic, with most of the knowledge emerging within the past 5 years (Fruhwirth et al., 2020; Wiener et al., 2020). Specifically, the design and realization of DDBMs, which has been addressed by only two articles, still lack empirical research (Wiener et al., 2020). This thesis will complement the literature using empirical research on multiple cases from global companies. Additionally, systematic literature research will be conducted to reveal the current state of DDBM design and realization. Findings from the systematic literature research will facilitate the empirical research design.

Challenge 2: Lack of knowledge on the implementation phase of data-driven business models.

The novelty of this topic for both academia and practice poses apparent difficulties. Most efforts have concentrated on understanding the nature of the DDBM phenomenon (Wiener et al., 2020), while details on the design and implementation of these socio-technical systems, from method, process, and tool perspectives, have received little attention (Fruhwirth et al., 2020; Kühne and Böhmann, 2019; Rashed and Drews, 2021; Wiener et al., 2020). Recently, there have been two literature review journal articles that identified DDBM deployment (Wiener et al., 2020) and DDBM innovation methods (Fruhwirth et al., 2020) as successful research avenues, focusing on the lack of methodological support. Furthermore, Fruhwirth et al. (2020) noticed a robust emphasis on the current literature on DDBM design over implementation and reiterated that connecting related fields could add to DDBM innovation research. As previous research focused on the design phase of DDBMs, this thesis will shed light on the implementation phase.

Challenge 3: Lack of knowledge on the potential support EA modeling and management can provide to data-driven business model endeavors.

Research on the interrelation between DDBM and EA is emerging in the literature bearing in mind the newness of data-driven business models (Vanauer et al., 2015; Wiener et al., 2020). Despite the potential for applying EA modeling and management concepts for DDBM design and realization, their utilization is under-researched. This thesis examines if and how EA modeling and management can help develop and realize DDBMs. Although previous research has highlighted EA's potential in this context, as it helps to gain transparency across relevant socio-technical elements and their interdependencies (Burmeister et al., 2018; Chen et al., 2017; Vanauer et al., 2015), this thesis strives to take an extra step. EA can provide answers to stakeholder concerns aided by models and tool support, especially in the design phase, where companies grapple with understanding, shaping, and designing existing as well as future capabilities and data resources.

Challenge 4: Lack of knowledge on how enterprise architecture modeling and management support data-driven business model design and realization in practice.

The rise of DDBMs brings unique opportunities for organizations to generate new revenue streams. A considerable number of articles have addressed this topic in the literature (Wiener et al., 2020). Nevertheless, most companies struggle to put DDBM projects into practice (Redman, 2019; Wixom et al., 2020). Even though EA has proven its potential for IT-related projects, the intersection with DDBMs has not been extensively investigated in the literature (Vanauer et al., 2015). The current state of the literature highlights the potential of interlinking the rich discipline of EA with the emerging demands of DDBM (Chen et al., 2017; Vanauer et al., 2015). The shortcomings of the current literature regarding EA support for DDBM are that it is purely conceptual, having no empirical grounding. This thesis addresses this research gap and examines EA modeling and management support for DDBM design and realization utilizing a qualitative-empirical study.

Challenge 5: Lack of knowledge on how to deploy data-driven business models.

Notably, DDBMs are highly dependent on big data analytics. DDBM innovation is integral to information systems design and implementation, requiring varying support in design and realization compared to offline BM innovation (Fruhwirth et al., 2020). Practitioners must overcome DDBM innovation obstacles (Günther et al., 2017; Redman, 2019), such as identifying relevant opportunities, conducting an evaluation, and, ultimately, implementing the DDBM (Fruhwirth et al., 2020). Despite the budding applications of EA modeling and management concepts for DDBM design and realization, their advantages are limited in practice. As previously introduced, reference models have the potential to accumulate knowledge and serve as a source of prescriptive and descriptive design knowledge in related fields such as data management (Legner et al., 2020). This thesis investigates how a reference model for the design and realization of DDBM with special consideration to EA practice can be derived.

1.3 Research Questions (RQs)

This thesis aims to enhance the understanding of DDBM innovation and, in particular, the support potential from EA modeling and management. We identified DDBMs as an emerging phenomenon in the literature and sought to understand how companies design and realize them. Thereby, we focus on how EA modeling and management can be beneficial for

DDBM innovation. We identified five challenges increasing the difficulty of DDBM innovation research. Based on these challenges, we conducted five distinct research endeavors (embedded publications in Chapter 4) that address specific research questions concerning these challenges. In the following, the motivations behind the research questions will be explained briefly.

In order to understand the current state of the literature on EA support for DDBM design and realization, it is important to investigate previous scholarly contributions. Therefore, the first research question of this thesis seeks to understand what application fields for EA modeling and management in DDBM design and realization exist in the literature and what EA concerns can be derived for the DDBM design. It aims to identify the support potentials of EA for DDBMs discussed in the literature. In order to obtain a comprehensive view, the related fields of business models and big data are included in the search. By deriving concerns, we provide the starting point for EA endeavors to address stakeholder concerns.

RQ1: What application fields for EA modeling and management in DDBM design and realization exist in the literature? What DDBM-specific EA concerns can be derived from the literature?

A central challenge of DDBM innovation is the lack of research. Especially from an empirical standpoint lacks the literature. Research has extensively highlighted this gap (Fruhwirth et al., 2020; Parvinen et al., 2020; Wiener et al., 2020), with the majority of studies focusing on the nature of the DDBM while emphasizing the scarcity of its empirical research (Wiener et al., 2020). In particular, the "dynamic aspects of DDBM deployments (process perspectives)" have received minimal attention (Wiener et al., 2020, p. 75). A further accent is the demand for research capturing stakeholder views and international perspectives instead of the current focus on Western worldviews. The authors highlighted the value of research on the design and realization challenges for practitioners from a superfluity of industries facing the journey to the realization of DDBMs.

RQ2: What pathways do companies take to design and realize DDBMs?

DDBMs rely heavily on information systems for their core operations of data capturing, processing, and distribution. Scholars have proposed a variety of DDBM representations. The latest efforts in academia have focused on extending the Business Model Canvas (BMC) as a widely accepted modeling framework for the special needs of data-driven businesses (Hartmann et al., 2014; Kühne and Böhmann, 2018). These models help practitioners envision and document the design of DDBM in a first step and to further detail and realize the design in a second step (Vanauer et al., 2015). Research on DDBM is still in its early infancy and requires detailed knowledge on tool support for DDBM design (Kühne and Böhmann, 2018). Primarily, the needs of incumbent companies, with their existing organizational and IT structures, are currently unaddressed. Therefore, we explore if and how EA modeling and management can help develop and realize DDBM.

RQ3: How does EA support the design and realization of DDBM models?

Considering the high dependency on big data analytics, DDBM innovation implies information systems design and implementation, which requires different design and realization support compared to offline BM innovation (Fruhwirth et al., 2020). Research on DDBMs is still in its infancy (Fruhwirth et al., 2020; Wiener et al., 2020). Opposition to DDBM innovation (Günther et al., 2017; Redman, 2019), in identifying relevant opportunities, evaluation, and implementation of the DDBM, must be overcome by practitioners (Fruhwirth et al., 2020). Due to this topic's innovativeness from both academic and practical points of view, copious efforts have focused on comprehending the nature of DDBMs (Wiener et al., 2020). Details on the design and implementation of these socio-technical systems, from method, process, and tool perspectives, have received little attention (Fruhwirth et al., 2020; Kühne and Böhmann, 2019; Wiener et al., 2020). In particular, the literature lacks design knowledge as prescriptive support for DDBM design and realization. Reference models are capable of knowledge accumulation as well as descriptive and prescriptive design knowledge in related fields such as data management (Legner et al., 2020). By serving as abstract representations of socio-technical systems (Schermann et al., 2009), they support practitioners in developing company-specific solutions (Fettke and Loos, 2007; Frank et al., 2014). They integrate knowledge from various disciplines to contribute to their respective fields. In essence, reference models are design boundary objects that elevate research, mature over time, and, ultimately, contribute to the formation of new reference models (Legner et al., 2020). However, reference models have not been investigated in the context of DDBM innovation.

RQ4: What are the essential components of a reference model for DDBM innovation?

Data-driven business model innovation has become a key challenge for executives (Redman, 2019). Many companies are under pressure or are enhancing their traditional business model with data or to realize new data-driven business models. Novel opportunities appear for organizations to update their business model using big data analytics or to develop new data-driven business models (Wiener et al., 2020). These DDBM innovation opportunities particularly expose incumbent companies, which are expected to sit on tremendous amounts of data, to increased pressure to act. Mobilizing capabilities for DDBM innovation is a key concern for executives. Analytical and technical capabilities are required from internal as well as external sources. However, the failure rate of big data and artificial intelligence projects remains disturbingly high (Redman, 2019). In order to support practitioners in designing and realizing data-driven business models, we examine what key recommendations executives should consider when embarking on a data-driven business model journey.

RQ5: What are the key recommendations for executives' mobilizing capabilities for data-driven business model innovation?

Table 1 presents an overview of the challenges we elaborated on in the previous section and the research questions to address them. The points illustrate which challenges are addressed by which research questions.

Table 1. Research Questions (RQs) and Addressed Challenges.

Challenge	**RQ1**	**RQ2**	**RQ3**	**RQ4**	**RQ5**
1. Lack of knowledge of how companies design and realize DDBMs from a process perspective.	•	•	•	•	•
2. Lack of knowledge on the implementation phase of data-driven business models.	•	•	•	•	•
3. Lack of knowledge on the potential support EA modeling and management can provide to data-driven business model endeavors.	•		•	•	
4. Lack of knowledge on how enterprise architecture modeling and management support data-driven business model design and realization in practice.			•	•	
5. Lack of knowledge on how to deploy data-driven business models.				•	•

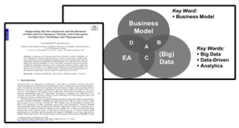
1.4 Structure

This cumulative thesis has been divided into 12 chapters. Chapter one provides an overview of the topic; it motivates this research, outlines the problem statement, and defines the RQs. The second chapter provides the conceptual background of this thesis by outlining existing research on BMs and their representations, big data analytics, EA modeling and management, and DDBM innovation. The third chapter provides an overview of the overall research strategy and describes the applied research methods.

Chapter four comprises the five articles embedded in this thesis. Figure 1 depicts the five studies, the research question they address, the methodology that has been applied, the contributions provided, and the outlets they have been published in/submitted to. Beginning with theoretical research, the first study examines the current state of the literature concerning enterprise architecture, business models, and big data. This is followed by an empirical study with practitioners from consultancy and industry firms. The findings have been published in studies two and three. Study four provides a reference model for DDBM innovation, applying EA and building on the previous studies' research results. Ultimately, study five builds on study four's research results and provides five key recommendations for executives implementing data-driven business models.

Chapter five discusses the results of this thesis. After a summary of the results, the findings are discussed (Chapter 5), followed by an outline of the limitations and implications (Chapter 6) as well as further research opportunities (Chapter 7). As outlined in Figure 1, the publications are included in that order from chapters 8 to 12.

Study 1



Research Question: What application fields for EA modeling and mgmt. in DDBM design and realization exist in the literature and what EA concerns can be derived for DDBM design?

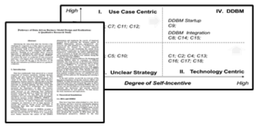
Methodology: Systematic literature review.

Results: 42 DDBM-related EA concerns.

Outlet: BIS 2020

Status: Published

Study 2



Research Question: What pathways do companies take to design and realize DDBMs?

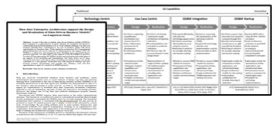
Methodology: Systematic literature review and semi-structured interviews (grounded theory approach).

Results: 19 cases of DDBM design and realization; 4 pathways of DDBM innovation.

Outlet: HICSS 2021

Status: Published

Study 3



Research Question: How does enterprise architecture support the design and realization of data-driven business models?

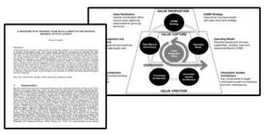
Methodology: Systematic literature review and semi-structured interviews (grounded theory approach).

Results: Pathway specific support of enterprise architecture.

Outlet: WI 2021

Status: Published

Study 4



Research Question: What are the essential components of a reference model for data-driven business model innovation?

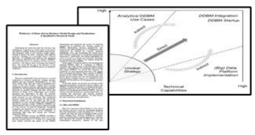
Methodology: Design science approach with two iterations.

Results: 7 design principles for DDBM innovation and reference model with 6 enablers.

Outlet: ECIS 2022

Status: To be Submitted (01.11.2021)

Study 5



Research Question: What are key recommendations for executives mobilizing capabilities for data-driven business model innovation?

Methodology: Design science approach with two iteration.

Results: 5 key recommendations for executives realizing DDBMs.

Outlet: MISQE

Status: Major Revision Submitted

Figure 1. Five Studies outlets and status included.

2 Conceptual Background

This thesis is grounded in three research fields. Recent papers have explored the challenges associated with the development of DDBMs while accounting for the available research on business models (BMs). As the DDBM is an interdisciplinary field, the research is reflected in the intersection of BM and big data (Engelbrecht et al., 2016). The third research field is EA. Research on EA has shown the potential benefits of EA models and EA management for projects related to business transformation. The following sections provide an overview of the relevant concepts in business models, big data analytics, data-driven business models, and enterprise architecture for this thesis.

2.1 Business Models and their Representation

In the past two decades, we have witnessed the rise of business models (BMs) as an important artifact for business and academia (Fruhwirth et al., 2020). Especially in the information systems literature, the BM concept has gained significance (Al-Debei and Avison, 2010). The essential structure of any business can be represented with business modeling techniques. Several modeling frameworks have been proposed in the past, varying in characteristics and components. Their primary purpose is to describe how an organization "creates and captures value" (Osterwalder and Pigneur, 2010). Business modeling gained importance as emerging technologies threatened established businesses and their traditional BMs.

"BMs provide powerful ways to understand, analyze, communicate, and manage strategic-oriented choices among business and technology stakeholders. The concept is also of importance as it informs the design of information systems (IS) supporting the BM of an organization. Consequently, no one organization can afford 'fuzzy thinking' about this concept." (Al-Debei and Avison, 2010, p. 1)

The literature provides a multitude of competing propositions to represent BMs. Various frameworks exist, differing in the components considered fundamental, all aiming to provide a simplification of reality to understand the business essence. However, the literature agrees on the three core value dimensions: value proposition, value creation, and value capture (Teece, 2010). By further detailing these three core dimensions, practitioners and scholars propose detailed frameworks for BM representation. All commonly agreeing that "the essence of a business model is in defining the manner by which the enterprise delivers value to customers, entices customers to pay for value, and converts those payments to profit." (Teece, 2010, p. 172). With these three dimensions in mind, managers are enabled to hypothesize what customers want, how the organization plans to deliver the value and how profits can be generated to justify the business venture. Business modeling becomes of particular relevance with regard to business strategy, business innovation, and economic theory as it represents the essence of a focal business. By abstracting the business in terms of these core dimensions (see Figure 2), the essence of any business can be conceptually represented to provide an improved understanding and foundation for strategic decision-making.

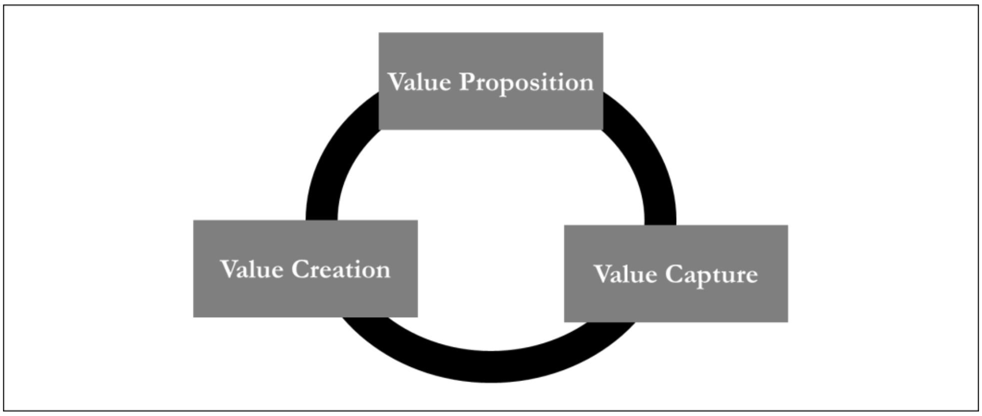


Figure 2. Business Model Dimensions (adapted from Teece 2010).

The most commonly applied BM framework is the Business Model Canvas (BMC; (Osterwalder and Pigneur, 2010), comprising nine components: partners, key activities, key resources, value proposition, customer relationships, channels, customer segments, cost structure, and revenue stream (see figure). The BMC was derived from the literature and gained significance as it provides a holistic, accessible view of the business model (Kühne and Böhmann, 2019). The populated framework helps practitioners envision and document the business model's design in the first step and further detail and realize the design in the second step (Vanauer et al., 2015). The latter provides a conceptual framework for the alignment of implementation efforts with the business strategy. The proposed building blocks represent the essential components of business design. It allows groups to collaboratively develop the business model as a joint effort, with great acceptance among diverse team settings. In addition to the static view for structuring the key components, the BMC provides its building block concept, dynamic representations of the business flow. This is often realized with arrows within the framework.

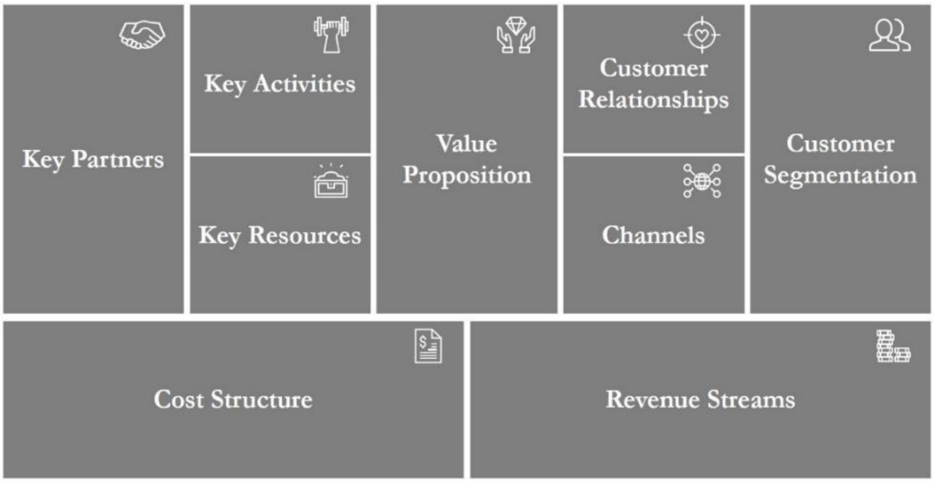


Figure 3. Business Model Canvas (adapted from Osterwalder and Pigneur, 2010).

The literature proposes several extensions of the BMC, which can be categorized into six types (Schoormann et al., 2016). Namely: 1) adding new blocks, 2) divide existing blocks, 3) modifying a block-content, 4) modifying the BMC structure (e.g., the customer as the central block), 5) linking elements in the blocks, and 6) adding views (e.g., layers to represent higher and lower elements (Schoormann et al., 2016). Thus, it is common practice to adapt the BMC to specific domains in order to capture the essence of the focal business.

In order to commercialize disruptive technologies, companies face the challenge of understanding their prevailing BM (Massa and Tucci, 2013). The critical components of the business and their interrelation are represented, allowing conclusions on technology integration. Thus, BMs can be seen as a "vehicle" (Fruhwirth et al., 2020, p. 3) for innovation, as they help to understand the traditional business in order to envision the targeted BM, providing a source of competitive advantage (Massa and Tucci, 2013). The procedural view from an as-is to a to-be BM has been investigated by scholars under the term *business model innovation* (BMI). BMI comprises the creation, implementation, and validation of new BMs (Massa and Tucci, 2013). "Thus, BMI can be perceived as a creative and collaborative task. BMI processes can serve as a procedural framework or guidance to structure BMI initiatives." (Fruhwirth et al., 2020, p. 3) In this thesis, BMs are used as a key concept to analyze DDBMs. The process of developing new DDBMs is understood through the DDBM innovation concept.

2.2 Big Data Analytics

Data have long been acknowledged as a key driver for business. This topic has been investigated under several terms in research, ranging from business intelligence, business analytics, and big data to big data analytics (BDA) (Chen et al., 2012). BDA and related fields have received a considerable amount of attention from the information systems sector over the past two decades (Abbasi et al., 2016; Baesens et al., 2016; Günther et al., 2017; Sharma et al., 2014). Gathering and analyzing a tremendous amount of data in real-time enables managers to improve decision-making and performance. New datasets reveal business opportunities that might have stayed untapped (Günther et al., 2017).

In order to capture the potential value contributions, BDA literature and practice propose techniques, technologies, systems, practices, methodologies, and applications for data processing and analysis (Chen et al., 2012). The efforts behind these propositions go beyond classic technology-related topics to more business-associated fields such as service development (Kühne and Böhmann, 2019) and business model innovation (Fruhwirth et al., 2020). Data are perceived as a useful instrument maintaining/improving efficiency but even more so as a business asset (Abbasi et al., 2016). BDA includes organizational characteristics that provide a source of competitive advantage. Evidence in the literature asserts that BDA phenomena go beyond the technological perspective and can not only be represented with this limited view (Dremel and Wulf, 2017).

Technological advancements have shaped the definition and scope of big data analytics. A multitude of definitions exists. In the following, a historical retrospect on the evolution of the term BDA is presented, drawing on the results of Chen et al. (2012). Emerging from a traditional, structured, relational database-driven paradigm (business intelligence and analytics 1.0), the term has advanced to a version that leverages Web and unstructured content (business intelligence and analytics 2.0; (Chen et al., 2012). With the rise of mobile- and sensor-based data, an advanced version was re-proposed as business intelligence and analytics 3.0. This led to a definition of big data comprising three Vs: volume, velocity, and variety (Laney, 2001). The tremendous amount of data that are processed using BDA is characterized by the first V, volume. Velocity describes the speed of data. Considering the multitude of data sources, structured as well as unstructured data must be processed, which makes variety the third characterizing V (Chen et al., 2012). As the literature matured, another V was proposed to capture veracity as a characterizing big data attribute. It refers to the reliability and credibility of data (Abbasi et al., 2016). For example, social media platforms have gained significance as data sources but contain predominantly unvalidated data. Abbasi et al. argue that "social media is plagued with spam, and Webspam accounts for over 20 percent of all content on the World Wide Web. Similarly, clickstreams from websites and mobile traffic are highly susceptible to noise. Furthermore, deriving deep semantic knowledge from text remains challenging in many situations, despite significant advances in natural language processing" (Abbasi et al., 2016, p. 5). In addition to the four described Vs, recent literature has proposed a fifth V for the value of data (Baesens et al., 2016). This goes along with the shift toward an increasingly business-driven perspective of BDA. Baesens et al. (2020) argue that "big data and the tools to perform deep analytics suggest that power now equals information (data) + trust. Our concern is that the former part of this equation, the data, has received the attention, while the latter, trust, has not" (Baesens et al., 2016, p. 809). In order to derive the desired value from data, both parts of the equation (information

+ trust) must be taken into consideration. Notably, the quality and reliability of data come into play when delivering certain value for the company.

In addition to the evolution in BDA's definition, technological advancements have contributed to a dramatic change in the role of big data. For artificial intelligence (AI), including machine learning and deep learning, data become essential when it comes to training data sets. With more and more efforts brought into the AI sphere, BDA as its enabler profits from this increased attention from business and academia. Furthermore, the sources of big data have been tremendously expanded in the past decade. With more datatypes becoming available, the datasets for AI training increase. Drawing on the findings of Baesens et al. (2016), five sources of big data are listed to provide an understanding of the data magnitude:

1. Data from large-scale enterprise systems: this includes enterprise resource planning (ERP) systems, customer relationship management (CRM) systems, and supply chain management (SCM) systems, as well as many others.

2. Social media data: social interactions increasingly rely on information technology. Facebook, WhatsApp, Instagram, WeChat, and Twitter (to name a few) collect, track, and analyze data from billions of people who leave daily data trails.

3. Mobile data: mobile devices are still the primary gateway to the Internet. Over 5 billion handsets serve as such channels, producing tremendous amounts of data and enabling the tracking and geotagging of its users.

4. Sensor data: the rise of Internet-of-things (IoT) technologies brings a future with an ecosystem of connected devices in our physical world into reach. Smart devices communicate with each other, producing big data.

5. Open/public data: an increasing amount of public data is available. This includes data on weather, traffic, maps, environment, households. The number of sources increases as governmental entities proceed on their digital journey.

The disruptive nature of big data analytics is a phenomenon with well-accumulating evidence. Research efforts go far beyond the information systems discipline and are represented in many others, especially in business research (Baesens et al., 2016). Its role in "behavioral, organizational, and strategic issues" was identified as essential research avenues (Sharma et al., 2014, p. 434). In particular, BDA's disruption of the information value chain within organizations has gained significance. Figure 4 illustrates the disruption of people, processes, and technologies along the information value chain. In order to realize BDA, organizations must implement new technologies to provide the infrastructure backbone. Solutions such as Hadoop and Spark have emerged as well-established platforms to process tremendous amounts of structured and unstructured data. The information value chain processes, in which insights are generated from the big data, transform into "pipelines" (Abbasi et al., 2016, p. 5). Furthermore, the processes allow self-service insight generation and data access. This, on the other hand, requires an increased understanding of analytical tools by the people. In particular, organizations rely on data analysts and data scientists for BDA processes. Upskilling and training initiatives become as essential as new hires for BDA realization (Abbasi et al., 2016). DDBM innovation is a field related to BDA. Value from BDA is derived with DDBMs. This thesis sheds light on BDA in the context of DDBM design and realization.

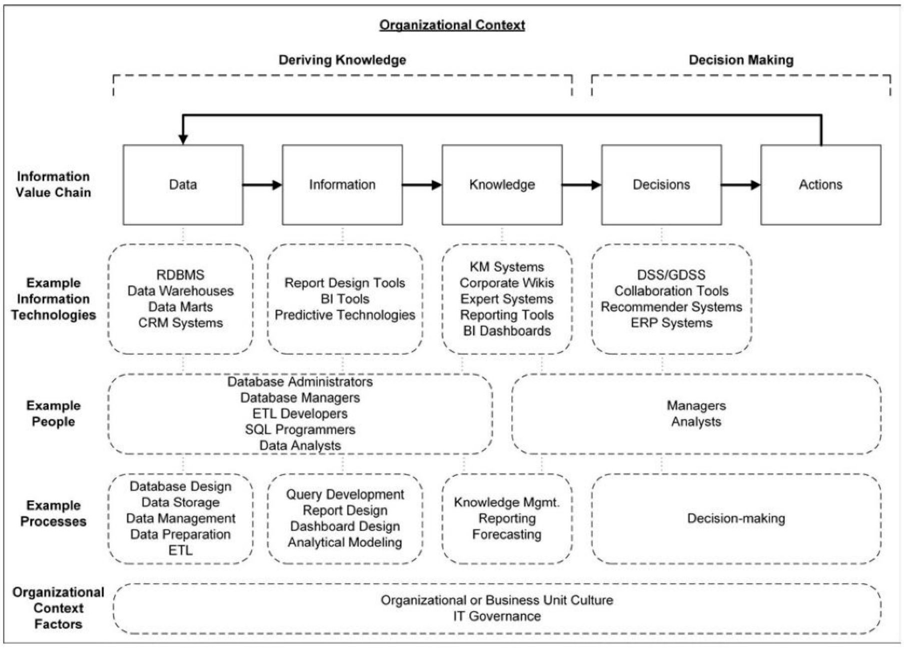


Figure 4. BDA Impact on Information Value Chain (Abbasi et al. 2016).

2.3 Data-Driven Business Model Innovation

Enhancements of products and services and new BMs have been investigated by scholars under the term *data-driven business model innovation* (Fruhwirth et al., 2020). The latest technological advancements have accelerated the recent call for the renovation and reconciliation of existing BMs with big data analytics and the deployment of new DDBM (Wiener et al., 2020).

Similar to the evolution of the term BDA from its related fields (e.g., business intelligence, business analytics, and big data), DDBM is associated with data capitalization research. DDBM design and realization has become an emerging research field (Bulger et al., 2014; Günther et al., 2017; Kühne and Böhmann, 2018; Najjar and Kettinger, 2013). On the raw data level, capitalization is conducted through sales of first-party data. First-party data are collected by a company and not freely available. Second-party data are collected in collaboration with another company. Lastly, third-party data are collected by someone else (Bulger et al., 2014). Deriving information from first-, second-, and third-party data can lead to value generation through insights, improved decision-making, and performance and enhancements of customer experience and value propositions (Brynjolfsson and McAfee, 2012; Günther et al., 2017). These improvements are reflected in profit increase and cost reduction. This information's value grows exponentially through the combination of existing knowledge (Abbasi et al., 2016). Data capitalization is either realized by improving the prevailing business model or through new data-driven business models with data as the key resource (Hartmann et al., 2014). Other propositions of this term have been made by scholars, such as big data business models. Wiener et al. (2020) state that the hype around value realization from big data "has led many organizations around the globe to invest heavily in, and experiment extensively with, BD technologies, often with the goal of "renovating" their traditional BM or deploying entirely new BDBMs"(Wiener et al., 2020, p. 68). Schuritz and Satzger (2016) use the term *data-infused business models* as a synonym for data-driven business models and state that "every business will sooner or later incorporate some amount of data - and analytics on top of it- into its core business model, which then may gradually become more 'data-driven'" (Schuritz and Satzger, 2016, p. 3). Similarly, Kühne and Böhmann (2019) "define data-driven business models as business models which use data as a key resource to create new insights for a value proposition for customers" (Kühne and Böhmann, 2019, p. 4). DDBM is manifesting as the leading term for this phenomenon.

The definitions of a DDBM proposed in the literature commonly state that data must be an essential component. Accordingly, DDBM was defined as "a business model that relies on data as a key resource" (Hartmann et al., 2014, p. 6). Bulger et al. (2014) and Brownlow et al. (2015) similarly emphasized the fundamental role of data for DDBMs. Schuritz and Satzger (2016) argued that a clear threshold of required data for a DDBM is not defined; companies shift from a traditional BM to a DDBM, with an increased application of data for the value proposition. In the context of this thesis, DDBMs are BMs that are centered on data and have data as a key resource and/or data processing as a key activity. DDBMs are new BMs with data as an essential component for the value proposition.

Many business leaders do not consider data synonymously with profits (Bulger et al., 2014). Simply assuming that optimistic data gathering will prove profitable is dupable (Günther et al., 2017). Organizations must evolve their business models, operating models, and EA in order to capitalize on data. Obstacles to DDBM design and realization are concerned with data privacy, new capabilities, and organizational transformation (Günther et al., 2017). Since May 2018, with the advent of GDPR and its strict regulations, data privacy has become increasingly important both to companies and European citizens. This law sensitizes companies to the moral and ethical responsibility of personal data usage. Data privacy and ethical constraints might have long-term impacts on a company realizing DDBMs.

The transformation of organizations into DDBM enabling companies with the required analytical and technical capabilities could prove to be the most challenging obstacle. In order for sensitive transformational interventions to be successful, the prevailing roles, processes, and technologies, and their interplay, must be properly grasped.

In order to overcome the challenges related to DDBM innovation, BM representations can support practitioners (Fruhwirth et al., 2020; Kühne and Böhmann, 2019). They help to capture the conceptual structure of any business (see section 2.1). Research on DDBMs is still at an early stage (Fruhwirth et al., 2020; Wiener et al., 2020). The latest efforts in academia have focused on extending the BMC to the special needs of data-driven businesses. For example, Hartmann et al. (2014) have proposed a taxonomy for DDBM representation in startup firms. By building on the BMC components, the potential attributes of these companies have been abstracted. Figure 5 presents the results of a recent systematic literature review highlighting the support for DDBMs. This type of contribution is illustrated together with the type of thinking and the addressed BM element. This type of thinking refers to either a divergent direction of collecting multiple potential solutions or convergent thinking of narrowing down the best suitable solution. While the literature has proposed some selective support, there is a clear gap in comprehensive methods, models, and tools for DDBM innovation. Within the ideation process, Kühne and Böhmann (2019) developed an artifact for data insight generation, which can be added to the value proposition field of the BMC. It complements the BMC with six data-specific elements. However, the literature lacks comprehensive methodological support for DDBM innovation.

