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The Data-Driven Business Value Matrix - A Classification Scheme for Data-Driven Business Models

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Abstract Increasing digitization is generating more and more data in all areas of business. Modern analytical methods open up these large amounts of data for business value creation. Expected business value ranges from process optimization such as reduction of maintenance work and strategic decision support to business model innovation. In the development of a data-driven business model, it is useful to conceptualise elements of data-driven business models in order to differentiate and compare between examples of a data-driven business model and to think of opportunities for using data to innovate an existing or design a new business model. The goal of this paper is to identify a conceptual tool that supports data-driven business model innovation in a similar manner:

We applied three existing classification schemes to differentiate between data-driven business models based on 30 examples for data-driven business model innovations. Subsequently, we present the strength and weaknesses of every scheme to identify possible blind spots for gaining business value out of data-driven activities. Following this discussion, we outline a new classification scheme. The newly developed scheme combines all positive aspects from the three analysed classification models and resolves the identified weaknesses.

Keywords: Business Model Innovation • Data Analytics • Data-Driven Business Model

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1 Introduction

The subject of business models (BM) has gained steadily increasing attention in the last 20 years both in the academic field and also in the entrepreneurial practice. By Business Model (BM) we understand a description or model that represents a firm's logic to create, provide and capture value from and for its stakeholders (Bouwman et al. 2008). According to Osterwalder et al. (2005), a business model is a "blueprint" for how to run a business. Concerning Business Model Innovation (BMI) there is a heterogeneous understanding in the literature (Wirtz et al. 2016). The definitions reaching from modifications or introduction of a new set of BM key components that enable the firm to create and capture value (Hartmann et al. 2016) to the reinvention of a BM by a fundamental rethinking of the existing customer value proposition (Johnson et al. 2008).

Nevertheless, the topic of business model innovation is more relevant than ever due to increasing awareness about the potential and possibilities of digitization and the use of (big) data as a key resource. In the area of digitization and Industry 4.0 data became the new strategic resource for business model development. Data can be utilized in every element of a business model starting from value creation processes (e.g. improving production processes), enriching the value proposition (e.g. enhancing products with data-driven add-on services) up to value capturing (e.g. selling data or data generated information). The development of data-driven business models (DDBM) requires expertise in several fields, like technology, data science, business strategy or ethics.

Although much BMI research has been done, there is limited knowledge on how data function as a business resource and how to support data-driven business model innovation with adequate, hands-on and easy to use tools and methods. Therefore, our main research objective is to identify, and if necessary develop, a classification scheme which is useful to differentiate and compare between examples of a data-driven business model, and to think of opportunities for using data to innovate an existing or design a new business model.

Specifically, we seek to answer the following research questions:

RQ 1: What are the characteristics of the applied classification schemes in terms of being able to differentiate and compare between examples for data-driven business model innovation?

RQ 2: Which parameters should a classification scheme contain that maintain the strength and overcome the weaknesses and how does it look like?

The paper is structured as follows: In section 2, we will outline the theoretical framework by describing different classification approaches and the selected three which are applied in the study. Section 3 explains the methodological procedure including criteria for data selection, an overview of the project. The analysis results and a proposition for a new classification scheme are outlined in section 4 and 5. Finally, a conclusion chapter presents a summary of the findings, limitations and ideas for further research.

2 Background and Related Work

In recent years, BMI research has already begun to develop taxonomies and classification schemes for DDBM. Below, we will briefly outline the most important classification schemes and some relevant literature in the field of DDBM. Based on defined selection criteria, three approaches were selected for the classification of the data-driven innovation projects (see chapter 4).

Hartmann et al. (2016) proposed a data-driven business model framework with six dimensions (data sources, key activities, offering, target customer, revenue model and specific cost advantage) and up to three sublayers based on information systems and business model literature. The sample was limited to 100 start-ups in the category of "big data" or "big data analytics. The analysed companies can be characterised as "born-online" as the majority of the companies offer digital products and services since the foundation. Wixom and Ross (2017) distinguished between three approaches to transform data into business value, by improving internal processes, wrapping information around products and finally, selling data or information offerings.

