WHAT MAKES A DATA-DRIVEN BUSINESS MODEL? A CONSOLIDATED TAXONOMY

Research Paper

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Abstract

The usage of data to improve or create business models has become vital for companies in the 21st century. However, to extract value from data it is important to understand the business model. Taxonomies for data-driven business models (DDBM) aim to provide guidance for the development and ideation of new business models relying on data. In IS research, however, different taxonomies have emerged in recent years, partly redundant, partly contradictory. Thus, there is a need to synthesize the common ground of these taxonomies within IS research. Based on 26 IS-related taxonomies and 30 cases, we derive and define 14 generic building blocks of DDBM to develop a consolidated taxonomy that represents the current state-of-the-art. Thus, we integrate existing research on DDBM and provide avenues for further exploration of data-induced potentials for business models as well as for the development and analysis of general or industry-specific DDBM.

Keywords: Business model, Data-driven, Taxonomy, Systematic Literature Review

1 Introduction

The 21st century can be considered as the data era. Phrases like "Data is the new oil" (Parkins, 2017) are widely used, and highlight the importance of data as a resource for businesses. Four of the six most valuable companies in 2020 are data-driven tech companies: Microsoft, Amazon, Alphabet, and Facebook (Murphy et al., 2020; Javornik et al., 2019). Globally and industry-wide, other companies try to follow and benefit from the developments in data-driven technologies like Big Data or Artificial Intelligence to extract the value of data (Chen et al., 2012; Günther et al., 2017). This provides new challenges and opportunities for both research and practice. Consequently, a new research strand has emerged around the topic of *data-driven business models* (DDBM) in recent years. Using data as a key resource, a DDBM enables value creation through activities of data processing and analytics (Hartmann et al., 2016; Schüritz and Wixom, 2017) to offer data, knowledge, actions, or non-data products/services as a value proposition (Hartmann et al., 2016; Schüritz et al., 2017), and captures its value through exploitation and monetization (Schüritz et al., 2017).

Available research provides empirical and qualitative evidence and approaches for tackling the challenges of creating and conceptualizating DDBM (e.g., Engelbrecht et al., 2016; Kühne and Böhmann, 2018). Particularly, a great part of the DDBM research focuses on the development of tools and methods for the design and ideation of DDBM (Fruhwirth et al., 2020; Lange and Drews, 2020), including taxonomies and frameworks. For instance, Hartmann et al. (2016) have provided a first framework for DDBM by adapting the logic of generic business model frameworks to the context of data as a key resource. Further research has explored such business models from a service-dominant logic and particularly explicates data-driven services (DDS) and the role of value co-creation therein (Azkan et al. 2020). Accordingly, a service-oriented business model describes the integration of services into the business model or the usage of services to design new ones. Examples of such taxonomies with a focus on data-driven services are Rizk et al. (2018) or Azkan et al. (2020).

Given the increasing relevance of data in contemporary business models and its economic importance, IS research should sharpen the understanding of the core elements of DDBM and DDS. However, there is yet little analytical consolidation of existing DDBM and DDS taxonomies and frameworks. Instead, IS-related research provides several partly contradictory or redundant conceptualizations. Against this background, we aim to synthesize existing literature for the development of a consolidated taxonomy. Taxonomies are important tools as they provide both researchers and practitioners with fundamental categories to analyze and understand complex domains (Nickerson et al. 2013). This particularly accounts to promising and under-researched phenomena like DDBM. Thus, our interest lies in the question: *What makes a data-driven business model and what are its core elements?* In response to this question, we build upon current research on DDBM and DDS and develop a consolidated taxonomy on the basis of 26 IS-related taxonomies and 30 empirical cases, following the guidelines from Nickerson et al. (2013). The remainder of this paper is structured as follows: In Section 2, we explain the applied methods, before we present and analyze our results in a systematic manner in Section 3 and 4. We close the paper with a conclusion and discussion on limitations and avenues for future research in Section 5.

2 Methodology

In view of our research question, we pursued a two-phase approach. First, we conducted a systematic literature review (SLR) on DDBM and DDS taxonomies. At this, we followed the guidelines from Webster and Watson (2002), and vom Brocke et al. (2009), which provide a rigorous and traceable approach to systematically identify and structure relevant literature on DDBM and DDS. Second, we compared and synthesized the identified taxonomies through defining the common building blocks, and developing a consolidated taxonomy of DDBM and DDS according to Nickerson et al. (2013). Here, we rely on 30 empirical cases with DDBM to validate and refine our taxonomy. The detailed research process is depicted in Figure 1 and described in the following sub-sections.

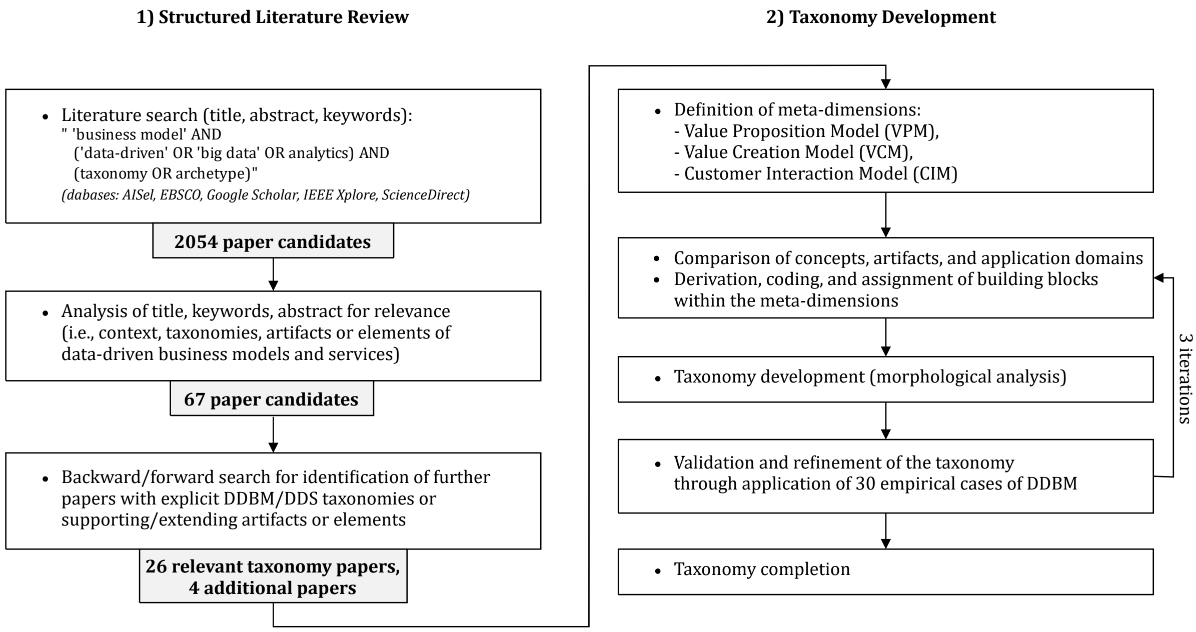

Figure 1: Two-step research design

2.1 Phase 1: Structured Literature Review

In phase 1, we conducted a SLR. In a first step, we searched for IS-related publications within relevant scientific databases (AISeL, Ebsco, Google Scholar, IEEE, ScienceDirect) with DDBM- and DDS-related terms to receive information about the core elements and taxonomies: "'business model' AND ('data-driven' OR 'big data' OR analytics) AND (taxonomy OR archetype)". This search left 2054 potential paper candidates for further analysis.