Data-driven business model innovation can be seen as the process of either renovating the existing BM with BDA or deploying new DDBMs (Fruhwirth et al., 2020). Thus, it is a collaborative and creative task that requires divergent and convergent thinking. DDBM innovation guides the procedural efforts manifested as initiatives. DDBM innovation is also described as a result that replaces the traditional BM with new value propositions (Fruhwirth et al., 2020). The methods and tools available for "classic" offline BM innovation must be adapted in order to be applicable to DDBM innovation. (Fruhwirth et al., 2020, p. 4) argued, "Following existing literature on general BMI, tools, and methods can support the innovation process. However, besides generally applicable tools and methods for BMI, organizations require specialized or adopted tools and methods that incorporate the specific characteristics of DDBMs, like data as key resource[s] or data analytics as a key activity." Accordingly, Hartmann et al. (2014) address the literature gap on comprehensive method and tool support for DDBM innovation. Similarly, Kühne et al. claim that "extant knowledge about the development process and tools for designing and implementing data-driven business models (DDBMs) is comparatively limited because the field is relatively new" (Kühne et al., 2019, p. 1).

"most research is available for the design phase of DDBMI. Thus, tools and methods are also predominantly available in the design phase. This implies the current focus of research and the specific need for supporting

organizations and individuals in the activities of design and idea generation in DDBMI." (Fruhwirth et al., 2020, p. 9)

In addition to the intense focus on the design phase, the current literature lacks empirical research for DDBM innovation. While most contributions have focused on defining the term and understanding the nature of DDBMs, this thesis contributes to the design and realization of DDBMs from a theoretical and empirical standpoint.

Publication	VHB-JOURQUAL3	Taxonomy / framework	Pattern / type	Visual tool	Method	IT-tool	Process	Divergent (ideation)	Convergent (evaluation)	Value creation	Value proposition	Value capturing
		Type of contribution						Type of thinking		BM element		
Agrawal et al. (2018)	C			●				●		●	○	
Benta et al. (2017)	n/a			●			○	●		○	○	○
Bock and Wiener (2017)	A	●						●		●	●	●
Brillinger (2018)	B			○	●				●	○	●	●
Brownlow et al. (2015)	n/a	○			●			●		●	●	●
Enders et al. (2019)	C	●							●			●
Engelbrecht et al. (2016)	B	●						●		○		○
Exner et al. (2017)	n/a	●		●	○			●		●	●	●
Förster et al. (2019)	C		●	○					●	●		
Hartmann et al. (2016)	C	●	●					●		●	○	●
Hunke et al. (2017)	n/a						●					
Hunke and Wambsganß (2017)	n/a			●				●		●		
Hunke et al. (2019)	B	●						●		●	○	
Hunke and Schüritz (2019)	D			●				●		●	○	
Kammler et al. (2019)	B			○	●			●		●		
Kayser et al. (2018)	n/a				○		○					
Kronsbein and Mueller (2019)	C			●	○			●		●	○	
Kühne and Böhmann (2018)	D			○						●	●	●
Kühne and Böhmann (2019)	B			●				●	○	●	●	
Mathis and Köbler (2016)	n/a			●	○			●		●		
Nagle and Sammon (2017)	B			●	●			●		●		
Rizk et al. (2018)	C	●						●		●	●	
Schmidt et al. (2018)	C		●					●		●	○	●
Schüritz and Satzger (2016)	n/a		●							●	●	●
Schüritz et al. (2017a)	B				○		●			●		
Schüritz et al. (2017b)	C		●					●				●
Spiekermann et al. (2018)	D					●				●		
Sprenger and Mettler (2016)	B		●					●		●	●	●
Terrenghi et al. (2018)	B			●		○		●		●	●	●
Wixom and Markus (2015)	n/a				○				●	●		
Wixom and Schüritz (2018)	n/a				○				●			●
Zolnowski et al. (2016)	B		●					●		●	●	●
Zolnowski et al. (2017)	D				●				●			●

Key: n/a (not available), ● (characteristic fully covered), ○ (characteristic partially covered)

Figure 5. DDBM Contributions (Fruhwirth et al., 2020).

2.4 Enterprise Architecture and Data-Driven Business Model Innovation

Research on EA can be traced back to the Zachman framework from 1987, which provides an ontology for modeling an organization's fundamental structure and information systems (John A. Zachman, 2008). Over the past decades, EA has become essential for many organizations to support technology-driven transformations, as it helps to maintain an overview of complex socio-technical systems (Aier and Winter, 2011). The Federation of Enterprise Architecture Organizations defines EA as

"a well-defined practice for conducting enterprise analysis, design, planning, and implementation, using a comprehensive approach at all times, for the successful development and execution of strategy" (Federation of EA Professional Organizations, 2013).

A more narrowed definition of EA has been provided by the Open Group, which is in line with the ISO/ICE/IEEE Standard 42010 of architecture definition: "the structure of components, their inter-relationships, and the principles and guidelines governing their design and evolution over time" (Federation of EA Professional Organizations, 2013). We acknowledge that researchers and practitioners sometimes refer to EA as the actual architecture and other times as the practices A of an organization. We use the term EA for the practice comprising related modeling techniques, frameworks, and management functions (EA management). The actual architecture of an organization is noted as an as-is architecture, while planned future states are called to-be architecture (Winter and Fischer, 2007). EA has consolidated its potential in refining the efficiency and effectiveness of information systems (Weiss et al., 2013). It is a vital element of strategic planning, top management decision-making, and project management (Aier and Winter, 2011; Burmeister et al., 2018). EA provides artifacts, such as metamodels, frameworks, tools, guiding principles, and management methods, to support an organization's evolution toward a target state. The key components of an organization and their interdependencies are represented in EA models (Musulin and Strahonja, 2018). The models are based on metamodels and deal with either the current state (as-is) or the desired state (to-be) of the enterprise. The EA management function supports the transition from the as-is to the to-be state through several intermediate architecture stages (Aier et al., 2011).

The key components of an organization and their interdependencies are represented in EA models (Winter and Fischer, 2007). The literature proposes a multitude of models and frameworks to represent the as-is and to-be architecture of an organization. The views relevant to these models are strategic positioning, organizational structure, organizational processes, information flow, and implementation regarding software systems and data structures. Figure 6 illustrates the EA views as compositions of views on each layer. "EA can provide systematic support to organizational change that affects business structures as well as IT structures by providing constructional principles for designing the enterprise. In order to provide support for transformation in an efficient way, EA has to be driven by business-and/or IT-oriented application scenarios based on stakeholders' concerns (goal orientation)" (Aier and Winter, 2011, p. 646). The Open Group Architectural Framework (TOGAF; The Open Group, 2009) is one of the most established EA frameworks (Drews and Schirmer, 2014). It provides modeling and management standards and methods that allow effective communication among stakeholders. This includes propositions for layers and views that should be included in EA representations, as well as a management method (TOGAF ADM). We acknowledge the EA framework diversity, providing different views and approaches. For the purpose of this study, TOGAF is a suitable representative framework providing a sophisticated development method and modeling techniques. By taking a strategic lens, the differences within the frameworks play a subordinate role.

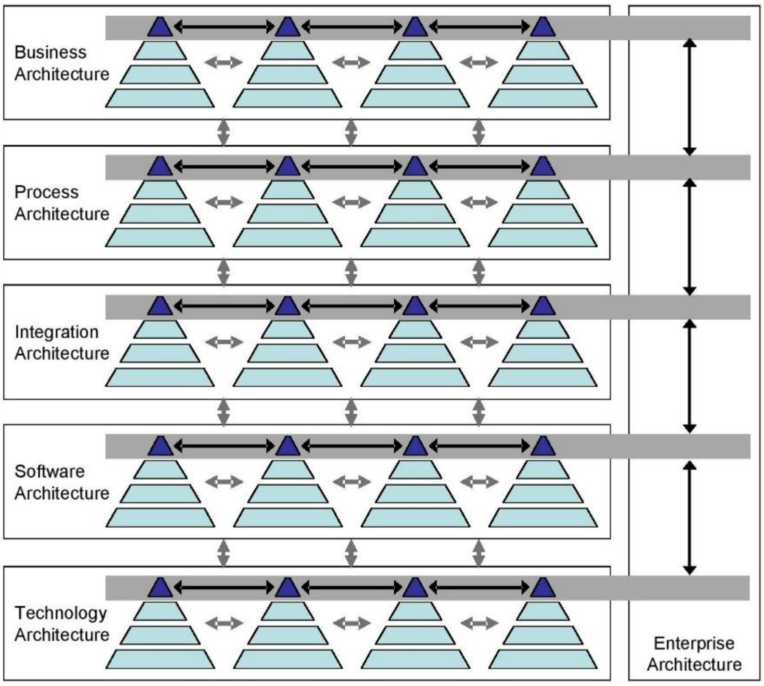


Figure 6. Enterprise Architecture Cross-Layer View (Winter and Fischer, 2007).

Enterprise architecture management (EAM) is associated with the information systems research body of knowledge (Winter and Fischer, 2007). Many organizations have established an EAM function concerned with the aforementioned aim. The TOGAF Architecture Development Method (ADM) provides a management method for organizations to develop their own architectures. Figure 7 illustrates the key elements of the TOGAF ADM that help companies transition from a state of EA vision to design, planning, development, and maintenance. Throughout the process, stakeholder concerns and derived requirements are essential for the approach. Element A contains the strategy and motivation of the EA endeavor. The business layer is addressed in the business architecture element. The data and application layers are both developed in the information systems architecture element.

Similarly, the technological architecture layer is addressed in the corresponding element D. Implementation and migration efforts are planned and executed in elements E to H.

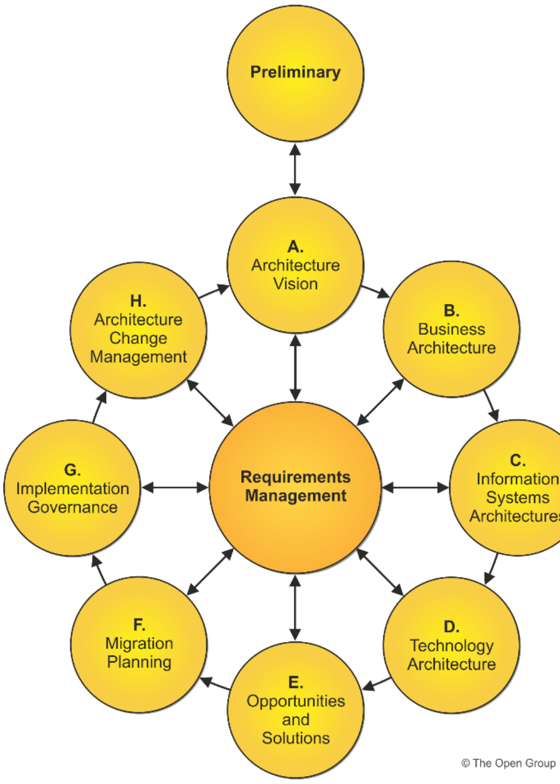


Figure 7. TOGAF Architecture Development Method (The Open Group, 2009).

EA has proven its potential in the project and BM realizations of big data analytics. EA supports the former with requirements and metamodels (specifically focusing on the data layer) as well as with management and modeling frameworks (Burmeister et al., 2018; Kearny et al., 2017; Kehrer et al., 2016). In the BM context, EA modeling and management concepts are used for further detailing BMs and support their implementation (Petrikina et al., 2014). Specifically, the integration of the BMC into the popular EA modeling language, ArchiMate and TOGAF, as well as TOGAF ADM have been investigated (Bouwman et al., 2012; Musulin and Strahonja, 2018).

Previous research already highlighted the potential of EA in the context of big data analytics and BM design as it helps to gain transparency across relevant social and technical elements and their interdependencies (Burmeister et al., 2018; Petrikina et al., 2014). EA can provide answers to stakeholder concerns based on models and tool support for the design and implementation of such socio-technical systems, where companies struggle to understand the existing data resources and capabilities.

Previous research efforts have investigated the application of EA in the context of BM and big data analytics. DDBM is associated with the intersection of BM and big data analytics, and, as such, it is reasonable that EA might be beneficial for DDBM innovation. EA can support the DDBM design by providing transparency and the tools for stakeholders to envision future systems. EA management can support the realization phase by managing the architecture toward the desired target state and providing various tools and methods (Vanauer et al., 2015). Beyond that, EA offers blueprints, reference models, frameworks, and assessment tools that might be beneficial in making the as-is state transparent and developing the to-be state of DDBMs. In order to justify huge investments in organizational transformation, as required for DDBMs, EA could first and foremost support the DDBM design phase. A good understanding of data assets and system components and their interrelation, as well as their link to the ecosystem, are key for successful DDBM realization. Nevertheless, the support of EA modeling and management for DDBMs has only been briefly described in the past.

Introducing a new DDBM requires deep intervention in the entire organizational structure. The current (as-is) architecture must be well understood, and the desired target (to-be) architecture, embedding the DDBM, must be crucially planned. EA practice is concerned with the aforementioned. EA has proven its potential in many IT-related projects and is deeply rooted in the information system body of knowledge. By providing artifacts such as metamodels, frameworks, and management methods, EA supports transparency building on an organization’s key components, from business, data, application to the technology level. Furthermore, EA helps to manage the architecture toward a common vision (Winter and Fischer, 2007). Research on the intersection of DDBM and EA is emerging in the literature, bearing in mind the novelty of DDBMs. This thesis investigates if and how EA can be beneficial for DDBM innovation.

3 Research Design

3.1 Research Strategy

In order to answer the RQs for this thesis, we followed an inductive and qualitative research design as well as the design science paradigm. There are several reasons why we considered these research approaches particularly suitable to examine the DDBM phenomenon. First, an appropriate empirical research inquiry in this context needs to cope with the complexity that comes with the tight integration of the rich discipline of EA modeling and management and design decisions in DDBM innovation. This can be addressed through qualitative research methods such as grounded theory (Corbin and Strauss, 1990). Second, this thesis focuses on DDBMs, prominent in practice but not thoroughly researched. We, therefore, pose the RQs in order to investigate DDBM innovation leveraging EA modeling and management. Last, we are interested in how DDBMs are designed and realized in practice rather than their functionalities per se. Thus, this thesis examines how organizations practically adopt DDBM innovation, leveraging the practice of EA. In this context, we examined how a new artifact for DDBM innovation can be developed and evaluated. This can be addressed through design science research (Hevner et al., 2004). Additionally, the work system theory can be utilized as kernel theory for artifact development (Alter, 2013).

The first step in this thesis involved the existing literature on the intersection of business models, big data analytics, and enterprise architecture being analyzed. In order to identify potentially relevant related works, we conducted a structured literature review, following the methodology proposed by vom Brocke et al. (2009). This allowed us to identify useful theoretical concepts and the state of the art of previous research efforts that can be used to stimulate research endeavors as well as for the category and concept development of the following grounded theory study (Corbin and Strauss, 1990). Throughout these studies, the primary data source will be semi-structured expert interviews, complemented by publicly available data such as company webpages and company performance reports.

We aimed at observing reoccurring patterns of activities in designing and realizing DDBMs. These observations allow us to build an explanatory theory that provides explanations of DDBM innovation (Gregor 2006). Thus, we seek to develop an initial reference model for knowledge accumulation that elevates research as it matures over time. Knowledge from different disciplines, in the form of accumulated design knowledge, is explicated and integrated to contribute to their respective fields (Legner et al., 2020). In this manner, we aim to provide an artifact for DDBM innovation and develop a type five theory according to Gregor (2006) for design and action; one that scrutinizes the *how* (i.e., the innovations) rather than the *what* (i.e., the "as is" state) of DDBM design and realization.

3.2 Research Approach

The mixed-method approach of this thesis draws on a systematic literature review, qualitative empirical research, and the design science research paradigm. In the following section, we describe the methods and their application in this thesis. We begin with a systematic literature review, which is used to understand the current state of the literature. This is followed by semi-structured interviews to gather cases on DDBM innovation. Ultimately, the design science research framework is described.

Literature Review

Reviewing the literature is an essential step when conducting a research project (Vom Brocke et al., 2009; Webster and Watson, 2002). The goal of a literature review is to identify publications relevant to the topic at hand. By identifying related literature, the danger of reinvestigating something that is already known is reduced, and the intended research project builds on the existing knowledge.

When conducting a literature review, the relevant publications must be identified, assessed, and analyzed. In order to identify the relevant literature, scholarly databases are reviewed using keywords as well as backward and forward searches (Vom Brocke et al., 2009). The selection of keywords is based on the unit of analysis and is redefined during the review. Identified publications from the keyword search are analyzed for references that may be relevant for the study at hand. This is referred to as a backward search. Forward search includes reviewing publications that cite the identified publications within the keyword search (Webster and Watson, 2002). The resulting publications must be assessed for relevance for the research project. The analysis of the relevant literature includes the identification, grouping, and structuring of the underlying concepts (Vom Brocke et al., 2009; Webster and Watson, 2002).

This thesis reviewed existing literature on DDBMs and EA. The relevant literature was identified using the keywords "data-driven," "business model," and "enterprise architecture." These terms were selected based on the resulting four intersections of big data, EA, and BM (Figure 8). In order to further extend the literature search, the terms "big data" and "analytics," which are associated with "data-driven," were integrated into the search as well. This led to a total of 10 search strings. The following databases have been queried with keyword searches: (1) AIS Electronic Library, (2) EBSCO Host Business Source Complete, (3) Google Scholar, (4) IEEE Xplore, (5) JSTOR, (6) Science Direct, and (7) Web of Science. The identified publications were reviewed for relevance based on their titles, keywords, and abstracts. The analysis focused on the contributions at the intersection of DDBMs and EA modeling and management. Intending to identify literature on the interplay between EA and DDBMs, we looked at intersection A (BM, big data, and EA) for articles with a central focus on this topic. In order to gain a broader understanding of potential application fields of EA for DDBMs, we examined intersection C (big data and EA) for articles addressing EA support in big data ideation and realization, as well as intersection D (BM and EA) for EA support for BM design and implementation. Additionally, we analyzed the literature in intersection B (big data and BM) for articles with a central focus on DDBMs in order to identify the requirements for EA. Based on these requirements, we derived DDBM-related EA concerns.

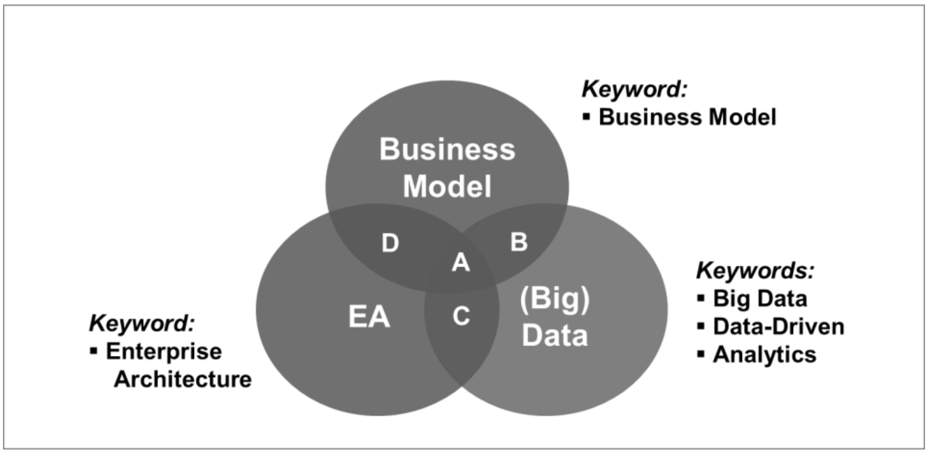


Figure 8. Literature Review Intersections.

Qualitative Research

One goal of this thesis is to examine how companies design and realize DDBMs. We want to explain "why" and "how" companies embark on realizing DDBMs by drawing on the work of Gregor (2006). Considering the novelty of DDBMs for academia and practice, we planned to conduct explorative qualitative research. Our goal was to derive a theory drawing on the proposed ideas of the grounded theory (Corbin and Strauss 1990). We conducted 16 semi-structured interviews with experts from consulting and industry firms to develop a theory on DDBM endeavors. Each interviewee has a track record of DDBM projects. We analyzed the data as we collected them. We adjusted the interview guide based on our experience from the first meetings, allowing one-third to be conducted in step with the insights we gained. Choosing a semi-structured interview approach allowed us to set the research direction as we collected the data. Recommendations from the work of Myers and Newman (2007) allowed us to foresee common pitfalls of qualitative interview research.

The unit of analysis is a company case for designing and realizing a DDBM. A case can comprise multiple projects, and multiple cases can occur within one company. Intending to understand what pathways companies choose, we structured the interview questions regarding two phases: designing and realizing DDBMs. These phases were derived from the literature on designing and realizing DDBMs (Chen et al., 2017; Vanauer et al., 2015). We refined the questions as we proceeded. The interviewees reported on their previous DDBM projects. First, they described the background and context of the project. Then, we asked about their approach to DDBM design before tapping into the DDBM realization phase. We documented the interviewees' experiences in case examples.

Additionally, this thesis aims to empirically examine the support of EA modeling and management for DDBM design and realization. In order to understand how EA modeling and management support DDBM design and realization, we asked the participants about the project's background and context, the general support from EA, and the DDBM design and implementation phase. We documented their experience along with the case examples.

In order to construct a coherent theory based on the gathered data, we draw on the grounded theory proposed by Corbin and Strauss (1990). We applied an open coding approach and selected ATLAS.ti for tool support. Not having a specific framework in mind, we conducted the interviews openly. However, we structured the questions in terms of the DDBM design and realization phases (Chen et al., 2017; Vanauer et al., 2015) and how EA supported each phase. In order to uncover relationships between the categories, we reassembled the data broken up during open coding. For this, we applied axial coding as described by Corbin and Strauss (Corbin and Strauss, 1990). Based on the factors the interviewees described the case's context and the steps for designing and realizing DDBMs, we refined the questions and built theoretical constructs. Dimensions frequently mentioned within the first set of data were asked about specifically during the following interviews.

Design Science Research

In order to provide an artifact for DDBM innovation, we developed a theory for design and action, which is the type five theory, according to Gregor (2006). The artifact's development is based on the design science paradigm and the design science research framework (Hevner et al., 2004). Figure 9 illustrates our application of the research framework. The DDBM innovation reference model artifact was inductively developed in two design iterations based on the design science paradigm and the design science research framework (Hevner et al., 2004). The first and second studies provide the foundation for the rigor and relevance cycles, respectively.

In order to achieve relevance, we built on the 16 semi-structured expert interviews in the first iteration. We derived design principles as a general blueprint of requirements (Drechsler and Hevner, 2018), which then served as a foundation for instantiation. Additionally, 19 international DDBM cases were collected and clustered to identify four approaches for DDBM innovation. Furthermore, we derived seven design principles as artifacts or entity-independent design knowledge from gathered key considerations and lessons learned. In order to do so, we drew on the propositions for design theorizing in "Mode 4B: Codifying

Effective Design Principles or Features" (Drechsler and Hevner, 2018, p. 92). The design principles, case clusters, and approaches for DDBM innovation were evaluated with the interviewees. For the evaluation, we conducted follow-up meetings with our interview participants to get their qualitative feedback. This led to restructurings and rewordings of the identified enablers. We adjusted the reference model as we proceeded with the meetings.

We drew on our systematic literature review to achieve rigor, following the methodology proposed by vom Brocke et al. (2009). On the bases of the four identified approaches and the application of the derived design principles, as well as the key methodologies and frameworks from the systematic literature review, we developed the DDBM innovation reference model artifact. Additionally, we derived five practical recommendations for DDBM capability building.

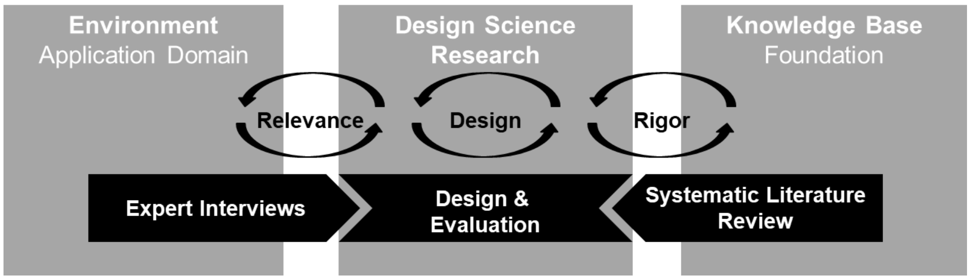


Figure 9. Research Approach (adapted from Hevner et al., 2004).

4 Publications

The publications included in this thesis are outlined in Table 2. They are embedded in this thesis in the same order from chapters 8 to 12.

Table 2. Embedded Publications.

No.	***Authors***	***Title***	***Outlet***	***Type***	***Status***
P1	Faisal Rashed, Paul Drews	Supporting the Development and Realization of Data-Driven Business Models with Enterprise Architecture Modeling and Management	BIS 2020	CON (VHB: C)	Published
P2	Faisal Rashed, Paul Drews	Pathways of Data-driven Business Model Design and Realization: A Qualitative Research Study	HICSS 2021	CON (VHB: C)	Published
P3	Faisal Rashed, Paul Drews	How does Enterprise Architecture support the Design and Realization of Data-Driven Business Models? An Empirical Study	WI 2021	CON (VHB: C)	Published
P4	Faisal Rashed, Paul Drews, Mohamed Zaki	A Reference Model for Data-Driven Business Model Innovation	ECIS	CON (VHB: B)	To be Submitted (01.11.2021)
P5	Faisal Rashed, Paul Drews, Mohamed Zaki	Mobilizing Capabilities for Data-Driven Business Model Innovation	MISQE	JNL (VHB: B)	Major Revision Submitted

BIS: Business Information Systems Conference; HICSS: Hawaii International Conference on System Sciences; WI: International Conference on Wirtschaftsinformatik: ECIS: European Conference on Information Systems; MISQE: Management Information Systems Quarterly Executive; CON: Conference; JNL: Journal; VHB: German Academic Association for Business Research.

5 Contributions

This thesis examined if and how EA can be beneficial for DDBM innovation. The first study investigated the existing literature on the intersection of EA and DDBMs. Here, we identified a clear gap in previous research efforts and derived 42 DDBM-related EA concerns. Furthermore, we found that the literature on DDBMs was not as mature as we expected. Most contributions focused on describing the nature of the phenomenon (Fruhwirth et al., 2020; Wiener et al., 2020). In particular, the literature lacked empirical research on DDBM design and realization. In order to understand what exactly EA should support in the context of DDBMs, our second study empirically investigated pathways for DDBM innovation. Four pathways of DDBM design and realization were identified. The third study of this thesis empirically examined the support of EA along the four pathways. An overview of DDBM innovation with EA application areas has been derived from the empirical and theoretical findings. In an attempt to support practitioners in DDBM innovation, the fourth study was concerned with the development of a reference model. Since previous research efforts did not address DDBM design and realization from process, method, and tool perspectives (Fruhwirth et al., 2020), the DDBM innovation reference model provides a broad view and applies EA where appropriate. Addressing the demand for support in DDBM innovation, the fifth study provides five recommendations for practitioners realizing DDBMs. The following summarizes the results of this thesis.

The first study explored the existing literature on the intersection of EA and DDBMs. For academia, we gathered and analyzed the extended literature on the intersection between EA and DDBMs. We derived 42 EA concerns from the literature, structured along the dimensions of the business model canvas and the status of realization (as-is, to-be). Additionally, the derived concerns lay the foundation for advanced support of EA in DDBM design. From a practitioner's perspective, an overview of the current literature is beneficial for targeted knowledge development. The potential application areas of EA for DDBMs can be inspiring for organizational EA practice. Ultimately, the derived concerns provide starting points for developing EA models to address DDBM-related concerns.

The second study empirically investigates pathways of DDBM design and realization. Conducting interviews with DDBM practitioners from around the globe allowed us to report the gathered cases descriptively. We presented insights into 19 cases in various industries and in cooperation with varying consulting firms. Furthermore, we were able to identify pathways for designing and realizing DDBMs grounded in the empirically collected cases. The novelty of the DDBM phenomenon in academia and practice makes this research unique and of great value to both. For academia, this paper contributes empirical insights to the gap in the literature by gathering 19 cases for DDBM design and realization. The four pathways lay the foundation for scholars to expand the thriving literature on DDBM design and realization. For practitioners, the results serve as a guide to navigate through the field of DDBM design and realization. It helps to understand the state-of-the-art and selection approaches to

DDBMs. Furthermore, these cases allow for common challenges and important considerations to be foreseen and learned from.

Our third study's results present four approaches to DDBM design and realization, including EA modeling and management support. By analyzing the literature, we demonstrated the potential lack of EA support and especially a gap in empirical findings. We contributed to this gap by gathering and analyzing 19 international DDBM innovation cases and investigating EA modeling and management support for the cases. Each of the DDBM innovation approaches has been analyzed in terms of EA methods, EA models, EA frameworks, EA services, and EA tool support. By combining the empirical findings with our literature review results, we derived an overview of EA support potentials in line with the DDBM innovation processes. With this, we have opened new research avenues, especially for deepened research on EA capabilities to support DDBM design and realization. For practitioners, the collected cases provide valuable insights into reference projects. The overview of the current literature is beneficial for targeted knowledge development. Additionally, the presented approaches and respective EA support can inspire EA departments to find new support opportunities.

Our fourth study provides a basis for knowledge accumulation, both descriptive and prescriptive (Legner et al., 2020). Our contribution to DDBM innovation is a reference model with six enablers, providing a static and a dynamic view. Additionally, we derived seven design principles for DDBM innovation to help scholars advance the proposed reference model. Furthermore, the design principles can be applied to develop additional artifacts for DDBM innovation in order to provide "a more granular level of specificity about deployment" (Wiener et al., 2020, p. 20). Ultimately, we demonstrated the instantiation of the design principles and the reference model with an exemplary application. The expository instantiation serves as a theoretical representation (Gregor and Jones, 2007) and design feature illustration. Our contributions implication for practice is fourfold. First, the reference model can be used to guide the design and realize DDBMs. Second, the design principles guide the instantiation of the reference model into the company context. Third, the collected cases can be used as a reference and to guide the companies' journey toward DDBMs. Fourth, the overview of the current literature is beneficial for targeted knowledge development.

Our fifth study provides a framework for capability mobilization in DDBM innovation as well as five recommendations for how incumbent companies can successfully introduce DDBMs. Our contribution to research is threefold. First, we provide detailed knowledge on DDBM innovation cases by presenting one case vignette per the DDBM pathway. Second, we provide a framework for capability building in DDBM innovation. Third, we present five practical recommendations for the successful introduction of DDBMs. For practitioners, our results provide knowledge on capability building in DDBM innovation with a framework as well as recommendations. Additionally, the presented cases serve as references for company-wide capability building.

Table 3. Contributions of Researched Papers.

Paper	*Contributions*	
P1	C1:	Gathered and analyzed the extended literature on the intersection of EA and DDBMs.
	C2:	Opened new research avenues for EA support in DDBM context.
	C3:	Derived 42 DDBM-related EA concerns lay the foundation for advanced support of EA in DDBM design.
P2	C4:	Contributed to the gap in the literature by gathering and presenting 19 cases for DDBM design and realization (providing empirical insights).
	C5:	Pathways lay the foundation for scholars to expand the thriving literature on DDBM design and realization.
	C6:	Provided a guide for practitioners to navigate through the unexplored field of DDBM design and realization.
P3	C7:	Presented four approaches and case insights of DDBM design and realization including EA modeling and management support.
	C8:	Analyzed the literature and demonstrated the gap of potential EA support as well as the lack of empirical findings.
	C9:	Opened new research avenues. Especially for deepened research on EA capabilities to support DDBM design and realization.
P4	C10:	Provided a reference model that can be used to guide the design and realize DDBMs.
	C11:	Developed design principles that guide the instantiation of the reference model into the company context.
	C12:	Provided case insights which can be used as a reference and to guide the companies journey towards DDBMs.
P5	C13:	Presented one case vignette (detailed case description) for each of the four DDBM innovation pathways.
	C14:	Elaborated capability mobilization (external and internal) along the DDBM innovation framework enablers.
	C15:	Provided five practical recommendations for executives realizing DDBMs.