Engelbrecht et al. (2016) developed a taxonomy for data-driven business models with three dimensions (data sources, target audience and technological effort) from a sample of 33 data-driven start-ups. Schüritz et al. (2016) described five "Data In-fused" BM patterns where data and analytics are directly impacting the core components of a business model (value creation, value capturing and value proposition). The analyzed sample use cases (115 companies) are mainly industry companies, which can be characterized as "born-offline" (established without digital products and services). Zolnowski et al. (2016) analysed how data and analytics transformed business models of established enterprises (20 cases from seven "born-offline" industries). A BITKOM study (2015) analysed 42 industry use cases using a four strategic dimension matrix (existing/new business, existing/new data) and described four main business model patterns.

Schmidt et al. (2018) revealed distinct patterns of DDBMs from start-ups and fin-techs respectively. Hunke et al. (2017) proposed a prototypical process model for data-driven business innovation with six process steps (mobilization, initiation, ideation, integration, realization, administration) following the model from Bonakdar and Gassmann (2016) and three process content layers (business, data, and ecosystem). Brownlow et al. (2015), Schröder (2016) and Schüritz et al. (2017) analysed barriers and challenges organizations face during data-driven business model innovation.

As present literature offers already plenty of different classification schemes, we applied the following selection criteria in order to support the identified research gap. The selected classification schemes should have a low level of complexity (easy to use, easy to understand). As our sample projects are mainly established enterprises (see chapter 3.1), we use as selection criteria "born online" (digital or data-driven start-ups) and "born-offline" (company founded without digital products and services).

Author	Sample mainly "born online"	Sample mainly "born offline"	Degree of complexity (ease of use)
Hartmann et al. (2016)	✓		high

Wixom and Ross (2017)		✓	low
Engelbrecht et al. (2016)	✓		middle
Schüritz et al. (2016)		✓	low
Zolnowski et al. (2016)		✓	high
BITKOM (2015)		✓	low

Table 1: DDBM classification literature

By applying the above-mentioned selection criteria, we selected classification schemes which matching "born offline" and low complexity to classify the data-driven innovation projects regarding business model implications. Hereafter the three selected classification schemes are described in detail.

(1) The strategic managerial approach is based on Ansoff's product-market framework (Ansoff 1965) adapted by BITKOM (2015). Big Data initiatives or projects are classified into four categories illustrated in Fig. 1

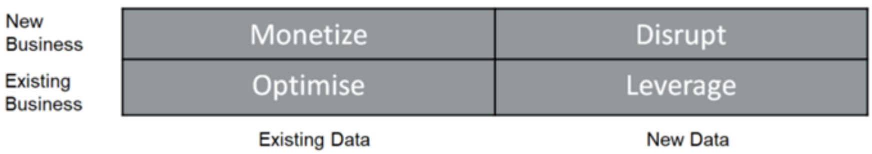

Figure 1: Strategic classification matrix based on Ansoff (1965) and BITKOM (2013).

Data-driven activities in the "Optimise" quadrant represent utilizing existing data sources for the current business. This could lead to improvements in many areas of the existing business model reaching from product quality topics to valuable insights into sales figures. The "Monetize" area aims to develop new products and/or services using existing data. Using new data could "Leverage" the existing business by enriching products and services. New product or service developments based on new data sets are positioned in the "Disrupt" quadrant.

(2) The data infused business model perspective: Schüritz et al. (2016) described five "Data In-fused" BM patterns (see Table 2) where data and analytics are directly impacting the core components of a business model (value creation, value capturing and value proposition). Schüritz et al. (2016) arguing conclusively that data may have a beneficial influence on each core building block of a business model, on two or all three simultaneously. The concept has been tested and evaluated based on 115 publicly available cases.

No.	Category / Pattern	Short description
I	Data-Infused Value Creation	Using existing or new data sources for optimizing value creation
II	Data-Infused Value Capturing	Identifying new customer segments or utilizing new revenue models based on data and/or data analytics
III	Data-Infused Value	Offering data-driven enhancements for existing products

	Proposition via Creation	and services or entirely new data-driven services
IV	Data-Infused Value Proposition via Capturing	Using data to improve the value proposition and concurrently changing the way the BM captures value
V	New Data-Infused Business Model (DiBM)	Using data and analytics to developing an entirely new data-driven service by changing all three parts of a BM

Table 2: Data-Infusion Patterns (Schüritz et al. 2016)

3) The specific value proposition view: As the value proposition is seen as a central part by many business model ontologies (Osterwalder & Pigneur 2010; Gassmann et al. 2013, Johnson et al. 2008) it is plausible to study how and to what extent data and data analytics influence the value offering. Based on recent research on data-driven business model pattern (Hartman et al. 2016; Schroeder 2016; Schüritz et al. 2017; Wixom & Ross 2017) five distinctive pattern based on a specific value proposition views were identified (see Table 3). The first two categories are similar to the previously described Data Infused BM pattern I (Data Infused Value Creation and III (Data Infused Value Proposition via Creation). In the third category, companies develop new services based on data, independently from the core offering (product or service) in order to generate additional revenues.