In a second step, we excluded all publications that were not peer-reviewed and three researchers independently analyzed the remaining publications' titles, keywords and abstracts for relevance. We analyzed the full texts of the remainders and proceeded with a forward and backward search to identify additional relevant papers. This analysis left a total of 67 potential paper candidates.

In a third step, we conducted an internal workshop with our working group to select and compare all papers that specifically either provide taxonomies, inherent elements, and characteristics, or design artifacts for DDBM or DDS. Design artifacts also include business model canvases, which provide a structured overview of DDBM elements. We excluded taxonomies that omit the data dimension, even if a business model's or service's foundation relies on data (e.g., carsharing or platform business models). Finally, we identified a total of 26 papers that contain taxonomies and/or characteristic elements of DDBM or DDS, and four additional papers that provide supplementary information on specific parts (e.g., the customer segment).

2.2 Phase 2: Taxonomy Development

The second phase focused on the development of a consolidated DDBM taxonomy on the basis of the 26 remaining papers from the SLR. At this, we basically rely on the guidelines from Nickerson et al. (2013) for a systematic taxonomy development that combines inductive and deductive reasoning. Accordingly, we first defined meta-characteristics for a first-level classification of any elements of our taxonomy. Given the nature of digital business models, we applied the three dimensions of digital transformation as meta-dimensions from Pousttchi et al. (2019).

In a second step, we collated the 26 papers with regard to their concepts, methods, artifacts, and application domains in order to derive and define the core elements of DDBM and DDS. These elements were first assigned to the meta-characteristics, and then inductively coded to first-level and second-level items. Here, we followed Mayring's proposed procedure for inductive categorizing as part of a qualitative content analysis (2000). The coding was conducted by three researchers separately, and disagreements were discussed until consensus was reached. Furthermore, we evaluated the identified items from the taxonomies and papers for their general applicability. We sorted them out, if they are too limited or use-case-specific, and do not allow for generalizability. For instance, Möller et al. (2020) provide the items "optimization service" and "visibility service", which imply very specific services. Likewise, Azkan et al. (2020) differentiate the platform type. However, a DDBM does not necessarily induce a platform. Based on the derived items from the identified taxonomies, we derived and defined building blocks and respective characteristics of DDBM.

In a third step, we condensed all building blocks and characteristics into a consolidated taxonomy. Here, we applied the morphological analysis, a highly systematic method to structure multi-dimensional problems (Ritchey, 2013; Zwicky, 1966), to synthesize all building blocks of a DDBM by means of a morphological box. Accordingly, the characteristics of each building block are mutually non-exclusive, meaning it is possible to select more than one characteristic for each building block (Nickerson et al., 2013). This was necessary because the identified building blocks were derived from existing taxonomies where the authors also used the approach of non-exclusive characteristics (Hunke et al., 2019; Möller et al., 2020).

In a fourth and final step, we validated the conceptually developed taxonomy through the application of 30 empirical DDBM cases. For the identification of suitable cases, we conducted online research to find economic reports and overviews of companies with DDBM. Among these reports, we selected as many cases as necessary to achieve saturation in terms of complexity, depth, variation, and context (Gentles et al., 2015). This step caused further refinements of our building blocks and their characteristics. In the following, we repeated step 2 to 4 three times in order to bring the conceptual findings in accordance with the empirical cases until our taxonomy was stable (Nickerson et al. 2013). As a result, we developed an integrated DDBM taxonomy with 14 building blocks and their characteristics of a DDBM.

3 Comparison and Analysis of Existing Taxonomies

As a result of our SLR, we identified 26 papers that contain taxonomies or structuring elements for data-driven business models or services. For the purpose of further comparison and analysis, we sort these taxonomies along with two distinguishing categories: value-proposition focus and application scope. Some publications do not structure DDBM but DDS, which is why we distinguish the two. However, a service can be a business model per se (Azkan et al. 2020). With respect to the application scope of existing taxonomies, we distinguish between industry-specific and general taxonomies to explore the unifying and distinctive elements of these taxonomies. Both differentiations will help us to elaborate on differences and similarities for the development of a consolidated taxonomy of sufficient generalization. Figure 2 provides an overview of the categorized taxonomies.

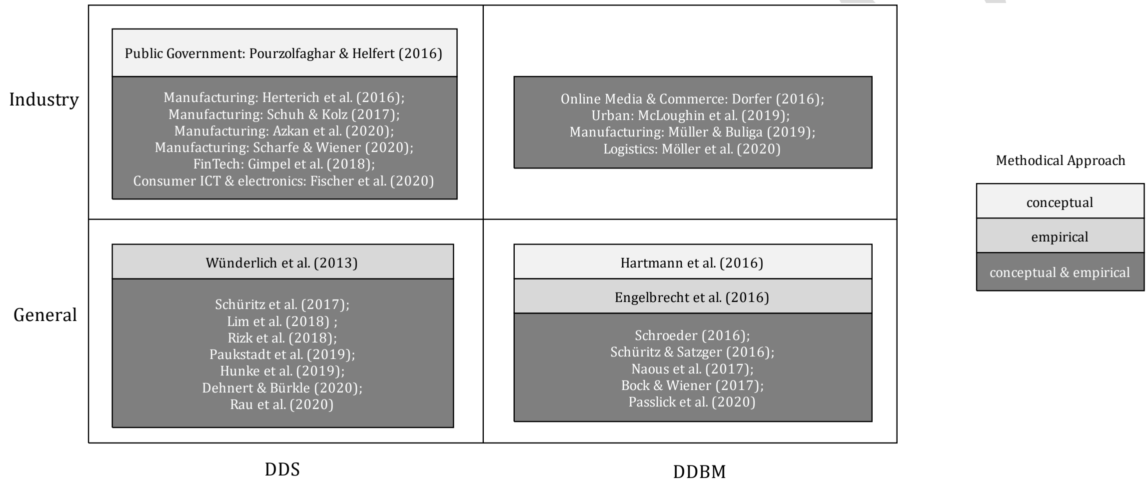

Figure 2: Categorization of existing taxonomies

Among the 26 taxonomy papers, eight provide *generally applicable* taxonomies for *DDS* (e.g., Dehnert and Bürkle, 2020; Hunke et al. 2019), while another seven papers provide *industry-specific DDS* taxonomies, of which four focus on manufacturing data (Azkan et al. 2020, Herterich et al., 2016; Scharfe and Wiener, 2020; Schuh and Kolz, 2017), one on public government and administration (Pourzolfaghar and Helfert, 2016), one on fintech and banking (Gimpel et al., 2016) and another one on smart home and consumer electronics (Fischer et al., 2020). In terms of *DDBM*, we identified seven *generally applicable* taxonomies (e.g., Bock and Wiener, 2017; Engelbrecht et al., 2016; Hartmann et al., 2016) and four with an industry-specific focus, i.e., online media and commerce data (Dorfer, 2016), urban data (McLoughin et al., 2019), manufacturing data (Müller and Buliga, 2019), and logistics data (Möller et al., 2020).