6 Limitations

Designing scientific research imposes certain limitations on the yielded results. While the design decisions made in this thesis were made to minimize potential problems, the findings must be evaluated within the context of these limitations. We acknowledge the threat to validity based on the fact that the thesis was written over a period of two years. As DDBMs are an emerging phenomenon in the literature, our thinking of the underlying concepts evolved as well over time. Our thinking evolved over time to include a wider range of literature, different terminology, and a broader empirical foundation. In the following, we want to highlight the limitations associated with each of our studies' results.

Our first study's results bear some limitations. We have gathered and analyzed the extended literature on EA and DDBM interconnectivity. However, the selection of keywords restricts the set of results. Though we have iteratively refined the search terms, some related work might have been overlooked. Although we have chosen an extended literature search approach, our research is not intended to be exhaustive. By using public databases, such as Google Scholar, we have also aimed at including work from other related research fields. Furthermore, the results are limited in terms of validity, as they are purely based on research articles but not validated in an evaluation or empirical study. Accordingly, our second and third studies addressed this need for empirical research.

Within our second study, we conducted qualitative research. The study has several limitations. Drawing on the results of Maxwell (2013), we structured the limitations of this qualitative research into four types. The first limitation is evaluative. We acknowledge the threat to validity based on the dependency on individual interpretation of the reported events. Although we validated the described facts with triangulation data, the threat cannot be completely diminished. The second limitation is the theoretical limitations. We applied a semi-structured interview approach to collect data with an open mind. However, this research topic was infused with our previous research. Therefore, the validity of the prevailing theoretical concepts imposes a threat as well. The third limitation was interpretative. The case clustering and the derived pathways are imbued with an interpretation of the data. Although both authors of the article processed the data independently, and the results were challenged with two directors from management consulting firms, the data were subjectively interpreted. The fourth limitation was descriptive. We acknowledge the threat to validity imposed in the description process. All results were written and interpreted by both authors iteratively. The working paper was sent to two interviewees to gather additional feedback. The number of interviews and cases was limited. However, we analyzed the data as we proceeded with the interviews. After the ninth interview, we were able to derive the case clusters and pathways. The remaining interviews were used to test the concepts. Additional research is required to further examine the DDBM pathways, proposing detailed methods for each pathway. Moreover, the intersection of DDBM and related research fields must be studied in light of the proposed pathways.

Accordingly, our third study focused on the EA modeling and management support for the pathways for designing and realizing DDBMs.

Regarding the limitations of our third study, we drew from the results of Maxwell (2013) and structured our qualitative research limitations along with four proposed types. First, in terms of evaluative limitations, we acknowledge the threat to validity based on the dependency on the individual interpretation of the reported events. Although we have validated the described facts with triangulation data, the threat cannot be completely diminished. Second, concerning theoretical limitations, we applied a semi-structured interview approach to collect the data in an open-minded manner. However, our research was imbued with our previous research on the interdependence of DDBM and EA. Third, interpretative limitations, the derived approaches, are imbued with our interpretation of the data. However, both authors have independently processed the data. Fourth, descriptive limitations, we acknowledge the threat to validity imposed in the description process. Although, all results have been written and interpreted by both authors iteratively. Ultimately, we have to emphasize that the number of conducted interviews and collected cases are limited. However, we analyzed the data as we proceeded with the interviews. After the ninth interview, we were able to derive the approaches. The remaining interviews have been used to test our concepts.

Our fourth study developed a reference model for DDBM innovation, applying EA modeling and management techniques for design and realization. The limitations of our study are as follows. Most notably, we have only conducted two design iterations. The results might hence not be stable yet. Primarily, an extensive empirical evaluation would benefit our developed concepts. In the design iteration, we acknowledge the threat to validity based on the dependency on individual interpretation. Although we applied a versed research framework, the threat cannot be completely diminished. For the relevance iteration, we acknowledge the methodology limitation. We applied a semi-structured interview approach to collect data with an open mind. However, this research topic was informed by our previous research. For the rigor iteration, we acknowledge that the prevailing theoretical concepts pose a threat to validity. Furthermore, the selection of keywords for the systematic literature review restricts the set of results. Though we have iteratively refined the search terms, some related work might have been overlooked.

There exist several limitations in our fifth study. As the results build upon study four, the same limitations apply. Additionally, we have only conducted one iteration of the design process for the DDBM innovation recommendations. The results might hence not be stable yet. In particular, the DDBM cases were gathered from interviews with DDBM consultants and experts. DDBMs are not yet routine in companies, with their only pioneers in the interviewed field, which may lead to sample bias. In order to increase the reliability of our results, we plan to conduct empirical evaluations.

7 Future Research

This thesis suggests several fruitful research avenues. Complementing the current concepts with additional data and with quantitative research methods could address the existing threats to validity. Concerning the limitations outlined in the previous chapter, additional research is required to further validate the current concepts. In the following, we want to outline future research avenues: 1) DDBM deployment, 2) DDBM realization, 3) EA support potentials for DDBM, and 4) EA transformation to support DDBMs.

Empirical research on DDBM innovation is still scarce. In particular, the dynamic aspects of DDBM deployment have received minimal attention from a process perspective (Wiener et al., 2020). The results of this thesis contribute to this gap, providing 19 cases on DDBM, representing the journeys taken by companies to design and realize DDBMs. For this, we gathered the perspectives of a diverse set of practitioners, revealing their understanding of DDBMs and their relationship to intermediate BDA projects for DDBM introduction. Second, we theorized the causality between the "why" and "how" of DDBM design and realization. Case clustering was proposed, taking the reported dimensions into account. Within the case clusters, the pathways that companies take to DDBMs were derived. However, additional research is required to further examine these pathways, especially in light of the detailed methods per pathway. As DDBM innovation is presently not a daily routine in companies, our interviewees might be among the most experience persons. In order to increase the reliability of our findings, future research could focus on extending the number of involved interviewees. Furthermore, we want to emphasize the demand for research capturing stakeholder views and broadening the current focus from Western worldviews to incorporate international perspectives.

Considering the high dependency on BDA, DDBM innovation orchestrates information systems design and implementation, which requires alternative support in design and realization compared to offline BM innovation (Fruhwirth et al., 2020). As research on DDBMs is still emerging (Fruhwirth et al., 2020; Wiener et al., 2020), practitioners face several challenges in DDBM innovation (Günther et al., 2017; Redman, 2019), such as identifying relevant opportunities, conducting an evaluation, and implementing the DDBM (Fruhwirth et al., 2020). Due to the novelty of this topic from academic and practice standpoints, most efforts have focused on understanding the nature of the phenomenon (Wiener et al., 2020). Particularly, details on the design and implementation of these socio-technical systems, from method, process, and tool perspectives, have received negligible attention (Fruhwirth et al., 2020; Kühne and Böhmann, 2019; Rashed and Drews, 2021; Wiener et al., 2020). Fruhwirth et al. (2020) divulged the current literature's staunch focus on DDBM design rather than implementation. They concurrently emphasize the benefits of bridging related fields in order to contribute to DDBM innovation research. This paper contributes to filling this gap, providing a reference model for DDBM innovation. The reference model serves as abstract representations (Schermann et al., 2009) to support practitioners in developing company-specific DDBMs (Fettke and Loos, 2007; Frank et al., 2014). As the problem space changes over time, the DDBM innovation reference models survive through adjustment and transmit design knowledge to new versions of the reference model. Thus, additional research is required to enhance the reference model. Furthermore, future researchers may focus on tool support for DDBM innovation.

Research at the interchange between DDBM and EA is emerging in the literature, with the modernity of DDBMs in mind (Rashed and Drews, 2020; Vanauer et al., 2015; Wiener et al., 2020). As part of this thesis, we have derived 42 DDBM-related EA concerns from the literature, emphasizing the potential of EA modeling and management support for DDBM design and realization. Additionally, we examined EA modeling and management support for DDBM design and realization with empirical research. However, additional research is required to enhance the support potentials we have identified. Specifically, by increasing the number of cases, the reliability of the value contribution from EA will be further strengthened. Accordingly, we suggest additional empirical research. In addition to our qualitative research, the literature would benefit from quantitative data on DDBM innovation and EA support along the process. Understanding correlations in DDBM innovation and EA could help identify success factors. The reference model developed in this thesis could serve as a framework to formulate hypotheses on correlations.

Our research conducted 16 semi-structured interviews with experts from consulting and industry firms working on DDBM projects in North America, Europe, and the Asia-Pacific region. Based on these interviews and triangulation data from publicly available sources, we collected 19 cases. We derived four approaches for DDBM design and realization and presented the support attained from EA modeling and management for each. In addition to this research method, it would be interesting to apply action design research methods. For example, investigating a single case study and exploring new application fields of EA in the DDBM context would be beneficial both in research and practice. Furthermore, implications for EA transformation areas could be investigated, resulting in a clear evolution of EA practice in order to serve DDBMs.

8 Supporting the Development and Realization of Data-Driven Business Models with Enterprise Architecture Modeling and Management

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Abstract. Designing and realizing data-driven business models (DDBMs) are key challenges for many enterprises and are recent research topics. While enterprise architecture (EA) modeling and management proved their potential value for supporting information technology-related projects, EA's specific role in developing and realizing DDBMs is a new and rather unexplored research field. We conducted a systematic literature review on big data, business models, and EA to identify the potentials of EA support for developing and realizing DDBMs. We derived 42 EA concerns from the literature, structured along the dimensions of the business model canvas and the status of realization (as-is, to-be).

Keywords: Enterprise architecture, data-driven, business model, concerns

8.1 Introduction

Advancements in information technology, especially in machine learning, big data, cloud, and Internet of Things (IoT) technologies, have continuously increased the importance of data for business development and innovation. Today, many practitioners in business, as well as academic communities, perceive data as the 'new fuel' of the economy [1]. Nevertheless, the failure rate of big data and artificial intelligence projects remains disturbingly high [2]. Especially, incumbent companies are expected to rest on huge unused data treasures, facing several challenges in monetizing their data and seizing new business opportunities [3].

Over the last years, a new research field has emerged, which investigates data-driven business models (DDBMs). DDBMs are characterized by data as a key resource, data processing as a key activity, or both [4]. They highly rely on information systems for their core operations of data capturing, processing, and distribution. Various DDBM representations have been proposed by scholars. The latest efforts in academia have focused on extending the Business Model Canvas (BMC) as a widely accepted modeling framework to the special needs of data-driven businesses [4–5]. These models help practitioners to envision and document the design of DDBMs in the first step and to further detail and realize the design in the second step [6]. Research on DDBMs is still at an early stage and requires detailed knowledge of tool support for DDBM design [5]. Especially, the needs of incumbent companies, with their existing data resources and structures, are currently not addressed.

In this paper, we explore if and how enterprise architecture (EA) modeling and management can be a beneficial approach for developing and realizing DDBMs. Previous research already highlighted the potential of EA in this context as it helps to gain transparency across relevant social and technical elements and their interdependencies [6]. Especially in the design phase, where companies struggle to understand the existing data resources and capabilities, EA can provide answers to stakeholder concerns based on models and tool support. However, the support of EA modeling and management has only been briefly described in the past. Therefore, our study focuses on the following research questions: What application fields for EA modeling and management in DDBM design and realization exist in the literature? What DDBM-specific EA concerns can be derived from the literature? To answer these questions, we conducted a structured literature search and analysis.

8.2 Research Background

Our study is grounded on two research fields. First, recent papers have explored the challenges associated with the development of DDBMs while taking into account the general research on business models (BMs). Second, research on EA has shown the potential benefits of EA models and EA management for projects related to business transformation.

8.2.1 Data-Driven Business Models and their Representations

Data is traditionally been perceived as a crucial component of business operations, strategic decision making, and new business development. The terms under which it has been investigated has varied in the past decades, ranging from business intelligence, business analytics, and big data to big data analytics [7]. The potential value contribution of data has been researched in three major areas, namely improved decision making, enhanced products and services, and new BMs [8]. In the third area, the latest technological advancements have contributed to the current enthusiasm for new DDBMs. Several definitions of DDBM have been proposed in the literature. All commonly state that data has to be an essential component. Accordingly, Hartmann, Zaki, Feldmann, and Neely define DDBM as “a business model that relies on data as a key resource” [4, p. 6]. Bulger, Taylor, and Schroeder [9] and Brownlow, Zaki, Neely, and Urmetzer [10] similarly highlight the fundamental role of data for DDBMs. Schüritz and Satzger argue that a clear threshold of required data for a DDBM is not defined and that companies alter from a traditional BM to a DDBM, with increased application of the data for the value proposition [11]. In the context of this study, we clearly distinguish between enhancements of existing BMs and new DDBMs that are centered on data (data as a key resource and/or data processing as a key activity).

The conceptual structure of any business can be represented with business modeling techniques. Several modeling frameworks have been proposed in the past, varying in characteristics and components. The most popular BM framework is the BMC [12], comprising nine components: partners, key activities, key resources, value proposition, customer relationships, channels, customer segments, cost structure, and revenue stream. The conceptualization and definition of DDBMs rely on the BMC, with data as a key resource and/or with key activities focusing on data processing. Research on DDBMs is still at an early stage. The latest efforts in academia have focused on extending the BMC to the special needs of data-driven businesses [4–5]. The literature in this area is analyzed as part of our literature review.

8.2.2 Enterprise Architecture

The EA discipline is rooted in the information system research body of knowledge [13]. Research on EA goes back to the Zachman framework in the 1980s, which provides an ontology for modeling the fundamental structure of an organization and its information systems [14]. Today, EA is essential for many organizations to support technology-driven transformations as it helps maintain an overview of complex sociotechnical systems. The Federation of Enterprise Architecture Organizations defines EA as "a well-defined practice for conducting enterprise analysis, design, planning, and implementation, using a comprehensive approach at all times, for the successful development and execution of strategy" [15, p. 1]. The Open Group provides a narrower definition of EA, in line with the ISO/ICE/IEEE Standard 42010 of architecture definition, that is, "the structure of components, their interrelationships, and the principles and guidelines governing their design and evolution over time" [16]. Hence, researchers and practitioners sometimes refer to EA as the practice and sometimes as the actual architecture of an organization. We use the term EA for the practice comprising the related modeling techniques, frameworks, and management function within an organization (EA management). The actual architecture of an organization is noted as as-is architecture, while planned future states are called to-be architecture [13].

EA aims to improve information system efficiency and effectiveness. For this purpose, it provides artifacts, such as meta models, frameworks, tools, guiding principles, and management methods. Many organizations have established an EA management function concerned with the aforementioned aim. An organization's key components and their interdependencies are represented in EA models [17]. These models provide transparency and support for strategic planning, top management decision making, and project management [18]. The modeling concepts and case-specific models help in quickly addressing stakeholder concerns. A diversity of modeling frameworks has been proposed in the literature, with different layers, elements, and relations to represent the enterprise [13]. The models built based on these meta models are concerned with either the current state (as-is) or the desired state (to-be) of the enterprise. The EA management function supports the transition from the as-is to the to-be state through several intermediate architecture stages.

8.3 Methodology

To identify the current state of the literature on the interplay of DDBMs and EA, we conducted a structured literature review, following a proposed methodology [19]. We queried the following databases with keyword searches conducted in August and September 2019: (1) AIS Electronic Library, (2) EBSCO Host Business Source Complete, (3) Google Scholar, (4) IEEE Xplore, (5) JSTOR, (6) Science Direct, and (7) Web of Science. Since the DDBM belongs to an interdisciplinary field, its research is reflected in the intersection of BM and big data [8]. Our search comprised keywords covering both areas. We added the research stream of EA to understand the interplay of these research fields. The keywords "data-driven," "business model," and "enterprise architecture" were selected based on the resulting four intersections (see Figure 10: A, B, C, and D). To further extend the literature search, the terms "big data" and "analytics," which are s associated with "data-driven," were integrated into the search as well. This led to a total of 10 search strings. All hits were screened based on their titles and abstracts. The first 100 hits from Google Scholar were considered, acknowledging their decreasing relevance. Irrelevant, duplicate, and non-peer-reviewed results were excluded. The remaining 80 articles were reviewed based on their full texts. With the objective of identifying the literature on the interplay of EA and DDBMs, we looked at intersection A for articles with a central focus on this topic. To gain a broader understanding of potential application fields of EA for DDBMs, we examined intersection C for articles addressing EA support in big data ideation and realization, as well as intersection D for EA support for BM design and implementation. Additionally, we analyzed the literature in intersection B, whose articles have a central focus on DDBMs, to identify the requirements for EA. Based on these requirements, we derived DDBM-related EA concerns. If required, we reallocated relevant articles to a better-fitting intersection. For example, one article from intersection B [20] was transferred to A.

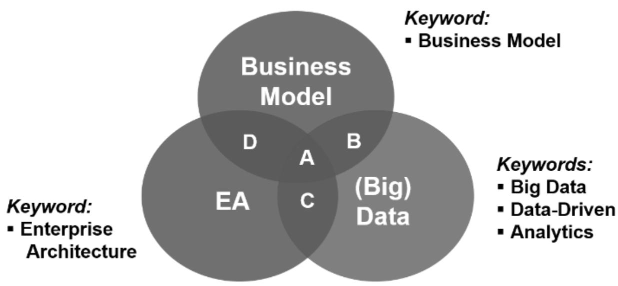

Figure 10. Research fields and keywords.

Only four articles were identified in intersection A, of which two demonstrate contributions to the interplay of EA and DDBMs. We analyzed both articles in depth to gain insights into the state of the literature on the interplay of EA and DDBMs. From a total of 45 results, 17 articles are concerned with DDBMs. From this set, eight articles provide results that demonstrate the usefulness of our derivation of the concerns. These contributions were further analyzed.

The literature search on EA and big data resulted in a total of 16 articles, of which five were evaluated based on their full texts. In intersection D, we identified 16 articles concerned with EA and BMs. From this set, six were further analyzed. The relevant articles from intersections C and D were coded, allowing the derivation of EA support in the big data and the BM contexts.

To gain a deeper understanding of the potential application areas of EA for DDBMs, we analyzed the literature in the overlap of EA and big data, as well as that of EA and BMs. Based on the findings in intersection B, we derived EA concerns to support the viewpoints of the people involved in DDBM design. For this purpose, we drew on the top-down conceptual analysis proposed by Uzzle [21]. We analyzed the literature in depth and structured the derived concerns along the BMC fields, as the BMC is the most popular framework for BM representation [22]. We coded the results.

The literature in intersection B discusses DDBMs from various angles with regard to design requirements, representation requirements, and challenges. By detecting these characterizing requirements and challenges for DDBMs, we were able to derive EA concerns through deduction. For example, Kühne and Böhmann present design requirements for DDBMs, such as "customers and partners can provide data which can cause a connection in the representation. [...] data can be provided from customers or acquired by external sources" [5, p. 7]. Similarly, Hunke, Seebacher, Schuritz, and Illi mention the need for "an alignment of value propositions with involved partners and a definition of the ownership and access rights of data of different parties" [23, p. 4]. We formulated the related EA concern for the as-is architecture as follows: "Which data resources exist in the ecosystem (customers, partners, and data providers)?" The forward-looking concern for the to-be architecture was derived accordingly, as follows: "Which data could be generated in collaboration with actors from the ecosystem?" To cite another example, Zolnowski, Anke, and Gudat investigate costs and revenues from DDBMs and state, "revenues can be generated from [...] the sale of data to third parties" [24, p. 188]. We derived the EA concern accordingly, as follows: "Which data objects/sets can be offered to third parties?"

8.4 Results

8.4.1 EA Support for DDBM Modeling and Management

The DDBM literature overwhelmingly addresses the challenges and the requirements in DDBM conceptualization and design. All eight articles in intersection B address the urgent need for transparency of data and system components for successful DDBM design and realization. For example, Bulger, Taylor, and Schroeder highlight data quality, reliability, and availability as "obstacles" to DDBMs and emphasize the need for the transparency of the technology and science behind data sources [9, p. 24]. Zolnowski, Anke, and Gudat take the financial standpoint, stressing the need for transparency from a cost and revenue perspective [24]. They underline the cost related to data storage and with this, the importance of accurate tracking and management. Furthermore, sensors and information system channels are described as key for data capture and revenue generation. The gained transparency across relevant social and technical elements and their interdependencies infuse the DDBM design, which is primarily captured in the BMC [6]. The latest efforts in academia have focused on extending the BMC to the special needs of data-driven businesses [4–5]. For example, Kühne and Böhmann propose nine key requirements for DDBM representation, concerned with data sources, security, quality, and data-processing capabilities [5]. We argue that EA can be beneficial in gaining transparency and infusing the design and realization of DDBMs.

EA has proven its potential in the context of big data project realization, as well as BM realization. EA supports the former with requirements and meta models, specifically focusing on the data layer, as well as with management and modeling frameworks [18, 25–28]. In the BM context, EA modeling and management concepts are used for further detailing BMs and support their implementation. Specifically, the integration of the BMC into the popular EA modeling language ArchiMate and The Open Group Architecture Framework (TOGAF), as well as TOGAF ADM, has been investigated [17, 29].

The literature results of intersections A, C, and D discuss potential application fields of EA in the contexts of big data, BMs, and DDBMs. Based on these contributions, we have constructed an overview of the potential EA support for DDBMs. The relevant articles in intersection A propose two major phases for DDBM development, namely design and realization [6, 20]. Additionally, these articles distinguish between support from EA modeling and EA management. The contributions of both are described along the two phases. This structure has been used to map the potential application fields of EA in the DDBM context, as derived from the literature. Table 4 illustrates the results.

EA supports the DDBM design phase by providing transparency and the tools for stakeholders to envision future systems. EA management supports the realization phase by managing the architecture toward the desired target state and providing various tools and methods. EA offers blueprints, reference models, frameworks, and assessment tools to make the as-is state transparent and to develop the to-be state. A large set of contributions concentrates on EA for the realization of big data and with that, on DDBMs, while very little research has focused on EA for the design of DDBMs. This scarcity of studies may be due to the complex nature of EA as a tool for system developers [17]. Nevertheless, EA has the potential to drive innovation and the discovery of new DDBMs [30]. The design and realization of DDBMs require support from EA beyond the traditional project realization support. To justify huge investments in organizational transformation, as required for DDBMs, EA must first and foremost support the DDBM design phase. A good understanding of data assets and system components and their intertwinement, as well as the interlink to the ecosystem, is key for successful DDBM realization.

Table 4. EA support for DDBMs.

		DDBM Design	**DDBM Realization**
EA modeling	As-is	• EA models for transparency [6,30]	• EA models for transparency [6,20] • EA meta-models for big data [18] • Big data-related EA concerns [18]
	To-be	• EA models for target state design [6,20]	• Development of target architecture [6,20] • Development of transition architectures [6, 20] • EA frameworks for big data realization [27-28] • EA meta-models for big data [18] • Big data-related EA concerns [18]
EA management			• EA management for technical feasibility assessment [6] • EA management for enterprise transition [6] • Development of implementation roadmap [6] • Big data-related EA management requirements [26] • EA management method for big data [25]

The extended literature provides insights on EA support for DDBM realization through various contributions on EA for big data and EA for BM realization. Furthermore, it highlights the scarcity of the contributions on EA for DDBM design. Our study supplements the research by depicting application fields of EA in the DDBM context using a structured literature-based approach and by contributing EA concerns to foster the intertwinement of EA in the DDBM design.

8.4.2 Derived EA Concerns

The literature results of intersection B are concerned with DDBMs. Based on the findings in this intersection, we have derived DDBM-related EA concerns. These concerns have been formulated from the viewpoints of practitioners in the DDBM design phase. They are related to either the current state of the architecture (as-is) or the desired state (to-be), which is envisioned in the design phase. Both have been derived deductively based on the coded literature. The results are structured along the BMC fields and illustrated in Table 5. Each concern corresponds to an element of the BMC. Most findings relate to data, which is the key resource of DDBMs. In the rest of this subsection, we present the concerns and illustrate their usage and value contributions in an exemplary use case.

The BMC is a popular framework to capture the design of a BM by populating the nine key characterizing fields. Even DDBM research has adopted the BMC for BM representation [4, 22]. Since DDBMs have information systems as their engines, compared to traditional BMs, a set of profound EA concerns might be faced while populating the BMC fields. The complexity is further heightened because most incumbent organizations do not build up on a green field, such as startups do [3]. The existing resources and structures can be advantages or disadvantages, depending on how well they are understood and leveraged. Considering EA in DDBM design does not intend to assess feasibility but to provide a basic understanding of organizational structures. Designing DDBMs requires an understanding of EA in the same way that traditional BMs require basic business knowledge. For example, EA considerations can help prevent the proposition of a BM that generates €500,000 per year but requires tremendous investments in the information system landscape and business capabilities amounting to over €20 million that would require 10 years for realization. Architects can infuse the DDBM design by providing information, models, guidance, and inspiration. The derived EA concerns equip architects to respond to the business demand while populating the BMC framework.

Günther, Rezazade Mehrizi, Huysman, and Feldberg [3] present the following example of how organizations may fail in realizing DDBMs. A European postal service organization aimed to sell addresses of potentially relevant households to business clients for targeted advertising. The company faced three major challenges. First, the company did not own the data, whose sale required the agreement of the owning party. Second, the company acquired a startup to obtain the data to implement its DDBM, which it failed to integrate into the organization model. "The decision to acquire appeared to be influenced largely by supra-organizational drivers, as the organization needed to access data from elsewhere and was pressured by a shrinking market" [3, p. 12]. The data resources' landscape and their availability within the organization and its ecosystem were not well understood. The existing structures had to be transformed in order to adopt the new resources. Lastly, due to the historical evolution of the company's BM , the sales team, who was used to selling contracts, struggled to interpret the data characteristics in their client conversations. The DDBM lacked the required business capabilities.

We assume that our derived EA concerns provide the equipment to prevent such a failure. The first challenge of data ownership could have been foreseen by utilizing EA concerns C10 (Who is the owner of the data, legally and within the company?) and C12 (What are the data privacy constraints for internal and external usage?) Raising these concerns leads to an early consideration of legal boundaries. EA models and the management function have to adopt in order to address these concerns effectively. The second challenge requires a good understanding of the existing data within the organization and throughout the ecosystem. Furthermore, it must be understood how well the data sources are integrated and what their availability status is. These concerns are reflected in C4 (Which data resources exist across the organization?), C5 (Which data resources exist in the ecosystem [customers, partners, and data providers]?), C6 (How well are the data resources integrated?), and C9 (What is the availability status of the data [e.g., company-owned existing data versus third-party-owned data that is not captured yet]?). The last challenge regarding the required business capabilities for the DDBM could have been addressed with C2B (What are the required data analytic capabilities at the business capability level?).

Table 5. DDBM-related EA concerns.

BMC Field	As-is	To-be	Sources
Key activities	***C1:*** What are the available data-processing capabilities at the application level?	***C1B:*** What are the required data processing capabilities at the application level?	[5, 22, 31-32]
	C2: What are the available data analytic capabilities at the business capability level?	***C2B:*** What are the required data analytic capabilities at the business capability level?	[5, 32-33]
	C3: How long does it take to process the data?	***C3B:*** How can the data be processed within the time constraints of the new business model?	[32]
Key resources	***C4:*** Which data resources exist across the organization?	***C4B:*** Which additional data resources are required for the new business model?	[22-23, 32-33]

	C5: Which data resources exist in the ecosystem (customers, partners, and data providers)?	***C5B:*** Which data could be generated in collaboration with actors from the ecosystem?	[5, 23]
	C6: How well are the data resources integrated?	***C6B:*** How can the data resources be integrated to enable the new business model?	[22]
	C7: How often are collected data resources synchronized?	***C7B:*** How often must the data be synchronized for the new business model?	[32]
	C8: Which measures are currently taken for realizing data security?	***C8B:*** Which measures are necessary to ensure data security within the new business model?	[23]
	C9: What is the availability status of the data (e.g., company-owned existing data versus third-party-owned data that is not captured yet)?	***C9B:*** What is the availability status of the data for the new business model?	[5, 22, 31]
	C10: Who is the owner of the data, legally and within the company?	***C10B:*** Who owns the data processed for the new business model?	[5, 22-23]
	C11: Where is the data stored (e.g., specific country, customer side)?	***C11B:*** Where is the required data for the new business model stored?	[22-23, 32]
	C12: What are the data privacy constraints for internal and external usage?	***C12B:*** How is data privacy ensured within the new business model?	[5, 9, 22-23]
	C13: What is the data quality in terms of consistency and completeness?	***C13B:*** How is data quality ensured in terms of consistency and completeness?	[5, 9, 22, 31]

	C14: How long can the data be stored, and when must it be deleted?	***C14B:*** How long must the data be stored for the new business model?	[22-23]
Revenue model	***C15:*** Which data objects/sets can be offered to third parties?	***C15B:*** Which data objects/sets could be made available to third parties?	[24]
	C16: *Which technical* value-capturing mechanisms exist?	***C16B:*** How can the value-capturing mechanism be realized from a technology perspective?	[23]
Cost structure	***C17:*** What computing efforts are required to process the data (e.g., cloud facilities, analytic platforms)?	***C17B:*** How can the computing efforts for data processing be reduced?	[22, 24]
	C18: How much does it cost to purchase/capture and store the existing data?	***C18B:*** How can the cost of data purchase/capture and storage for the new business model be reduced?	[24]
Channels	***C19:*** Where are the data import and export interfaces?	***C19B:*** What are the required data import and export interfaces?	[22-24, 32]
	C20: How are the systems connected to customers and providers?	***C20B:*** What are the required connections to customers and providers?	[22, 24]
	C21: What is the existing infrastructure to integrate data sources?	***C21B:*** What are the required infrastructure components to enable the new business model?	[31-32]

8.5 Discussion

Designing and realizing DDBMs require a creative yet analytic and structured set of activities. Both can benefit from the rich discipline of EA and its management. To shed light on the interplay of EA and DDBMs, we have investigated the literature using a structured search process. Our paper makes a twofold contribution to research. First, we have summarized the state of the knowledge about EA and DDBMs by conducting an extended literature search. We have analyzed the sources from the intersection of three research areas to provide a comprehensive view on previous research efforts. Our work has revealed the limited number of articles focusing on this highly demanded topic. The results of the literature related to this interdisciplinary research field have been used to construct an overview of potential application areas of EA in DDBM design and realization. With this overview, we have demonstrated the diverse application possibilities of EA in DDBM realization and have highlighted the current gap in EA support for DDBM design. Second, we have identified DDBM-related EA concerns to foster EA support for DDBM development and realization. By deriving 42 concerns from our literature-based approach, we have demonstrated the clear need for EA support in DDBM design and have laid the foundation for researchers to further investigate the contributions of EA for data-driven businesses.

Our study's results bear some limitations. First, the selection of keywords restricts the set of results. Though we have iteratively refined the search terms, some related work might have been overlooked. Although we have chosen an extended literature search approach, our research is not intended to be exhaustive. By using general databases, such as Google Scholar, we have also aimed at including work from other related research fields. Second, the results are limited in terms of validity as they are purely based on research articles and are not validated in an evaluation or an empirical study. Nevertheless, our work should help in guiding further studies in this area. We recognize the need for empirical research to extend and test the derived concerns.

Our study's results have implications for both academia and practice. For academia, we have gathered and analyzed the extended literature on the intersection of EA and DDBMs. Our findings have opened new research avenues. Additionally, the derived concerns lay the foundation for advanced support of EA in DDBM design. From a practitioner perspective, the overview of the current literature is beneficial for targeted knowledge development. Furthermore, the potential application areas of EA for DDBMs can be inspiring for organizational EA practice. Ultimately, the derived concerns provide starting points for the development of EA models to address DDBM-related concerns.