The data-as-a-service category offers the possibility to sell data which were generated by their core business processes or aggregated from third-party data providers (Otto & Aier, 2013) to customers, like any other good. Data is usually not modified, but pre-processed, analyzed and anonymized to be turned into a sellable product. Finally, companies can offer data-driven services, like analytics-as-a-service, infrastructure-as-a-service, software-as-a-service and consulting services (Schroeder, 2016). These activities were summarized in a fifth category named auxiliary big data services.

Category/ Pattern	**Short description**	**Value Proposition**
Data-enabled Improvements	Leveraging data and analytics for company internal (process) optimization.	Value proposition is not affected
Data-enriched products and services	Existing products and services are enhanced with data and data analytics to provide additional value	Product/service with data/ information as an add-on
Data-enabled Services	Stand-alone data-driven services based on internal data or data from third parties are provided	Information, knowledge or answers
Data-as-a-Service	Data is sold like a common good. Activities in this pattern also include data aggregation, storage and broking.	Data
Auxiliary "big-data" services	Supporting data and analytics activities, when organizations do not have the core competencies in this field (e.g. Analytics as a Service, IaaS, SaaS, consulting services)	Non-data product or service

Table 3: Patterns focused on Value Proposition

3 Method

3.1 Data Selection

We base our analysis on innovation projects carried out at a European applied research institution. The research centre's mission is to carry out excellent research in the fields of data-driven business and big data analytics, to enable innovation in national and European companies, and to support qualification of professionals and organizations in these fields.

The projects we selected come out of a pool of 56 innovation projects executed at the institution in the years 2015-2017. All projects we analysed were research and innovation-oriented and were carried out always by at least two participating organizations, i.e. the institute and at least one non-research organization (the organization who intended to explore data analytics with the goal to create business value). In addition, we selected only projects were at least 2/3 of the project volume was assigned to data analytics related activities, such as data acquisition, data pre-processing, data analytics, data visualization, etc.

As a result, we worked on the following 30 projects listed in Table 4.

Number	**Project Topic**	**Type of Business**	**Industry**
1	Enhanced and new services through new data	Start-up	Services
2	Add on services based on new data insights	SME	Retail
3	Demand forecasting based on historical market/ sales data	LE	Retail
4	Increase security at major events through monitoring and data analytics	Public	Mobility
5	Intra-Logistics optimization	LE	Automotive
6	Social media analysis for traffic prediction	LE	Mobility
7	Guiding through data-intensive work processes	LE	Automotive
8	New services using biodata analysis	SME	Life Science
9	Increase work safety through data analytics	LE	Automotive
10	Interactive production data visualizations	LE	Manufacturing
11	Predictive maintenance	LE	Manufacturing
12	Pattern detection in big (measurement) data	LE	Automotive
13	Early detection of production errors	LE	Automotive
14	New services using biodata analysis	Start-up	Life Science
15	Data-driven coaching	Start-up	Life Science
16	Optimizations in intra-logistics	LE	Manufacturing
17	Guiding through data-intensive processes	SME	Life Science

18	Guiding through data-intensive processes	SME	Services
19	Strategic Intelligence	SME	Services
20	Process support	Start-up	Retail
21	Potential analysis of sensor data	LE	Manufacturing
22	New services using data-driven recommendation algorithms	Start-up	Retail
23	Developing new services using data-driven recommendation algorithms	SME	Services
24	Interactive data visualizations	LE	Automotive
25	Early detection of production errors	LE	Manufacturing
26	Semantic Search Support	LE	Services
27	Utilizing Mobility Data	SME	Mobility
28	New services based on machine data	LE	Manufacturing
29	Quality improvements through data analytics	LE	Manufacturing
30	Product enhancements through data analytics	SME	Life Science

Table 4: Overview of selected projects

The sample is characterized as follows:

- Type of projects: 88% funded research projects, 12% not funded research projects.
- Industry: 24% Retail, 24% Automotive, 16% Life Sciences, 12% Mobility, 12% Manufacturing, 12% Service Sector (consulting, public administration).
- Type of business: 52% Large Enterprises (LE), 16% Small and Medium Enterprises (SME), 16% Start-Up, 8% public administration.