Additionally, we classified the taxonomies by their methodological background, i.e., conceptual and/or empirical. Most publications combined conceptual and empirical approaches, as proposed by the guidelines for taxonomy development from Nickerson et al. (2013). Nevertheless, some researchers used purely conceptual (e.g., Hartmann et al., 2016) or purely empirical approaches (e.g., Engelbrecht et al., 2016). The following sub-sections provide a detailed comparison and analysis of the quadrants.

3.1 DDBM Taxonomies

General. Seven identified papers provide industry-agnostic taxonomies for DDBM. For example, the paper from Hartmann et al. (2016) is one of the first (and most-cited) contributions that scrutinizes the elements of DDBM. Particularly, the researchers focus on such companies that rely on "data as a resource of major importance" to develop a taxonomy "that allows systematic analysis and comparison of DDBM". At this, they pursue a conceptual approach with deductively generated dimensions (value proposition, key resource, key activity, market and customer segment, revenue stream, and cost structure). Through the review and synthesis of the literature on business models, data mining, and analytics, they inductively derive characteristics for each dimension. Key resource, for example, becomes *data source* (internal or external). While internal data is generated inside or through the company, external data is acquired, customer-provided, or freely available. According to the authors, the *key activity* of a DDBM is likewise important. This dimension describes how data is used to generate value. At this, the authors rely on Rayport and Sviokla's (1995) concept of virtual value chains. Hartmann et al. (2016) identify the steps of data generator, acquisition, processing, aggregation, analytics, visualization, and distribution. With respect to DDBM, the authors also emphasize the importance of the *value offering*, which is based on Fayyad et al. (1996) and can be divided into two categories of raw and interpreted data in form of information or knowledge. Hartmann et al. (2016) extend these by non-data-based products and services as a possible offering.

Contrarily, the paper from Engelbrecht et al. (2016) provides an empirically developed, industry-agnostic taxonomy for DDBM based on expert assessments of 33 DDBM from startups. The researchers coded these qualitative data to derive the three most relevant characteristics of DDBM: *data source* (user or non-user), *target audience* (consumers or organizations), and *technological effort* in terms of the complexity of data collection, processing, and analytics (low or high). Therefore, this contribution does not focus on a complete DDBM taxonomy but rather on the relevance of its components. The other publications pursue a combined conceptual-empirical approach to scrutinize the elements of DDBM.

Industry-specific. Four identified papers provide taxonomies with a focus on certain industries. For instance, McLoughlin et al. (2019) apply the taxonomy structure of Hartmann et al. (2016) to 40 cases in order to explore the value generating elements and value propositions of urban data business models. In this context, the researchers argue against the data source dimension. Instead, they highlight the importance of key resources, which not only imply data but also software and hardware components to capture and deliver value. Consequently, they propose a self-contained data framework to sub-classify data by the categories *velocity*, *variability*, *variety,* and *type*.

For another thing, Möller et al. (2020) provide a taxonomy of optimization and visibility services for DDBM in the logistics industry. At this, they pursue a combined conceptual-empirical approach with 49 cases. The key resource data is assigned to the meta-dimension *service platform*, which is further divided into five dimensions: *resource*, *source*, *flow*, *activity*, and *feed*. These dimensions describe what the data is about (resource), who creates it (source), how it is provided (flow), what has to be done before it can be further used (activity), and the delivery frequency (feed). In view of our research question, especially these four taxonomies provide a solid foundation for our integrated taxonomy. While the taxonomy from Hartmann et al. (2016) offers some common ground, those publications help to identify eligible components in the intersection of different industries.

3.2 DDS Taxonomies

General. Eight of the identified papers provide industry-agnostic taxonomies for DDS. For example, Rizk et al. (2018) provide a taxonomy for data-driven digital services, which is based on a conceptual-empirical approach. At this, they propose four main characteristics through the value chain of big data and extracted knowledge. *Data acquisition mechanism* describes how data is generated or acquired, while *data exploitation* explains how value is extracted from data, especially through information processing and advanced analytics. *Data utilization* describes how the generated insights are provided to the customer (e.g., through visualization or recommendations). Finally, *service interaction* describes how the customer interacts with the service (e.g., application, product, or embedded service).