8.6 Conclusion and Future Work

Data has long been acknowledged as a key driver for business. Nevertheless, the recently emerging opportunities rooted in technological advancements, which allow BMs centered on data, are fairly new to research and practice. The design and realization of such DDBMs can benefit from the sophisticated EA practice, which not only enables strategic planning but also supports organizational transformation. We have conducted a systematic review to investigate the current state of the literature in the intersection of EA and DDBMs. Considering the related literature on big data and BMs, we have presented potential application areas of EA for DDBMs. Our findings reveal a gap in EA support in the DDBM design phase. To foster EA support in this phase, we have derived DDBM-related EA concerns.

Additional research is required to enrich our findings with empirical evidence. We plan to conduct expert interviews to advance the research in the intersection of EA and DDBMs. The rich literature on big data, EA, and BMs shows that DDBM implementation is not hindered by technological or methodical restrictions but more by creative design concepts that justify tremendous investments in DDBM realization.

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9 Pathways of Data-driven Business Model Design and Realization: A Qualitative Research Study

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Abstract. Maximizing the value from data has become a key challenge for companies as it helps improve operations and decision making, enhances products and services, and ultimately, leads to new business models (BMs). Aiming to achieve the latter, companies take different pathways. Building on a grounded theory research approach, we identified four pathways for designing and realizing data-driven business models (DDBMs). To achieve this goal, we conducted 16 semi-structured interviews with experts from consulting and industry firms. The results fill the gap in the literature on the design and realization of DDBMs and act as a guide for companies.

9.1 Introduction

Data have traditionally been perceived as a crucial component of business operations, strategic decision making, and new business development [1, 2]. The terms under which data have been investigated have varied in the past decades, ranging from business intelligence, business analytics, and big data to big data analytics [1]. Advancements in information technology, especially in machine learning, big data, cloud, and Internet of Things (IoT) technologies, have further increased the importance of data for business development and innovation [2, 3]. Many companies are under pressure or are enhancing their traditional business mode with data or to realize new data-driven business models [3, 4]. The latter has led to the emergence of a new research field, which investigates data-driven business models (DDBMs). DDBMs are characterized by data as a key resource, data processing as a key activity, or both [5]. Especially, incumbent companies are expected to rest on huge amounts of unused data treasure, facing several challenges in monetizing their data and seizing new business opportunities [4].

Recent literature reviews of DDBMs revealed a considerable number of publications since 2014 in this thriving research field [3, 4]. Wiener et al. argued that most studies describe the nature of the DDBM phenomenon and emphasize the scarcity of empirical research [3]. In particular, the “dynamic aspects of BDBM deployments (process perspective)” has received very little attention [3:75]. Furthermore, they emphasized the demand for research capturing stakeholder views and broadening the current focus from Western worldviews to incorporate international perspectives. Additionally, the authors highlighted the value of research on design and realization challenges for practitioners from almost every industry facing the journey for realizing a DDBM.

In this paper, we explore pathways for designing and realizing DDBMs taken by companies in different industries. In this context, we define pathways as generalized courses of DDBM innovation projects. The study focuses on the following research question: What pathways do companies take to design and realize DDBMs? To answer this question, we conducted 16 semi-structured interviews with experts from consulting and industry firms working on DDBM projects in the United States (US), Europe, and Asia Pacific. Based on these interviews and triangulation data from publicly available sources, we collected 19 cases and derived four pathways for designing and realizing a DDBM.

In the next section, we provide an overview of the theoretical foundation of big data analytics (BDA) and DDBMs. We then describe how we conducted the semi-structured interviews and clustered the cases to derive pathways for designing and realizing DDBMs. The case clusters and derived pathways are presented before we conclude the discussion and provide practical recommendations for each pathway. We then discuss the study limitations and implications.

9.2 Theoretical foundations

9.2.1 BDA and DDBM

Data have long been acknowledged as a key driver for business and have received considerable attention from the information system discipline [6, 7, 8, 9]. In research, the topic has been investigated under several terms ranging from business intelligence, business analytics, and big data to big data analytics [1]. Scholars have advanced the research on BDA from only the technological perspective, defined by the four characteristics volume, variety, velocity, and veracity as a multisided socio-economic phenomenon [3, 6, 10].

Researchers have examined the potential value from data in three major areas: improved decision making, enhanced products and services, and new BMs [11]. Regarding the last, the latest technological advancements have contributed to the recent call for new DDBMs. The definitions of a DDBM proposed in the literature commonly states that data must be an essential component. Accordingly, Hartmann et al. defined a DDBM as "a business model that relies on data as a key resource" [5:6]. Bulger et al. [12] and Brownlow et al.[13] similarly emphasized the fundamental role of data for DDBMs. Schüritz and Satzger argued that a clear threshold of required data for a DDBM is not defined and that companies shift from a traditional BM to a DDBM, with increased application of the data for the value proposition [14]. However, other scholars such as Wiener et al. [3], distinguish between updating the existing BM with data and developing new models. In this study, we clearly distinguish between enhancements of existing BMs and new DDBMs that are centered on data (data as a key resource and/or data processing as a key activity).

Business modeling techniques are used to represent the conceptual structure of any business. Several modeling frameworks, varying in characteristics and components, have been proposed. The most popular BM framework is the Business Model Canvas (BMC) [15], comprising nine components: partners, key activities, key resources, value proposition, customer relationships, channels, customer segments, cost structure, and revenue stream. The conceptualization and definition of DDBMs rely on the BMC, with data as a key resource and/or with key activities focusing on data processing. Research on DDBMs is still at an early stage.

9.2.2 Related work

To identify potential relevant related work, we conducted a structured literature review, following a methodology proposed by vom Brocke et al. [16]. We queried the following databases with keyword searches: (1) AIS Electronic Library, (2) EBSCO Host Business Source Complete, (3) Google Scholar, (4) IEEE Xplore, (5) JSTOR, (6) Science Direct, and (7) Web of Science. As the DDBM is an interdisciplinary field, the research is reflected in the intersection of BM and big data [11]. The search comprised keywords covering both areas. The keywords “data-driven” and “business model” were selected. To extend the literature search, the terms “big data” and “analytics,” which are associated with “data-driven,” were also integrated in the search. This led to a total of three search strings (e.g. “big data business model”). All hits were screened based on their titles and abstracts (see Table 6). The first 100 hits from Google Scholar were considered, acknowledging their decreasing relevance. Irrelevant, duplicate, and non-peer-reviewed results were excluded. The remaining 45 articles were reviewed based on their full texts.

Table 6. Literature search.

Database	***Hits***	***Results***	***Relevant***
AIS	51	12	9
EBSCO	61	8	0
Google Scholar	100	7	4
IEEE	81	10	3
JSTOR	0	0	0
Science Direct	196	4	0
Web of Science	141	4	1
		45	17

We analyzed the 17 articles concerned with DDBMs and conducted a forward and backward search. To identify literature on designing and realizing DDBMs, we considered only articles that focused on this topic. This means we considered only articles that focused on DDBM design and realization. In particular, we found three insightful structured literature reviews [3, 4, 8], six theoretical framework, method, and concept-building articles [5, 14, 17, 18, 19, 20], and two empirical studies [21, 22]. As part of a structured literature review, Günter et al. [8] presented an example of a European postal service organization failing to realize its DDBM, highlighting common pitfalls. Elevating the research on process models and frameworks, Schüritz and Satzger [14] derived patterns for DDBMs. Similarly, Hartmann et al. [5] proposed a framework for DDBMs used by startup firms. An architectural and transformative perspective was taken by Vanauer et al. [18], who developed a methodology for realizing DDBMs drawing on enterprise architecture management and business model generation techniques. Dedicated empirical research was conducted by Chen et al. [22] during the transformation of the Lufthansa BM, emphasizing critical success factors for the pathway taken by the airline. Similarly, Najjar and Kettinger [21] conducted a case study based on a U.S. retailer realizing DDBMs. The data monetization journey was described in four stages of data value realization. However, both studies were only single case studies.

The literature on DDBMs is still in its infancy. A limited number of articles address this topic with most contributions emerging within the past 5 years [3, 4]. The design and realization of DDBMs in particular, which was addressed by only two articles, lack empirical research [3]. We complement the literature with empirical research on multiple cases from global companies.

9.3 Research design

9.3.1 Method

The goal of this study is to reveal pathways companies take to design and realize DDBMs. Drawing on Gregor's work, we want to explain "why" and "how" companies embark on realizing DDBMs [23]. Considering the novelty of DDBMs for academia and practice, we planned to conduct qualitative research. Our approach was to derive theory drawing on the ideas of grounded theory proposed by Corbin and Strauss [24]. We conducted semi-structured interviews with experts from consulting and industry firms to develop a causal theory on DDBM endeavors. Each interviewee has a track record of data monetization projects. We analyzed the data as we collected them. We adjusted the interview guide based on our experience from the first meetings and again after one third had been conducted in step with the insights we gained. Choosing a semi-structured interview approach gave us the opportunity to set the direction of the research as we collected the data. Drawing on Myers and Newman' recommendations allowed us to foresee common pitfalls of qualitative interview research [25].

The unit of analysis is a company case for designing and realizing a DDBM. A case can comprise multiple projects, and multiple cases can occur within one company. With the goal of understanding what pathways companies choose, we structured the interview questions regarding two phases: designing and realizing DDBMs. These phases were derived from the literature on designing and realizing DDBMs [18, 19]. We refined the questions as we proceeded. The interviewees reported on their previous DDBM projects. First, they described the background and context of the project. Then we asked about their approach to DDBM design, before tapping into the DDBM realization phase. We documented the interviewees' experiences in case examples.

9.3.2 Data

Between November 2019 and May 2020, we conducted 16 semi-structured expert interviews. All interviews were recorded, transcribed, and coded by the authors. Except for IP5, which was a physical meeting, all interviews were conducted remotely via internet communication tools. We started with an initial list of interviewees leveraging our professional network, who named well-fitting candidates with expert reputations. This allowed us to get a set of practitioners with diverse cultural, gender, and regional perspectives. The interviewees have extensive experience in cross-industry firms as well as consulting firms with different specialization, and included participants from leading consulting companies such as McKinsey, Bain, and Boston Consulting (MBB), as well as the Big Four companies and large IT consulting firms. We included practitioners from various levels but focused on senior management after the first results demonstrated their broader perspective on the perceived factors (less senior tend to focus on one work package). We acknowledged that the interviewees have different backgrounds and expertise, and we modified the questions as required. For example, interviewees had either a stronger business or IT view on the cases they reported. Analyzing the interview data as we proceeded and asking for additional interviewees allowed us to look for specific experiences, which we might have missed. For example, after the eighth interview, we acknowledged a regional limitation as we collected only European cases. We then specifically asked for cases outside Europe. Similarly, we emphasized the female perspective after taking into account the male dominance. The participant list is shown in Table 7.

Table 7. Interview participants.

IP	*Role*	*Organization*	*Experience*
1	Senior Manager	IT Consulting	+ 8 years
2	Director	IT Consulting	+ 20 years
3	Senior Manager	IT Consulting	+ 10 years
4	Director	Insurance Co.	+ 20 years
5	Director	MBB	+ 12 years
6	Senior Manager	MBB	+ 10 years/ PhD

7	Director	MBB	+ 20 years/ PhD
8	Consultant	IT Consulting	+ 4 years
9	Director	IT Consulting	+ 15 years/ PhD
10	Director	IT Consulting	+ 20 years
11	Director	IT Consulting	+ 15 years/ PhD
12	Senior Manager	IT Consulting	+ 10 years/ PhD
13	Director	Public Services	+ 12 years/ PhD
14	Senior Manager	Financial Services	+ 10 years
15	Senior Manager	Big Four	+8 years
16	Senior Manager	Life Science	+ 8 years/PhD

The interviews were scheduled for 60 minutes. Depending on the course, the interviewee reported one or two cases. We asked for "success" and "failure" cases, referring to designing and realizing DDBMs. Success constitutes the delivery of the project within time, scope, and budget. At the end of each interview, we asked for publicly available data sources for triangulation. Furthermore, we applied internet research to gather additional triangulation data.

9.3.3 Analysis

To construct a coherent theory based on the gathered data, we draw on the grounded theory as proposed by Corbin and Strauss [24]. We applied an open coding approach and selected ATLAS.ti for tool support. Not having a specific framework in mind, we conducted the interviews openly. However, we structured the questions in terms of the DDBM design and realization phases [18, 19]. To uncover relations among the categories, we reassembled the data that had been broken up during the open coding. For this, we applied axial coding as described by Corbin and Strauss [24]. Based on the factors the interviewees described about the case context and the steps for designing and realizing DDBMs, we refined the questions and built theoretical constructs. Dimensions mentioned frequently within the analysis of the first set of data were asked about specifically in the following interviews. After the ninth interview, we were able to build clusters for the collected cases. We used the remaining interviews to test the case cluster with the interviewees.

We acknowledge the threats to validity. Considering the four types of validity as described by Maxwell [26], we put great effort to ensure the interviewees could speak openly and were not in a conflicting situation. The developed concepts were critically assessed by both authors. We triangulated the interview results with publicly available data.

9.4 Results

In this section, we present an overview of the cases, and then we describe the context and the "why" behind the endeavors. Following that, we summarize the pathways identified for designing and realizing DDBMs, which describes the "how."

9.4.1 Insights from expert interviews

Discussing the definition of a DDBM with the interviewees revealed practitioners' differing interpretations of this term. Analogous to the perspectives in the literature, some interviewees shared our view of a DDBM as a new BM with data as the key resource and/or data processing as a key activity. Others interpreted the gradual enhancement of the traditional BM with data as a DDBM as well. The latter group used the term data monetization as a synonym, stating the meaning as "maximization of data's commercial value" [IP9]. However, it transpired that even for this group the ultimate goal of DDBM projects is the establishment of new BMs. Our definition of DDBM did not change, but we acknowledge that the gradual enhancement of the traditional BM can be interpreted as a transitional step toward a DDBM. When we asked the interviewees about the DDBM cases they had experienced, they highlighted the scarcity of DDBM cases in line with our interpretation. Most DDBM cases reported imply the ambition for a new BM centered on data but started with use cases (UCs) focusing on the enhancement of the existing BM. As an explanation for this phenomenon, the interviewees emphasized that "improving the existing services, products, and operations is more obvious to the business, easier to grasp, and bears less risk" [IP11]. Only four cases described the establishment of a new DDBM.

The companies behind the reported cases are large regional and global players whose origin and main business are in Asia Pacific, Europe, and North America. Two of the four DDBM cases described European firms, and two described Asian Pacific firms. The majority of the cases were in the insurance, financial services, and life sciences industry. The projects were sponsored either directly by the chief executive officer (CEO), through a joint sponsorship between the business unit (BU) and the chief information officer/chief digital officer (CIO/CDO), or by only the BU or CIO/CDO. The interviewees reported that the endeavors were motivated by a clear business opportunity, a common vison for the company, their digital strategy, the BU vision, or as a competitive response. Four financial sources were described. The first was the business unit budget, which is relatively small compared to the other sources but is under full control of the business unit. The second was the budget allocated to the digital transformation of the organization, comprising multiple digital initiatives. The third was investments in the entire organization to transform toward a common vision. The fourth was investment in the exploitation of new business opportunities. The business unit initiating the project chose the expected value and application of the data. The case list is shown in Table 8.

9.4.2 Case clusters

Among all interviews, two contextual dimensions determined the case clusters: the degree to which the data were understood and the degree of self-incentive. These two dimensions allow the allocation of the cases into four quadrants. For cases within the same cluster, we noticed correlations between the motivation to initiate the endeavor, the sponsoring entity, the lever of data value, and the funding allocation.

Table 8. Case list.

C	*IP*	*Industry*	*Reg./Glo.*	*HQ*	*Motivation*	*Sponsor*	*Funding*
1	IP1	Insurance	Local	D	Digital strategy	CDO/CIO	Digital transformation
2	IP2	FS	Global	AUT	Digital strategy	CDO/CIO	Digital transformation
3	IP2	FS	Global	AUT	Competitive response	CDO/CIO	Digital transformation
4	IP3	Insurance	Global	D	Digital strategy	CDO/CIO	Digital transformation
5	IP4	Insurance	Global	CH	Competitive response	CDO/CIO	Digital transformation
6	IP5	FS	Global	CH	BU vision	Head of M&S and CDO	BU budget
7	IP5	FS	Global	CH	BU vision	Head of HR	BU budget
8	IP6	IE	Global	D	Company vision	CEO	Trans. budget
9	IP7	Insurance	Global	CHN	Clear business opportunity	CEO	New business opportunity
10	IP8	Chemicals	Global	D	Digital strategy	CDO/CIO	Digital transformation
11	IP9	LS	Global	CH	BU vision	Head of R&D and CDO	BU budget
12	IP9	LS	Global	D	BU vision	Head of M&S and CDO	BU budget
13	IP10	Insurance	Local	US	Digital strategy	CDO/CIO	Digital trans.
14	IP11	FS	Global	AUS	Clear business opportunity	CEO	New business opportunity
15	IP12	Energy	Local	D	Clear business opportunity	CEO/CIO	New business opportunity
16	IP13	PS	Local	D	Digital strategy	CDO/CIO	Digital transformation
17	IP14	FS	Global	CH	Digital strategy	CDO/CIO	Digital transformation
18	IP15	LS	Global	D	Digital strategy	CDO/CIO	Digital transformation
19	IP16	LS	Global	UK	BU vision	Head of R&D and CDO	Trans. budget

FS= Financial Services; IE= Industrial Equipment: LS= Life Science; PS= Public Services

Cases comprising companies with high data understanding and low self-incentive (see Figure 11: quadrant I) start the journey toward a DDBM by developing use cases for BDA. The initiatives are funded by the business units which also have the analytical capabilities. These companies tend to develop use cases in a lab environment with external parties to justify larger investments once the value was proven. The endeavor is motivated by the BU's vision and sponsored by the BU lead with support from the CIO/CDO. Cases comprising companies with low data understanding and high self-incentive (see Figure 11: quadrant II) invest in the technology first. These companies have little understanding of their data and potential application fields but have decided to heavily invest in BDA as part of their digital initiatives. Great effort is made to understand technology options and solution functionalities. However, the BDA use is described with short use cases, and the technology selection is prioritized. The endeavor is sponsored by the head of the IT department and funded by the budget for the digital transformation. Companies with low data understanding and low self-incentive (see Figure 11: quadrant III) remain in a pending state. They invest in use case development within the business units and conduct software selection projects but do not take the next step toward a DDBM. These companies tend to initiate cases reactively as a competitive response and under digital pressure. On the opposite side are cases in companies with a high degree of data understanding and self-incentive (see Figure 11: quadrant IV). Having a clear vision and deep analytical capabilities allow these companies to invest in new DDBMs immediately. The initiatives are sponsored by the CEO and financed with funds for new business opportunities. The new DDBM is either integrated into the existing organizational structure, or a new company is established putting the new DDBM forward as a startup. Use case– and technology-centric cases have the ambition to develop DDBMs as goal, “BDA projects pave the way for DDBM” [IP2]. Similar statements were made by IP1, IP3, IP4, IP8, and IP9. We received use case descriptions from IP1 and IP9. The use cases for gradual enhancement of the traditional business model were very detailed, but the potential new DDBMs were described on a higher level. Furthermore, the realization of the use cases was suggested in a sequence beginning with the enhancement of the traditional BM and introducing the DDBM as a so-called “north star.” For example, the use case of a pharma company for data-driven automation that would lead to cost optimization was described in detail with quantifications, but the use case that would imply a new DDBM was outlined with less detail and quantification ranges [IP9].

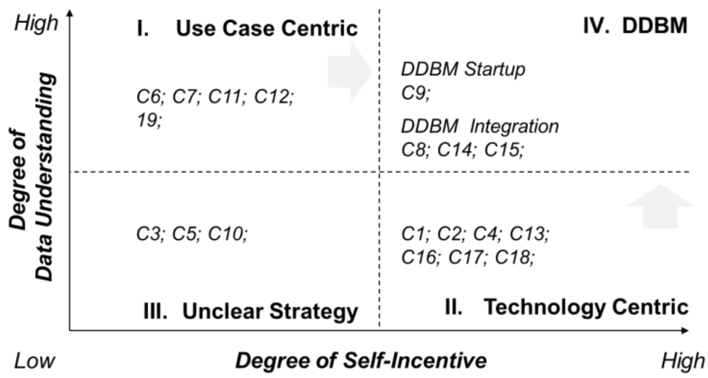

Figure 11. Case clusters.

9.4.3 Pathways for DDBM design and realization

The interviewees described the approaches that were taken to gain value from data. We identified four pathways. For quadrant I cases, we theorized a use case–centric pathway. Similarly, we derived a technology-centric pathway for quadrant II cases. Cases in quadrant III did not demonstrate a clear approach; they remained in a vague state not proceeding with a clear strategy for design and realization. For quadrant IV cases, two distinct pathways were reported by the interviewees. The companies in these cases either integrated a new DDBM into their existing structure or established a new company dedicated to driving the DDBM in a startup setup.

Use case centric. Beginning with the use cases implies the vital role of the BU in the pathway, who fund the initial efforts with their budget (see Figure 12). Use cases are often ideated, selected, and prioritized with external support. Often, consultants bring in use case catalogues from various industries and additional capacity. Ideally, the use cases are sequenced in order to allow gradual development of the required capabilities. Based on the identified use cases, a solution architecture is designed considering existing data resources, technological and analytical capabilities, as well as organizational and structural enablers. A minimum viable product (MVP) is developed in a lab environment to test the feasibility. Once the MVP is approved by the leadership, the implementation begins with the IT driving the process. Collaboration between the business unit and the IT department during the process is crucial for successful MVPs. For example, IP 5 provided two cases with the same client but with different BUs. The case with marketing and sales had early and extensive IT involvement which in the end made the MVP successful and led to implementation.

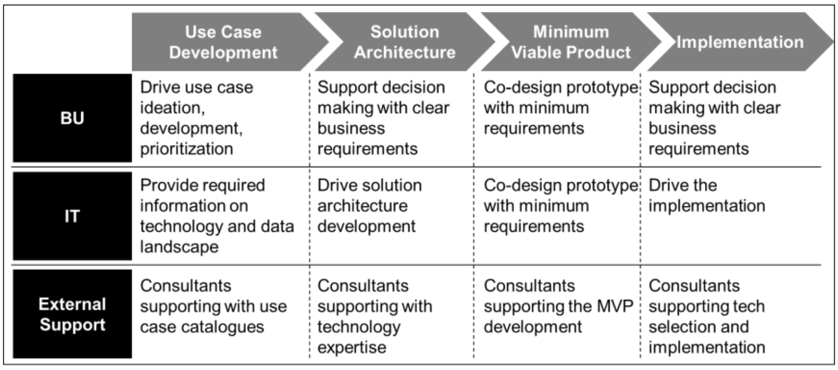

Figure 12. Use case centric.

The theorized approach was grounded in five cases within the life science and financial service industry of which one is in the transition from solution architecture toward an MVP (C12) and one in the UC development stage (C19). The latter is concerned with the R&D BU of a life science company that leverages data to identify biomarkers for clinical trials. The focal company acquired a niche firm for identifying data-driven biomarkers and struggled with integration efforts and parallel use case development [IP16].

Technology centric. Companies beginning with technology capability development decided to invest heavily in BDA platforms as part of their digital strategy. The business requirements are blurry and poorly derived from high-level use cases. The process is initiated with technology selection efforts, considering internal and external capabilities (see Figure 13). Within this phase, a request for proposal (RFP) is addressed to providers which have been selected by external consultants. Technology is selected with limited understanding of the business requirements. The second phase is the proof of concept conducted with the preferred vendor and with the second-best choice put on hold. Subsequently, the implementation follows. Selecting the most sophisticated solution to provide best-in-class technology capabilities was stated as a common strategy. For example, a financial services company decided to invest in a BDA platform as part of their digital strategy for data-driven banking. The decision to implement Hadoop as the most sophisticated platform was made without extensive technology fit assessments. The use cases for the data lake utilization were detailed out during the project. As it turned out, the implemented solution was very advanced and not required for the developed use cases. The interviewee highlighted "the investment was not justified" [IP2].

The approach illustrated in Figure 13 was derived from seven cases, each describing the three phases. However, we want to give one more interesting example within the public services industry. As part of smart city initiatives, many sensors have been implemented within a Germany city. The funds were made available for this purpose by the government as part of their smart city strategy. The interviewee and his team were in the process of implementing a platform to leverage the increasing data sources for enhanced and new services. Use cases were developed at a high level, for example, for navigating within the city for blind people, or tracking and dynamically planning the routes for garbage and clothes collection [IP13].

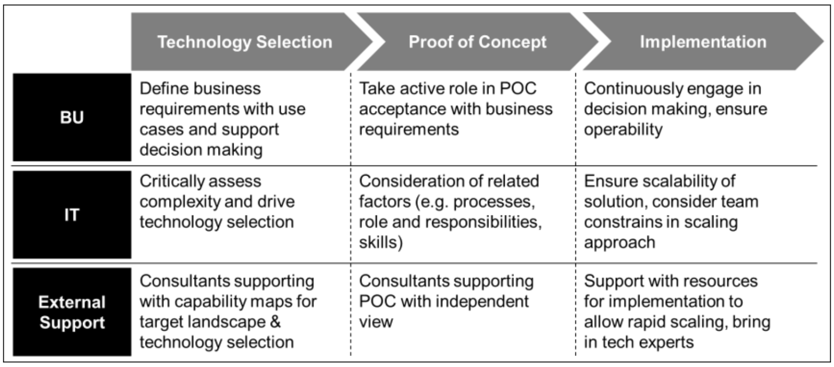

Figure 13. Technology centric.

DDBM integration. Transforming an organization to integrate the new DDBM into existing structures requires a clear business opportunity, a common vision, and CEO sponsorship. Based on the cases the interviewees reported, we theorized a three-phase process (see Figure 14). It begins with the DDBM design, which is supported by external consultants infusing the ideation process with relevant industry and cross-industry DDBM cases. This process step results in a populated BM comprising the relevant fact of the identified business opportunity. Based on this design, an MVP is initiated presenting early tangible results. Once the MVP reaches certain maturity, it gets passed to the implementation stage, where the developed product is scaled for commercialization. The pathway is grounded in three cases we gathered. First, a German industrial equipment company identified new data-driven services as a future opportunity. The vision was developed with management consultants, enabling the firm to complement their device-centered BM with new data-driven services for maintenance and value-based pricing [IP6]. Second, a global Australian bank was approached by management consultants with an opportunity to sell banking transaction data for targeted offerings. The bank designed a DDBM with the consulting firm and developed an MVP in a trial-and-error approach. Presenting agile and iterative results shortened the time to market [IP11]. Third, an energy provider decided to develop a data monetization platform, allowing customers to purchase data-driven services and service providers to offer services enriched with energy consumption data. This decision to monetize data was motivated by shrinking revenues in the energy industry and technology advancements, such as smart meters, which became a European standard. Anonymized energy consumption data open up many business opportunities for various industries. For example, disaggregating the energy consumption data of an elderly person allows conclusions to drawn if the oven was turned on for more than 3 hours. The DDBM was designed with the BMC for platform economies, which incorporates multisided customer and provider perspectives. The interviewee reported that the project is ongoing and transitioning toward the development of an MVP [IP12].

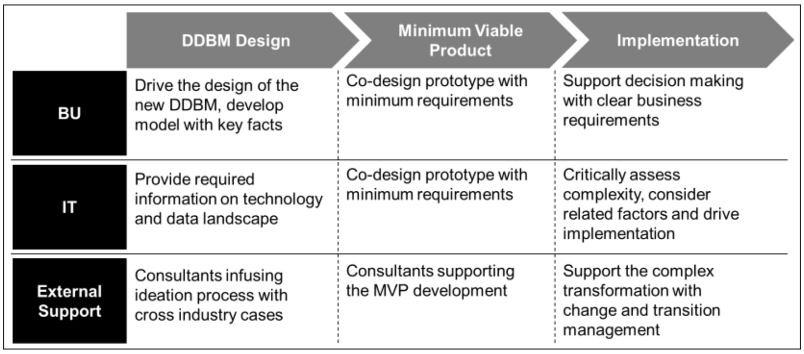

Figure 14. DDBM integration.

DDBM startup. In contrast, the establishment of a DDBM through a new company requires a different approach (see Figure 15). However, a clear business opportunity and CEO sponsorship are vital here as well. Having a clear understanding of the data and its monetization opportunity paired with willingness to invest allow new revenue streams to be harvested. This boldness leads to the decision to set up a new company. The capabilities are built up from scratch. Ideally, the new subsidiary remains completely separate, conceptually and spatially. Access to the data is granted through APIs. The team works in a startup fashion with end-to-end responsibilities from designing the DDBM to realizing it. We used the term realization to emphasize the difference between the implementation phase in an enterprise, which is often conducted by the IT department. In contrast to the previous pathways, there are no conceptual breaks during this process caused by consulting firm or organizational handovers. For example, an insurance company headquartered in China decided to monetize their 10 years of insurance data from 650 million clients. Based on this idea, a company was established with newly hired employees. A team of 20–30 members with special capabilities worked on the DDBM from design to realization in an agile startup fashion. The DDBM was detailed during the process resulting in an MVP that was discussed early with potential clients. Data were extracted from the parent company as required. The architecture was designed to allow rapid scaling with minimum effort. The interviewee highlighted the importance of keeping the company separate and not using the prevailing infrastructure and capabilities of the parent company. This would increase cost and complexity, and furthermore, the team would not have had the innovation level that such an endeavor requires [IP7].

Separating the DDBM into a new startup at a later stage might be possible but implies many challenges. Therefore, we want to emphasize three important considerations for the decision to set up a new company. We revisit the DDBM integration case with an energy provider mentioned above where these considerations are under discussion. The first consideration is human capital. The DDBM was designed by an internal company team who claimed to proceed with the realization. The team lead persisted to retain his team members. However, it was questioned whether they had the required skillset to ramp up the DDBM in an agile startup way. The second consideration was the technology landscape. The DDBM design was based on the prevailing IT architecture, which turned out to be a threat for DDBM scaling due to legacy systems and other architectural constraints. The third consideration was the ecosystem. The new DDBM required collaborations with partners but also competitors. To disaggregate energy consumption data, the focal company required energy profile data from various device manufacturers. Furthermore, to train the algorithms with rich test data sets, the focal firm depended on smart meter data from other energy providers.

	New Company Setup	DDBM Design	DDBM Realization
Sponsor	Contracting, legal requirements, hiring and new company setup	Support DDBM design by enabling the team with resources from parental company	Support DDBM realization by enabling the team w. resources from parental company
Team	Support ramp up (first hired senior manager as CEO)	Develop and align BM with required operating model & architecture; Continue hiring	Prototype early & discuss with clients, scale fast; Adjust design as requi.
External Support	Consultants supporting ramp up e.g. role descriptions and candidate screening	Consultants supporting with BM template population and operating model design	Support the complex transformation with change and transition management

Figure 15. DDBM startup.

9.5 Discussion

Conducting interviews with DDBM practitioners from around the globe allowed us to report the gathered cases in a descriptive way. We presented a list of 19 cases in various industries and in cooperation with varying consulting firms. Furthermore, we were able to derive pathways for designing and realizing DDBMs grounded in the empirically collected cases. The novelty of the DDBM field in academia and practice makes this research unique and of great value to both.

Following academia's call for empirical research and practitioners' demand for reference cases, we presented 19 cases. The results complement the existing literature on DDBM methods and concepts [14, 17, 18, 19, 20]. Two recent literature reviews on DDBMs revealed the gap in detailed design and realization knowledge [3, 4]. We complement the literature by presenting four pathways of DDBM innovation. These pathways deepen the knowledge of DDBM processes and can refine the method suggested by Vanauer et al. for designing and realizing DDBMs [18]. The research on DDBM tool support conducted by Kühne and Böhmann can also be enriched with the proposed pathways and interview results, as we provide detailed knowledge of the approaches taken for DDBM design and realization [20]. During the interviews, it transpired that "value is often generated with DDBM, the important question is if the potential revenue streams behind the DDBM leads to profitable operations considering the associated costs" [IP13].

