Design Options for Data-Driven Business Models in Data-Ecosystems

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Design Options for Data-Driven Business Models in Data-Ecosystems

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Abstract: Data has fundamentally changed the way companies cooperate. Traditional strategies of companies require to be rethought, revisioned, and reimagined based on the new environment of the data economy. Data as a key resource opens up new opportunities that companies need to leverage in data-driven business models (DDBM). Instead of acting in a vacuum, working together and creating value conjointly in an ecosystem based on data is paramount to success. Although DDBMs and ecosystems are not new, per se, there has been a lack of an overarching view of how many DDBMs interact in the context of ecosystems. The paper starts at this point as it develops a taxonomy of these business models in ecosystems. Thus, it contributes to helping researchers and practitioners understand the specifics of data-driven business models working in ecosystems.

Keywords: Data-Driven Business Model, Data Ecosystem, Taxonomy Development, Case Study Research, Design Options.

1 Introduction

Digitalization leads to a fundamental change in the business world, resulting from the increasing availability and importance of data [BO15]. A study by the Cologne Institute for Economic Research [In21] in 2020 finds that companies already attest to the increasing value of data. However, data in its raw state is of little value to companies. Only its meaningful use generates benefits and creates value [FBP20]. This leads to the need to incorporate data into how companies operate, i.e., their business models and how they interact with each other [EGW16]. The faster and easier ways of exchanging information and thus benefiting from the strengths of others have also changed the environment in which companies find themselves. Today, companies often have an extensive network where participants generate value together in so-called *ecosystems* [YCL14, Az20]. The literature discusses various streams of ecosystem research, which usually cannot be concretely distinguished from each other [Gu20a, OL18]. In the context of data-driven business models, data ecosystems are of particular interest because they focus distinctly

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on data as the focal object (e.g., [OL18]). A study by the European Commission shows that the integration and meaningful use of data in ecosystems is essential to break down existing data silos and prevent the formation of future silos in the interests of sustainability and ecosystem self-sustainability [Ma21]. The use of data can also contribute to the achievement of sustainability goals. For example, research by [Sc21] shows that in many cases, access to data sets lays the foundation for achieving sustainability goals.

The paper aims to assist companies and researchers in grasping the complexity of data-driven business models working in data ecosystems. For this purpose, we propose a taxonomy of these data-driven business models. A taxonomy is a way of classifying, sorting, and structuring knowledge to understand a specific subject area [GV95, NVM13, SSK19]. Taxonomies originate in biology and have experienced high popularity in Information Systems (IS) research [NVM13], in particular, through their importance to business model research (e.g., [La15, KH12]). Business model taxonomies are a prevailing artifact that supports managers and researchers in understanding, analyzing, and designing new business models (e.g., [La15]). [Mö21] provide an overview of existing business model taxonomies based on the domains they cover (e.g., logistics [Mö20] or car-sharing [Re16]) and the technologies they use (e.g., digital platforms [FRP20b]). Subsequently, while business model taxonomies exist, there is yet none that sheds light on an increasingly relevant field, i.e., data-driven business models in ecosystems. This research aims to help companies understand the complexity of synergies in an ecosystem to achieve an optimal alignment of their business models. Based on the above, we formulate the following research question:

Research question: *What are the design options for data-driven business models in a data ecosystem environment?*

We pursue this research question to understand how a DDBM should operate in the environment of a data ecosystem. Based on understanding a data-driven business model in an ecosystem environment, the next step is to analyze the existing literature to derive design options. This paper is structured as follows. First, we present the background of our work, i.e., data-driven business models and data ecosystems. Next, we present the research approach we took to designing the taxonomy. The fourth section of the paper presents the final taxonomy and its specific manifestations. Section 5 discusses the results and Section 6 concludes with an overview of the contributions, limitations, and an outlook for future work.

