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A Reference Model for Data-Driven Business Model Innovation Initiatives in Incumbent Firms

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A REFERENCE MODEL FOR DATA-DRIVEN BUSINESS MODEL INNOVATION INITIATIVES IN INCUMBENT FIRMS

Research Paper

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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 start initiatives to 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 initiatives. Building upon a design science research approach and the Work System Theory as a kernel theory and a set of design principles, we 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. The developed reference model fills a gap mentioned in the DDBM innovation literature and provides practical guidance for companies.

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

1 Introduction

Big data analytics has received considerable attention from academia and practice (Chen *et al.* 2012, Abbasi *et al.* 2016, Baesens *et al.* 2016). 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 *et al.* 2020). These DDBM innovation (Fruhwirth *et al.* 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 *et al.* 2014) and/ or have data processing as a key activity (Rashed and Drews 2020) which makes data essential for the value proposition (Schüritz *et al.* 2017). Considering the high dependency on big data analytics, DDBM innovation initiatives comprise 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, Lange *et al.* 2021, Wiener *et al.* 2020). Practitioners face several challenges in DDBM innovation (Günther *et al.* 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 (Lange *et al.* 2021, Wiener *et al.* 2020). In particular, details on designing and implementing DDBMs as socio-technical systems have received little attention (Kühne and Böhmann 2019, Fruhwirth *et al.* 2020, Rashed and 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 for guiding DDBM innovation. 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 this gap of prescriptive design knowledge about DDBM innovation initiatives by developing a reference model which includes the design as well as the implementation of DDBMs. We address the following research question: What are the essential components of a reference model for data-driven business model innovation initiatives in incumbent firms?

2 Related Research and Theoretical Foundations

As this study seeks to contribute to the emerging field of DDBM, we first provide an overview of recent work in this field including studies on DDBM innovation. Second, we briefly introduce enterprise architecture research and work system theory as foundational work which helped us to develop and structure the results.

Data have long been acknowledged as a key driver for business and have received considerable attention from the information system discipline (Sharma *et al.* 2014, 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 (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 *et al.* 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 and Böhmann 2019, Rashed and 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 (Kühne and Böhmann 2019, Fruhwirth *et al.* 2020, Lange *et al.* 2021, Rashed and Drews 2020, Wiener *et al.* 2020).

Data-driven business model innovation can be seen as "the process when an organization adopts a novel approach to commercialize data as its new underlying asset to deliver value to existing or new customers" (Fruhwirth *et al.* 2020, p. 4). Thus, it is a collaborative and creative task that requires divergent and convergent thinking. DDBM innovation guides the procedural efforts manifested as DDBM innovation 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." Hartmann et al. (2014) first mentioned the 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". Latest research focused on better understanding the DDBM realization, but it does not present a prescriptive reference model intended to guide action (Lange *et al.* 2021).

Aiming to advance literature in DDBM innovation including design and especially implementation, we draw on the enterprise architecture research to inform the development of a reference model for DDBM innovation initiatives. EAM provides management and modelling concepts that help organizations to transform from an as-is to a to-be status. The literature in DDBM innovation can profit from the integrative perspective of EAM which seeks to align organizational and technical design with strategic goals and initiatives. Research on enterprise architecture management can be traced back to the Zachman framework from 1980 (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 and 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 and 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 and 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. EAM and EA modeling are capable of supporting the transition from the as-is to the to-be state as part of a DDBM innivation initiative through several intermediate architecture stages (Rashed and Drews 2020).

We draw on the work system theory as a kernel theory for guding the development of the reference model as it offers fundamental dimensions relevant for the domain of interest. 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. Drawing on Gregor (2006), Alter further argues that the “work system theory 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). The work system theory provides the fundamental structure for the reference model developed in this study. Accordingly, the reference model for DDBM innovation initiatives comprises a static and dynamic view. Furthermore, the fundamental elements for developing a socio-technical system are addressed with the reference model for DDBM innovation initiatives.

3 Research Methodology

To provide a reference model for DDBM innovation initiatives, 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). 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 *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 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). The reference model for DDBM innovation initiativesis inductively developed in two design iterations.

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 initiatives. 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 about the cases 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 identified four approaches for DDBM innovation initiatves. 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. 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. Table 1 illustrates the 19 DDBM innovation cases with further information on the interviewees and the initiatives.

Furthermore, we derive seven design principles as artifact or entity-independent design knowledge. 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). For example, statements like "having CEO support allowed our team to access the data from different business units" [IP11], "without the active involvement of the CEO this endeavor would have been a failure" [IP6], and "what we missed was support from the leadership" [IP3] led to the derivation of design principle 1: senior management engagement. 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.

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

Table 1. Interview participants

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 (Vanauer *et al.*

2015, Chen *et al.* 2017, Rashed and Drews 2020). 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 and Hevner 2018). Therefore, the design of the reference model for DDBM innovation initiatives fis 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 reference model, we conducted follow-up meetings with our interview participants to receive 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.