Several important practical recommendations emerged in the expert interviews. Although interviewees reported about pathways, they stressed the importance of specific considerations that had a great impact on the course of the DDBM cases. We believe sharing these important considerations allows practitioners to navigate the DDBM journey and gives researchers insights into practice. In the following, we present these important practical recommendations for each pathway (see Table 9).

Companies taking the use case–centric pathway benefit from central organization of the use cases. BUs tend to operate independently from each other and develop MVPs in lab environments that cannot be implemented in production due to the effort exceeding the potential value. Early and continuous involvement of the IT department can prevent the latter, especially when it comes to considering prevailing data assets, technology capabilities, and infrastructure. Use case realization should be sequenced considering the required and existing capabilities. Teams should have end-to-end responsibility to prevent conceptual breaks due to handovers and external party fluctuation.

Taking the technology-centric pathway requires a clear understanding of the business requirements for the BDA platform, as well as continuous BU involvement during the technology selection process. The decision to invest in a D&A platform should be critically assessed in terms of the requirements. Furthermore, it is vital to conduct the technology selection provider agnostic. A critical assessment of the complexity and the effort for the potential transformation is essential. This includes a view on the effort to scale the solution for the business need, as well as the effect on the business model, operating model, processes, skills and talents.

Integrating the new DDBM within existing organizational structures requires a complex transformation. Senior management support is vital to ensure the thriving business model is not smothered by the traditional business model, especially when it comes to data access across the organization. The prevailing processes, applications, and infrastructure must be understood. A clear design for the target state of the organizational and technological structures is vital. Efforts for developing talent, skills, and processes should not be underestimated. Breaks from the organizational vision over business model design and realization should be minimized.

Establishing a new data-driven company brings many opportunities which should be well exploited. Separating the new company from the parental company was mentioned as the most important factor. This includes minimization of the parental infrastructure and capabilities. The team should be newly hired with talents matching the demand of a startup for highly skilled and innovative roles. End-to-end responsibility and agile ways of working are key requirements for the team. Results should be discussed early in the process with the client, ensuring a co-design of the data products and services. The architecture of the new company has to be designed for rapid scaling.

Table 9. Practical recommendations.

Pathway	***Practical recommendations***
Use case centric	- Centrally coordinate use cases - Sequence use cases to allow gradual capability development - Consider implementation efforts in MVP phase - Consider prevailing technology landscape, processes, and analytical capabilities - Minimize conceptual internal organizational and consulting firm breaks (handovers) - Involve IT early and continuously
Tech. centric	- Set clear business requirements - Continuously involve the BU(s) - Conduct provider-agnostic technology selection - Critically asses the investment decision - Consider related factors (e.g., processes, role, and responsibilities, skills) - Critically asses the complexity
DDBM integration	- Ensure senior management support - Consider prevailing technology landscape, processes, and analytical capabilities - Consider transformation effort from structural, process, skill, and technology perspectives - Consider impact of dominant/traditional business model - Consider innovation level of team members - Minimize conceptual internal organizational and consulting firm breaks (handovers)

DDBM startup	- Separate new DDBM firm from parent company conceptually and spatially - Minimize utilization of parent company capabilities and infrastructure - Design an enterprise architecture ready for rapid scaling - Ensure end-to-end responsibility - Establish agile ways of working with early client involvement for prototype testing

9.6 Conclusion and outlook

Data have proven their value as a key business driver. The latest technology advancements have further elevated the importance of data for operational efficiency, business development, and innovation. However, DDBMs is a new field of research with little empirical research [3, 4, 22]. Building on a grounded theory approach, we identified four pathways for designing and realizing DDBMs. To achieve this goal, we conducted 16 semi-structured interviews with experts from consulting and industry firms. The contributions of this study are twofold. First, we provided a descriptive overview of 19 cases representing the journeys companies take for designing and realizing DDBMs. For this, we gathered the perspectives of a diverse set of practitioners revealing their understanding of DDBMs and the relation to intermediate BDA projects for DDBM introduction. Second, we theorized the causality between the "why" and "how" of DDBM design and realization. Case clustering was proposed, taking the reported dimensions into account. Within the case clusters, the pathways companies take for DDBMs were derived.

The results of this research have implications for academia and practice alike. For academia, we contribute to the gap in the literature and gathered 19 cases for DDBM design and realization, providing empirical insights. The pathways lay the foundation for scholars to expand the thriving literature on DDBM design and realization. For practitioners, the results serve as guide to navigate through the unexplored field of DDBM design and realization. It helps to understand the state of the art and the selection of an approach to DDBMs. Furthermore, common challenges and important considerations can be foreseen, learning from these cases.

This study has several limitations. Drawing on Maxwell [26], we structured the limitations of this qualitative research in four types. The first limitation is evaluative. We acknowledge the threat to validity based on the dependency on individual interpretation of the reported events. Although we validated the described facts with triangulation data, the threat cannot be completely diminished. The second limitation is theoretical limitations. We applied a semi-structured interview approach to collect data with an open mind. However, this research was infused by our previous research on the topic. Therefore, the validity of the prevailing theoretical concepts imposes a threat as well. The third limitation was interpretative. The case clustering and the derived pathways are imbued with an interpretation of the data. Although both authors processed the data independently, and the results were challenged with two directors from management consulting firms, the data were subjectively interpreted.

The fourth limitation was descriptive. We acknowledge the threat to validity imposed in the description process. All results were written and interpreted by both authors iteratively. The working paper was sent to two interviewees to gather additional feedback. The number of interviews and cases was limited. However, we analyzed the data as we proceeded with the interviews. After the ninth interview, we were able to derive the case clusters and pathways. The remaining interviews were used to test the concepts.

Additional research is required to further examine the DDBM pathways to propose detailed methods for each pathway. Moreover, the intersection of DDBM and related research fields must be studied in light of the proposed pathways. Our future work will focus on the enterprise architecture modeling and management support for the pathways for designing and realizing DDBMs.

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10 How does Enterprise Architecture support the Design and Realization of Data-Driven Business Models? An Empirical Study

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Abstract. As part of the data evolution, data-driven business models (DDBMs) have emerged as a phenomenon in great demand for academia and practice. Latest technological advancements such as cloud, internet of things, big data, and machine learning have contributed to the rise of DDBM, along with novel opportunities to monetize data. While enterprise architecture (EA) management and modeling have proven its value for IT-related projects, the support of EA for DDBM is a rather new and unexplored field. Building upon a grounded theory research approach, we shed light on the support of EA for DDBM in practice. We derived four approaches for DDBM design and realization and relate them to the support of EA modeling and management. Our study draws on 16 semi-structured interviews with experts from consulting and industry firms. Our results contribute to a still sparsely researched area with empirical findings and new research avenues. Practitioners gain insights into reference cases and find opportunities to apply EA artifacts in DDBM projects.

Keywords: Data-driven, business model, enterprise architecture.

10.1 Introduction

Data has received considerable attention from business and academia. Latest technological advancements such as cloud, internet of things, big data, and machine learning have contributed to the rise of data-driven business models (DDBM) as an emerging phenomenon [1]. DDBMs are characterized by data as a key resource, data processing as a key activity, or both [2, 3]. Novel opportunities appear for organizations to monetize their data. Especially incumbent companies, resting on tremendous amounts of data, are expected to develop new and transform existing business models. However, the failure rate of big data and artificial intelligence projects remains disturbingly high [4].

Considering the high dependency on big data analytics, DDBM deployment implies information system design and implementation, which requires different support in design and realization compared to offline business model innovation [5]. Introducing new DDBM requires deep intervention in the entire organizational structure. The current (as-is) architecture must be well understood and the desired target (to-be) architecture, embedding the DDBM, must be crucially planned. The enterprise architecture (EA) practice is concerned with the aforementioned. EA has proven its potential in many IT-related projects and is deeply rooted in the information system body of knowledge. By providing artifacts such as meta models, frameworks, and management methods, EA supports transparency building on an organization's key components, from business, data, application to the technology level. Furthermore, EA helps to manage the architecture towards common vision [6].

Research on DDBMs is still in its infancy, with most contributions emerging in the past five years [1, 5]. Practitioners face several challenges in DDBM deployment [4, 7], from identifying relevant opportunities, proceeding with evaluation and ultimately implementing the DDBM [5]. Scholars have started to combine the two lenses of EA and DDBM in order to support DDBM deployment [3]. However, existing literature has examined the intersection from a conceptual standpoint. In this paper, we question the underlying assumption of the existing literature about how EA can be beneficial for DDBM design and realization by conducting empirical research. We want to investigate how EA modeling and management supports DDBM design and realization in practice. Accordingly, our study focuses on the following research question: How does enterprise architecture support the design and realization of data-driven business models? To answer this question, we conducted 16 semi-structured interviews with experts from consulting and industry firms working on DDBM projects in North America, Europe, and the Asia Pacific. Based on these interviews and triangulation data from publicly available sources, we collected 19 cases. We derived four approaches for DDBM design and realization and present for each the support from EA modeling and management.

In the next section, we provide an overview of the theoretical background and related work in the intersection of EA and DDBM. We then describe how we conducted the semi-structured interviews. The cases we gathered will be presented before describing the approaches for DDBM deployment and EA support along the process. Ultimately, we discuss our findings and conclude by discussing future research avenues.

10.2 Background and Related Work

10.2.1 Big Data Analytics and Data-Driven Business Models

The research on big data is deeply rooted in the information system discipline [7–10]. However, the term under which it was examined has evolved in the past decades from business intelligence, business analytics, and big data to big data analytics (BDA) [11]. In this context, the potential value contribution of data has been researched in three major areas, namely improved decision making, enhanced products and services, and new business models [12]. For the latter, the latest technological advancements have contributed to the urge for new DDBMs. Since 2014, a significant number of papers have been published dealing with the need for DDBM research [1]. Accordingly, several definitions of DDBM have been proposed by scholars. All point out that data has to be an essential component of the business model. For example, Hartmann, Zaki, Feldmann, and Neely [2] define DDBM as "a business model that relies on data as a key resource". Bulger, Taylor, and Schroeder [13, 14] and Brownlow, Zaki, Neely, and Urmetzer [13, 14] similarly highlight the fundamental role of data for DDBMs. Since there is no clear threshold of data utilization for a DDBM, Schüritz and Satzger [15] argue that companies alter from a traditional business model to a DDBM, with increased use of data for the value proposition. In the context of our research, we distinguish between enhancements of existing business models and new DDBMs that are centered on data (data as a key resource and/or data processing as a key activity) [3]. Research on DDBM is thriving but still in an early stage [1]. The latest efforts in academia have focused on extending the most popular business model canvas framework to the special needs of data-driven businesses [2, 16, 17].

10.2.2 Enterprise Architecture

Research on enterprise architecture can be traced back to the Zachman framework from 1980, which provides an ontology for modeling the fundamental structure of an organization and its information systems [18]. Over the past decades, EA has become essential for many organizations to support technology-driven transformations as it helps maintain an overview of complex sociotechnical systems. The Federation of Enterprise Architecture Organizations defines EA as "a well-defined practice for conducting enterprise analysis, design, planning, and implementation, using a comprehensive approach at all times, for the successful development and execution of strategy" [19]. A more narrowed definition of EA has been provided by the Open Group, which is in line with the ISO/ICE/IEEE Standard 42010 of architecture definition, that is, "the structure of components, their inter-relationships, and the principles and guidelines governing their design and evolution over time" [20]. We acknowledge that researchers and practitioners sometimes refer to EA as the practice and sometimes as the actual architecture of an organization. We use the term EA for the practice comprising the related modeling techniques, frameworks, and management function within an organization (EA management). The actual architecture of an organization is noted as as-is architecture, while planned future states are called to-be architecture [3, 21]. EA has proven its potential in improving information system efficiency and effectiveness. It is a critical component for strategic planning, top management decision making, and project management [22]. EA provides artifacts, such as meta-models, frameworks, tools, guiding principles, and management methods to support the evolution of an organization towards a target state. The key components of an organization and their interdependencies are represented in EA models [23]. The models are based on meta-models and deal with either the current state (as-is) or the desired state (to-be) of the enterprise. The EA management function supports the transition from the as-is to the to-be state through several intermediate architecture stages [3].

10.2.3 Related Work

To identify the potential relevant related work on the intersection of EA and big data analytics, we conducted a literature review [24]. We queried the following databases with keyword searches: AIS Electronic Library, EBSCO Host Business Source Complete, Google Scholar, IEEE Xplore, JSTOR, Science Direct, and Web of Science. We selected the keywords “enterprise architecture” and “big data”. To further extend the literature search, the terms “data-driven” and “analytics,” which are associated with “big data” were integrated into the search as well. This led to a total of three strings (“enterprise architecture” and “big data”, “enterprise architecture” and “data-driven”, “enterprise architecture” and “analytics”) for our database queries. We screened all hits based on their title and abstract. Though it limits reproducibility, we included the first 100 search hits from google scholar as an additional source. After reducing irrelevant, duplicate, and non-peer-reviewed articles, a total of 16 articles remained, which we analyzed based on their full text. Additionally, we conducted a backward and forward search.

Table 10. Literature Search.

Database	***Hits***	***Results***	***Relevant***
AIS	10	3	0
EBSCO	5	0	0
Google Scholar	100	6	0
IEEE	35	5	2
JSTOR	0	0	0
Science Direct	13	1	0
Web of Science	14	1	0
		16	2

The results of our literature review revealed a large number of contributions examining EA support for BDA. Scholars have investigated how EA modeling and management can support the design and implementation of BDA [22, 25, 26]. However, with the objective to identify articles focusing on EA support for DDBM, only two contributions remained. First, Vanauer et al. presented a methodology for DDBM design and realization by combining EA and business model canvas techniques. Their theoretical methodology comprises two phases and addresses two different approaches for DDBM deployment. Second, Rashed and Drews have conducted a systematic literature review to illustrate the potential support areas of EA for DDBMs. Furthermore, they have derived 42 DDBM-related EA concerns structured along the business model canvas fields [3]. Both contributions highlight the vast potential of interlinking the rich discipline of EA with the emerging demand of DDBM. However, both articles are purely conceptual with no empirical grounding. We address this research gap an examine EA modeling and management support for DDBM design and realization with a qualitative-empirical study.

10.3 Methodology

The goal of our study is to empirically examine the support of EA modeling and management for DDBM design and realization. Considering the novelty of DDBM for academia and practice, we planned to conduct an explorative qualitative study. Our approach is to derive theory by building upon the grounded theory approach proposed by Corbin and Strauss [27]. We conducted semi-structured interviews with experts from consulting and industry firms to develop explanatory theory, the second type of theory according to Gregor [28]. Each interviewee has a track record of data monetization projects. The data was analyzed as we proceeded with the data collection. We adjusted the interview guide based on our experience from the first interviews and once again after one third was conducted. Choosing a semi-structured interview approach allowed us to set the direction of our research as we collected the data. Drawing on the recommendations from Myers and Newman allowed us to foresee common pitfalls of qualitative interview research [29].

The unit of our analysis are cases of companies that design and realize DDBMs. To understand how EA modeling and management support DDBM design and realization, we structured our interview questions along two phases, namely DDBM design and realization. These phases have been derived from the literature on DDBM design and realization [30, 31]. We sharpened our questions as we proceeded. In the interviews, we asked the participants about the background and context of the project, the general support from EA, and the DDBM design and implementation phase. We documented their experience along with the case examples.

Between November 2019 and May 2020, we conducted 16 semi-structured expert interviews. All interviews have been recorded, transcribed, and coded by the authors. Except for IP 5, which was a physical meeting, all remaining interviewees have been conducted remotely via internet communication tools. We started with an initial list of interviewees leveraging our professional network, who named well-fitting candidates enjoying expert reputation. Each interviewee has a track record of DDBM projects. This allowed us to get the perspectives of cultural, gender, and regional diverse set of practitioners. Our interviewees have extensive experience in cross-industry firms as well as consulting firms with different specialization. This includes candidates from leading consulting firms, namely McKinsey, Bain, Boston as well as big four companies and large IT consulting firms. We included practitioners from various levels but focused on senior management after the first results demonstrated their broader perspective on the perceived factors (less senior tend to focus on one work package). We acknowledged that our interviewees have different backgrounds and expertise, we adjusted the questions as required. For example, our interviewees had either a stronger business or IT view on the cases they reported. Analyzing the interviewees as we proceeded and asking for further interview candidates allowed us to look for specific experiences, which we might have missed. For example, after the eighth interview, we acknowledged a regional restriction having only European cases collected. We then specifically asked for cases outside of Europe. Similarly, we emphasized the female perspective after taking into account the male dominance. An overview of the candidates' list is illustrated in Table 11.

The interviews were scheduled with a length of 60 minutes. Depending on the course, the interviewee reported from 1 or 2 cases. We asked for "success" and "failure" cases, referring to the DDBM design and realization. Success constitutes the delivery of the project within time, scope, and budget. In the beginning of each interview, we defined the term DDBM and elaborated on the type of cases we were looking for. At the end of each interview, we asked for project documentation and publicly available data sources for triangulation. Furthermore, we applied internet research to gather additional triangulation data.

To construct a coherent theory based on our gathered data, we drew on grounded theory as proposed by Corbin and Strauss [27]. We applied an open coding approach and selected ATLAS.ti for tool support. Not having a specific framework in mind, we conducted the interviews openly. To uncover relationships among the categories, we reassembled the data that was fractured during open coding. For this, we applied axial coding as described by Corbin and Strauss [27]. Based on the EA support our interviewees described along with the case context and taken steps for DDBM design and realization, we further specified our questions and built theoretical constructs. Dimensions that reached great density within the analysis of the first data were asked specifically for in the following interviews. After the ninth interview, we were able to derive four types of approaches for the collected cases. We used the remaining interviews to test our case cluster with the interviewees.

Table 11. Interview candidates.

IP	***Role***	***Organization***	***Experience***
1	Senior Manager	IT Consulting	+ 8 years
2	Director	IT Consulting	+ 20 years
3	Senior Manager	IT Consulting	+ 10 years
4	Director	Insurance Co.	+ 20 years
5	Director	MBB	+ 12 years
6	Senior Manager	MBB	+ 10 y/ PhD
7	Director	MBB	+ 20y/ PhD
8	Consultant	IT Consulting	+ 4 years
9	Director	IT Consulting	+ 15y/ PhD
10	Director	IT Consulting	+ 20 years
11	Director	IT Consulting	+ 15y/ PhD
12	Senior Manager	IT Consulting	+ 10y/PhD
13	Director	Public Services	+ 12y/PhD
14	Senior Manager	Financial Services	+ 10 years
15	Senior Manager	Big four	+8 years

16	Senior Manager	Life Science	+ 8y/PhD

We acknowledge the threats to validity. Considering the four types of validity as described by Maxwell [32], we put great effort to ensure our interviewees can speak openly and are not in a conflicting situation. The developed concepts were critically assessed by both authors. We triangulated the interview results with project documentation and publicly available data. Furthermore, we discussed our results with four of our interviewees in a second iteration. These interviewees were: IP4, 7, 11, and 13, who reported voluntarily. Their feedback was used to further sharpen our derived design and realization approaches for DDBM. However, we received great support for the developed concepts from these directors and senior managers within industry and consulting firms.

10.4 Results

In this chapter, we will first present an overview of the cases that were discussed in the interviews. Second, we describe the reported approaches for DDBM design and realization. Third, the support of EA modeling and management is illustrated for the identified approaches.

10.4.1 Case Overview

Discussing the terms DDBMs and EA at the beginning of our interviews was beneficial for our detailed debates. Furthermore, it gave us an understanding of the divergent interpretation of the term DDBM by practitioners. While some share our view of DDBM as new business model with data as a key resource and/or data processing as a key activity, others interpret the gradual enhancement of the existing business model with data as DDBM as well. Four cases represent DDBMs in line with our interpretation. Our interviewees highlighted the scarcity of latter mentioned cases, as they require a "clear business vision, well understood data and the technological backbone" [IP7]. The remaining cases represent organizational endeavors to gradually enhance technological and analytical capabilities to build the foundation for DDBMs. The term EA was clear to all interviewees. However, in most interviews, we had to emphasize that the EA practice goes beyond the EA department established within an organization. This means, even without the involvement of the mentioned department, EA artifacts can support the DDBM design and realization.

Table 12. Case list.

C	*IP*	*Industry*	*Reg./Glo.*	*HQ*	*Motivation*	*Sponsor*
1	IP1	Insurance	Local	D	Digital strategy	CDO/CIO
2	IP2	FS	Global	AUT	Digital strategy	CDO/CIO
3	IP2	FS	Global	AUT	Competitive response	CDO/CIO
4	IP3	Insurance	Global	D	Digital strategy	CDO/CIO
5	IP4	Insurance	Global	CH	Competitive response	CDO/CIO
6	IP5	FS	Global	CH	BU vision	Head of M&S and CDO
7	IP5	FS	Global	CH	BU vision	Head of HR
8	IP6	IE	Global	D	Company vision	CEO
9	IP7	Insurance	Global	CHN	Clear business opportunity	CEO
10	IP8	Chemicals	Global	D	Digital strategy	CDO/CIO
11	IP9	LS	Global	CH	BU vision	Head of R&D and CDO
12	IP9	LS	Global	D	BU vision	Head of M&S and CDO
13	IP10	Insurance	Local	US	Digital strategy	CDO/CIO
14	IP11	FS	Global	AUS	Clear business opportunity	CEO
15	IP12	Energy	Local	D	Clear business opportunity	CEO/CIO
16	IP13	PS	Local	D	Digital strategy	CDO/CIO
17	IP14	FS	Global	CH	Digital strategy	CDO/CIO
18	IP15	LS	Global	D	Digital strategy	CDO/CIO
19	IP16	LS	Global	UK	BU vision	Head of R&D and CDO

The gathered cases reflect organizational endeavors to deploy DDBMs. The companies behind these endeavors are predominantly from the insurance, financial services, and life sciences industry. This may be due to the proximity of the core business to data processing [IP7,9,11]. All companies are large size global and local players with origin in Europe, Asia, and the North America. Two of the four DDBM cases comprise European firms and two Asian Pacific firms. The business unit initiating the project was decisive for the expected value and application of the data. For example, the R&D unit of a pharma company seeks maximization of data value for drug development. This might come from shortened clinical trial phases or identification of new drugs [IP9]. Independent from the initiating business unit, CEO sponsorship and support was reported as vital for the cases. Considering the fragmented and isolated data sources throughout the company, timely data access becomes crucial. The majority of the described cases had CEO or CEO-1 level sponsorship. The quantitative analysis as illustrated in Figure 16. The companies behind all reported cases had an EA department established. However, the duties and impact varied among the companies. For 17 cases our interviewees mentioned that EA must play a vital role in DDBM design and realization. Along all cases our interviewees faced EA concerns, regarding transparency of the prevailing architecture, planning of the target architecture and/or managing the transformation from as-is to to-be state. However, for only 10 cases our interviewees stated that EA modeling and management techniques were instrumentalized.

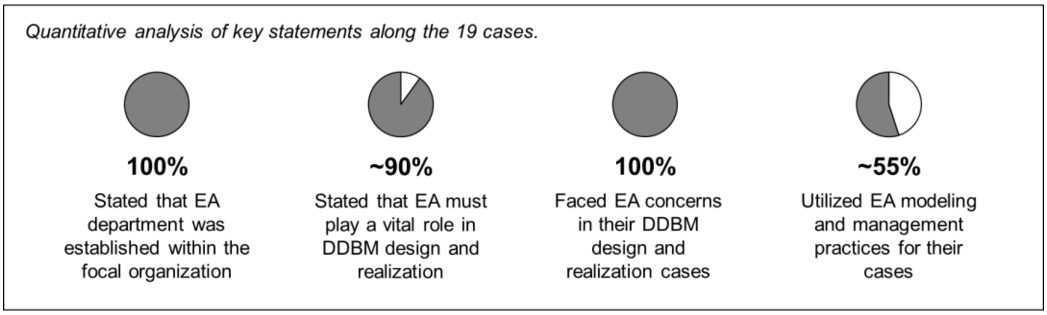

Figure 16. Key statements.

10.4.2 Approaches for DDBM Design and Realization

The support of EA depends on the company context and the approach taken towards DDBM design and realization. Across the 19 cases we have identified four approaches for DDBM deployment. The companies behind the cases, either take a gradual approach or a direct approach. For the first, they start building technology capabilities first or analyze the existing data to develop use cases for DDBMs. For the latter, they either integrate the new DDBM into the existing organizational structures or establish a new DDBM startup. All companies behind the cases had a dedicated EA management function established. Our interviewees commonly reported that EA must play a vital role for DDBM design and realization, regardless if EA fulfilled the requirements or not. With this critical role, EA can become a “bottleneck” for DDBM design and realization, and the EA management function might be actively excluded from the process. In the following, we will describe the EA support along with the four approaches for DDBM design and realization, referring to Figure 17.

Technology centric. Seven cases comprise companies that embark on the journey towards DDBM realization by developing technology capabilities first. Business requirements are blurry and derived from high-level use cases. The process is driven by the IT department and initiated with technology selection efforts. Followed by a proof-of-concept phase and ultimately the implementation. EA supports the technology selection by enabling the development of business and technology capability maps that allow an understanding of the required technologies. These models are used to map technology solutions to the target business capabilities [IP1-3, 14,15]. Furthermore, EA models were used to grant transparency on the prevailing data and technology landscape [IP1-3, 10,13]. To proceed after the proof-of-concept phase, a formal sign-off from the architecture board is required. The proposed solution must comply with the prevailing EA principles and overall target architecture [IP2,3,13-15]. EA methods and models have been used to cascade from capability domains to technology requirements. The EA management function was actively engaged by providing transparency and guidance. EA frameworks and tools have only been partially mentioned. TOGAF has been used for EA documentations [IP2,3,14].

Use case centric. Five cases represent companies that begin with the ideation, prioritization, and sequencing of BDA use cases. The use case development is driven by the business units (BUs), followed by a solution architecture development phase. The designed solution is then prototyped and tested via a minimum viable product phase, which results in an implementation in case of success. In two out of the five cases, the EA management function supported the use case development with models to provide transparency on the data and technology landscape [IP5,16]. Further EA services were required to get sign-offs from architecture boards to proceed with the implementation. EA models were developed for the solution architecture and the implementation roadmap. One consulting firm has applied a self-developed EA method to support the use case and solution architecture development [IP9]. EA frameworks and tools have not been perceived as mentionable.

DDBM integration. Three cases comprise actual DDBM deployments. The companies behind these cases transformed their existing organizational structure to integrate the new DDBM. The process is initiated with a DDBM design phase, followed by prototyping with a minimum viable product and ultimately implementation. EA models are used to provide transparency over the prevailing data and technology landscape. The models are developed by consulting firms for specific concerns. Standard EA models are only used to derive own models answering the DDBM-related EA concerns. EA models are also developed to envision the solution architecture and guide the implementation. The EA management function is actively excluded from the DDBM design and realization process. The EA services are only required to get formal sign-off from the architecture boards. EA methods, frameworks, and tools have not been perceived as a mentionable component of the design and realization phase [IP6,11,12].

DDBM startup. In contrast to the latter presented path towards DDBM design and realization, the establishment of DDBM through a new company requires a different approach. A new company must be established. The new team moves the DDBM design and realization in a startup way of working forward. The parental company provides the data. EA support is required to access the data via APIs, providing transparency over data and technology landscape. EA services are required to develop models and find solutions for data extraction. However, the EA management function is actively excluded and perceived as a bottleneck that slows down processes. The new company is staffed with technology experts, capable to design and manage the realization of the startup architecture. The importance of rapidly scalable architecture was emphasized by our interviewee [IP7]. Standard EA methods, models, and tools have not been perceived as mentionable along the process.

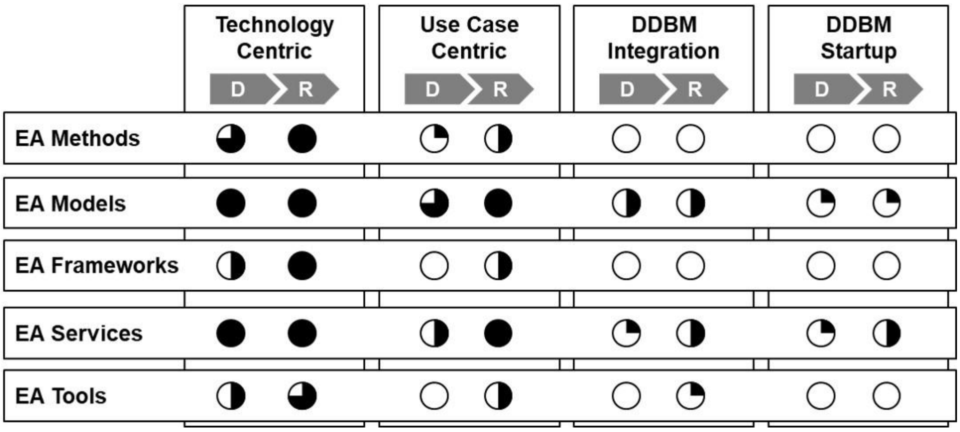

Figure 17. EA support for DDBM design and realization.

The highest application of EA artifacts was reported in the technology centric approach for DDBM deployment. EA supports in its traditional role in the integration of new technology, both strategic planning and project realization. The use case centric approach requires a different EA support. The traditional EA models, framework, and tools are too complex, and technology-focused for business discussions in individual BUs [IP9,16]. However, our interviewees reported that lightweight models are developed, project-specific together with business users [IP5,9,16]. With the DDBM integration and startup approach, EA is facing new challenges. Traditional models, frameworks, and tools are rarely applied. The EA management function with its principles and standards is perceived as a bottleneck and actively excluded [IP6,7,11,12].

10.4.3 Support Gap of Enterprise Architecture for Data-Driven Business Models

In the previous section, we have described how EA supports the design and realization of DDBMs. The illustration in Figure 17 implies a gap of support for the DDBM Integration and Startup approach. To demonstrate this gap, we have derived the support potentials of EA for DDBM from our interview results as well as from our literature search. Figure 18 illustrates the potential application areas of EA modeling and management for each of the approaches.

EA finds a higher application in the technology centric approach since the traditional EA capabilities are demanded. Technology selection and implementation are driven by the IT department. The use case centric approach is driven by BUs and requires EA support for use case design and realization. For the DDBM integration approach, EA can be beneficial for ideation, solution sketching, and feasibility testing as well as for the implementation. The DDBM startup approach demands from the EA to support agile teams, rapidly proposing, and developing solutions. In contradiction to its traditional role, EA must adapt to a *fail fast* and *learn* culture.

10.5 Conclusion and Future Research

The rise of DDBMs brings unique opportunities to organizations to monetize their data. A considerable number of articles has addressed this topic in the literature [1]. However, most companies struggle to implement DDBM projects [4]. Prevailing methods and tools for the deployment of offline business models do not capture the unique perspectives of data and analytics, that DDBM endeavors require [1, 5]. Even though EA has proven its potential for IT-related projects, the intersection with DDBMs has not been extensively investigated in the literature [3, 30]. First attempts of combining the two lenses of EA and DDBM, imply underlying assumptions about how EA can be beneficial for DDBM deployment. In this study, we questioned these underlying assumptions and examined how EA modeling and management supports DDBM design and realization in practice. To contribute to research, we conducted 16 semi-structured interviews with experts from consulting and industry firms, to empirically investigate the EA – DDBM intersection. We derived four approaches for DDBM design and realization and described for each the support of EA modeling and management. Our results have revealed that EA is a common practice in many companies. Accordingly, is the expectation of EA support for DDBM high. All our interviewees have faced EA concerns along their DDBM journey. However, we found that regardless of the potential support opportunities, many practitioners perceive the EA practice as a bottleneck for innovative project setups like DDBM deployment. Consequently, we have found that EA was utilized high in the technology centric approach, which demands the traditional capabilities of EA and is driven by the IT department. While the more innovative settings like DDBM integration and startup approaches have utilized EA only very rarely. The latter approaches are driven by the business with support from IT. Considering the interview results and the existing literature on the intersection of DDBM and EA, it further comes apparent that EA is not leveraged to its full potential in DDBM design and realization.