2 Theoretical Background

2.1 Data-driven business models

Although the term “business model” has been around since the 1950s, interest did not surge until the late 1990s [Os04]. [AEA08, S. 1] highlights that the concept of business models has evolved into "one of the most important domains in the field of Information Systems (IS), thanks to recent rapid advances in Information and Communication Technologies (ICTs)" with "(…) as many definitions as there are business models" [Te18, S. 41]. Thus, the understanding of what makes a business model is not consistent. However, for this paper, we follow the general definition of [Te10, S. 173], who defines a business model as "the logic (…) how a business creates and delivers value to customers" and, further, as "the architecture of revenues, costs, and profits associated with the business enterprise delivering that value". Sometimes, a subrange of a business model is understood under the term "business model", which does not represent a holistic business model [LC00, Os04]. According to [Os04], it is not sufficient to look at individual parts of a business model. Instead, it is crucial for success to see the complete picture. Likewise, the potential for success of a business model must not be taken for granted. Ultimately, success depends on the implementation and execution of those responsible [Os04].

Motivated by the increasing amount of data in business, new business model streams have emerged investigating data-driven business models. Given the nature and timeliness of the topic, DDBMs are still a young and emerging field in IS and business model research [KB19, Gu20b, Ha16, Ha20]. The literature does not yet provide a clear definition of a data-driven business model [EGW16, Mö20]. For example, the terms "data-driven" and "data-based" can be found in the literature [SS16]. In this paper, we see these terms as equivalent and, in the following, will only use "data-driven" business models. Contrary to similar terms, DDBM definitions have a shared focus: the use of data as the core resource in the business model (e.g., [Mö20, Ha16]).

2.2 Data ecosystems

[OL18] define a data ecosystem as a multitude of networks consisting of autonomous actors that directly or indirectly consume, offer, or provide linked resources, such as software or infrastructure, to data. Actors take one or more roles within the networks and are linked through relationships with other actors to maintain collaboration but also competition within a data ecosystem [OBF19]. According to [OL18], data ecosystems consist of the following four elements: *Actors*, *Roles*, *Relationships*, and *Resources*.

In an ecosystem, an actor can be a company or an individual who takes on one or more roles. It must be able to fulfill requirements placed on its role by other participants in the ecosystem [OBF19]. Basically, actors have different expectations and other motivational drivers that are reconciled in terms of the data ecosystem [OL18]. [OL18] define a role as a function that is linked to a variety of tasks and activities. At least the data consumer and the data producer typically exist in a data ecosystem. In addition, there may be other roles, such as the intermediary, which may overlap in their responsibilities. The tasks of a producer include data selection and the preparation, maintenance, and publication of data sets [OBF19]. On the other hand, consumers gain access to the datasets, analyze them, and provide feedback if desired. For the role of the intermediary, tasks such as developing and providing solutions and maintaining them are envisaged [OL18]. The relationship aspect covers the interaction between different actors based on common interests or depending on economic or technological reasons. For example, data or other resources are exchanged via transactions, and, ideally, new business models can be derived from such relationships [OL18].

According to [OL18], resources are products or capabilities produced, provided, or consumed by actors. In a data ecosystem, resources can be data sets on the one hand and data-based software or infrastructure on the other. The resources are defined by fixed standards or licenses and can be transferred between actors both individually and in combination [OL18]. Overall, benefits can be derived from establishing or developing a data ecosystem beyond political, social, and economic factors. These include, for example, an improvement in the quality of data and services or also the increased exchange between the actors [OBF19]. In general, activities such as the joint generation, processing, and use of data for analyses form the core of a data ecosystem and thus represent a clear added value for the participating actors [Az20]. Reasons for deciding against this development include aspects such as a lack of knowledge around ecosystems, the high level of complexity in dealing with data, and the lack of actors for an ecosystem [OBF19].

3 Research Design

In our research, we propose a taxonomy. The foundation of the taxonomy is a systematic literature review using the terms „data-driven business models“ and „data ecosystem“. The keywords were developed according to the three-stage procedure by [Sc18]. To develop the taxonomy, we use the method of [NVM13], which is the *de facto* standard in developing business model taxonomies (e.g., see [Mö21]). In a first step, we searched three databases, i.e., Google Scholar, Scopus, and AISeL, for the terms "data-driven business model" and "data ecosystem". We filtered the initial corpus of literature based on [WW02] and generated a sub-corpus to include in the taxonomy design (see Figure 1).