Authors	Focus	First-order Items	Second-order Items
Bock & Wiener (2016)	DDBM	n/a	Digital offering; Digital experience; Digital platform; Data analytics; Digital pricing
Engelbrecht et al. (2016)	DDBM	n/a	Data Source; Target Audience; Technological Effort
Hartmann et al. (2016)	DDBM	n/a	Data Source; Key Activity; Offering; Target Customer; Revenue Model; Specific Cost Advantage
Naous et al. (2017)	DDBM	Value creation (VC), Resource-based and value configuration (RBVC)	VC: Value Proposition; Customer Segments; Customer relationships; Channels; Revenue streams RBVC: Key resources and activities; Key partners
Passlick et al. (2020)	DDBM	n/a	Key activities; Value promise; Payment model; Deployment channel; Customer segment; Clients; Information layer
Schroeder (2016)	DDBM	n/a	Data users; Data suppliers; Data faciliators
Schüritz & Satzer (2016)	DDBM	Data infusion patterns	Data-infused Value Creation; Data-infused Value capturing; Data-infused value proposition via creation; Data-infused value proposition via capturing; New data-infused business model
Möller et al. (2020)	DDBM (Logistics)	Value Proposition (V), Service Platform (S), Interface (I), Organizing Model (O), Revenue Model (R)	(V): Optimization Service; Visibility Service; Modality; (S): Data Resource; Data Source; Data Flow; Data Activity; (I): Data Feed; Delivery Mechanism; Data Interface; (O): Access to API; API Documentation; (R): Revenue Model; Price Basis; API-Based Revenue
McLoughlin et al. (2019)	DDBM (Urban Data)	n/a	Key Resource; Key Activity; Target Customer; Revenue Models; Cost Structure; Data
Müller & Buliga (2019)	DDBM (Manufacturing)	n/a	Value Creation; Value Offer; Value Capture
Dorfer (2016)	DDBM (Online media & commerce)	BMs for cognitive benefits, (CB); BMs for social-interactive ND cognitive benefits, (SICB); BMs for social-interactive benefits (SIB)	CB: General Information gathering; Transaction specific information gathering SICB: General information gathering over social interaction; Social-driven initation of transactions SIB: Networking and contact-management in the context of relationship management; Sharing of content in the context of identity-management
Dehnert & Bürkle (2020)	DDS	n/a	Autonomous acting capability; Sensing capability; Interoperability; Coupling control; Ecosystem; Interaction; User mapping; Data capability; Analytical capability; Output medium
Hunke et al. (2019)	DDS	n/a	Data Generator; Data Origin; Data Target; Analytics Type; Portfolio Integration; Service User Role
Lim et al. (2018)	DDS	n/a	Data source; Data collection; Data; Data analysis; Information on the data source; Information delivery; Customer (information user); Value in information use; Provider network of the service provider and partners
Paukstadt et al. (2019)	DDS	Service Concept (SC), Service Delivery (SD), Service Monetization (SM)	(SC): Value Proposition; Bundle; Main Outcome; (SD): Visibility; Mode of Operation; Actor Interaction; Main Interface; (SM): Payment Mode; Pricing Model
Rau et al. (2020)	DDS	Consumer (C), Data (D), Interaction (I)	C: Consumer Relief; Consumer Benefit; Consumer Risk D: Data Source; Data Analysis; Smartness I: Trigger (T); Representation (R); Integration (I)
Rizk et al. (2018)	DDS	n/a	Data Acquisition Mechanism; Data Exploitation; Insights Utilization; Service Interaction
Schüritz et al. (2017)	DDS	n/a	Subscription; Usage Fee; Gain Sharing; Endure-ads; data-tailored offering; buy-and-sell-data; pay-with-data
Wünderlich et al. (2013)	DDS	Interaction patterns	Interactive service; Self-service; Machine-to-machine service; Provider active service
Azkan et al. (2020)	DDS (Manufacturing)	Value Creation (VCr), Value Delivery (VDe), Value Capture (VCa)	(VCr): Value; Outcome; Analytics Type; Data Sources, Data Types; Aggr. Level; (VDe): Service Delivery; Service Flow; Platform Type; (VCa): Pricing Model; Payment Mode
Fischer et al. (2020)	DDS (consumer electronics)	Digital Service (DS), Smart Product (SP)	DS: Configuration; Data Analytics; Service Object; Benefit; Duration of Service SP: Capability Level; Communication; Data Source
Gimpel et al. (2018)	DDS (FinTech)	Interaction (I), Data (D), Monetization (M)	I: Personalization; Information exchange; Interaction type; User network; Role of IT; Hybridization; Channel strategy D: Data source; Time horizon; Data usage; Data type M: Payment schedule; User's currency; Partner's currency; Business cooperation
Herterich et al. (2016)	DDS (Manufacturing)	Material properties (MP), Organizational characteristics (OC)	MP: Data origin; Initiation of data transmission; Relevant data; Data analysis; Digital platform access; OC: Service automation; Lifecycle context; Service innovation
Pourzolfaghar & Helfert (2016)	DDS (Public Government)	n/a	Types; Purpose; Design
Scharfe & Wiener (2020)	DDS (Manufacturing)	Application (A), Integration middleware (IM), Connectivity (C), Machine (M)	A: Application domains; Service type IM: Data analytics; Data sources; Deployment scenarios; Middleware solution C: Interoperability; Communication direction; Interaction partners M: Control autonomy; Actutator purposes; Sensor measure. Objects; Production types
Schuh & Kolz (2017)	DDS (Manufacturing)	n/a	Focus of service provision; Key activities; Revenue model; Connection/implementation; Key resources; Effort for Individualization; Customer access/system integration; Duration of business relationship; Data sources; Data base

Table 2: Identified first- and second-order items from literature

Lim et al. (2018) provide a nine-factor framework for data-based value creation in information-intensive services based on a literature review and case study research. They provide more information on how to close the gap between having data from various sources and creating real value with it in services. The steps can be clustered into three meta-steps: *data collection, information creation, and value creation.* For data collection, the *data source*, the *data collection* itself, and the *data* are the three factors that need to be considered. For information creation, the factor data is the input to the factor *data analysis* that finally leads to the factor *information on the data source.* In the subsequent value creation step, the *information* needs to be *delivered*, e.g., through visualization to the *customer (or information user).* The outcome is the final factor *value in information use* like, for example, a driving person who is assisted by a car infotainment service that guides easily through the traffic.

Hunke et al. (2019) provide another dominant taxonomy to conceptualize the use of data and analytics in services, based on a conceptual-empirical approach. At this, they identify meta-characteristics through a literature review and conduct four iterations with 85 cases from IBM, Microsoft, and Oracle. The taxonomy has six dimensions: *data generator*, *data target*, *data origin*, *data analytics type*, *portfolio integration*, and *service user role*. The authors offer an interesting perspective by the separation of data generator and data target. Here, data generator describes a person, process, or object that generates the data. This might be an object with sensors. In contrast, the data target is what the generated data is about. Therefore, they are extending data target with the characteristic environment. The data generator (the object with sensors) could measure weather data and therefore needs a distinct data target. Another interesting dimension is the *data analytics type.* Here, the authors provide four types based on four respective questions: *Descriptive* answers the question to “what happened?”, *diagnostic* to “why did it happen?”, *predictive* to “what will happen?” and *prescriptive* to “what should be done?”.

Industry-specific. Azkan et al. (2020) provide a DDS taxonomy for manufacturing industries, also based on the conceptual-empirical approach from Nickerson et al. (2013). As meta-dimensions, they define *value creation* and *value delivery* (from service science), as well as *value capture* (from business model literature). Value creation includes the main value and outcome, the data analytics type, the data sources and types, and the aggregation level, while value delivery describes how the service is delivered, how the service flow is managed, and what type of platform is offered. Finally, value capture contains the pricing model (i.e., subscription-based, transaction-based, or indirect), and how the customer pays (i.e., through the product or service, or data).

Altogether, the service perspective provides useful elements for the development of our consolidated taxonomy. For one thing, data turns out to be pivotal for DDS (and thus, DDBM), be it in terms of generation or exploitation. For another thing, value creation, proposition, and capture appear to be key dimensions to categorize DDBM and DDS. For value creation, especially the factor data analysis play a key role in the identified taxonomies as these are the steps that finally extract the value out of data. Finally, customer communication, integration, and interaction seem to be considerable components in the design of DDBM or DDS. Table 2 summarizes all components of DDBM and DDS derived from the 26 taxonomies and builds the basis for further elaboration.