3.2 Analysis

For analysing the thirty selected projects, we applied a multi-case study research (Yin, 2014) which allows the investigation of complex real-world phenomena. Case study research is the preferred approach to study data-driven innovations and related business models and has been used by different authors (Schüritz et al. 2016, Engelbrecht et al. 2016, Otto and Aier 2013). The goals of the analysis were to understand the business value that was created within these innovation projects and to identify the characteristics of the three classification schemes 1) Strategic managerial approach (BITKOM matrix) 2) Data-infused Business Model perspective and 3) Specific value proposition view.

In a first step, we analysed the available project documents (reports, presentations, and prototypes) to ensure a deep understanding of the project content as well as the applied data analytics methods and the reached project goals. This approach provides a solid basis for the subsequent classification process. Hereafter, all projects were classified by two independent researchers. Any disagreements have been resolved by consultation of the respective project manager at the research institution and joint discussions. After completion of the classification of each scheme, the researchers documented the results (see chapter 4.1, 4.2 and 4.3) and evaluated each scheme regarding support of data-driven business model innovation. Based on these results described in form of strength and weaknesses (see chapter 4.4), a proposition for a holistic classification scheme have been developed and outlined as “Data-Driven Business Value Matrix” in chapter 5.

4 Results

4.1 Strategic and managerial classification (BITKOM Matrix)

As shown in Table 5, more than half of the projects (57%) are located in the Optimization quadrant (project example: improving the demand forecasting process by taking historical market and sales data into account). Most of these are well-established companies (mainly LE) that using existing data as a starting point, focusing primarily on process improvements e.g. lead time reduction and increasing product quality. A small percentage of the analysed company projects followed the strategic approach of "Monetization" in order to develop new products and/or services using existing data (project example: enriching already provided inventory and shop management solutions with new additional data-driven insight services). The main topics here were data-driven additional services in the field of maintenance and service.

Projects related to the “Leverage” quadrant focused on improved services through new data (e.g., social media data or other external data sources) at the centre of business model considerations (project example: using social media data for traffic analysis and prediction). The two associated projects in the “Breakthrough" quadrant are start-ups looking out for completely new products/ services or business models (project example: using data from wearables and mobile sensors for emotion-based services).

Category / Pattern	**Projects**	**%**	**No.**
Optimise	3,5,7,8,9,11,13,16,17,18,20,21 24,25,26,29,30	57%	17
Monetize	2,10,12,15,27,28	20%	6
Leverage	4,6,19,22,23	17%	5
Disrupt	1,14	6%	2

Table 5: Strategic and managerial classification

4.2 Data-infused business model classification

The majority of the projects (57%) were assigned to one business model category, the “data infused value creation” pattern (project example: analysis of internal log data for optimization of logistics processes). This is due to the high number of projects based on production data aiming for detection of process improvement potential. More than one-third of the projects (37%) heading for enhancements to the offered product or services via utilization of data out of the “creation” process (project example: monitoring and analysis of movement data for increasing security services at major public events). This category offers a wide range of activities starting with small digital add-on's to product/service up to completely new service offerings based on own "creation" data.

Two projects were mapped to the "New Data-Infused Business Modell" because in these projects changes were made in all three main segments of a business model (value creation, value proposition, value capturing). Project example: building up a common data-infrastructure for aggregated data sharing and analysis. None of the analysed projects was classified to "Data-Infused Value Capturing" and "Data-Infused Value Proposition via Capturing" pattern.