According to [NVM13], the usability of a taxonomy is confirmed by its applicability. Therefore, practical examples from the Gaia-X environment were used to test whether the taxonomy is applicable for an iteration of the taxonomy. Gaia-X is a European initiative that aims to enable secure data sharing. Gaia-X cases were chosen for the practical examples because they are dedicatedly data ecosystems [GA21]. Furthermore, we used the taxonomy evaluation framework by [SSK19] to evaluate the taxonomy through various workshops reviewing the taxonomy. In total, we required five iterations until all ending conditions were met (see Fig. 1). The figure's representation is inspired by [DGR21].

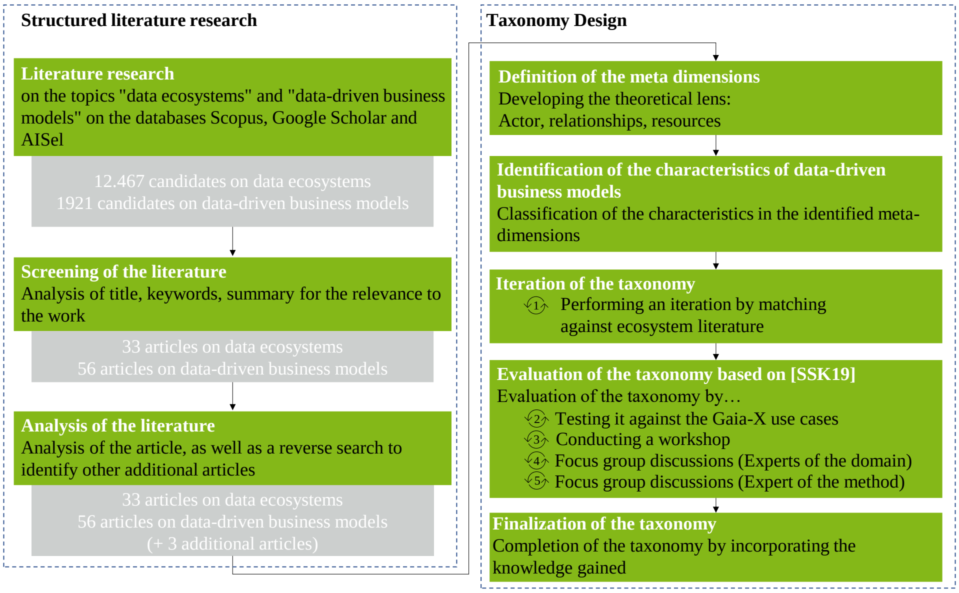

Fig. 1. Taxonomy building approach

4 Design Options of Data-Driven Business Models in Ecosystems

Since our goal is to assist others in finding design options for these business models, the *meta-characteristic* of the taxonomy is as follows: *"Provide design options for a data-driven business model in the environment of a data ecosystem."*

Thus, one goal is to first analyze the corresponding characteristics from the literature. To achieve this goal, the core characteristics of a data ecosystem were first identified. Based on the literature, the aspects of actors, roles, relationships, and resources represent the core components of a data ecosystem that we use as meta-dimensions (e.g., [Mö21]).

- *Actor:* What role does the company play in the ecosystem?
- *Relationship:* How does the interaction with partners and customers take place?
- *Resources:* What resources are used to generate value?
- *Value:* How is value created for the company itself and its customers?

The final taxonomy is shown in Fig. 2. To make the taxonomy more tangible, two examples of possible expressions are also given in Figure 2. These were filled in during the evaluation using the Gaia-X use cases. The basis for this is the Agri-Gaia [BM21] and the Collaborative Condition Maintenance use cases [Bu21].