The results of our research have implications for academia and practice alike. For academia, our contribution is threefold. First, we have presented 19 international DDBM cases and derived four approaches for DDBM deployment. Along these approaches we demonstrated how EA modeling and management are applied in practice to support DDBMs. Second, we revealed the discrepancies between the underlying assumptions of the literature on EA support for DDBM and the practical manifestation. For example, Rashed and Drews (Rashed and Drews, 2020) describe EA support along one approach for DDBM design and realization. Our findings demonstrate four different approaches with varying demand on EA support. Furthermore, the literature neglects the perceived value from EA by practitioners (Rashed and Drews, 2020; Vanauer et al., 2015). Although a high value potential can be derived from the literature (Rashed and Drews, 2020), it involves many underlying assumptions that must be questioned when looking into the practical manifestation. Third, by analyzing the literature and conducting empirical research, we have opened new research avenues. Especially for deepened research on EA capabilities to support DDBM design and realization, the role of architects in DDBM endeavors, as well as the perceived value from EA and the negative connotation of a "bottleneck". Future research could investigate the conceptualization of EA as "control point" offering value. For practitioners, the collected cases provide valuable insights into reference projects. The overview of the current literature is beneficial for targeted knowledge development. Additionally, the presented approaches and the respective EA support can be inspiring for EA departments to find new support opportunities.

Our study's results bear some limitations. Drawing upon Maxwell [18], we structure the limitations of our qualitative research along the four proposed types. First, for evaluative limitations, we acknowledge the threat to validity based on the dependency on the individual interpretation of the reported events. Although we have validated the described facts with triangulation data, the threat cannot be completely diminished. Second, for theoretical limitations, we applied a semi-structured interview approach to collect the data open-minded. However, our research was infused by our previous research on the intersection of DDBM and EA. Third, interpretative limitations, the derived approaches are imbued with our interpretation of the data. Although both authors have independently processed the data and the results have been challenged with two directors from management consulting firms, a binding to the interpreter's perspective will remain. Fourth, descriptive limitations, we acknowledge the threat to validity imposed in the description process. In prevention, all results have been written and interpreted by both authors iteratively. The working paper has been sent to two interviewees in order to gather additional feedback. Ultimately, we have to emphasize that the number of conducted interviews and collected cases are limited. However, we analyzed the data as we proceeded with the interviews. After the ninth interview, we were able to derive the approaches. The remaining interviews have been used to test our concepts.

Despite the vast potential of applying EA modeling and management concepts for DDBM design and realization, their utilization is limited in practice. We plan to develop a reference model for the design and realization of DDBM under special consideration of the EA practice. Additionally, we opened new research avenues in the directions of EA capabilities to support DDBM design and realization, the role of architects in DDBM endeavors, as well as the perceived value from EA and the negative connotation of a "bottleneck".

EA Capabilities

Traditional ⟷ *Innovative*

	Technology Centric: Design	Technology Centric: Realization	Use Case Centric: Design	Use Case Centric: Realization	DDBM Integration: Design	DDBM Integration: Realization	DDBM Startup: Design	DDBM Startup: Realization
EA Management	▪Architects informing the technology selection process ▪Solution architecture development ▪Assess and communicate complexity ▪Conduct technical feasibility test	▪Architects guiding vendor implementation process ▪Provide guidelines and principles to accelerate realization ▪ Architects developing roadmap for target architecture and guiding realization	▪Architects supporting quantification, prioritization and sequencing of UCs ▪Clear collaboration processes for UC development ▪Envisioning solution architecture	▪Architects developing roadmap for target architecture and guiding realization ▪Provide guidelines and principles to accelerate realization ▪Architecture sign-off process initiated in early design phase	▪Infusing the BM ideation with data and technology opportunities ▪Architects supporting BM detailing by answ-ering EA concerns ▪Sketching of solutions for strategic planning and decision making	▪Architects supporting the development of the operating model for DDBM ▪Support the technology selection and implementation process ▪Ease principles to allow implementation	▪Architects support data extraction from parental company through APIs ▪Develop startup target architecture in an agile way (fail fast & adjust) ▪Sketching of solutions for strategic planning and decision making	▪Develop MVPs with a "quick & dirty" solution and adjust ▪Guide architecture realization in greenfield ▪Scale solutions according to (exponential) growth ▪Provide flexibility embedded in principles
EA Modeling	▪Business and technology capability maps for as-is & to-be architecture ▪Technology mapping to business capabilities ▪Fit for purpose models for potential technological solutions	▪Representations of target architect. guiding the POC development and implementation ▪Transparency of intertwinement of prevailing data, applications and infrastructure	▪Transparency of data resources (data catalogue), analytics capabilities and infrastructure components incl. ecosystem view ▪ Solution architecture models and intermediate stages	▪Representations of target architect. guiding the implementation ▪Transparency of intertwinement of prevailing data, applications and infrastructure	▪Models to answer DDBM related EA concerns ▪Transparency of data, applications, and infrastructure layer ▪Solution architecture models and intermediate stages	▪Models to answer DDBM related EA concerns ▪Transparency of data, applications, and infrastructure layer ▪Target architecture for DDBM integration into existing structures	▪Lightweight models for transparency of data, applications, and infrastructure layer ▪Target architecture models for new startup ▪Intermediate architectures for strategic planning of realization	▪Lightweight models for transparency of data, applications, and infrastructure layer ▪Infrastructure access points to ecosystem for data/insights sales ▪EA models for technology implementations
Sources	[IP1-3,10,13-15], Vanauer 2015, Najjar 2013		[IP5,9,16], Vanauer 2015, Chen 2017, Dremel 2017, Najjar 2013		[IP6,11,12], Kühne 2019, Schüritz 2017, Bulger 2014 Rashed&Drews 2020, Exner 2018, Hunke 2017, Kühne 2019, Vanauer 2015, Najjar 2013		[IP7], Hartmann2014, Shüritz 2017, Rashed&Drews 2020	

Figure 18. Potential support of EA for DDBM.

POC = Proof of concept; MVP = Minimum viable product; UC = Use case

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11 A Reference Model for Data-Driven Business Model Innovation

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Abstract. In the past decade, we have witnessed the rise of big data analytics to a well-established phenomenon in business and academic fields. Novel opportunities appear for organizations to maximize the value from data through improved decision making, enhanced value propositions and new business models. The latter two are investigated by scholars as part of an emerging research field of data-driven business model (DDBM) innovation. Aiming to deploy DDBM innovation, companies either renovate their existing BM or develop a new DDBM. Responding to the recent calls for further research on design knowledge for DDBM innovation, we developed a reference model for DDBM innovation. Building upon a design science research approach and the Work System Theory as a kernel theory, we identified seven design principles for DDBM innovation and propose a reference model comprising a static and a dynamic view. Our results are based on a research study with empirical insights from 18 companies, 19 cases and 16 expert interviews as well as theoretical grounding from a systematic literature research on key concepts of DDBM innovation. By deriving the design principles and applying them to develop a reference model, we fill the gap in the literature on DDBM innovation and provide guidance for companies.

Keywords: Data-driven, Business Model, Innovation, Reference Model.

11.1 Introduction

Big data analytics has received considerable attention from academia and practice (Abbasi, Sarker, & Chiang, 2016; Baesens, Bapna, Marsden, Vanthienen, & Zhao, 2016; Hsinchun Chen, Chiang, & Storey, 2012). Trying to exploit value from big data analytics, companies have started to deploy data-driven business models (DDBMs). Latest technological advancements such as cloud, internet of things, big data, and machine learning have contributed to the rise of DDBM. Novel opportunities appear for organizations to renovate their business model (BM) with big data analytics or to develop new DDBMs (Wiener, Saunders, & Marabelli, 2020). These DDBM innovation (Fruhwirth, Ropposch, & Pammer, 2020) opportunities expose especially incumbent companies, expected to rest on tremendous amounts of data, to increasing pressure to act. DDBMs rely on data as a key resource (Hartmann, Zaki, Feldmann, & Neely, 2014) and/ or have data processing as a key activity

(Rashed & Drews, 2020) which makes data essential for the value proposition (Schüritz, Seebacher, & Dorner, 2017). Considering the high dependency on big data analytics, DDBM innovation implies information system design and implementation, which requires different support in design and realization compared to offline BM innovation (Fruhwirth et al., 2020). Research on DDBMs is still in its infancy, with most contributions emerging in the past five years (Fruhwirth et al., 2020; Wiener et al., 2020). Practitioners face several challenges in DDBM innovation (Günther, Rezazade Mehrizi, Huysman, & Feldberg, 2017; Redman, 2019), from identifying relevant opportunities, proceeding with evaluation and ultimately implementing the DDBM (Fruhwirth et al., 2020).

Due to the novelty of this topic for academia and practice, most efforts have concentrated on understanding the nature of the phenomenon (Wiener et al., 2020). In particular, details on designing and implementing DDBMs as socio-technical systems, from a method, process and tool perspective, have received little attention (Fruhwirth et al., 2020; Kühne & Böhmann, 2019; Rashed & Drews, 2020; Wiener et al., 2020). Two recent literature reviews identified DDBM deployment (Wiener et al., 2020) and DDBM innovation methods (Fruhwirth et al., 2020) as future research avenues, highlighting the lack of a reference model. Furthermore, Fruhwirth et al. (2020) revealed a stronger focus of the current literature on DDBM design rather than implementation and emphasize the benefits of connecting related fields to contribute to DDBM innovation research. Fruhwirth et al. (2020) and Wiener et al. (2020) revealed the scarcity of literature contributions in DDBM innovation and stressed the gap in the implementation of DDBMs. The current literature approaches DDBM innovation with a design and user-centric lens, neglecting the strategic and organizational implications on implementing DDBMs as socio-technical system inside an organization. Our research aims to address the literature gap in DDBM innovation, applying a strategic organizational lens focusing on the design and especially implementation of DDBMs. Reference models have proven their potential for knowledge accumulation and as a source for descriptive and prescriptive design knowledge in related fields such as data management (Legner, Pentek, & Otto, 2020). They serve as abstract representations of socio-technical systems (Schermann, Böhmann, & Krcmar, 2009) to support practitioners in developing company-specific solutions (Fettke & Loos, 2007; Frank et al., 2014). Reference models are design boundary objects and elevate research as it matures over time. Knowledge from different disciplines is explicated and integrated to contribute to the respective field in form of reference models (Legner et al., 2020). As the problem space changes over time, reference models survive through adjustment and pass design knowledge to new versions of the reference model (Legner et al., 2020).

Motivated by the research gap in DDBM innovation design knowledge and the potential value from reference models, we turn to this intersection. We address the following research question: What are the essential components of a reference model for data-driven business model innovation? To answer this question, we draw on the Work System Theory (Alter, 2013) as the kernel theory and follow the design science paradigm and the design science research framework (Hevner, March, Park, & Ram, 2004). The Work System Theory as a well-established theory in the information system body of knowledge provides the fundamental structure for developing socio-technical systems, which is the main goal in DDBM design and implementation. To integrate additional disciplines (Legner et al., 2020), our research especially emphasizes the application of enterprise architecture management (EAM) which is associated with the information system body of knowledge and a key concept for designing and especially implementing socio-technical systems (Aier & Winter, 2011). While the Work System Theory provides with its views and key elements the fundamental structure for our DDBM innovation reference model, EAM support with detailed design knowledge for the elements of the reference model.

Within two design iterations we developed a reference model for DDBM innovation. In the first iteration, we conducted 16 semi-structured interviews with experts from consulting and industry firms working on DDBM projects in the United States (US), Europe, and Asia Pacific. Based on these interviews and triangulation data from publicly available sources, we collected 19 cases of DDBM innovation. Building on these cases, we derived seven design principles for DDBM innovation. Furthermore, we clustered the cases and identified four approaches for DDBM innovation. In the second iteration, we grounded our research with a theoretical foundation. We conducted a systematic literature review to identify the key concepts of DDBM innovation and EAM. The results were used to develop the reference model on the basis of the identified DDBM innovation approaches and by applying the derived design principles.

In the next section, we provide an overview of the theoretical foundation of data-driven business model innovation and EAM. We then describe the research method we applied, explicating the two design iterations and emphasizing the relevance and rigor cycles. The derived design principles and the reference model are presented before we exemplary apply the reference model on one case from the interviews. We then discuss the study limitations and implications. Ultimately, we give an outlook on future research avenues.

11.2 Theoretical Background

11.2.1 Data-driven business model innovation

Data have long been acknowledged as a key driver for business and have received considerable attention from the information system discipline (Abbasi et al., 2016; Baesens et al., 2016; Günther et al., 2017; Sharma, Mithas, & Kankanhalli, 2014). In research, the topic has been investigated under several terms ranging from business intelligence, business analytics, and big data to big data analytics (Hsinchun Chen et al., 2012). The potential value contribution of data has been researched in three major areas, namely improved decision making, enhanced products and services, and new BMs (Engelbrecht, Gerlach, & Widjaja, 2016). The latter two areas are investigated by scholars under the term data-driven business model innovation (Fruhwirth et al., 2020). Latest technological advancements have accelerated the recent call for renovation of existing BMs with big data analytics and the deployment of new DDBM (Wiener et al., 2020).

The definitions of a DDBM proposed in the literature commonly states that data must be an essential component. Accordingly, Hartmann et al. (2014, p. 6) defined a DDBM as "a business model that relies on data as a key resource". Bulger, Taylor, and Schroeder (2014) and Brownlow et al. (2015) similarly emphasized the fundamental role of data for DDBMs. Schüritz and Satzger (2016) argued that a clear threshold of required data for a DDBM is not defined and that companies shift from a traditional BM to a DDBM, with increased application of the data for the value proposition. In the context of this study, DDBMs are BMs with data as central element, they have data as a key resource and/or data processing as a key activity. Recent literature reviews of DDBMs revealed a considerable number of publications since 2014 in this thriving research field (Fruhwirth et al., 2020; Wiener et al., 2020). However, most studies describe the nature of the DDBM phenomenon (Wiener et al., 2020) emphasizing the role of the BM elements of value proposition, value creation and value capture (Fruhwirth et al., 2020). Furthermore, they discuss the conceptual structure of DDBM with BM modelling concepts such as the Business Model Canvas (Hartmann et al., 2014; Kühne & Böhmann, 2019; Rashed & Drews, 2020). Research on DDBMs is still at an early stage and in particular under-investigated (Fruhwirth et al., 2020) from a process perspective (Wiener et al., 2020). The literature lacks detailed knowledge on designing and implementing DDBMs, from a method, process and tool perspective (Fruhwirth et al., 2020; Kühne & Böhmann, 2019; Rashed & Drews, 2020; Wiener et al., 2020).

Data-driven business model innovation can be seen as the process of either renovating the existing BM with BDA or deploying new DDBMs (Fruhwirth et al., 2020). Thus, it is a collaborative and creative task that requires divergent and convergent thinking. DDBM innovation guides the procedural efforts manifested as initiatives. DDBM innovation is also described as a result that replaces the traditional BM with new value propositions (Fruhwirth et al., 2020). The methods and tools available for "classic" offline BM innovation must be adapted in order to be applicable to DDBM innovation. Fruhwirth et al. (2020, p. 4) argued, "Following existing literature on general BMI, tools, and methods can support the innovation process. However, besides generally applicable tools and methods for BMI, organizations require specialized or adopted tools and methods that incorporate the specific characteristics of DDBMs, like data as key resource[s] or data analytics as a key activity." Accordingly, Hartmann et al. (2014) address the literature gap on comprehensive method and tool support for DDBM innovation. Similarly, Kühne et al. (2019, p. 1) claim that "extant knowledge about the development process and tools for designing and implementing data-driven business models (DDBMs) is comparatively limited because the field is relatively new".

11.2.2 Enterprise architecture management

Research on enterprise architecture management can be traced back to the Zachman framework from 1980 (John A. Zachman, 2008), which provides an ontology for modelling the fundamental structure of an organization and its information systems. Over the past decades, EAM has become essential for many organizations to support technology-driven transformations as it helps to translate business strategies into initiatives to shape complex sociotechnical systems. The Open Group define enterprise architecture in line with the ISO/ICE/IEEE Standard 42010 definition of architecture, that is, "the structure of components, their inter-relationships, and the principles and guidelines governing their design and evolution over time" (The Open Group, 2009). EAM is concerned with the establishment, maintenance and purposeful development of the EA (Aier & Winter, 2011).

EAM has proven its potential in improving information system efficiency and effectiveness. It is a critical component for strategic planning, top management decision making, and project management (Aier & Winter, 2011). EAM provides artifacts, such as meta-models, frameworks, tools, guiding principles, and management methods to support the evolution on an organization towards a target state. Many organizations have established an EAM function concerned with the aforementioned aim. The key components of an organization and their interdependencies are represented in enterprise architecture models (Winter & Fischer, 2007). The models built based on these meta-models are concerned with either the current state (as-is) or the desired state (to-be) of the enterprise. The EAM function supports the transition from the as-is to the to-be state through several intermediate architecture stages (Rashed & Drews, 2020). The intersection of EAM and DDBM has been under-researched (Rashed & Drews, 2020). Aiming to advance literature in DDBM design and especially implementation, we draw on the enterprise architecture practice to develop a reference model for DDBM innovation. EAM provides management and modelling concepts that help organizations to transform from an as-is to an to-be. The literature in DDBM innovation is currently missing the strategic organizational lens provided by EAM.

11.2.3 Work System Theory

The term work system has been used by researcher in the information system discipline for decades (Trist 1981, Alter 1999). Its origination is the socio-technical system research where it was described as "a set of activities that made up a functioning whole" (Trist, 1981, p. 1). As the research on socio-technical systems matured over time (Mumford, 2006), a more precise definition of work systems has been proposed. Alter (2013) defined work systems as "a natural unit of analysis for thinking about systems in organizations. In organizational settings, work is the application of human, informational, physical, and other resources to produce products/services" (Alter, 2013, p. 75). In addition to this definition, Alter (2013) introduced a framework (static view) and a life cycle model (dynamic view), which together compose the Work System Theory (WST). Drawing on Gregor (2006), Alter further argues that the "(WST) is an integrated body of theory that includes a Type 1 analytical theory (the work system framework) and a Type 2 explanatory theory (the work system life cycle model), which in combination give the basis of a Type 5 design theory" (Alter, 2013, p. 75). We draw on the WST as a kernel theory to develop design theory. The WST provides the fundamental structure for the DDBM innovation reference model. Accordingly, the DDBM innovation reference model comprises a static and dynamic view. Furthermore, the fundamental elements for developing a socio-technical system are addressed with the DDBM innovation reference model.

11.3 Research Methodology

To provide a reference model for DDBM innovation, we develop theory for design and action, which is the fifth class of theory according to Gregor (2006). The development of the reference model is based upon the design science paradigm and the design science research framework (Hevner et al., 2004). Figure 19 illustrates our application of the research framework.

The DDBM innovation reference model is inductively developed in two design iterations following the ideas of grounded theory approach (Corbin & Strauss, 1990). To achieve relevance, we conducted 16 semi-structured expert interviews in the first iteration. Depending on the course, the interviewee reported about one or two cases. At the end of each interview, we asked for publicly available data sources for triangulation. We collected 19 cases for DDBM innovation. The unit of analysis is a company case for DDBM innovation. A case can comprise multiple projects, and multiple cases can occur within one company. We derived design principles as general blueprint of requirements (Drechsler & Hevner, 2018) which then serve as foundation for instantiation. Additionally, 19 international cases of DDBM endeavors were collected and clustered to identify four approaches for DDBM innovation. The design principles and the case clusters as well as the pathways have been evaluated with the interview participants. To achieve rigor, we conducted a systematic literature review, following a methodology proposed by vom Brocke et al. (2009). On the bases of the four identified approaches and by applying the derived design principles as well as the key methodologies and frameworks from the systematic literature review, we developed the DDBM innovation reference model. The results of the second iteration have also been evaluated with the interviewees.

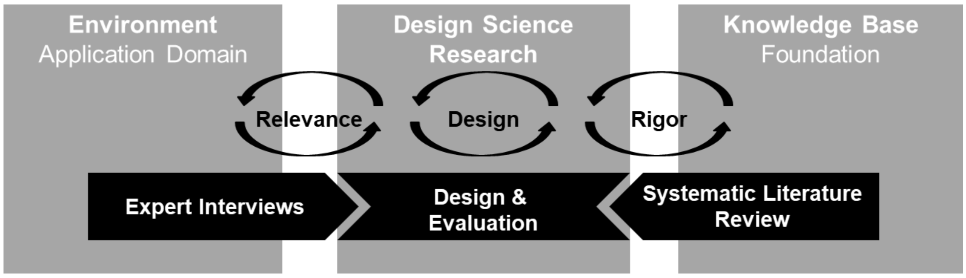

Figure 19. Research approach (adapted from Hevner et al., 2004).

11.3.1 First iteration

To gain a deeper understanding of "why" and "how", companies embark on DDBM innovation journeys, we conducted semi structured interviews with experts from consulting and industry firms. Each interviewee had a track record of DDBM innovation projects. We analyzed the data as we collected them. Drawing on Myers and Newman' (2007) recommendations allowed us to foresee common pitfalls of qualitative interview research (e.g. lack of trust, lack of time, level of entry). Between November 2019 and May 2020, we conducted 16 semi-structured expert interviews. All interviews were recorded, transcribed, and coded by the authors. We started with an initial list of interviewees leveraging our professional network, who named well-fitting candidates with expert reputations. This allowed us to get a set of practitioners with diverse cultural, gender, and regional perspectives. The interviewees have extensive experience in cross-industry firms as well as consulting firms with different specialization and included participants from leading consulting companies such as McKinsey, Bain, and Boston Consulting, as well as the Big Four companies and large IT consulting firms. The interviews were scheduled for 60 minutes and lasted on average 53 minutes. Depending on the course, the interviewee reported about one or two cases. At the end of each interview, we asked for publicly available data sources for triangulation.

To construct a coherent theory based on the gathered data, we draw on the grounded theory as proposed by Corbin and Strauss (1990). We applied an open coding approach and selected ATLAS.ti for tool support. Not having a specific framework in mind, we conducted the interviews openly. To uncover relations among the categories, we reassembled the data that had been broken up during the open coding. For this, we applied axial coding as described by Corbin and Strauss (1990). We clustered the 19 collected cases and derived four approaches for DDBM innovation. Table 13 illustrates the 19 DDBM innovation cases with information on the interview partner, the industry of the focal company, the approach for DDBM innovation, the company headquarter, the motivation to embark towards the DDBM journey and the sponsoring party for the endeavor as well as the funding source. Furthermore, we derive seven design principles as artifact or entity-independent design knowledge, from gathered key considerations and lessons learned. To do so, we drew on the propositions for design theorizing in "Mode 4B: Codifying Effective Design Principles or Features" (Drechsler & Hevner, 2018, p. 92).

Table 13. Interview participants.

C	*IP*	*Industry*	*Approach*	*HQ*	*Motivation*	*Sponsor*	*Funding*
1	IP1	Insurance	Technology centric	D	Digital strategy	CDO/CIO	Digital transformation
2	IP2	FS	Technology centric	AUT	Digital strategy	CDO/CIO	Digital transformation
3	IP2	FS	Unclear strategy	AUT	Competitive response	CDO/CIO	Digital transformation
4	IP3	Insurance	Technology centric	D	Digital strategy	CDO/CIO	Digital transformation
5	IP4	Insurance	Unclear strategy	CH	Competitive response	CDO/CIO	Digital transformation
6	IP5	FS	Use case centric	CH	BU vision	M&S and CDO	BU budget
7	IP5	FS	Use case centric	CH	BU vision	HR	BU budget
8	IP6	IE	DDBM integration	D	Company vision	CEO	Transformation budget
9	IP7	Insurance	DDBM start-up	CHN	Clear business opportunity	CEO	New business opportunity
10	IP8	Chemicals	Unclear strategy	D	Digital strategy	CDO/CIO	Digital transformation
11	IP9	LS	Use case centric	CH	BU vision	R&D and CDO	BU budget
12	IP9	LS	Use case centric	D	BU vision	M&S and CDO	BU budget
13	IP10	Insurance	Technology centric	US	Digital strategy	CDO/CIO	Digital transformation
14	IP11	FS	DDBM integration	AUS	Clear business opportunity	CEO	New business opportunity
15	IP12	Energy	DDBM integration	D	Clear business opportunity	CEO/CIO	New business opportunity
16	IP13	PS	Technology centric	D	Digital strategy	CDO/CIO	Digital transformation
17	IP14	FS	Technology centric	CH	Digital strategy	CDO/CIO	Digital transformation
18	IP15	LS	Technology centric	D	Digital strategy	CDO/CIO	Digital transformation
19	IP16	LS	Use case centric	UK	BU vision	R&D and CDO	Transformation budget

C= Case Number; FS= Financial Services; IE= Industrial Equipment: LS= Life Science; PS= Public Services

Based on the degree of data understanding and degree of self-incentive, have the cases been clustered in use case centric, technology centric, unclear strategy and DDBM quadrants. This led to the derivation of the approaches. The companies behind the cases, either take a gradual approach or a direct approach. For the first, they start building technology capabilities first or analyze the existing data to develop UCs for DDBM. For the latter, they either integrate the new DDBM into the existing organizational structures or establish a new DDBM start-up. Additionally, we derived seven design principles for DDBM innovation from the cases by building upon Drechsler and Hevner (2018). Between May 2020 and July 2020, we conducted follow-up interviews with our initial interview participants to present the case clusters, the derived approaches and the design principles. Furthermore, we gathered their qualitative feedback to incorporate into the next version. We discussed their specific cases once again and tested the appropriateness of the generic approach and the design principles. However, the results showed that our proposed principles and approaches are comprehensive, which is reflected by only needing minor revisions in phrase and style like e.g. refinement of principles' descriptions. For example, IP11 proposed to rename DP1 from "top management engagement" into "senior management engagement" during our online video- and screen-sharing meeting via Microsoft Teams.

11.3.2 Second iteration

To enrich our research with the theoretical foundation, we conducted a systematic literature review to integrate the existing knowledge base. Our goal was to identify the current state of the literature on the interplay of DDBMs and EA. We queried the following databases with keyword searches: (1) AIS Electronic Library, (2) EBSCO Host Business Source Complete, (3) Google Scholar, (4) IEEE Xplore, (5) JSTOR, (6) Science Direct, and (7) Web of Science. As the DDBM is an interdisciplinary field, the research is reflected in the intersection of BM and big data (Engelbrecht et al., 2016). Our search comprised keywords covering both areas. We added the research stream of EAM to understand the interplay of these research fields. The keywords "data-driven," "business model," and "enterprise architecture" were selected based on the resulting four intersections. To further extend the literature search, the terms "big data" and "analytics," which are associated with "data-driven," were integrated into the search as well. This led to a total of 10 search strings. All hits were screened based on their titles and abstracts. The first 100 hits from Google Scholar were considered, acknowledging their decreasing relevance. Irrelevant, duplicate, and non-peer-reviewed results were excluded. The remaining 80 articles were reviewed based on their full texts. We analyzed them and conducted a forward and backward search. Three articles discuss the DDBM deployment with EAM (H.-M. Chen, Kazman, Garbajosa, & Gonzalez, 2017; Rashed & Drews, 2020; Vanauer, Bohle, & Hellingrath, 2015). Articles in the intersection of big data and BM were used to identify methods used for DDBM innovation (Fruhwirth et al., 2020; Wiener et al., 2020). The results from the remaining intersections provide knowledge on EAM application in BM and big data context. The literature results were used to refine the design principles and for the reference model development. Aiming to develop descriptive and prescriptive design knowledge (Legner et al., 2020) we abstracted from project design knowledge to derive solution design knowledge (Drechsler & Hevner, 2018). Therefore, the design of the DDBM innovation reference model is guided by the derived design principles and informed by the Work System Theory (Alter, 2013) as kernel theory. We used the holistic enterprise perspective of the Work System Theory as conceptual basis to address all relevant facets of a company that performs DDBM innovation to deliver new products/services or to improve existing ones. The nine components of the work system (Alter, 2013), were structured along the key elements of BM innovation (Fruhwirth et al., 2020), namely value proposition, value creation and value capture. This structuring frame has been further enriched with the four derived approaches. Additional insights were incorporated from the TOGAF ADM, which is the most popular EAM framework. To evaluate the DDBM innovation reference model, we conducted follow-up meetings with our interview participants to get their qualitative feedback. This led to restructurings and to rewordings of the identified enablers. We adjusted the reference model as we proceeded with the meetings.

11.4 Results

11.4.1 Design principles for DDBM innovation

As part of the 19 cases for DDBM innovation, we gathered key considerations and lessons learned from the endeavors our interview participants shared. Coding and analyzing this data allowed to us derive seven design principles for DDBM innovation, which are illustrated in Table 14.

Considering the multitude of involved parties in DDBM innovation endeavors, senior management engagement (DP1) and active involvement is crucial for the successful deployment. A joint effort from business units (BUs) and IT is required. The first bring the functional knowledge and the understanding of the data to the table and the latter technological know-how for the realization. The DDBM endeavors were sponsored either directly by the chief executive officer (CEO), through a joint sponsorship between BU and the chief information officer/chief digital officer (CIO/CDO), or by only the BU or CIO/CDO. The interviewees reported that the endeavors were motivated by a clear business opportunity, a common vison for the company, their digital strategy, the BU vision, or as a competitive response. Transforming an organization to integrate a new DDBM into existing structures requires a clear business opportunity, a common vision, and CEO sponsorship [IP11, 12]. "Senior management support is vital to ensure the thriving business model is not smothered by the traditional business model, especially when it comes to data access across the organization" [IP 6]. DDBM innovation projects that remained in an unclear stage had isolated efforts from BU and IT side with-out central leadership [IP2, 4, 8]. "Conducting the technology selection without business involvement, led to the implementation of a big data analytics platform which was over sophisticated. The investment was not justified" [IP2]. DDBM innovation endeavors require a clear plan for involving the senior management in the progress and decision point along the journey.

The complexity of DDBM innovation endeavors is further increased through the involvement of external parties. In particular, consulting firms support the DDBM innovation process with data monetization use cases from various industries in the design phase and implementation capacity in the realization phase. For the former, consulting firms infuse the ideation of new DDBMs with use case catalogues. Company specific use cases are developed based on reference cases. Consultants support the assessment and sequencing of use cases for successful implementation. For the latter, they provide technological know-how and capacity to rapidly scale solutions. This strong involvement of additional stakeholders, their fluctuation and the resulting threat of knowledge loss through handovers, makes an end-to-end responsibility (DP2) of a core team for DDBM innovation vital. Frictions from the organizational vision over business model design and realization will be minimized. To give an example, IP6 reported the involvement of a leading strategy consulting firm in the vision phase of the project. The implementation on the other hand, was conducted with an IT consulting firm, which highly depended on interpretation guidance of the core team to cope with the overall strategy. Similarly, has IP3 described a case where the technology selection was conducted in isolation with an IT consulting firm without integration into the overall DDBM innovation strategy.

DDBM innovation must be conducted in an iterative/agile (DP3) approach. As requirements are blurry and adhere many uncertainties. Use case and business model description provide only high-level guidance for an explorative procedure. A multitude of conceptual DDBMs are generated throughout the ideation process, which requires theoretical evaluation, sequencing and cyclic realization. Successful cases described the urge of establishing an iterative and agile team culture which goes beyond theoretical methods. For example, an insurance company headquartered in China decided to monetize their 10 years of insurance data from 650 million clients. Based on this idea, a company was established with newly hired employees. A team of 20–30 members with special capabilities worked on the DDBM from design to realization in an agile start-up fashion. The DDBM was detailed during the process resulting in a minimum viable product (MVP) that was discussed early with potential clients. The interviewee highlighted “such endeavors require teams with certain innovation level, embracing iterative and agile ways of working deeply in their mindset” [IP7].

Sponsoring, managing and delivering DDBM innovation endeavors under uncertainty and high level of risk, demands close tracking of time to results/fail fast (DP4). From a delivery perspective, the team learns from early prototyping. Managers have greater monitoring and intervention levers along the engagements and project sponsors a better ability to stop the endeavor. Early results have been reported as prove of concepts for the technology centric approach, MVPs and rapid prototyping as part of the use case centric, DDBM integration and DDBM start-up approach. To give an example, a global Australian bank was approached by management consultants with an opportunity to sell banking transaction data for targeted offerings. The bank designed a DDBM with the consulting firm and developed an MVP in a trial-and-error approach. Presenting agile and iterative results shortened the time to market

[IP11]. Another example was given by IP12, an energy provider decided to develop a data monetization platform, allowing customers to purchase data-driven services and service providers to offer services enriched with energy consumption data. The interviewee reported that the project is ongoing and transitioning towards the development of an MVP, which will be decisive for the implementation decision.