4 Results

4.1 Design principles for DDBM innovation

As part of the interviews, we gathered key considerations and lessons learned from the initiatives of our interviewees. Coding and analyzing this data allowed to us derive seven design principles for DDBM innovation initiatives, which are illustrated in Table 2 and described in the following.

Considering the multitude of involved parties in DDBM innovation initiatives, 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 initiatives 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 initiatives 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 initiatives 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 initiatives require a clear plan for involving the senior management in the progress and decision point along the journey.

The complexity of DDBM innovation initiatives 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 initiatives should proceed 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 initiatives 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 initiatives. To ensure sufficient funds, the management for DDBM innovation initiative 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.

To prevent falling into the "hype trap" of DDBM innovation, it is vital to keep a data value realization (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. 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].

#	*Design Principle*	*Description*
1	**Senior management engagement and joint effort of business and IT**	DDBM innovation initiatives require sponsorship from senior management with active engagement and support and joint effort of business and IT.
2	**Ensure end-to-end responsibility across different DDBM innovation phases**	DDBM innovation initiatives must be conducted by interdisciplinary and rather stable teams with end-to-end responsibility.
3	**Follow an iterative / agile approach**	A cyclic approach for DDBM innovation initiative with clear goals per iteration and agile ways of working are crucial.
4	**Deliver fast, learn quickly**	The DDBM innovation initiative's results must be delivered fast to ensure rapid learning cycles and quicker allocation of resources and efforts.
5	**Work cost/effort driven**	Each cycle of a DDBM innovation initiative must be well budgeted and tracked with go/no-go decision points for additional funding.
6	**Ensure orientation towards value generation**	The generated value must be kept in focus throughout the DDBM innovation initiative.
7	**Treat data as the key resource**	The high dependency on data as the key resources makes it quality and reliability decisive for the DDBM innovation initiative's impact.

Table 2. Design principles for DDBM innovation initiatives

Successful DDBM innovation initiatives require an understanding of 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.

4.2 Reference model for DDBM innovation initiatives – Static view

Drawing on the work system theory, which proposes two views for representation, we developed a reference model for DDBM innovation initiatives 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 2), namely value proposition, value creation, and value capture (Fruhwirth *et al.* 2020). It contains six enablers, which build on the nine work system theory framework components and the reported approaches for DDBM innovation initiatives. 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 approach, with a value realization office 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 value realization office. 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 value realization office tracks the complexity and the readiness of the data infrastructure to source data as the key resource (DP7).

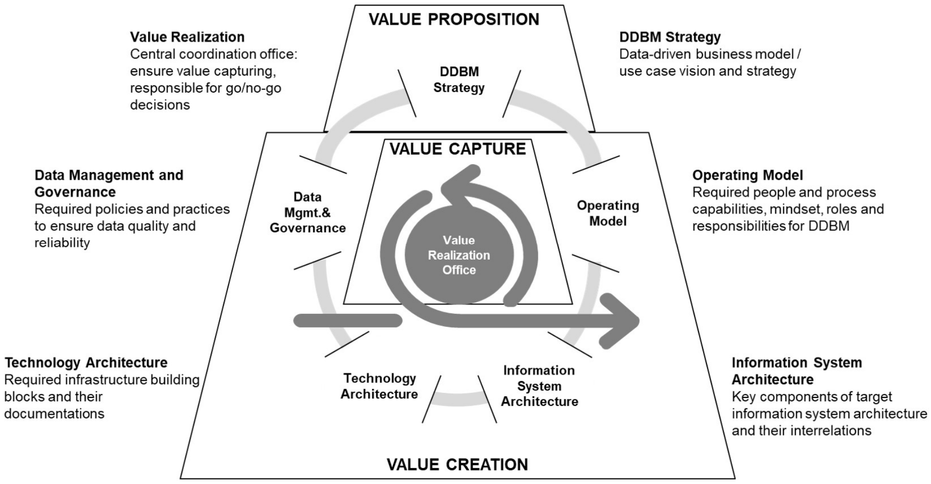

Figure 2. DDBM innovation initiative reference model – static view

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 value realization office to guide the development of the remaining enablers. Referring to the work system theory, 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 work system theory. 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 initiative 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 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 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 initiative is steered by the value realization office and contributes to the detailing of the remaining enablers to justify implementation. Funding rounds determine if additional investments are allocated to the DDBM endeavor.

4.3 Reference model for DDBM innovation initiatives – Dynamic view

The dynamic view of the DDBM innovation innovation reference model is illustrated in Figure 3. Drawing on the work system theory, 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 initiatives are still in early stages and did not exceed implementation, the renovation iteration was added from literature on BM innovation (De Reuver *et al.* 2013). In each iteration, the DDBM enablers evolve, gaining more details through sprints.