4 Development of a Consolidated Taxonomy

Based on the identified items of DDBM and DDS from available literature, we followed the further guidelines from Nickerson et al. (2013). Thus, we defined building blocks of our consolidated taxonomy from literature and cases through 4 iterations (in total), and assigned these building blocks to meta-dimensions. Regarding these meta-dimensions, we rely on the three dimensions of digital transformation (Pousttchi et al., 2019), i.e., value proposition model (VPM), value creation model (VCM), and customer interaction model (CIM). Given the digital nature of DDBM, this classification seems particularly suitable. First, the VPM determines the products and services proposed to the market and their revenue models. This view is appropriate because the extraction of data offers both new types of products or services and ways of generating revenues. Second, the VCM determines how digital technologies affect business processes, organization types, and staff. With regard to DDBM, this view is eligible because such business models force new ways of data usage and skills for value generation. Third, the CIM includes all types and mechanisms of interaction with customers. This dimension can be interesting for DDBM, as data can transform the interaction between the customers and enterprises. Table 1 presents the final 14 building blocks (and their guiding questions) with the three meta-dimensions.

Meta-Dimension	#	Building Block	Description
Value Proposition Model (VPM)	[1]	Value Proposition	What does the company offer to the customer?
	[2]	Value Capture	How does the company earn money through the business model?
Value Creation Model (VCM)	[3]	Data Generator	Who or what is generating the data?
	[4]	Data Origin	Where does the data come from?
	[5]	Data Target	About whom or what is the generated data?
	[6]	Data Activity	How is the data handled?
	[7]	Data Analytics	How is the data analyzed?
	[8]	Insights Utilization	In which form are the insights provided to the customer?
	[9]	Cost Structure	How are the costs determined?
Customer Interaction Model (CIM)	[10]	Customer Segment	What kind of customer is it?
	[11]	Target Customer	Who is the customer group?
	[12]	Interaction Type	How does the customer interact with the offering?
	[13]	Service Flow	When is the service provided?
	[14]	Customer Relationship	How is the company supporting the customer?

Table 1: Guiding questions for each building block of the consolidated taxonomy

4.1 Building Blocks in the Value Proposition Model

The value proposition model includes two building blocks. **Value Proposition (1)** describes what the company offers to the customer. This building block determines the overall outcome of the business model and is strongly influenced by the aspect of data. This building block consists of the following characteristics: *Data*, *Information/Knowledge*, *Actions*, and *Non-Data Product* (Fayyad et al., 1996; Hartmann et al., 2016; Rizk et al., 2018; Schüritz and Wixom, 2017). Except for Non-Data Product, these characteristics represent the structure of the Data-Information-Knowledge-Wisdom Pyramid (Jifa and Lingling, 2014). *Data* describes offering the raw data without the attached meaning, while *Information/Knowledge* describes the provision of interpreted or analyzed data. This could be, for example, provided in form of recommendations or visualizations and the customer can use these to make decisions. *Actions* come one step further and describe how the company itself takes action for the customer, based on the analyzed data. These actions can be, for example, the decision making,the execution of specific process steps or the matchmaking of the customer. A more concrete example is predictive maintenance, where the company proactively replaces the part of a machine based on predictive analytics. The last characteristic of the Value Proposition is the Non-Data Product or Service. An example is an object that receives added value through data (Hartmann et al., 2016) like a watch that is equipped with a sensor.

Value Capture (2) highlights how to gain revenues from the DDBM. It is an important building block because a business model can only sustain in the long run if it creates revenue to cover the costs. The characteristics are based on Hartmann et al. (2016) and Schüritz et al. (2017). *Subscription* describes a periodical payment from the customer. Contrastingly, through a *usage fee,* the customer has to pay as much as he uses the service or product. One factor to measure the usage could be data volume. *Gain sharing* describes how the service or product provider receives a percentage of the revenue that the customer makes through the usage of the offering. *Advertising* describes revenues that are received through advertisers. *Buy-and-sell-data* describes a multi-sided approach, where the provider gains revenues by creating data profiles of the customer and selling them to third parties. *Pay-with-data* describes how the customer provides personal data that can be used in new services or to create new services. Finally, an *asset sale* describes a modus where the offering is provided for a fixed one-time payment.

4.2 Building Blocks in the Value Creation Model

The value creation model consists of seven building blocks that are closely related to the key resource data. **Data Generator (3)** describes who or what generates data for the BM. Hence, this important building block describes one core aspect of the key resource data. For this building block, we rely on the approach of Hunke et al. (2019) for analytics-based services. First, *customer* refers to data that is generated by the direct consumer types of the business model through the usage of an analytical service. This also includes customers of the customer (B2B2C). *Non-customer* refers to humans who generate data for an analytical service but do not consume the service themselves directly, such as social media portals (Hunke et al., 2019). *Process* describes data that is generated through structured activities or tasks performed by people or devices (Hunke et al., 2019). Examples here might be business processes, like manufacturing or consumption processes. *Object* describes data that is generated through physical objects that are equipped with sensors (Hunke et al., 2019). To include other possible Data Generators, we added the characteristic *other*.

Data Origin (4) depicts if the data is generated inside the company (*internal*) or outside of the company (*external*) (Hartmann et al., 2016; Hunke et al., 2019; Lim et al., 2018). This building block determines if the company needs to acquire or obtain the data from external sources or if it is provided through internal sources. External and internal sources are both containing specific restrictions and challenges, like privacy, cost, or effort that needs to be considered to get the data. A DDBM may use internal and external data sources to create its offering.

Data Target (5) represents the flip side of the building block data generator and describes the focus of the collected data. Thus, we can not only identify what or who generates the data but also what or whom the data is about. At this, we extend the structure from Hartmann et al. (2016) by the approach from Hunke et al. (2019) for the generalization because it provides a broader perspective through explicating the data generator more specifically. Consequently, the characteristics resemble those from the building block data generator. One example to clarify this distinction is the following: A smartwatch can generate health data about the customer. Therefore, the smartwatch is the Data Generator, and the Data Target is the customer. Regarding the data target, we add *environment* (e.g., weather), which is oftentimes the objective of data collection and analytics. Plus, we propose o*ther* to include potential future data targets that are not covered by the existing characteristics.

Data Activity (6) summarizes all activities that have to be done after the data is generated and before it is analyzed (Fayyad et al., 1996; Hartmann et al., 2016; Hunke et al., 2020; Lim et al., 2018; Rizk et al., 2018). This building block sharpens the understanding of what to do with the data after its generation. The generated data oftentimes is not directly utilizable where it is generated. Therefore, it is important to understand and determine what needs to be done with data. Here, *data collection* describes the activity of collecting and accessing the generated data, while *data organization* describes the activity of storing the collected data. *Data preparation* describes how the collected data needs to be manipulated for the purpose of further analysis or usage (Hunke et al., 2020).

Data Analytics Type (7) describes what advanced analytics methods can be applied to the data in order to extract information or knowledge from it (Fischer et al., 2020; Hartmann et al., 2016; Hunke et al., 2019; Hunke et al., 2020; Lim et al., 2018; Rizk et al., 2018; Scharfe & Wiener, 2020). This is an important building block within most taxonomies. It determines what has to be done to actually generate the value from data (and gaining a comptetitive advantage). The explicit characteristics are *descriptive, diagnostic, predictive,* and *prescriptive* (Hartmann et al., 2016; Hunke et al., 2019). Additionally, we added *none* as a characteristic in case the business model relies on the raw data only as the offering.