Effective financing is a crucial component of DDBM innovation endeavors. To ensure sufficient funds, the procedure for DDBM innovation must be continuously cost/effort driven (DP5). Ideally, the funding is structured in a staged approach, similar to start-up funding rounds. To get additional funding, DDBM endeavors must demonstrate early results (DP4) delivered in an iterative approach (DP3). Sponsors have clear go/no-go decision points to stop further investments in unfruitful projects. For example, IP5 provided two cases with the same client but with different BUs. The case with marketing and sales was delivered in an iterative/agile approach, delivering early results through an MVP. This case received additional funding and is currently under implementation. The second case, with the HR department, consumed the initial investment to define extensive requirements for full-fledge implementation, but failed to demonstrate first results which ultimately led to a rejection for additional funding after the first iteration.

Table 14. DDBM innovation design principles.

#	*Design Principle*	*Description*
1	**Senior management engagement**	DDBM innovation requires sponsorship from senior management with active engagement and support.
2	**End-to-end responsibility**	DDBM innovation must be conducted by interdisciplinary teams with end-to-end responsibility.
3	**Iterative / agile**	A cyclic approach for DDBM innovation with clear goals per iteration and agile ways of working are crucial.
4	**Time to results/ fail fast**	Results must be delivered fast to ensure rapid learning cycles and quicker allocation of resources and efforts.
5	**Cost/effort driven**	Each DDBM innovation cycle must be well budgeted and tracked with go/no-go decision points for additional funding.
6	**Value driven**	The generated value must be kept in focus throughout the DDBM innovation endeavor.
7	**Data as the key resource**	The high dependency on data as the key resources makes it quality and reliability decisive for the DDBM impact.

To prevent falling into the "hype trap" of DDBM innovation, it is vital to keep a value driven (DP6) mindset through the endeavor. Organizations falling into this trap tend to have little understanding of their data and potential application fields but have decided to heavily invest in big data analytics as part of their digital strategy. Great effort is made to understand technology options and solution functionalities. However, the big data analytics use is described with short use cases, and the technology selection is prioritized. The endeavor is sponsored by the head of the IT department and funded by the budget for the digital transformation. These endeavors are denoted as investments, "big data analytics projects pave the way for DDBM innovation" [IP2]. Which may turn DDBM innovation effort to purely prestige projects, not justifiable with the value they provide [IP2,4,8]. "Considering all element of the business model, especially revenue streams, value proposition and customer segmentation supports evaluation and value tracking" [IP11].

Data is the key resource of DDBMs (Hartmann et al., 2014; Rashed & Drews, 2020). Data quality and reliability are decisive for the value proposition (Fruhwirth et al., 2020; Schuritz & Satzger, 2016). Successful DDBM innovation requires this understanding for data as the key resource (DP7). All companies behind the reported cases, sourced their data internally. Coping with DP7 demands organizations to build the data foundation for DDBMs. This includes data governance and data management procedures, regulations and policies. A reliable data infrastructure is essential for DDBM innovation. Seven of the reported cases started the DDBM endeavor by building the full-fledged data foundation through the technology centric approach [C1,2,4,13,16,17,18]. Five of the cases had the data quality ensured by the BUs [C6,7,11,12,19]. The remaining four cases with clear approach, had the data infrastructure gradually developed which guaranteed high quality data resources for DDBM innovation.

11.4.2 Reference model for DDBM innovation – Static view

Drawing on the Work System Theory (WST), which proposes two views for representation, we developed a reference model for DDBM innovation that offers a static view (framework) and a dynamic view (life cycle) (Alter, 2013). The former is structured along the key elements of BM innovation (see Figure 20), namely value proposition, value creation, and value capture (Fruhwirth et al., 2020). It contains six enablers, which build on the nine WST framework components and the reported approaches for DDBM innovation. The reference model provides key building blocks to enable an organization to innovate their business model. Applying the seven design principles led to an agile DDBM innovation approach, with a value realization office (VRO) in its center. The enablers evolve with each iteration (DP3). One core team has end-to-end responsibility (DP2) with increasing team size per iteration. The endeavor is sponsored by senior management (DP1), that actively engages through the VRO. The latter keeps track of the progress in terms of cost estimation (DP5) and value projection (DP6). Clear go/no-go decision points enable the senior management to stop unfruitful endeavors and cultivate a fail fast (DP4) mindset. Additionally, the VRO tracks the complexity and the readiness of the data infrastructure to source data as the key resource

(DP7). As the order of enabler development varied in the cases, a fixed sequence is not prescribed. However, the dynamic view proposes a sequence based on interviewee feedback.

The value proposition element contains the DDBM strategy, which set the direction for the endeavor. Use cases and business models are developed as central artifacts (Fruhwirth et al., 2020) applying common techniques such as the Business Model Canvas (BMC) for DDBMs(Hartmann et al., 2014; Kühne and Böhmann, 2019). The populated BMC templates are handed over to the VRO to guide the development of the remaining enablers. Referring to the WST, the DDBM strategy enabler covers mainly the strategy component but addresses all remaining components partially.

The core components ("completely inside" (Alter, 2013, p. 79)) of the work system are contained in the value creation element. Processes, activities and participants are part of the operating model enabler. Required capabilities, mindset, roles and responsibilities as well as processes are defined for the targeted DDBM. This includes critical assessments of sourcing options for the demanded capabilities. Considering that DDBM projects premise certain innovation skills which the prevailing resource base might not have [IP7,13]. Data/information and its processing are addressed in the information system architecture enabler. Referring to the interview results, this enabler comprises the TOGAF (The Open Group, 2009) data and application layers which support the modelling of data and its processing. This includes informational entities and how they "are used, created, captured, transmitted, stored, retrieved, manipulated, updated, displayed, and/or deleted by processes and activities" within the DDBM (Alter, 2013, p. 80). In addition, Rashed and Drews (2020, p. 6) found for DDBM that "EA modeling and management concepts are used for further detailing BMs and support their implementation". Similarly, the technology architecture can be represented with TOGAF's technology layer to develop the required technologies for the DDBM. "Addressing related EAM concerns helps the team to iteratively sketch and develop the required tools and hardware components" [IP11]. The data management and governance enabler goes beyond the core of the work system, it entails the environment and infrastructure components of the WST. The DDBM is not build in isolation and mostly depends on a reliable data infrastructure with policies and practices in place to provide the required level of data quality. The organizational, cultural, technological- and regulatory environment must be considered to provide the required data as input resource for the DDBM. A multitude of the gathered cases focused on building the data infrastructure first (technology centric approach) [C1,2,4,13,16,17,18]. Companies taking the use case centric approach had narrowed data sets for the DDBM, for which the data quality was provided by the BUs [C6,7,11,12,19]. For the DDBM start-up approach, the data resource was provided by the parental company over APIs. In the remaining cases, the data infrastructure was developed gradually.

The value capture element contains the value realization office, which is central to the DDBM innovation reference model [IP8,9,11,12]. The development of the above-mentioned enablers is coordinated through this central unit. Beginning with the use cases/ business model vision, the VRO keeps track of the progress, monitors the costs, estimates the complexity and reports regularly to the senior management. The core team with its cross functional expertise contributes to the continuous evaluation and reporting. A clear meeting schedule with steering committee go/no-go decision point and standardized reporting templates enables senior management involvement [IP7,11,12]. Each cycle of the DDBM innovation approach is steered by the VRO and contributes to the detailing of the remaining enablers to justify implementation. Funding rounds determine if additional investments are allocated to the DDBM endeavor.

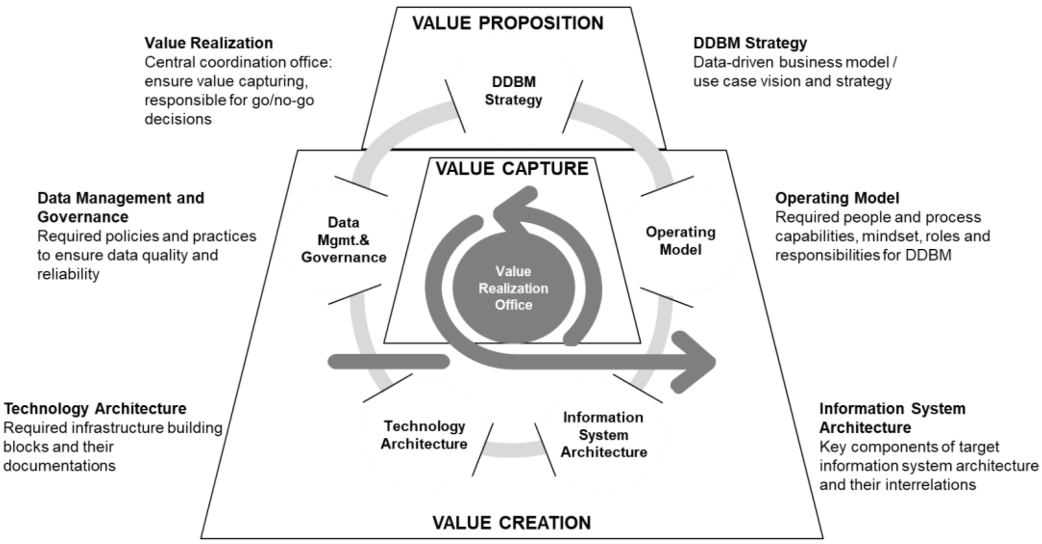

Figure 20. DDBM innovation reference model – Static view.

11.4.3 Reference model for DDBM innovation – Dynamic view

A dynamic view to the DDBM innovation reference model is illustrated on Figure 21. Drawing on the WST, the dynamic view relates to the life cycle model (Alter, 2013).Four iterations are represented in which the enablers evolve. Design, MVP and implementation are derived from the reported cases. Since the gathered DDBM innovation endeavors are still in early stages and did not exceed implementation, the renovation iteration was added from literature on BM innovation (De Reuver, Bouwman, & Haaker, 2013). In each iteration, the DDBM enablers evolve, gaining more details through sprints. The VRO monitors and steers the DDBM endeavor throughout the cyclic approach.

The first iteration is an analysis of the conceptual design. As part of the DDBM strategy the key elements of the business model are defined using common practices such as the BMC. The populated BMC framework represents the skeleton of the business model. It guides the efforts in the value creation element of the DDBM innovation reference model. Use cases for the DDBM are sequenced, considering implementation efforts and dependencies. Required capabilities and processes are analyzed within the operating model enabler. A high-level view on business capabilities and their sourcing is provided to support complexity and effort assessments. This includes in particular cultural aspects, which might become decisive for DDBM innovation success. The data required for the DDBM and its processing are analyzed as part of the information system architecture. Sketches of the data and application architecture are developed to support complexity and effort estimations. This supports the understanding of the required data for the DDBM and the data processing capabilities on application level. The infrastructure perspective to the data and application layer is analyzed in the technology architecture enabler. The required DDBM infrastructure is defined on a high-level, assessing the technical feasibility. As part of the data management and governance enabler, the team analyses the environment in which the DDBM will be implemented. This includes critical assessments of the prevailing policies and practices for data governance and management as well as the reliability and quality of the data. While the required data and its processing within the DDBM is defined in the information system enabler, the data governance and management enabler is concerned with previous steps of providing the data as the key resource to the DDBM as input. The cross functional core team, comprising a diverse set of skills including business, IT and especially EAM, collaboratively develops the enablers and contribute to the VRO as key stakeholders. This includes continuous assessment of the design and coordination of an additional funding round for the MVP iteration.

Passing the funding rounds successfully results in further detailing of the enablers in the MVP iteration, in which the previously developed design is realized as a prototype. The MVP builds on learnings from the design iteration, further defines requirements and provides practical insights. As part of the DDBM strategy, the BMC is detailed with requirements for the MVP. Vision and strategy for the DDBM are refined and passed to the VRO. The delivery team and the processes in which they realize the MVP are setup as part of the operating model enabler. Data and application sketches support the development of the MVP in sandbox environments (testing environment that isolates untested code changes). Feasibility and complexity are constantly assessed and reported. The technology architecture is part of the sandbox environment and defines the infrastructure on which the MVP is build. Data management and governance practices are established to provide first data sets for the MVP as input resource. The VRO tracks the enabler development and reports to senior management. Additional funding is required to reach the next iteration of realization. Critical assessment of the cost and complexity as well as the potential value are decisive for senior management decision for additional investments. Successful cases are passed for implementation, where the MVP is scaled to the reach commercialization scope.

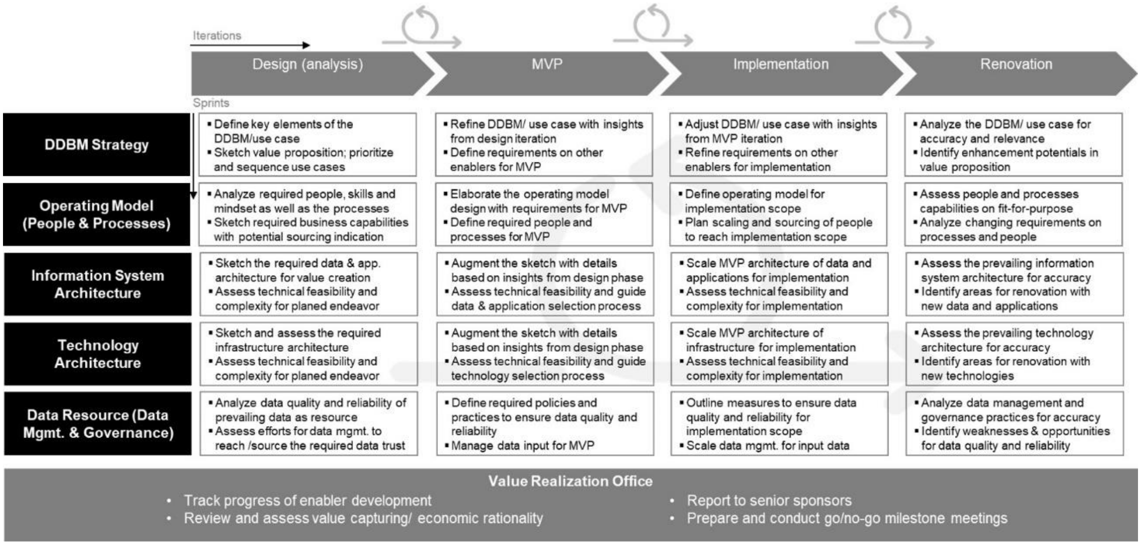

Figure 21. DDBM innovation reference model – Dynamic view.

To implement the DDBM, the requirements of the MVP must be revisited. Enablers muss be setup in flexible and scalable structures to enable growth. The business model for go-live must be developed, building on practical learnings form the previous iteration. An explicit value proposition for targeted customer segments is defined to offer clearly outlined products/services. This DDBM strategy is detailed with value creation enablers. People and process to run the DDBM are setup in the operating model enabler. Potential growth opportunities must be considered while building the team structures. Accordingly, is the data and application architecture designed to scale fast. The same is applicable for the technology architecture. Cloud options and on-demand services might become key components of the live environment. Data management and governance practices are expanded as the DDBM grows. While targeted "test" data sets might have been sufficient for the MVP, the implementation demands consistent input of data as the key resource with clearly defined quality standards. Complexity and value drivers are continuously tracked and reported by the VRO. The team expands as the implementation proceeds. The VRO gains importance as it coordinates the implementation. This includes security and ethical constraints of the DDBM. Proposed enabler structures must comply with overall company security and ethical guidelines to ensure sustainability and trust. With an established DDBM, the core team of the DDBM and the VRO are relived from the development duties. The DDBM operates as running business. However, revision milestones are defined to assess potential renovations.

Renovation cycles are an essential component of BM innovation. For this purpose, either a clear schedule for revision is setup or the VRO runs with minimum resources to continuously monitor the DDBM. In case renovations are required the VRO coordinates the targeted implementation efforts. The review process is structured along the DDBM enablers. As part of the DDBM strategy, the team reviews accuracy of the BM considering all components of the BMC. The value proposition and the BM structures are critically assessed. A narrowed analysis of people and process is conducted as part of the operating model enabler. As technology capabilities rapidly evolve, potential cost efficiencies through automation might become visible. The infrastructure components are revisited through the technology architecture enabler. The policies and practices to provide the input data are analyzed though the data governance and management enabler. The renovation efforts and the potential value are tracked and reported by the VRO.

11.4.4 Exemplary application

In this section, we demonstrate instantiations of our artifact, drawing on the gathered cases from our interviews. We selected the DDBM integration approach case, as this embodies new DDBMs rather than a gradual improvement of the existing BM. The expository instantiation serve for theory representation (Gregor & Jones, 2007) and for design feature illustration.

EnergyPro, a German energy provider decided to find data monetization opportunities, allowing customers to purchase data-driven services and service providers to offer services enriched with energy consumption data. This decision to monetize data was motivated by shrinking revenues in the energy industry and technology advancements, such as smart meters, which became a European standard. Anonymized energy consumption data open up many business opportunities for various industries.

The CIO and the Innovation business unit head (DP1) were appointed by the CEO for the DDBM innovation project. A cross functional team with end-to-end responsibility (DP2) was assembled from both their departments. The team agreed on a reporting schedule for their iterative approach. A value realization office was established to coordinate the monitoring and reporting activities. The team started with the DDBM strategy by conducting a divergent design thinking workshop to collect as many ideas as possible. Experts from academia and consulting firms guided and supported these workshops. As a next step the team sequenced the ideas in regard to their realization potential. This convergent thinking allowed a one-by-one analysis of the proposed ideas. Following the sequence, the team populated a BMC template for the business idea at hand. The design phase continued with an operating model analysis. The team defined headcount, capabilities and high-level role descriptions on the basis of the BMC. The first idea passed this stage successfully and was analyzed for realization from an information system perspective. Architects within the team sketched the data and application layer, developing early results (DP4). As the proposed idea required tremendous investments in application development and the cost (DP5) would exceed the projected revenue streams (DP6), the team stopped this analysis and continues with the next idea. The second idea passed the information system architecture hurdle as well as the technology architecture assessment but was dismissed within the data management and governance analysis. It required input data that was not available in the demanded quality and reliability. The third idea, proposing a multi-sided platform for energy consumption data successfully passed all hurdles of the analysis and an MVP was developed. A limited number of use cases were realized with the MVP, focusing on one industry and test client. Looking into elderly care, the team tried to disaggregate energy consumption data of an elderly person to allow conclusions to draw, if she/he needs help or assistance. Energy consumption patterns from household appliances had to be requested from the manufacturer and analyzed. For example, if an elderly person leaves the oven turned on for more than 3 hours, the energy consumption data will provide insights and intervention opportunities. The required operating model was defined to realize the MVP, appointing a team for operations. The platform architecture was developed in a sandbox environment, providing the key functionalities for the use cases. The required input data was further specified as part of the data governance and management efforts. Disaggregating the energy consumption data and getting the energy consumption patterns from all household appliances within the use cases, was crucial for the success of the DDBM (DP7). The DDBM MVP was successful proposing a BMC for platform economies, which incorporates multisided customer and provider perspectives. Energy consumption data was fed into the platform from EnergyPro, partners got the opportunity to provide energy consumption patterns to allow co-creation of new business opportunities. The successful MVP phase led to the full-fledged implementation. As the core team grew the project structure turned into program structure, transforming enablers into project streams. The VRO remained responsible for tracking, monitoring and reporting. Platform implementation, team hiring and partnering with providers was planned for 14 months. The VRO was running with minimum headcount after the implementation to monitor appropriateness of the DDBM and to learn for future projects.

11.5 Discussion

Data have long been acknowledged as a key driver for business and have received considerable attention from the information system discipline (Abbasi et al., 2016; Baesens et al., 2016; Günther et al., 2017). In research, the topic has been investigated under several terms ranging from business intelligence, business analytics, and big data to big data analytics (Hsinchun Chen et al., 2012). Researchers have examined the potential value from data in three major areas: improved decision making, enhanced products and services, and new BMs (Engelbrecht et al., 2016). Regarding the last, the latest technological advancements have contributed to the recent call for new DDBMs. The literature on DDBMs is still in its infancy. A limited number of articles address this topic with most contributions emerging within the past 5 years (Fruhwirth et al., 2020; Wiener et al., 2020). Due to the novelty of this topic for academia and practice, most efforts have concentrated on understanding the nature of the phenomenon (Wiener et al., 2020). In particular, details on designing and implementing DDBMs as socio-technical systems, from a method, process and tool perspective, have received little attention.

To identify potential relevant related work, we conducted a literature review. We found three insightful structured literature reviews (Fruhwirth et al., 2020; Günther et al., 2017; Wiener et al., 2020), six theoretical framework, method, and concept-building articles (H.-M. Chen et al., 2017; Hartmann et al., 2014; Kühne & Böhmann, 2019; Schuritz & Satzger, 2016; Schüritz et al., 2017; Vanauer et al., 2015), and two empirical studies (Hong Chen, Kazman, Schütz, & Matthes, 2017; Najjar & Kettinger, 2013). As part of a structured literature review, Günter et al. (Günther et al., 2017) presented an example of a European postal service organization failing to realize its DDBM, highlighting common pitfalls. Elevating the research on process models and frameworks, Schüritz and Satzger (2016) derived patterns for DDBMs. Similarly, Hartmann et al. (2014) proposed a framework for DDBMs used by startup firms. An architectural and transformative perspective was taken by Vanauer et al. (2015), who developed a methodology for realizing DDBMs drawing on enterprise architecture management and business model generation techniques. Dedicated empirical research was conducted by Chen et al. (Hong Chen et al., 2017) during the transformation of the Lufthansa BM, emphasizing critical success factors for the pathway taken by the airline. Similarly, Najjar and Kettinger (2013) conducted a case study based on a U.S. retailer realizing DDBMs. The data monetization journey was described in four stages of data value realization. However, the literature lacks detailed design knowledge for DDBM innovation.

Addressing the recent call for research on DDBM innovation (Fruhwirth et al., 2020; Wiener et al., 2020), our study provides a reference model for DDBM innovation. Within two design iterations we developed a reference model for DDBM innovation. In the first iteration, we conducted 16 semi-structured interviews with experts from consulting and industry firms working on DDBM projects in the United States (US), Europe, and Asia Pacific. Based on these interviews and triangulation data from publicly available sources, we collected 19 cases of DDBM innovation. Building on these cases, we derived seven design principles for DDBM innovation. Furthermore, we clustered the cases and identified four approaches for DDBM innovation. In the second iteration, we grounded our research with a theoretical foundation. We conducted a systematic literature review to identify the key concepts of DDBM innovation and EAM. The results were used to develop the reference model on the basis of the identified DDBM innovation approaches and by applying the derived design principles.

11.6 Conclusion

Our contribution for DDBM innovation is a reference model with six enablers, providing a static and a dynamic view. Additionally, we derived seven design principles for DDBM innovation, which we applied in order to develop the reference model. Both, the reference model and the design principles, are based on qualitative analysis within two design iterations with empirical evidence and theoretical grounding. For research, we contribute with the DDBM innovation reference model to the literature gap as revealed by Fruhwirth et al. (2020) and Wiener et al. (2020). Both articles present recent systematic literature reviews and conclude that procedures "of developing data-driven business models [..] have been under-investigated" (Fruhwirth et al., 2020, p. 1), in particular the "dynamic aspects of BDBM deployments (process perspective)" has received very little attention (Wiener et al., 2020, p. 75). While some selective support (e.g. DDBM ideation (Kühne & Böhmann, 2019)) has been proposed by the literature, it especially lacks an approach for DDBM innovation.

By building on 19 international DDBM cases, we developed a reference model, which provides a basis for knowledge accumulation, both descriptive and prescriptive (Legner et al., 2020). We grounded the reference model with the Work System Theory as kernel theory. Although the reference model applies known concepts, their use and combination for DDBM innovation is uniquely presented in this research study. Additionally, we derived seven design principles for DDBM innovation, to guide scholars in advancing the proposed reference model. Furthermore, the design principles can be applied for developing additional artefacts for DDBM innovation, to provide "a more granular level of specificity about deployment" (Wiener et al. 2020, p. 80). Ultimately, our research presents an overview of the recent DDBM literature with a systematic literature review and empirical insights from experts in consulting and industry firms working on DDBM projects in the United States (US), Europe, and Asia Pacific.

Our contribution for practitioners is fourfold. First, the reference model can be used to guide the design and realize DDBMs. Second, the design principles guide the instantiation of the reference model into the company context. Third, the collected cases can be used as a reference and to guide the companies' journey towards DDBMs. Fourth, the overview of the current literature is beneficial for targeted knowledge development.

Our study's results bear some limitations. The first limitation is evaluative. We acknowledge the threat to validity based on the dependency on individual interpretation. Although we applied a versed research framework, the threat cannot be completely diminished. The second limitation is methodology limitation. We applied a semi-structured interview approach to collect data with an open mind. However, this research was infused by our previous research on the topic. Therefore, the validity of the prevailing theoretical concepts imposes a threat as well. Furthermore, the selection of keywords for the systematic literature review restricts the set of results. Though we have iteratively refined the search terms, some related work might have been overlooked. The third limitation was interpretative. The reference model and the design principles are imbued with an interpretation of the data. Although the results were qualitatively evaluated by the interview participants and both authors independently, the data were subjectively interpreted. The fourth limitation was descriptive. We acknowledge the threat to validity imposed in the description process. All results were written and interpreted by both authors iteratively. The number of interviews and cases was limited. Additionally, we have only conducted two iteration of the design process for the DDBM innovation reference model. The results might hence not be stable yet. In particular, the DDBM cases were gathered from interviews with DDBM consultants and experts. DDBM is not a routine in companies yet, having only pioneers in the filed interviewed might cause sample bias.

Our future work will focus on further sophisticating the reference model with additional cases. To increase the reliability of our results, we plan to conduct additional empirical evaluations.

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12 Mobilizing Capabilities for Data-Driven Business Model Innovation

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Abstract. Maximizing the value from data by renovating existing business models or introducing new data-driven business models has become a key concern of business leaders. Realizing data-driven business models requires capability mobilization to provide the data foundation as well as the key components of the new business model. Based on 19 data-driven business model innovation cases from the United States, Europe, and the Asia-Pacific, we derived four pathways and a capability framework to provide recommendations for how incumbent companies can successfully introduce data-driven business models.

Keywords: Data-driven, Business Model, Innovation, Big Data Analytics, Data-based.

12.1 Value Realization from Data

Business leaders today are eager to maximize the value from data. It has become a key challenge for incumbent companies as it helps improve operations and decision making, enhances products and services, and ultimately leads to new business models. The terms under which data value realization have been investigated have varied in the past decades, ranging from business intelligence, business analytics, and big data to big data analytics. Advancements in information technology, especially in machine learning, big data, cloud computing, and Internet of things (IoT) technologies, have further increased the importance of data for business development and innovation. Many companies are under pressure and, therefore, enhance their traditional business models using data or realizing new data-driven business models. Novel opportunities appear for organizations to renovate their business model with big data analytics or develop new data-driven business models. These data-driven business model innovation opportunities particularly expose incumbent companies, expected to sit on tremendous amounts of data, to increasing pressure to act. Data-driven business models rely on data as a key resource and/or have data processing as a key activity, making data essential for the value proposition. Research on data-driven business models is still in its infancy, with most contributions emerging in the past five years.3,4 Practitioners face several challenges in mobilizing capabilities (capabilities are firm specific assets – e.g., people, processes, technology – used to transform other assets in order to generate value) for data-driven business model innovation, including identifying relevant opportunities, proceeding with evaluation, and, ultimately, implementing the data-driven business model. , Due to the novelty of this topic for academia and practice, most efforts have concentrated on understanding the nature of the phenomenon. Existing efforts have focused on data monetization journeys. Data monetization (data sales), which is defined as the direct or indirect conversion of data into financial capital, is one type of data-driven business model. Other types are sales of analysis, which involve data-based analyses, and sales of data-based services. This article describes the data-driven business model journeys of early-adopting companies and highlights the capability mobilization along the different pathways. We draw on our research with 19 data-driven business model innovation cases from the United States, Europe, and the Asia-Pacific.

12.2 Data-Driven Business Model Innovation is a Key Challenge for Incumbent Companies

Incumbent companies accumulate data ever since they have been established. These data sources might turn out as data treasures. However, the advantage of tremendous amounts of data collected over decades comes with the disadvantage of prevailing organizational structures that hinder value realization from data. Unlike digital-native companies, such as Google, Netflix, or Facebook, traditional companies find it challenging to unlock the data value with data-driven business models. The former has data value realization at its core, which paves the way for introducing data-driven business models, including sales of advertising spaces (Facebook) or new insurance services (Amazon and Berkshire Hathaway). Regarding the latter, introducing new data-driven business models implies organizational transformation and capability mobilization. Deep interventions in the entire organizational structures are required. Incumbent companies face challenges in understanding the existing data resources and mobilizing capabilities from different sources. Developing strategies for data-driven business model innovation during a scarcity of highly skilled capabilities, such as data scientists and full-stack developers, have become a key concern of executives. In particular, enabling seamless collaboration between business and IT while fostering innovative working methods imposes a tremendous challenge. Establishing the required structural, capability, cultural, and procedural conditions for data-driven business models to thrive in the context of the prevailing organizational structures and scarce resources needs to be understood. It requires a gradual development of the business model components and an understanding of the data from analytical and technical standpoints. Thus, this article focuses on data-driven business model innovation pathways for capability mobilization in the context of established companies.

12.3 Pathways of Data-Driven Business Model Innovation

When aiming to realize data-driven business models, companies need to mobilize analytical as well as technical capabilities. The former is required to understand the data that are central to the new business model, and the latter comprises technological components that are needed for data processing. Companies take either direct or indirect pathways for mobilizing the required capabilities (see Figure 22). Our cross-industry research with early adopters suggests four pathways. With indirect pathways, companies start building either analytical or technical capabilities first. These companies have the goal of realizing data-driven business models but begin with projects that gradually develop capabilities. Companies taking use case-centric and technology-centric pathways aim to develop data-driven business models but pave the way using projects that build analytical and technical capabilities. Beginning with analytical capabilities, companies start developing an increased understanding of their data within the business units, which also fund these endeavors. The use cases for the gradual enhancement of the traditional business model were very detailed, but this allowed the potential data-driven business models to be described at a higher level. Companies that start building technical capabilities have decided to invest in big data analytics platforms as part of their digital initiatives. For them, having the platforms in place is the first step toward the realization of a data-driven business model. Taking direct pathways implies a clear vision and the willingness to invest in new data-driven business models immediately. The initiatives are sponsored by the chief executive officer (CEO) and financed by funds for new business opportunities. The new data-driven business model is integrated into the existing organizational structure, or a new company is established (i.e., a start-up), putting the new data-driven business model forward. Companies that fail to take one of the four pathways remain in a pending state with an unclear strategy. These companies invest in use case development within the business units and conduct software selection projects but do not take the next step toward a data-driven business model. Decisive factors for the taken pathways are the sponsor of the endeavor, the funding source, and the motivation to embark on the journey. In the following, we will describe each of the four pathways and provide a representative case.

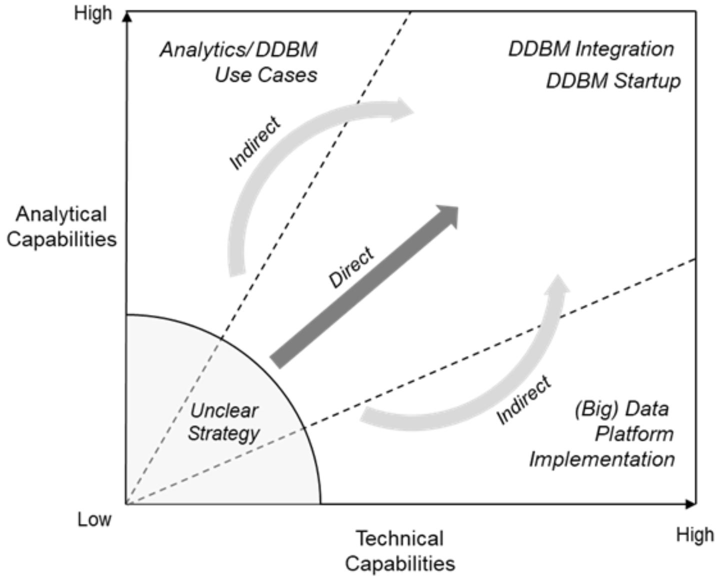

Figure 22. Pathways of Data-Driven Business Model Innovation.