Category / Pattern	**Projects**	**%**	**No.**
Data-Infused Value Creation	3,5,7,8,9,11,13, 16,17,18,19,20, 21,24,25,26,29	57%	17
Data-Infused Value Capturing		0%	
Data-Infused Value Proposition via Creation	2,4,6,10,12,15, 22,23,27,28, 30	37%	11
Data-Infused Value Proposition via Capturing		0%	
New Data-Infused Business Model (DiBM)	1,14	6%	2

Table 6: Generic business model classification

4.3 Specific value proposition classification

17 projects were mapped into the "Data-enabled Improvement" pattern (project example: providing preventive maintenance functionality for production lines). Projects in this category did not lead to a change in the value proposition, but created value to the company in form of internal process optimisation. This category corresponds to the category optimization pattern from the BITKOM matrix; and the same projects were assigned to the Data Infused Value Creation cluster according to Schüritz. 11 projects were assigned to the "Data-enriched products and services" pattern (project example: using hybrid recommender engines for proposing suitable hotels). The additional value created out of this category is usually considered as a unique selling feature and is in most cases not charged.

The "Data-enabled Services" pattern matched for two projects which relate to the stand-alone characteristics (not related to the existing product/service) of the developed data-driven service. One project was mapped to the "Auxiliary Big-Data Services" category (project example: providing pattern search and detection for huge amounts of measurement data). No project was targeted towards direct data sales; hence we classified no project into "Data-as-a-service" category.

Category / Pattern	**Projects**	**%**	**No.**
Data-enabled Improvements	3,5,7,8,9,11,13,16,17,18, 19, 20,21,24,25,26,29	57%	17
Data-enriched products and services	2,4,6,10,15,22,23,27,28, 30	33%	10
Data-enabled Services	1,14	7%	2
Data-as-a-Service		0%	
Auxiliary "big-data" services	12	3%	1

Table 7: Specific value proposition classification

4.4 Discussion of Results

Regarding RQ 1 (*What are the characteristics of the three applied classification schemes in terms of being able to differentiate and compare between examples for data-driven business model innovation?*) it can be stated that all three applied classification models do have certain pro's and con's in use for classification and evaluation of data-driven innovation projects regarding business model development.

The strengths of the BITKOM matrix lie in the area of strategic orientation. Considerations along the four quadrants could help to find the right gateway for further data-driven activities. Based on the experience of us, the matrix is less suitable for analysis and support of data-driven business model innovation processes. Nevertheless, it is an easy to use approach and a good starting point for reflections using data (existing/own or third party data) as a resource for creating (new) business value. Moreover, the BITKOM matrix visualizes three levels of increasing degree of innovation and increasing level of uncertainty (Optimization →low uncertainty; Monetization and Leverage → middle uncertainty, Disrupt → high uncertainty) which could give an implication of the effort needed for implementation.

The data-infused business model classification based on Schüritz et al. (2016) requires a deep understanding of business model ontologies in order to apply the provided scheme. The outlined statements in chapter 4.2 reveal a deficit in utilizing data in the core business model component "value capturing", in other words how the value proposition is turned into (monetary) remuneration for the company. Our analysis shows that data and/or data analytics are barely used for identifying new customer segments or changing/adapting the revenue models. The classification results of Schüritz et al. (2016) displays a similar distribution into the five patterns as illustrated in Table 6. The analyses show a low use of data analytics in the marketing area.

The specific value proposition classification (see Table 7) illustrates the various uses of data in the central part of a business model. Similar to the other schemes there is a focus in the area of improvements and enriched products and services through data recognizable. Since there were just three projects assigned to “Data-enabled services” and “Auxiliary big-data services” a lot of data-driven business potential can be raised in these areas. This also applies to the pattern “Data-as-a-Service” which means selling data as common good including activities in data aggregation, storage and broking. Throughout the detailed breakdown of business value possibilities, this scheme can be used well for idea generation of data-driven use cases.

The weakness of the latter two schemes lies in the lack of data reference e.g. use of internal/external or existing/new data. All three models lack a meaningful demarcation between data-driven improvements or innovation (regarding processes and or services) and real data-driven business model innovations.

5 Synthesis: Data-Driven Business Value Matrix

In order to improve the above-mentioned classification models, we outlined a new classification scheme with regard to RQ 2 (*Which parameters should a classification scheme contain that maintain the strength and overcome the weaknesses and how does it look like?*). The new classification scheme depicted in figure 2 combines all positive aspects from the three analyzed classification models and resolves the identified weaknesses.