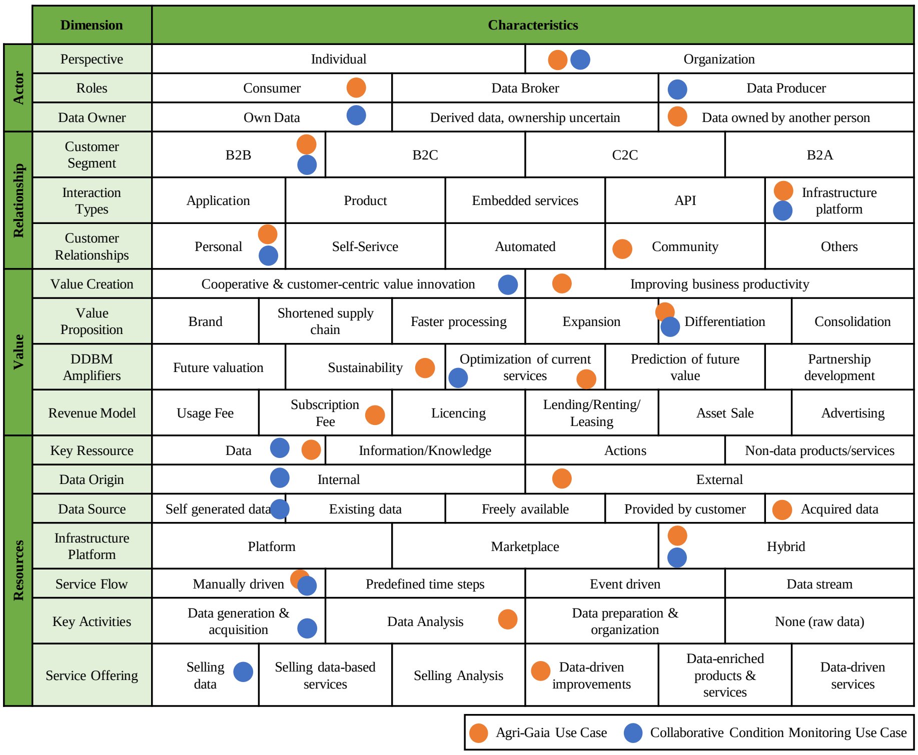

Fig. 2. Taxonomy of data-driven business models in ecosystems

4.1 Meta-Dimension: Actor

A pivotal decision for data ecosystem participants is deciding on how to participate. They must first determine what **perspective** they want to take in the data ecosystem. They can choose between an *individual* perspective or an *organization* [Ol18]. Once actors are clear about their capabilities and motivations, the last thing they must decide is which **role** they want to take. Choosing a role is not exclusive, as actors can also take on several roles simultaneously [OL18, Ge21]. For example, if the company only wants to receive data to leverage them in its business model, it should choose the role of the *data user* [BTS14, OL18, Ol18]. If an actor produces data and wants to make it available to other companies, it will find itself in the role of *data producer* [Ol18, OL18, BTS14]. The third identified role represents that of the *data broker* [BTS14]. This person or company is responsible for distributing the data between the different actors and assigning user permissions. In this way, this role supports the other actors using the data. The data broker thus takes his place between the data user and the data producer, thus linking these two roles.

4.2 Meta-Dimension: Relationship

The consideration and subsequent selection of a targeted **customer segment** represent another important point connected to business model elaboration. By selecting a customer segment, the company can tailor its value proposition precisely to its target customers and generate maximum value [DGR21, Os04]. In many consistent cases, the two customer segments identified by [Ha14] are classically mentioned at this point in the literature: *B2B* (business-to-business) and *B2C* (business-to-customer). The traditional segmentation of customer groups is supplemented by the segments *C2C* (customer-to-customer) [Br15] and *B2A* (business-to-administrative) [DGR21]. Once an organization has decided on a customer segment, it can plan the **type of interaction** with the corresponding customer segment based on this. According to [DGR21], the interaction type shows how the customer receives the actual product value. Based on [DGR21], there are four interaction types: *Application, Product*, *Embedded Services* [RBE18], and *Application Programming Interface (API)* [Mö20].

In addition to the choice of interaction type, the **customer relationship**'s type and nature also determine the business model. The type of customer relationship refers to how the customer receives the product or data. This does not mean whether the customer receives a product or an application (cf. interaction type), but whether they interact with their business partner, for example, through personal contact or in an automated manner. This aspect is crucial for the business model's long-term success in cultivating and permanently maintaining customer and business partner relationships [DGR21]. Further, [DGR21] states that there are four specific ways of customer interaction. Based on the findings of [DGR21], the listed interaction types are also adopted as possible interaction types in this research. These include *personal interaction*, *self-service*, *automated interactions*, *communities*, or *other* variants that are not clearly defined.