12.3.1 Indirect Pathways

Use Case-Centric Pathway

The data-driven business model endeavors, starting with analytical capability building, are motivated by the business unit's vision and sponsored by the business unit leaders, with support from the chief information officer (CIO)/chief digital officer (CDO). The initiatives are funded by the business units, which also have analytical capabilities. These companies tend to develop use cases in a lab environment, obtaining larger investments from external parties once the first results prove their potential value. Beginning with the use cases implies the BU's critical role in the pathway; in funding the initial efforts through their budget. Use cases are often ideated, selected, and prioritized with external support. Often, consultants bring in use case catalogs from various industries and additional capacity. Ideally, the use cases are prioritized in order to allow the gradual development of the required capabilities. Based on the identified use cases, solution architecture is designed considering existing data resources, technological and analytical capabilities, as well as organizational and structural capabilities. A minimum viable product (MVP) is developed in a lab environment to test the feasibility. Once the leadership approves the MVP, its implementation begins with the IT driving the process. Collaboration between the business unit and the IT department during the process is crucial for successful MVPs. Figure 23 describes how PharmaCorp, a large multinational pharmaceutical company (which has been anonymized for confidentiality reasons), leveraged its analytical capabilities to embark on the data-driven business model journey. Another example is offered by a large Swiss bank, initiating two cases with different BUs: the case involving marketing and sales had an early and extensive IT involvement, which enabled the gradual evolvement of the technology capabilities and, in the end, made the MVP successful and led to implementation.

PharmaCorp is a large multinational pharmaceutical company that has many geographically spread locations. It is one of the largest drug development companies and leading in many product segments. The organizational structure is a matrix divided into countries, regions, functions, and product domains.

With the ambition to be a data-led pharmaceutical enterprise, PharmaCorp invests heavily in digital initiatives. As part of that, business units have dedicated funds to drive analytical use cases for data-driven business model realization.

PharmaCorp's marketing and sales division worked with consulting firms to identify analytics use cases. Those use cases were distinguished in cases for new data-driven business models and enhancement of the existing business model. In joint workshops and based on use case catalogs, the team developed, prioritized, and sequenced their use cases. IT staff from the innovation division supported the process. Cases for reducing operational costs and increasing revenues within the existing business model were prioritized over new data-driven business models, as they bear less risk and required fewer transformation efforts. Based on the set priorities, the IT developed a solution architecture for realization, containing intermediate architectures that consider the gradual expansion of use cases and capabilities. Consulting firms supported this stage with technology expertise. The realization of the first use cases is demonstrated with a minimum viable product, which is developed in a sandbox environment (testing space). After successfully implementing the minimum viable product, the results are presented to the leadership. PharmaCorp's leadership decided to push the endeavor to implementation. Additional funding was granted, and a transformation project was initiated, which is currently still in progress.

Figure 23. Use Case-Centric Pathway at PharmaCorp.

Technology-Centric Pathway

Companies taking the technology-centric pathways start building technical capabilities first. The endeavor is sponsored by the head of the IT department and funded by the digital transformation budget. These companies have little understanding of their data and potential application fields but have decided to invest heavily in big data analytics as part of their digital initiatives. Great effort is made to understand technology options and solution functionalities. However, big data analytics use is described with short-use cases, and the technology selection is prioritized. The business requirements are blurry and poorly derived from high-level use cases. The process is initiated with technology selection efforts, considering internal and external capabilities. Within this phase, a request for proposal is addressed to providers whom external consultants have selected. Technology is selected with a limited understanding of the business requirements. The second phase is the proof of concept conducted with the preferred vendor, with the second-best choice put on hold. Subsequently, the implementation follows. Selecting the most sophisticated solution to provide best-in-class technology capabilities was stated as a common strategy. Figure 24 describes how BankCorp, a large European bank (which has been anonymized for confidentiality reasons), expanded its technical capabilities to embark on the data-driven business model journey. Another example is offered from the public service industry. As part of smart city initiatives, many sensors were implemented within a German city. The funds were made available for this purpose by the government as part of their smart city strategy. A platform implementation has been initiated to leverage the increasing data sources for enhanced and new services. Use cases were developed at a high level, for example, for assisting blind people in navigating the city or tracking and dynamically planning routes for garbage and clothes collection.

BankCorp is a large European Bank with global business operations. Its services mainly focus on other financial services institutions, providing an equalization of liquidity services and a means of refinancing.

The significant role of data for the provisioning of financial services was recognized by BankCorp's leadership. As part of the digital strategy, a new big data platform was planned to be implemented. BankCorp had the ambition to establish the backbone for emerging digital offerings using this "prestige project."

BankCorp's CIO sponsored a data lake implementation. Accordingly, the project responsibility lay in the IT department. High-level use cases for the platform were captured, describing improved decision making and next best action cases. The value behind the use cases was not assessed. The ambition was to develop more use cases and the business units with greater detail once the platform was implemented. The IT team initiated a vendor selection process to identify the most sophisticated platform. BankCorp invited the top-ranked vendor to conduct a proof of concept for the planned data lake implementation. The second-best vendor was put on hold. After successfully demonstrating the proof of concept, the team proceeded with the implementation. Having the platform in place, BankCorp realized its missing analytical capabilities, creating more value-generating use cases. Generating the required data models and enabling analytics cases to be realized has become a key challenge.

Figure 24. Technology-Centric Pathway at BankCorp.

12.3.2 Direct Pathways

Data-Driven Business Model Integration

Transforming an organization to integrate the new data-driven business model into existing structures requires a clear business opportunity, a common vision, and CEO sponsorship. A large-scale transformation is initiated to mobilize required capabilities for the data-driven business model realization. The endeavor begins with the data-driven business model design supported by external consultants infusing the ideation process with relevant industry and cross-industry data-driven business model cases. This process step results in a populated business model comprising the relevant fact of the identified business opportunity. Based on this design, a minimum viable product is initiated, presenting early tangible results. Once the minimum viable product reaches a certain maturity, it enters the implementation stage, where the developed product is scaled for commercialization. Figure 25 describes how EnergyCorp, a European energy provider (which has been anonymized for confidentiality reasons), identified data-driven business model opportunities by implementing a multisided platform and initiating a large-scale transformation. Another example is provided by a German industrial equipment company that identified new data-driven services as a future opportunity. The vision was developed with management consultants, enabling the firm to complement its device-centered business model with new data-driven services for maintenance and value-based pricing. A third example is provided by a global Australian bank that was approached by management consultants with an opportunity to sell banking transaction data for targeted offerings. The bank designed a data-driven business model with the consulting firm and developed a minimum viable product in a trial-and-error approach. Presenting and improving results in an agile and iterative way shortened the time to market.

EnergyCorp is one of the largest energy providers in central Europe. It focuses on the development of energy grids, renewable energy, and energy-provisioning services. EnergyCorp's main business sectors are in energy generation from renewable and traditional energy sources, as well as the global trade of electricity and gas.

EnergyCorp decided to develop a data monetization platform, allowing customers to purchase data-driven services and service providers to offer services enriched with energy consumption data. This decision to monetize data was motivated by shrinking revenues in the energy industry and technology advancements, such as smart meters, which became a

European standard. Anonymized energy consumption data open up many business opportunities for various industries.

The innovation division of EnergyCorp was appointed directly by the CEO to develop new data-driven business models. A cross-functional team resolutely worked with experts to identify new opportunities. After ensuring that the energy consumption data were owned by the company, it designed a business model for a multisided platform to allow new data-driven services with ecosystem partners. The team worked with the business model canvas for platform economies, incorporating multisided customer and provider perspectives. For instance, disaggregating the energy consumption data of an elderly person allows conclusions to be drawn, e.g., if the oven was turned on for more than 3 hours. This use case would require the energy patterns of the focal devices (oven). Subsequently, the team designed the required operating model, the information system architecture, and the technology architecture to realize a minimum viable product. The project is ongoing and transitioning toward the implementation of the minimum viable product.

Figure 25. Data-Driven Business Model Integration Pathway at EnergyCorp.

Data-Driven Business Model Start-up

In contrast, the establishment of a data-driven business model through a new company requires a different approach. However, a clear business opportunity and CEO sponsorship are vital here as well. Having a clear understanding of the data and their monetization opportunity paired with a willingness to invest allows new revenue streams to be harvested. This boldness leads to the decision to set up a new company. The capabilities are built from scratch. Ideally, the new subsidiary remains completely separate, both conceptually and spatially. Access to the data is granted through APIs. The team works in a start-up fashion with end-to-end responsibilities from the design to the realization of the data-driven business model. We used the term realization phase to emphasize the difference to the implementation phase in an enterprise, which is often conducted by the IT department. In contrast to previous pathways, there are no conceptual breaks during this process caused by the consulting firm nor organizational handovers. Figure 26 illustrates how InsureCorp (which has been anonymized for confidentiality reasons) established a new start-up to realize data-driven business models.

Separating the data-driven business model into a new start-up at a later stage might be possible but implies many challenges. Therefore, we want to emphasize three important considerations for the decision to set up a new company. The first consideration is human capital. The data-driven business model was designed by an internal company team that claimed to proceed with the realization. The team leader persisted in retaining his team members. However, it was questioned whether they had the required skillset to ramp up the data-driven business model in an agile start-up way. The second consideration was the technology landscape. The data-driven business model design was based on the prevailing IT architecture, which turned out to be a barrier for data-driven business model scaling due to legacy systems and other architectural constraints. The third consideration was the ecosystem. The new data-driven business model required various collaborations, not only partners but also competitors. In order to disaggregate energy consumption data, the focal company required energy profile data from various device manufacturers. Furthermore, to train the algorithms with rich test data sets, the focal firm depended on smart meter data from other energy providers.

Over the past decade, the Chinese insurance industry has experienced rapid expansion. InsureCorp is one of the largest (by market share) insurance companies in China. Its main business is in property and casualty insurance (general insurance).

InsureCorp decided to develop new data-driven business models with its 650 million clients' health data collected over the past 10 years. This decision to make additional revenue streams with new business models has been made by the CEO. InsureCorp is the legal owner of health data and has processing rights.

The CEO appointed a senior manager to drive the engagement. A management consulting firm was hired to derive data-driven business models together with experts in the health insurance field. A company with newly hired employees was established based on three derived data-driven business models. A team of 20–30 members with special skills worked on the data-driven business model from design to realization in an agile start-up fashion. The data-driven business model was detailed during the process resulting in a minimum viable product that was discussed early with potential clients. Data were extracted from the parent company as required. The architecture was designed to allow rapid scaling with minimum effort. The interviewee highlighted the importance of keeping the company separate and not using the prevailing infrastructure and capabilities of the parent company. This would increase cost and complexity; furthermore, the team would not have had the innovation level that such an endeavor requires.

Figure 26. Data-Driven Business Model Start-up Pathway at InsureCorp.

12.4 Key Enablers for Data-Driven Business Model Innovation

A framework with key enablers for data-driven business model realization emerged from our research with pioneer companies. In order to analyze the capability mobilization, we propose a data-driven business model innovation framework. The framework is derived from the four pathways for data-driven business model innovation. Figure 27 illustrates the data-driven business model innovation framework with its key enablers. It comprises three elements, containing enablers that guide the capability mobilization. Executives can use the framework as a guide for their data-driven business model transformation journey. It provides an overview of the major areas demanding capability mobilization. The strategy element contains the vision and value proposition of the endeavor. Data-driven business models and use cases are described to set the direction. The core element contains the operating model, the information system architecture (comprising the data and application architecture), and the technology architecture, all central components in the realization of a data-driven business model. The foundation element contains the data governance and management enabler. Data are the key resources for data-driven business models and, as such, need special consideration to ensure that their quality and reliability are maintained. The capabilities are mobilized in an agile and iterative approach. Clear go/no-go decision points and funding rounds ensure active senior management engagement.

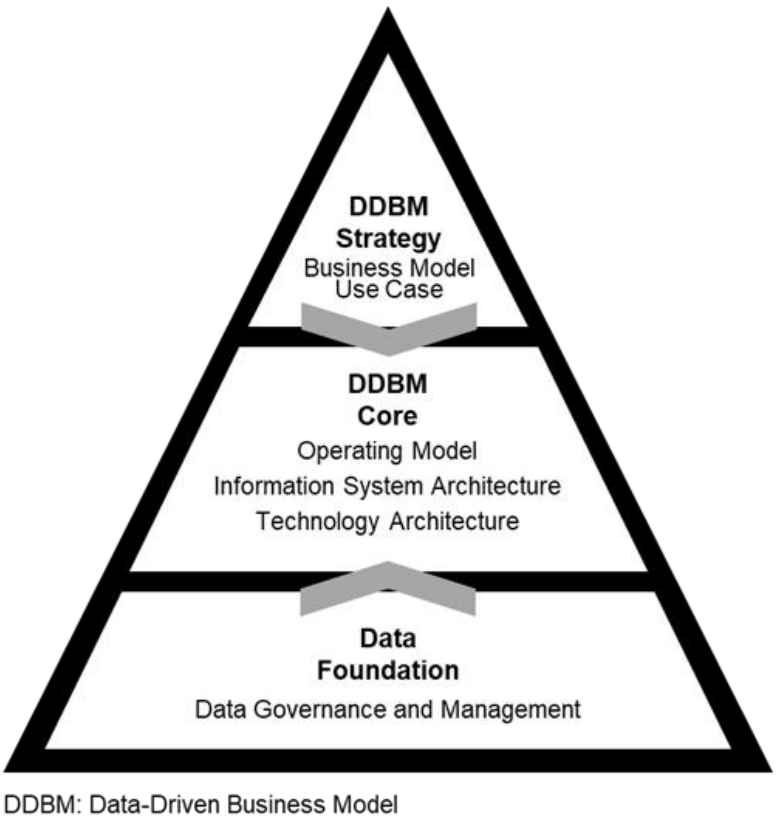

Figure 27. Data-Driven Business Model Innovation Framework.

12.4.1 Data-Driven Business Model Strategy

The data-driven business model strategy element contains the value proposition, which sets the direction for the endeavor. Use cases and business models are developed as central artifacts applying common techniques such as the Business Model Canvas for data-driven business models. In order to populate the Business Model Canvas templates, cross-functional teams from the IT department and business units work with external consultancies and experts. The concept for the new business model is developed and assessed, mobilizing market-relevant capabilities. Technology consulting firms support the process with technical capabilities and industry experts with analytical capabilities. Consulting firms provide use case catalogs to envision the companies' journey toward data-driven business model innovation. The populated Business Model Canvas templates are used to guide the development of the remaining enablers. The strategy element mainly covers the value proposition but partially addresses all remaining components (value creation and value capture).

12.4.2 Data-Driven Business Model Core

The core element contains the value creation enablers of the data-driven business model. Processes, activities, and participants are parts of the operating model enabler. Required skills, mindset, roles, responsibilities, and processes are defined for the targeted data-driven business model. This includes critical assessments of sourcing options for the demanded capabilities, considering that data-driven business model projects premise certain innovation skills, which the prevailing resource base might not have. Separating the new data-driven business model from the prevailing organizational structures and resource base turned out to be an option in the cases. The technology capabilities are reflected in the information system architecture and technology architecture. Data/information and its processing are addressed in the information system architecture enabler. In reference to our research results, this enabler comprises the data and application layers of the enterprise architecture, which support the modeling of data and their processing. This includes informational entities and how they are used, created, captured, transmitted, stored, retrieved, manipulated, updated, displayed, and/or deleted by processes and activities within the data-driven business model. In addition, enterprise architecture modeling and management concepts can further detail data-driven business models and support their implementation. Similarly, the technology architecture can be represented with a technology layer to develop the data-driven business model's required technologies. Addressing related enterprise architecture management concerns helped teams to sketch and develop the required tools and hardware components iteratively.

12.4.3 Data Foundation

The data management and governance enabler goes beyond the core of the data-driven business model; it entails the environmental and infrastructure components of the new business model. The data-driven business model is not built-in isolation and mostly depends on a reliable data infrastructure with policies and practices in place to provide the required level of data quality. The organizational, cultural, technological, and regulatory environments must be considered in order to provide the required data as input resources for the data-driven business model. A multitude of the gathered cases focused on building the data infrastructure first (technology-centric approach). Companies taking the use case-centric approach had narrowed data sets for the data-driven business model for which the data quality was provided by the business units. For the data-driven business model start-up approach, the parent company provided the data resource over application programming interfaces. In the remaining cases, the data infrastructure was developed gradually.

12.4.4 Capability Mobilization

Data-driven business model capabilities are mobilized in an agile and iterative approach, considering the indistinct requirements and presence of numerous uncertainties. Use case and business model description provide only high-level guidance for an explorative procedure. A multitude of conceptual data-driven business models is generated throughout the ideation process, which requires a theoretical evaluation, sequencing, and cyclic realization. Successful cases described the urge to establish an iterative and agile team culture that goes beyond theoretical methods. Considering the multitude of players involved in data-driven business model innovation endeavors, senior management engagement and active involvement are crucial for the successful deployment of a new model. Cross divisional capabilities from business units and IT are required. The first adds functional knowledge and an understanding of the data to the table, while the latter brings the technological know-how for the realization phase. The complexity of data-driven business model innovation endeavors is further increased through the involvement of external parties. In particular, consulting firms support the data-driven business model innovation process with data-driven business model use cases from various industries in the design phase and implementation capacity in the realization phase. For the former, consulting firms infuse the ideation of new data-driven business models with use case catalogs. They support the assessment and sequencing of use cases for successful implementation. For the latter, they provide technological know-how and capacity to rapidly scale solutions. This strong involvement of additional stakeholders, their fluctuation along the design and realization of the data-driven business model, and the resulting threat of knowledge loss due to handovers requires the placement of end-to-end responsibility in the hands of a core data-driven business model innovation team. Frictions from the organizational vision over business model design and realization will be minimized. The enablers evolve over four phases: design, minimum viable product, implementation, and renovation. In each iteration, the data-driven business model capabilities evolve, gaining more details through sprints. The first iteration is an analysis of the conceptual design. As part of the data-driven business model strategy, the business model's key elements are defined using common practices such as the Business Model Canvas. The populated Business Model Canvas framework represents the skeleton of the business model. It guides efforts in the value creation element of the data-driven business model innovation framework. Use cases for the data-driven business model are sequenced, considering implementation efforts and dependencies. Required capabilities and processes are analyzed within the operating model enabler. A high-level view of business capabilities and their sourcing is provided to support complexity and effort assessments. This includes, in particular, cultural aspects, which might become decisive for data-driven business model innovation success. The data required for the data-driven business model and its processing are analyzed as part of the information system architecture. Sketches of the data and application architecture are developed to support complexity and effort estimations. This supports an understanding of the data-driven business model's required data and the data processing capabilities at the application level. The infrastructure perspective to the data and application layer is analyzed in the technology architecture enabler. The required data-driven business model infrastructure is defined on a high-level, assessing the technical feasibility. As part of the data management and governance enabler, the team analyses the environment in which the data-driven business model will be implemented. This includes critical assessments of the prevailing policies and practices for data governance and management, as well as the reliability and quality of the data. While the required data and their processing within the data-driven business model are defined in the information system enabler, the data governance and management enabler are concerned with previous steps of providing the data as the key resource to the data-driven business model as input. Successfully passing the funding rounds results in further detailing the enablers in the minimum viable product iteration, in which the previously developed design is realized as a prototype. In order to implement the DDBM, the requirements of the MVP must be revisited. Enablers must be set up in flexible and scalable structures in order to enable growth. The development of the enablers is coordinated through a central unit (value realization office). The value realization office addresses the value capturing feature of the new business model. Beginning with the use cases/ business model vision, the value realization office keeps track of the progress, monitors the costs, estimates the complexity, and regularly reports to the senior management. The core team, with its cross-functional expertise, contributes to continuous evaluation and reporting. A clear meeting schedule, with steering committee go/no-go decision points and standardized reporting templates, enables senior management involvement. Each cycle of the data-driven business model innovation approach is steered by the value realization office and contributes to detailing the remaining enablers to justify implementation. Funding rounds determine if additional investments are allocated to the data-driven business model endeavor.

12.5 Recommendations for Data-Driven Business Model Innovation

Established companies face several challenges as they embark on the data-driven business model journey. Especially the mobilization of required capabilities exposes a critical challenge. Below, we provide five recommendations for mobilizing capabilities in established firms to realize data-driven business models.

12.5.1 Treat Data as the Key Resource

Data-driven business model innovation requires an understanding of data as the key resource. Data quality and reliability are decisive for the value proposition. Data privacy and ethical constraints might have long-term impacts on the company and should be crucially assessed. For data-driven business model innovation, two perspectives on data should be distinguished. On the one hand, data processing within data-driven business models is described via business model frameworks and use cases with a high abstraction level. Detailed views on the data and their processing are provided in the information system enabler. This includes informational entities and how they are used, created, captured, transmitted, stored, retrieved, manipulated, updated, displayed, and/or deleted by processes and activities within the data-driven business model. The internal perspective answers the questions: What data is required? and How is it processed for the value proposition? On the other hand, data is an input resource for the data-driven business model. Regarding data as input resources for the data-driven business model makes their harvesting crucial. All companies behind the reported cases sourced their data internally, necessitating the organizational building of a data foundation for data-driven business models. This includes data governance and data management procedures, regulations, and policies. Reliable data infrastructure is essential for data-driven business model innovation. The required effort for laying this foundation should not be underestimated. Establishing standardized data management and governance procedures can be a transformation in and of its own. Building required capabilities are either done simultaneously or displaced. Simultaneous capability building (data-driven business model integration, data-driven business model start-up) is recommended when a clear business opportunity exists. It involves more risk and requires a willingness to invest, as presented in the direct pathways for data-driven business model innovation. For displaced capability mobilization, prioritizing the understanding for the data (use case-centric pathway) over establishing the technology backbone (technology-centric pathway) is recommended. Both pathways start with building the foundation with a bottom-up approach. However, ensuring the data quality by the business units first led to earlier results with less risk than building full-fledged technology capabilities.

12.5.2 Apply a Start-up Way of Working

For established companies, the prevailing organizational structures might become a blessing or a curse. On the one hand, a great data and capability pool can be leveraged to put forward the new business model. On the other hand, the same capability pool and inflexible structures might become a bottleneck, as the required innovation level is not met. In order to deal with the inflexibility of the existing structures and allow the striving business model to unfold, a start-up way of operation is recommended. In terms of capability mobilization, the sourcing efforts must be broadly conducted beyond the internally available resources. Establishing a new business model implies different ways of working than operating in an existing one. Role descriptions for capabilities to realize the data-driven business model should be done independently from an internal view of prevailing resources. Matching the demand with the available capabilities should be done as a subsequent step. Additionally, one core team with end-to-end responsibility should be appointed. The strong involvement of external stakeholders, their fluctuation from the data-driven business model endeavor, and the resulting threat of knowledge loss through handovers, makes one core team vital. The complexity of data-driven business model innovation endeavors is increased through the involvement of external parties. In particular, consulting firms support the data-driven business model innovation process with use cases from various industries in the design phase and implementation capacity in the realization phase. For the former, consulting firms infuse the ideation of new data-driven business models with use case catalogs. They support the assessment and sequencing of use cases for successful implementation. For the latter, they provide technological know-how and capacity in order to scale solutions rapidly. Frictions from the organizational vision over business model design and realization will be minimized. The prevailing technology infrastructure might become hindering for innovation as well. Separating the new business model from the existing technology stack should be considered in order to allow rapid implementation. Minimum viable products are built-in sandbox environments to prove early results. Integrating the proven concept into the prevailing technology architecture comes with a risk and requires a high integration effort. Scaling the minimum viable product segregated utilizing on-demand technology components is recommended.

12.5.3 Establish an Agile Mindset

Capability mobilization in data-driven business model innovation should be conducted with an iterative/agile mindset. The requirements for the planned endeavor are blurry and contain many uncertainties. Use case and business model description provide only high-level guidance for an explorative procedure. A multitude of conceptual data-driven business models is generated throughout the ideation process, which requires theoretical evaluation, sequencing, and cyclic realization. Successful cases described the pressure to establish an agile team culture that goes beyond theoretical methods. Such endeavors require teams with certain innovation levels to embrace iterative and agile ways of deeply working. The data-driven business model should be detailed during the process, resulting in minimum viable products that can be discussed early with potential clients. In the first iteration, capabilities should be conceptually mobilized along with the data-driven business model framework enablers. The team shall analyze if and how the data-driven business model can be realized. The developed concept should be passed on to the next iteration, where capabilities are mobilized for a minimum viable product. Discussing early results with the leadership and potential clients allows the team to learn as they develop. Adjustments to the concept can be made. A successful minimum viable product iteration results in an implementation iteration where the product is scaled to commercialization. Learnings from the previous iteration should be applied. The data-driven business model should be realized in a trial-and-error approach. Presenting agile and iterative results will shorten the time to market. Sponsoring, managing, and delivering data-driven business model innovation under uncertainty and a high level of risk demands a detailed tracking of time to results/fail fast. From a delivery perspective, the team learns from early prototyping. Managers have greater monitoring and intervention levels during the engagements, whereas project sponsors possess a potent ability to stop the endeavor. Early results have been reported as proof of concepts for the technology-centric approach, minimum viable products, and rapid prototyping as part of the use case-centric, data-driven business model integration and data-driven business model start-up approach.

12.5.4 Foster a Central Decentralization

Establishing an agile and start-up way of working requires low hierarchy structures and autonomous team setups. For data-driven business model endeavors, independent teams with end-to-end responsibility should mobilize capabilities along with the key enablers, with a central unit (value realization office) coordinating the decentralization-related work. The value realization office ensures senior management engagement with regular reports, progress tracking, and decision points. Additionally, it coordinates the allocation of financial resources for the planned endeavor. Effective financing is a crucial component of data-driven business model innovation endeavors. In order to ensure sufficient funds, the procedure for data-driven business model innovation must be continuously cost/effort driven. Ideally, the funding is structured in a staged approach, similar to start-up funding rounds. In order to get additional funding, data-driven business model endeavors must demonstrate early results delivered in an iterative approach. Sponsors have clear go/no-go decision points to stop further investments in unfruitful projects. The development of the data-driven business model enablers should be coordinated through the value realization office. Beginning with the use cases/ business model vision, the value realization office keeps track of the progress, monitors the costs, estimates the complexity, and reports regularly to the senior management. The core team, with its cross-functional expertise, contributes to continuous evaluation and reporting. A clear meeting schedule, with steering committee go/no-go decision points and standardized reporting templates, enables senior management involvement. Each cycle of the data-driven business model innovation approach is steered by the value realization office and contributes to the detailing of the remaining enablers to justify implementation. For example, while developing a minimum viable product, the value realization office tracks the capability development and reports to senior management. Additional funding is required to reach the implementation iteration. A critical assessment of the cost and complexity, as well as the potential value, are integral for senior management decisions for additional investments. Successful cases are passed for implementation, where the minimum viable product is scaled to the reach commercialization scope.

12.5.5 Prioritize and Pipeline Business Models/ Use Cases

Data-driven business model innovation endeavors bear high risk for established companies, as they require capability building in various domains with unclear returns. Implementation requirements are indistinct, and the business impact difficult to estimate. Analytical capabilities must be established to understand the data and technical capabilities for their analysis. In order to prevent falling into the "hype trap" of data-driven business model innovation, it is vital to keep a value-driven mindset through the endeavor. Within the ideation phase of data-driven business model innovation, a multitude of business model ideas/use cases are developed. Each option promises returns and demands capability mobilization. Sequencing the business model ideas/ use case for testing and realization is crucial. An exploratory approach involving iterations of testing, prototyping, and, ultimately, implementing is recommended. Starting with business model ideas/ use cases that bring early results and build the foundation for "north star" endeavors has proven to be a prevalent method. Organizations falling into the technology hype trap tend to have little understanding of their data and potential application fields but decide to invest heavily in big data analytics as part of their digital strategy. Great effort is put into understanding technology options and solution functionalities. However, the big data analytics use is described with short use cases, and the technology selection is prioritized. The endeavor is sponsored by the head of the IT department and funded by the digital transformation budget. These endeavors are denoted as investments. Big data analytics projects pave the way for data-driven business model innovation, which may focus data-driven business model innovation efforts on purely prestige projects that are not justifiable in terms of the value they provide. Consequently, all elements of the business model, especially revenue streams, value proposition, and customer segmentation, support evaluation and value tracking.

12.6 Concluding Comments

As part of the data evolution, data-driven business models have emerged as a phenomenon in great demand for academia and practice. The latest technological advancements, such as cloud computing, the Internet of things, big data, and machine learning, have contributed to the rise of data-driven business models, along with novel opportunities to monetize data.

Based on 19 data-driven business model innovation cases from the United States, Europe, and the Asia-Pacific, we derived four pathways and a capability framework to provide recommendations for how incumbent companies can successfully introduce data-driven business models. This article illustrates the four pathways providing one case vignette for each. Successfully deploying data-driven business models requires capability building and sourcing. The cultural transformation aspects are the most challenging. Agile collaboration modes between business and IT are required, applying lean start-up methods. Senior sponsorship is vital here as well. Having a clear understanding of the data and their capitalization opportunities, paired with a willingness to invest, allows new revenue streams to be harvested. This boldness leads to the decision to embark on a data-driven business model innovation journey.

12.7 Appendix: Research Method

The article's research was a qualitative research study of 19 international cases for data-driven business model innovation. The development of the data-driven business model framework is based upon the design science paradigm and the design science research framework. The data-driven business model innovation framework is inductively developed in two design iterations that follow the ideas of the grounded theory approach. In order to achieve relevance, we conducted 16 semi-structured expert interviews in the first iteration. We derived design principles as a general blueprint of requirements which then serve as the foundation for instantiation. Additionally, 19 international cases of data-driven business model endeavors were collected and clustered to identify four approaches for data-driven business model innovation. The design principles, case clusters, and pathways have been evaluated with all 16 interview participants. Each interviewee had a track record of data-driven business model innovation projects. We analyzed the data as we collected them. Drawing on Myers and Newman's (2007) recommendations allowed us to foresee common pitfalls of qualitative interview research (e.g., lack of trust; lack of time; level of entry). In order to construct a coherent theory based on the gathered data, we draw on the grounded theory as proposed by Corbin and Strauss (1990).14 We applied an open coding approach and selected ATLAS.ti for tool support. Not having a specific framework in mind, we conducted the interviews openly. In order to uncover relations among the categories, we reassembled the data that had been broken up during open coding. For this, we applied axial coding as described by Corbin and Strauss (1990). We clustered the 19 collected cases and derived four approaches for data-driven business model innovation. Furthermore, we derive five recommendations from gathered key considerations and lessons learned. In order to achieve rigor, we conducted a systematic literature review, following a methodology proposed by vom Brocke et al. (2009). On the bases of the four empirically identified approaches for data-driven business model innovation and the application of key methodologies and frameworks from the systematic literature review, we developed the data-driven business model innovation capability framework. The results of the second iteration have also been evaluated with the interviewees. We used the holistic enterprise perspective of the Work System Theory as a conceptual basis to address all relevant facets of a company that performs data-driven business model innovation to deliver new products/services or improve existing ones. This structuring frame has been further enriched with the four derived approaches. Additional insights were incorporated from The Open Group Architecture Framework's (TOGAF) Architecture Development Method (ADM), the most popular enterprise architecture management framework. In order to evaluate the data-driven business model innovation framework, we conducted follow-up meetings with our interview participants to get their qualitative feedback. This led to restructurings and rewordings of the identified enablers. Suitably, we adjusted the framework as we proceeded with the meetings.

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