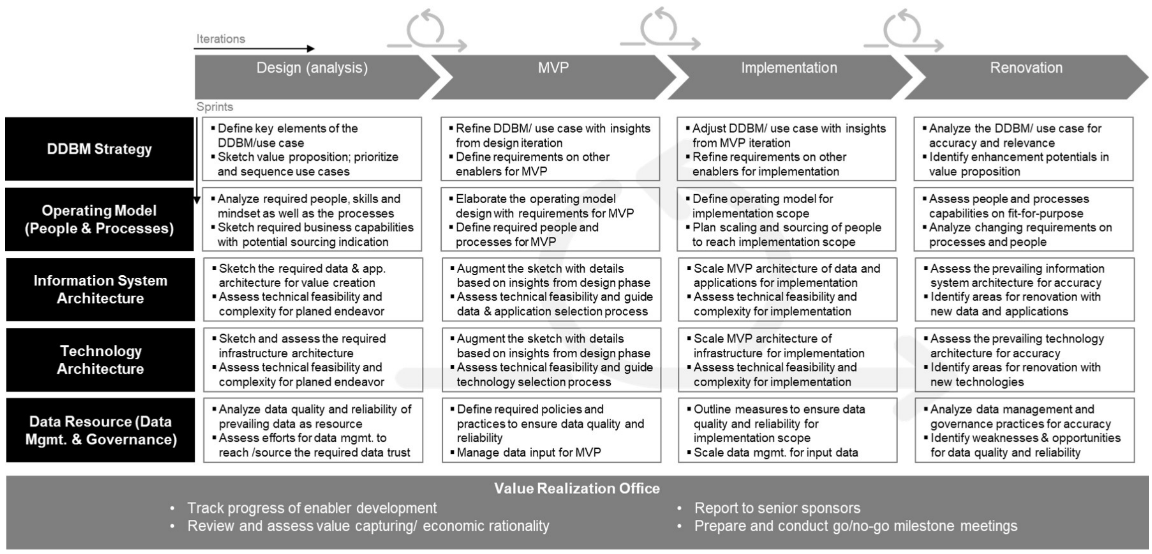

Figure 3. DDBM innovation initiative reference model – dynamic view

The value realization office 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 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 initiatives' 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 value realization office 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 value realization office. 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 value realization office 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.

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 value realization office. The team expands as the implementation proceeds. The value realization officegains 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 value realization officeare 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 value realization officeruns 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 value realization office.

4.4 Exemplary application

In this section, we demonstrate the instantiation of our artifact, drawing on the gathered cases from our interviews. We selected a 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 and 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 initiative. 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 value realization officeremained responsible for tracking, monitoring and reporting. Platform implementation, team hiring and partnering with providers was planned for 14 months. The value realization office was running with minimum headcount after the implementation to monitor appropriateness of the DDBM and to learn for future projects.

5 Discussion and Conclusion

Our contribution for DDBM innovation is a reference model with six enablers, providing a static and a dynamic view. The development of this reference model was guided by the seven design principles for DDBM innovation initiatives which we developed from the interviews. Both, the reference model and the design principles, are based on the results of the qualitative analysis. The reference model incorporated relevant knowledge on DDBM innovation and enterprise architecture from the literature. Thus, the model is empirically grounded and embeds existing knowledge from the literature. We contribute to research by presenting a DDBM innovation reference model which addresses a gap gap revealed by previous research from 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)" received very little attention so far (Wiener *et al.* 2020, p. 75). While some selective support (e.g. DDBM ideation (Kühne and Böhmann 2019)) has been proposed by the literature, it especially lacks an comprehensive approach for DDBM innovation which also covers the realization activities. 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). The reference model is grounded in the work system theory as the kernel theory. Although the reference model applies known concepts, their use and combination for DDBM innovation is uniquely presented in this research study. Before this study, there was no refence model dedicated to the field of DDBM innovation. Existing papers which comprise design knowledge where mainly focused on the design of DDBM, while our study also includes the implementation of the DDBM and the setup of the operating 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).

Our contribution for practitioners is threefold. First, the reference model can be used to guide the design and realization of DDBMs in incumbent companies in different industries. It provides a structural and a dynmic perspective and includes activities which need to be carried out in DDBM innovation initiatives. It also includes novel elements like the value realization office. Second, the design principles incorporate generalized design knowledge which can serve as guidelines for developing additional artifacts which guide guide DDBM innovation initiatives. Third, the cases presented briefly in section 4.4 might serve as an inspiration for companies.

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 a methodological 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 number of interviews and cases was limited. Our future work will focus on further sophisticating the reference model with additional cases. Further research should pay attention to the "content" of the DDBM innovation activities and seek to structure them (e. g. by advancing existing DDBM taxonomies).

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