4.3 Meta-Dimension: Value

To generate revenue with a product, service, or similar, a **revenue model** must first be selected. This dimension represents a highly crucial point in a data-driven business model, as the evaluation of the relevant literature shows. 46 out of 58 data sets deal with or at least mention the topic of the **revenue model**. Specifically, the revenue models *Usage Fee*, *Subscription Fee*, *Licencing*, *Lending/Renting/Leasing*, *Asset Sale,* and *Advertising* are dealt with [BN18, Br15, DGR21, Ha14, KB18, SSD17, Za19]. Furthermore, when choosing a business model, it must be defined how exactly value is created with the product. This question is also very central to the profit of the business model. In their research, [ZCG16] examined various patterns of **value generation**. They identified four possible variants that could be considered for this purpose: cooperative value innovation, customer-centric value innovation, cooperative productivity improvement, and company-centric production improvement. Finally, further analyses have shown that there is a combination of the different variants in most cases. Thus, it can be summarized that mostly either *cooperative and customer-centric value innovation or enterprise* and *cooperative productivity improvement* are present [ZCG16]. The **value proposition** is closely related to the way value is created. The selection of characteristics mentioned here is based on a study by [Br15]. One evaluation point concerned the intended goal of the companies to be achieved using data. Consequently, the following characteristics emerge: *Brand*, *shortened supply chain*, *faster processing*, *expansion*, *differentiation,* and *consolidation* [Br15]. **Business model amplifiers, or DDBM amplifiers**, provide information on how a company plans to establish its business model in the long term. In their research article, [Is20] identified several key factors critical to the success of a company and its data-driven value creation. Overarchingly, these are summarized under the term's optimization of *current services*, *prediction of future value*, and *development of partnerships*. They are additionally supplemented by the aspect of *sustainability* [BM20, BTS14, ESK17, Is20, LD20, MB19, FRP20a]. The focus of the sustainability characteristic is the analysis of how a company can achieve longer life cycles but also recycle different components or products [ESK17]. Business model enhancers are rounded off by their future evaluation in the form of a shared *vision* or a unique selling proposition [ESK17].

4.4 Meta-Dimension: Resources

Key resources are another core component and represent what the company delivers to the customer as a core product [DGR21]. A data-driven business model includes *data*, *information and knowledge*, *actions*, and *non-data products or services* [Ha14]. This is a continuous further development of the data in each step. [Ha14] identified seven **data sources** through their research. These data can have an *internal or external origin* [DGR21, Ha16]. If the **origin** is internal, the data is owned by the company. On the one hand, it can be data that is already present in the existing IT systems (*existing data*) or that is *generated through use* but has not yet been used (*self-generated data*). On the other hand, external data is data that has not been generated within the company. This can be acquired data, data *provided by the customer*, or *freely available* data [Ha14]. The process of how the product reaches the consumer describes the **service flow**. The consumer can receive the offered product *manually,* in *predefined time steps*, triggered by certain *events*, or in a *stream* [DGR21]. The various manifestations differ primarily in the activity of the individual participants.

The service flow is closely related to the service offering. In a data-driven business model, the **service offering** represents the sale of data, sale of *data-based services*, *sale of analytics*, *data-driven improvements*, *data-enriched products and services*, and *data-enabled services* [Br19, Pa20]. **Key activities** form a crucial part of a business model. They represent the activities that a company performs to be able to produce the planned service offering and then deliver it to its customers [Ha14]. Key activities are what give data its true value [Br15]. Since data does not represent a product in the classic sense in the physical world and the classic value chain sees information only as a supporting element and not as a source of value, the view must be adapted at this point [Ha14]. The key activities identified in the taxonomy include *data generation and collection*, *data analysis, data preparation and organization*, and *raw data* that has not undergone any processing [Br15, DGR21, Ha14].