Insights Utilization (8) describes how the generated insights are provided to the customer (Hartmann et al., 2016; Hunke et al., 2020; McLoughlin et al., 2019; Rizk et al., 2018). This building block might seem redundant on its face with the building block value proposition. However, we decided to create a separate building block as it completes the concept of the virtual value chain or the knowledge-discovery-in-databases chain (Fayyad et al., 1996; Rayport and Sviokla, 1995), and thus sharpens the focus on how the company will finally provide the value proposition to its customers. The characteristics of insights utilization are distribution, visualization, and execution (Hunke et al., 2020; Rizk et al., 2018). First, *distribution* describes the simple supply of the data or information to the customer. This could be, for example, through a data file or an application. Second, *visualization* describes if the company uses advanced techniques to provide the information more comprehensively or graspably to the customer. For instance, infographics present data and information by means of visual and graphical charts and figures to provide the message more catchily and intuitively. Third, *execution* describes if the company uses the information to guide the customers' actions (e.g., digital nudges, or recommendations) or if the company itself processes information for the customer (e.g., schedule query from a database).

Cost Structure (9) adds the perspective of how costs are determined (Hartmann et al., 2016; McLoughlin et al., 2019; Osterwalder and Pigneur, 2010). This building block represents the flipside of the revenue model, and thus decides on the success of the entire business model. Here, we rely on Osterwalder and Pigneur (2010) and McLoughlin et al. (2019) to determine the main distinction between value-driven and cost-driven. While *value-driven* determines the price of a product or service through the value that the product or service might give to the customer, *cost-driven* determines the price through the concrete costs that are caused by the creation and offering of the product or service. Additionally, we added the characteristic *other* if the DDBM relies on mixed or other cost structures.

4.3 Building Blocks in the Customer Interaction Model

The customer interaction model consists of five dimensions. **Customer Segment (10)** describes if the DDBM is *business-to-business (B2B)*, *business-to-customer (B2C)*, or *business-to-administrative (B2A)* (Engelbrecht et al., 2016; Hartmann et al., 2016; Lim et al. 2018; Passlick et al., 2020; Wirtz, 2019). This building block is a foundation for any business model as it determines to whom the offering is provided and therefore, why the business model may even exist.

Target Customer (11) describes if the business model addresses a *new customer group*, an *existing customer group,* or a *multi-sided customer group* that consists of different actors (Osterwalder and Pigneur, 2010; Weking et al., 2018). Thus, this building block complements the customer segment because it offers a different strategic alignment and influence of data-driven products and services in a business model. Especially for incumbent companies, it might be interesting to define if they should focus on their existing customers, try to reach for new segments, or intermediate between two or more groups together.

Interaction Type (12) highlights how the customer is interacting with the company. This is an important building block because it displays how the customer actually receives the offered value. Characteristics within the interaction type are *application*, *product*, or as an *embedded service* in another service or product. (Rizk et al., 2018). Consequently, the interaction can be orchestrated through hardware, software, or combined components. However, especially in terms of B2B, a fourth possible interaction type might be an *API* that provides the data for further processing or usage (Möller et al., 2020).

Service Flow (13) describes if the customer receives the offering manually, in pre-defined time-steps, through specific events, or in a stream (Azkan et al., 2020; Lim et al., 2018; Rau et al., 2020). At *manually*-driven service flows, the customer is proactive in requesting the service. For instance, if it is required to download a document. *Predefined time-steps* describe processes if the service flow comes in intervals. This might be a configured push news service that delivers the latest information on a daily basis. Contrastingly, *event-driven* means that specific (possibly pre-determined) conditions have to occur to trigger or activate the service flow. For example, the detected (or predicted) failure of a production machine might cause an alarm warning in the monitoring system of the production site. *Stream* describes a service that is continuously offered. This might be a smartwatch that always provides the heartbeat or a dashboard over the actual processes in real-time. Altogether, this building block is important because it gives a glance at the time- and activity-related requirements that the corresponding data resources need to fulfill (e.g., availability, currentness) as well as the upstream and downstream events and processes that need to be considerer for the further offering of the value proposition.

Customer Relationship (14) is the last building block in the taxonomy and basically relies on Osterwalder and Pigneurs (2010) Business Model Canvas. This building block determines how the company interacts with its customers for marketing and communication reasons. We added this building block even though it was not mentioned in one of the eight DDBM or DDS taxonomy papers. However, we argue that it is important to understand how the company supports the customer in the long term and how the relationship can be built and sustained. Therefore, we included this building block to complete the Dimension of Customer Interaction. The characteristics contain: *personal* (i.e., face-to-face or virtual communication with humans), *self-service* (i.e., customers can troubleshoot by themselves through, e.g., FAQs), *automated* (i.e., IT-based service control points like chatbots), *community* (i.e., special interest groups of customers like social media channels), or *othe*r types of interaction (i.e., mixed or indefinite). Figure 3 provides an overview of all building blocks and their characteristics. The figures in parentheses within the cells represent the counts of the applied empirical cases.

	Building Block	Characteristics						
VPM	Value Proposition	Data (3)	Information / Knowledge (29)	Actions (9)	Non-Data Product/Service (6)			
VPM	Value Capture	Subscription (22)	Usage Fee (7)	Gain Sharing (0)	Advertising (1)	Buy & Sell Data (1)	Pay-with-data (1)	Asset Sale (9)
VCM	Data Generation	Customer (13)	Non-Customer (12)	Process (10)	Object (19)	Other (0)		
VCM	Data Origin	Internal (15)	External (25)					
VCM	Data Target	Customer (18)	Non-Customer (15)	Process (7)	Object (8)	Environment (6)	Other (0)	
VCM	Data Activity	Data Collection (26)	Data Organization (26)	Data Preparation (30)				
VCM	Data Analytics Type	Descriptive (8)	Diagnostic (7)	Predictive (26)	Prescriptive (16)	None (0)		
VCM	Insights Utilization	Distribution (28)	Visualization (25)	Execution (17)				
VCM	Cost Structure	Value-Driven (27)	Cost-Driven (3)	Other (0)				
CIM	Customer Segment	B2B (27)	B2C (7)	B2A (1)				
CIM	Target Customer	New Customer (24)	Existing Customer (8)	Multi-Sided (3)				
CIM	Interaction Type	Application-based (24)	Product-based (4)	Embedded Service (7)	API (7)			
CIM	Service Flow	Manual (25)	Pre-defined Time (4)	Event-Driven (15)	Stream (16)			
CIM	Customer Relationship	Personal (25)	Self-Service (9)	Automated (8)	Community (5)	Other (0)		