DDBM Improvement → | DDBM Innovation

	Data-enabled Improvements (processes)	Data-enriched Products & Services	Data-enabled Services (stand alone)	Auxiliary (big) Data Services (AaaS/PaaS/DaaS)
Existing Data (internal/external)	Proj. 5	Proj. 10	Proj. 1	
New Data (internal/external)		Proj. 10	Proj. 1	
New Revenue Model (Pricing Model)			Proj. 1	
New Customer Segments (Customer Group)			Proj. 1	

DDBM Innovation

Figure 2: Data-Driven Business Value Matrix

The horizontally arranged parameters focus the value proposition aspects. The separate category “Data-as-a-Service” (see table 7) was assigned to the category “Auxiliary (big) Data Services” due to better affiliation. Analytics-as-a-Service (AaaS) and Platform-as-a-Service (PaaS) are also summarised in this category. The vertical axis covers data sources (existing, new, internal, external), value capturing aspect (new revenue model) and the customer perspective “new customer segments”.

The latter two aspects are important for developing business model innovations. The introduced separation line between DDBM Improvement and DDBM Innovation should help to indicate if an existing or new use case or project (see classified project examples from analysed data set in Figure 2) belongs to the respective area. This demarcation should be seen only as an indication. As shown in Figure 2, project 1 (enhanced and new services through new data) is assigned to all four categories of a data-enabled service, which can be identified as an example for a data-driven business model innovation. In contrast, projects 5 and 10 (see Table 4) in Figure 2 are assigned to data-driven business model improvements due to not touching the DDBM innovation parameters.

The new classification scheme can be used for analyses and evaluation purposes of past and existing use cases/projects as well as for supporting the development process (exploration and design phase) of new data-driven business ideas.

DDBM Improvement → | DDBM Innovation

	Data-enabled Improvements (processes)	Data-enriched Products & Services	Data-enabled Services (stand alone)	Auxiliary (big) Data Services (AaaS/PaaS/DaaS)
Existing Data (internal/external)	16	10	2	1
New Data (internal/external)	1	4	2	
DDBM Innovation				
New Revenue Model (Pricing Model)			2	1
New Customer Segments (Customer Group)			2	1

Figure 3: Classified 30 data set projects into Data-Driven Business Value Matrix

In Figure 3, we assigned the 30 data set projects into the Data-Driven Business Value Matrix by summing up the projects which belong to each category. As projects can be assigned to more than one box, the overall sum exceeds the total number of projects. We also colour coded the matrix in form of a heat map.

The classification results support in principle the same statements described in the results chapter (see 4.1, 4.2 and 4.3) which points out that the majority of projects are realised in the “Improvement Section”. The new classification scheme visualizes and demonstrates in more detail (value proposition, customer view and value capturing aspect) the widespread potential of data as a central resource for business model development.

6 Conclusion

The economic opportunities that promise the use of the resource "data" (own, existing and third-party data), are recognized by most companies and some are already gaining value out of it. Unfortunately, the potential of data-driven business is still underutilized, except for the area of optimization and incremental improvements. A fundamental reason for this inequality refers to the limited knowledge regarding the development process of data-driven business models.

The development of a new business model is generally challenging and especially when new data-driven technologies (machine learning, artificial intelligence, etc.) and capabilities (data analytics, data management, etc.) are needed and so far not established in organizations. Furthermore, the use of data for new products and/or services usually has a great influence on a large number of (also external) business processes or business model areas associated with e.g. new customer segments (new markets), new distribution channels, sources of revenue, etc. These changes are fraught with many uncertainties that are particularly challenging for established companies. The aim of the Data-Driven Business Value Matrix is to make a valuable contribution to the development process of data-driven business model innovation.

Limitations and Future Research

Overall, the selection of the projects and the relatively small number of analyzed projects implicates certain limitations. The broad spectrum of company sizes (LE, SME, Start-ups) and different domains impede concrete and general statements. Although the new classification scheme has already been used in business model workshops, a detailed evaluation of the scheme needs to be done.

Future research projects could address various sub-aspects of a data-driven business models such as specific competencies (data analytics, data management), technical infrastructure (server, cluster) or organizational challenges (integration of data scientists, set up of internal competence center). Furthermore, there is a need for “hands-on” field-tested DDBM frameworks, tools and methods, especially for companies with a well-established business model e.g. SMEs and large enterprises. If possible using the BMI path and tool approach (Heikkilä 2016) as a “blueprint” for developing a DDBM framework.

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