5 Contributions, Limitations, and Outlook

The importance of data is increasing due to digitalization. The resulting influence leads to a change in structures from traditional business models to business models that use data as their key resource [BO15]. Companies that use data as their key resource have a data-driven business model. They stand out by not only owning the data but using it to generate value for themselves and their customers [EGW16, Gu20b, Ha14, KB18, SSD17, ZAG17]. The increasing focus on data is not the only side effect of rising digitization. One reaction is a change in the way companies work together. Instead of acting on their own as before, so-called ecosystems are forming. These ecosystems require new thinking within companies [FJR19], which we analyzed in this paper codified as a taxonomy.

As a result, new opportunities for interaction and marketing of new products emerge, ultimately sustained by participants making the best possible contribution to the ecosystem based on their intrinsic motivation [OL18, Ol18]. Now, to derive design options for data-driven business models in ecosystems, an overview of the basic components of a data ecosystem is first needed. Looking at the research by [Ol18] and [OL18], one recognizes four main aspects that make up a data ecosystem: Actors, Roles, Relationships, and Resources. These four core elements form the basis for a data-driven business model in an ecosystem. In addition, other characteristics are relevant that primarily relate to the business model in general. These include the value proposition, the required interfaces, the service platform, the organizational model, and the revenue model [EP13]. Starting from the beginning of a company’s participation or realignment in an ecosystem, the first step is to position itself in the ecosystem.

For this, the company must be aware of its motivation as well as its capabilities, which our taxonomy assists. Motivation and capabilities form the basis on which the company selects its role in the ecosystem. Then, value generation, relationships, and resources need to be defined. The relationships define the interaction paths and the associated organizational aspects, such as selecting customer segments or even the manner of customer relations. The resources and the value generation explain how the company can generate monetarily or also other individual values for itself and/or its customers through the resources at its disposal. In addition, aspects such as the key activities and the range of services are defined, along with the key resources, forming a core component of the business model.

While evaluating the developed taxonomy based on a literature review and the exemplary application of various testers, it became clear that it is suitable for representing data-driven business models in ecosystems. Obstacles that became apparent during the evaluation iterations were modified step by step to enable the taxonomy to be applied intuitively. What emerged from this is knowledge about the versatility of DDBMs. From different data sources to various value propositions to diverse service offerings, DDBMs can differ significantly.

This research is subject to various limitations. First, further research projects with the same research objective may lead to different results. The reason for this is that the evaluation of the taxonomy is subject to the subjective point of view of the researcher. The same applies to the evaluations carried out. Furthermore, the literary basis is based on reviewing the databases Scopus, AISeL, and Google Scholar. Using other databases or conducting the literature search at an earlier or later date may identify other research articles, which would produce additional results. Another limiting aspect is the search terms used. For example, more specific or broader search terms will yield different results in the literature search, which would also have implications for the results. Likewise, further research can be action guidelines for developing or adapting data-driven business models to an ecosystem. Conceivable at this point would be using a visual inquiry tool, such as a canvas, which offers companies support in visualizing requirements for these types of business models. In this area, there are already basic variants, such as the Business Model Canvas by [OP10] but not yet a version that relates explicitly to data-driven business models in ecosystems. The taxonomy is also a starting point for others to enrich our findings. For example, by conducting interviews, it is possible to derive recommendations for action based on the explanations provided by the companies interviewed and thus support newly emerging companies.

The taxonomy is also a starting point for others to enrich our findings. For example, by conducting interviews, it is possible to derive recommendations for action based on the explanations provided by the companies interviewed and thus support newly emerging companies. The topic of data-driven business models and the connection to the structures of an ecosystem still holds a lot of potential. This is shown by the small number of research articles addressing this. Even if this work offers a further contribution, especially deeper topics such as data sharing and role constructs within an ecosystem are promising starting points for the future. Furthermore, it is essential to offer companies assistance on how they can adapt their business models even better to the resource of data. Many companies are critical of the sharing of data due to trust issues or a lack of transparency of the options available to date [FPT19, GO20]. It is a task of science to create incentives for data exchange and to show companies the possibilities of how this data exchange can be integrated into their business model and how they can interact in an ecosystem.

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