Figure 3: Consolidated taxonomy of DDBM

4.4 Application of the Taxonomy

We applied the final taxonomy to thirty cases of DDBM to validate the identified building blocks. Figure 3 shows in parentheses the actual number of cases for each characteristic in the building blocks. The strongest impact in terms of value propositions has the characteristic information/knowledge (29 cases), while DDBM also offer actions (9), additional non-data products and services (6), and data (3). The value is captured mostly via subscription-based (22), asset sale (9) as well as usage fee (7) revenue models. The data stems largely from (smart) objects (19), customers (13), or potential customers (12) as well as processes (10). Hence, a greater share of the data comes from external (25) rather than internal (15) sources. The data target is in most cases the customer (18), while non-customers could also receive data (e.g., for advertising purposes) in many cases (15), with objects (8), processes (7), and environment (6) following. Most of the activities are related to all three aspects of data collection, organization, and preparation. While most DDBM draw on descriptive (28) and predictive (26) data analytics, less do so for prescriptive (16) and diagnostic purposes (7). The insights are utilized for visualization (25) to a greater extent, while less for execution (17) and distribution (8). Most DDBM take a value-driven perspective (27) instead of a cost-driven one (3). The sampled DDBM especially have B2B customers (27), while B2C (7) and B2A (1) customers are far less in the focus. These DDBM especially provide an opportunity to gain access to new target customers (24) instead of existing ones (8) or to become part of a platform interaction model (3). The interaction itself largely corresponds to different types, such as embedded services (7) and APIs (7) as well as proprietary applications (24) and products (4). The corresponding services often require data manually (25), automatically in continuous data streams (16), or event-driven (15) in most cases, while less often they draw on pre-defined time modes (4). Finally, most of the DDBM are used for personal customer relationships (25), while many of them also rely on self-service (9) as well as automated (8) or community services (5).

In the following, we provide an exemplary instantiation of the taxonomy application. Synfioo is providing a data-driven service for supply chain and logistics. The concrete offering (building block [1]) is *information/knowledge* through making the supply chain transparent, providing track and trace functions, and offering fault reports. Synfioo captures [2] value through a *subscription-based* model. The data generator [3] is done by *processes* like transport, loading, and sending. Another data generator can be *objects* that are for example equipped with RFID-technology. The data origin [4] is *external*, through logistic companies and the customers of Synfioo. The data targets [5] are *processes* and *objects* that are part of the supply chain, e.g., traffic, vehicles, stocks, and transportation processes. The data activity [6] that Synfioo needs to do is *collecting* the different data from over fifty global data sources, then *organizing* this data and *preparing* it to make [7] *predictions* of the estimated arrivals or provide a *description* of the current dispatching process. The insights are utilized [8] through *visualization* and the *distribution* of the insights. For this DDBM it is not possible to make a clear statement of the cost structure [9] because of a lack of information but we estimate that it is *value-driven*. The customer segment [10] are the supply chain managers and therefore *B2B*. Synfioo is trying to reach a *new target group* [11] because they are currently a start-up and do not own an existing customer base. The interaction type [12] is determined through their *application* or the *API* that they are providing for the integration into third-party software like ERP-Systems. The service flow [13] is *manual*, *event-driven*, and also in form of a *stream* regarding the tracking of the current supply chain. Regarding their website, the customer relationship [14] seems to be *personal* through direct interaction through demo versions or consultancy. The appendix provides an overview of all cases applied to the consolidated taxonomy.

5 Conclusion, Limitations & Outlook

Our starting point was to understand the building blocks of a DDBM from the current standpoint of IS research and to give an overview of the existing taxonomies in this area, particularly in view of the economic potentials of DDBM and DDS. To integrate the different aspects from prior research, we conducted a structured literature review and followed the taxonomy development approach from Nickerson et al. (2013). The outcome of the paper is a consolidated taxonomy for DDBM with 14 building blocks within the dimensions of digital transformation, based on a systematic taxonomy development approach with 26 existing taxonomies from literature and 30 DDBM cases for validation.

For researchers, the consolidated taxonomy provides a systematic synthesis of available academic DDBM taxonomies and thus adds a puzzle piece towards a coherent understand of DDBM from an IS perspective. Plus, it offers the possibility to further investigate the different building blocks that can be used as a blueprint for the development of further industry-specific taxonomies. For practitioners, the consolidated taxonomy primarily serves as a guidance tool. The developed taxonomy provides a simple and precise overview of the building blocks that practitioners need to consider when developing or transforming a DDBM. Although the developed overview and taxonomy provide both scientific and practical value, it still underlies limitations. As we followed a qualitative research approach, biases in terms of search terms, selected papers, and building blocks cannot be excluded.

Follow-up activities could include further cases to derive potential archetypes of DDBM and DDS. Further research could also analyze specific taxonomies and archetypes of DDBM and DDS, such as in retail, legal, or digital health. Another possible step would be a combination of the conceptual approach for DDBM with a design science implementation approach to explore potentials and barriers from developing and introducing DDBM.

Appendix: Taxonomy Application with Cases

		Value Proposition Model (VPM)											Value Creation Model (VCM)																											Customer Interaction Model (CIM)																			
	DDBM feature	Value Proposition				Value Capture							Data Generation					Data Origin		Data Target						Data Activity			Analytical Goal					Insight Utilization			Cost Structure			Target Customer			Customer Segment			Interaction Type				Service Flow				Customer Relationship					
Case	Description	Data	Information/Knowledge	Actions	Non-Data Product /Service	Subscription	Usage Fee	Gain Sharing	Advertising	Buy-and-sell-data	Pay-with-data	Asset Sale	Customer	Non-Customer	Process	Object	Other	Internal	External	Customer	Non-Customer	Process	Object	Environment	Other	Data Collection	Data Organization	Data Preparation	Descriptive	Diagnostic	Predictive	Prescriptive	None	Distribution	Visualization	Execution	Value-Driven	Cost-Driven	Other	B2B	B2C	B2A	New Customer	Existing Customer	Multi-Sided	Application-based	Product-based	Embedded Service	API	Manual	Pre-defined time	Event-Driven	Stream	Personal	Self-Service	Automated	Community	Other	Link
Aiservce	Smartglass that describes blind people's environment through audio output		X		X							X				X		X		X				X		X	X	X	X		X					X	X				X		X				X						X	X	X	X			https://www.aiserve.co/
Alerts for Engagement (IBM)	Provision of alerts for dangered workers by analyzing the geo-location and open data		X			X										X		X	X					X		X	X	X	X		X	X		X	X			X		X			X	X		X				X	X	X	X	X		X			https://www.ibm.com/products/weather-company-alerts-for-engagement
devAIce	AI-Based emotion recognition in different contexts			X		X										X			X	X	X			X				X	X	X						X	X			X			X					X				X	X	X					https://www.audeering.com/
Augmented Analytics (adverity)	Analysis of marketing data with ML for recommendations for action		X			X						X		X	X				X		X					X	X	X	X		X	X			X		X			X			X			X				X		X		X					https://www.adverity.com/analytics-platform/ai-powered-analytics/#augmentedanalytics
Campaign Analytics (LOTAME)	Platform to define target audiences and behavior tarcking of ads interactions		X			X							X	X	X				X		X					X	X	X	X		X				X	X	X			X			X			X				X			X	X					https://www.lotame.com/products/lotame-analytics/campaign-analytics/
Chat & Messegaing (Bold360)	Chatbot for customer support		X	X		X							X	X	X				X	X	X					X	X	X	X		X	X			X	X	X			X			X					X				X		X		X			https://www.bold360.com/features/conversational-ai
Cobrainer (Cobrainer)	ML-based matching platform for employee recruitment		X	X		X							X	X	X				X	X	X	X				X	X	X	X		X				X	X	X			X			X			X				X			X	X					https://www.cobrainer.com/recruiters
Fitbit (Fitbit)	Tracking band for gathering and analyzing health and movement data		X		X							X				X		X		X								X	X			X			X	X	X				X		X				X	X	X	X		X	X		X		X		https://www.fitbit.com/de/home
FoodTracks (Antegon)	AI-based predictions for the assortment to be produced by bakeries		X			X							X		X	X			X		X	X				X	X	X	X	X	X	X			X	X	X			X			X			X				X		X		X					https://www.foodtracks.de/en/
Google (Google)	A search engine for the web that creates revenues through advertising		X	X					X		X		X	X				X	X	X	X					X	X	X	X	X	X	X			X	X	X	X		X	X				X	X		X		X		X			X	X			https://www.google.com/
Helium10 (Helium 10)	Analysis of Amazon purchase trends for retailers		X			X							X	X					X	X	X					X	X	X	X	X	X	X		X	X		X			X	X		X			X				X	X	X			X		X		https://www.helium10.com/
I2x.ai (i2x.ai)	Analytics of customer support phone calls through AI		X			X							X						X	X								X	X	X	X	X			X		X			X			X			X		X		X			X	X					https://i2x.ai/de/
iCorr Production Analyzer (BHS C.)	App Plattform for information about the machine processes through sensors		X			X									X	X			X			X	X			X	X	X	X		X				X		X			X				X		X				X			X	X					https://store.icorr.io/apps/production-data-analyzer
iGurt (BPW)	Security belt that monitors the tension and gives an alarm if it is too low		X									X				X		X					X					X			X					X	X			X				X		X	X					X		X					https://www.bpw.de/produkte/digitale-loesungen/bpw-igurt
Insights (Factual)	Provision of customer analysis through location and behavior data		X			X							X	X					X	X	X					X	X	X	X		X	X			X		X			X			X			X				X			X	X					https://www.factual.com/products/insights/
In-Store Analytics (Bosch)	Security cameras that generate customer data, and analysis of customer behavior		X		X	X						X				X		X		X	X					X	X	X	X		X	X			X		X			X				X		X				X			X	X					https://www.boschsecurity.com/de/de/loesungen/dienstleistungen/in-store-analytics/
LANA Process Mining (Lana Labs)	Process mining for better performance in business processes		X			X									X	X			X			X	X			X	X	X	X		X																												https://lanalabs.com/en/lana-process-mining/
MVPindex (MVPindex)	Analysis of partnership investments for companies		X			X							X	X		X			X	X	X					X	X	X	X	X	X	X			X	X	X			X			X			X				X			X	X					https://www.mvpindex.com/solutions/brands
Plantix (PEAT)	App to identify diseases of plants by analyzing a photo through an AI system		X				X									X			X				X	X		X	X	X			X	X		X	X	X	X			X	X		X			X			X	X				X	X	X			https://plantix.net/en/
Real-Time Traffic (HERE)	Live traffic data to help drivers find the best routes	X	X			X	X							X		X		X	X	X	X					X	X	X	X	X	X	X		X	X		X			X			X	X		X		X	X	X			X	X	X		X		https://www.here.com/platform/traffic-solutions/real-time-traffic-information
Recommendation Engine (Inspora)	Chatbot that helps a customer's consumers during the shopping process		X	X		X	X						X	X				X	X	X	X					X	X	X	X			X			X	X	X			X			X			X		X		X		X		X	X	X			https://www.inspora.com/
Smart Thermostat V3 (Tado)	Thermostat with app that recognizes customer behaviour and adapts to it		X	X	X	X						X				X		X	X	X				X		X	X	X	X		X				X	X	X			X	X		X			X	X			X		X		X	X	X	X		https://www.tado.com/all-en/smart-radiator-thermostat
Synfioo (Synfioo)	Monitoring of supply chain and prediction of arrival times and logistic problems		X			X									X	X			X			X	X			X	X	X	X		X			X	X		X			X			X			X			X	X		X	X	X					https://synfioo.com/technology/
Target group data (Microm)	Creation of target groups for marketing by analyzing different data sources	X	X			X	X			X		X	X	X				X	X	X	X					X	X	X	X		X			X	X		X			X		X	X	X		X			X	X				X					https://www.microm.de/
ThinkSono (ThinkSono)	Use of ultrasonics and ML to detect deep vein thrombosis		X			X						X				X		X		X						X	X	X	X						X		X			X			X			X				X				X					https://thinksono.com/#detailed
TotalCare (Rolls Royce)	Full-service airplane turbines enabled through predictive maintenance		X	X	X		X								X	X		X	X			X	X			X	X	X	X		X	X			X	X		X		X				X		X				X	X	X	X	X					https://www.rolls-royce.com/media/our-stories/discover/2017/totalcare.aspx
Trends (Pulsar)	Tracks and visualizes social media trends		X			X							X	X					X	X	X					X	X	X	X		X				X	X	X			X			X			X				X			X	X					https://www.pulsarplatform.com/solutions/pulsar-trends/
Turbomonitor (Industrial Analytics)	Monitoring and analysis of vibrations and acoustic signals of turbomachines		X	X	X	X									X	X		X	X			X	X			X	X	X	X		X	X		X	X	X	X			X			X		X	X			X	X	X	X	X	X					https://industrial-analytics.io/en/turbomonitor/
Uber (Uber)	Matchmaking of drivers and ride takers through location-based data		X	X			X						X			X		X	X	X			X			X	X	X	X		X				X	X	X			X	X				X	X				X		X			X	X	X		https://www.uber.com/
Weather data packages (IBM)	Provision of weather-based insights per API	X	X				X					X				X		X	X					X		X	X	X	X					x			X			X			X	X					X	X				X					https://www.ibm.com/products/weather-company-data-packages
	Count	3	29	9	6	22	7	0	1	1	1	9	13	12	10	19	0	15	25	18	15	7	8	6	0	26	26	30	28	7	25	16	0	8	25	17	27	3	0	27	7	1	23	8	3	24	4	7	7	25	4	15	16	25	9	8	5	0	

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