Making Data Tangible for Data-driven Innovations in a Business Model Context

Completed Research

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Abstract

As digital transformation has occurred over the last decade, organizations have been compelled to seek new business models. As a consequence of this development, the impact of data on business models has become a focus of interest in research as well as in practice. Based on typical characteristics of data-driven business models (DDBMs), this paper develops 19 design principles for their visual representation. The design principles were derived from semi-structured interviews with experts in the field of DDBMs and were clustered into the Business Model Canvas (BMC). The contribution of this paper is threefold. First, the developed design principles deepen the knowledge base on DDBMs. Second, other business model representations can be assessed against these design principles and new or aligned representations can be developed. Third, the design principles can be used by practitioners to develop a DDBM.

Keywords
data-driven business models, business models, design principles, digitalization

Motivation

In the wake of a far-reaching digital transformations, corporations have leveraged information technology to establish service-oriented business models (Weiner and Weisbecker 2011). Such service-oriented business models often rely on data-driven services (Williams et al. 2008), such as predictive maintenance. The effective use of data is thus becoming key to competitiveness and to the survival of business organizations (Brownlow et al. 2015). Data analysis can generate new knowledge, which can in turn improve decision making and the performance of a company (McAfee et al. 2012). Customer relationships can also be optimized via data analysis (Morabito 2015). As a consequence, digital transformation not only impacts improvements to the efficiency of organizations (Schüritz and Satzger 2016) but also affords the opportunity for radical transformations of business models (Bocken et al. 2014).

Therefore, a business model representation can serve as a helpful strategic tool for making important decisions regarding external factors (Bocken et al. 2014). In general, ample methods and tools are available for the development and representation of business models. That said, many of these artefacts are shaped by the field of research in which they originate (Beha et al. 2015) and are thus specialized for these fields. Yet, so far, extant knowledge about the development process and tools for designing and implementing data-driven business models (DDBMs) is comparatively limited because the field is relatively new (Hartmann et al. 2014). First and foremost, the specific characteristics of DDBMs and the resulting design principles for their representation have not yet been explicated. As a consequence, what constitutes a successful DDCM remains unclear, as we do not yet understand this phenomenon in detail. While the first proposal for the development of DDBMs (Mathis and Köbler 2016) pointed in the right direction, it lacked a comprehensive conceptual underpinning. Therefore, this paper seeks to provide a comprehensive set of design principles for representing DDBMs in order to facilitate design-science research on new or improved business model representations.
Thus, this paper proposes a set of design principles for DDBMs from practice to close the identified research gap. The focus of the paper is on data-specific design principles because existing business model representations already represent general design principles (Hartmann et al. 2014; John and Szopinski 2018). Hence, the paper answers the following research question:

**RQ:** “Which data-specific design principles can be used to assess business model representations regarding their applicability for data-driven business models?”

To answer this question, the paper is structured as follows: First, conceptual foundations with regard to DDBMs are outlined. Based on these foundations, the research methodology is explained, and the relevant design principles are then discussed. These design principles are identified, presented and explained based on our interview data. As a summary, the paper provides a conclusion as well as an outlook for further research.

**Foundations**

Although the term business models is frequently used, it entails different understandings and definitions (Sorrentino and Smarra 2015; Zott et al. 2011). Nevertheless, most of them have some characteristics in common. A key statement underlying business models is value creation (Lund and Nielsen 2014), and some of their key components are inputs and business activities (Sorrentino and Smarra 2015). However, as a result of different definitions, business models have been represented in a variety of ways (Al-Debei and Avison 2010; Osterwalder et al. 2005; Zott et al. 2011). Examples for common meta models with different characteristics are e3-value (Gordijn 2002), ArchiMate (Lankhorst et al. 2009) and the Business Model Canvas (BMC) (Osterwalder and Pigneur 2010), which is based on the Business Model Ontology (Osterwalder 2004). The e3-value characteristic represents an inter-organizational network of actors that create, distribute and consume value together (Gordijn 2002). ArchiMate is an enterprise architecture modelling language that uses three different layers to describe the company: business, application, and infrastructure (Lankhorst et al. 2009). One of the most prominent strategic management templates is the BMC (John et al. 2017). The BMC visually displays nine different building blocks, including product’s value proposition, customers, finances, and infrastructure (Osterwalder et al. 2005). Business model representations should nevertheless be inspected in detail and validated, and further development will be necessary (Veit et al. 2014).

In recent years, extensions to the BMC have been proposed. One example is the service-based business model (Zolnowski and Böhmann 2011). Due to a change in value creation by services (Svensson and Grönroos 2006), such business models have special characteristics (Vargo and Lusch 2014). Compared to product-based business models a service-based business model considers customer interactions especially. A service is a set of different activities that comprise a process which occurs between different entities and it aimed at supporting the customer’s everyday practice (Svensson and Grönroos 2008; Vargo and Lusch 2008). Service-oriented business models integrate the customer and partner more so than traditional models, e.g. value co-creation is possible in these models (Lusch and Nambisan 2015). The specific characteristics of these models accordingly require specific business model representations. In this respect, one extension of the BMC (Osterwalder and Pigneur 2010) is the Service Business Model Canavas (SBMC) (Zolnowski 2015). Such extensions can be accomplished in five different ways: (1) divide existing canvas fields, (2) modify canvas field content, (3) change the position of the fields, (4) add new fields and (5) link elements in the fields (Schoormann et al. 2016). Moreover, a two-layered model can be integrated into a canvas field, consisting of higher- and lower-level elements (Fielt 2014).

Based on the service-oriented paradigm, new services have appeared in science as well as in praxis, these are called “Data-as-a-Service” or “Analytics-as-a-Service” (Beha et al. 2015; Sorrentino and Smarra 2015). DDBM represent a further development of business models. A DDBM “relies on data as a resource of major importance” (Sorrentino and Smarra 2015). Nevertheless, there is no defined data threshold when comparing traditional business models with DDBMs (Schüritz et al. 2017a). Implementing data as a focus in the business model can have effects on value proposition, value creation and value capturing (Schüritz et al. 2017a). Thus, the transformation from a product-based business model to a service-oriented offering can be influenced by data-driven innovations (Schüritz et al. 2017b). All in all, there are few guidelines in either practice or literature which can be used for the specific design and development of a business model that can apply the resource data in an effective way (John and Szopinski 2018). This is due to a lack
of understanding of DDBMs to provide such artefacts. Such criteria can be provided by design principles (Chandra et al. 2015) for the development of a DDBM. Some principles have been derived from a literature review (Kühne and Böhmann 2018); however, as yet of, no design principles have been derived from the practice.

**Research Method**

In order to analyze and design DDBM demands, this research employed results from qualitative research a part of a design science research process.

Experts from different industries were interviewed. The interviews were based on a semi-structured interview guide (Myers and Newman 2007). Accordingly, questions were raised based on answers to previous questions. In this way, the interviewed experts were able to talk about their experiences in an unrestrained fashion and were encouraged to provide information beyond that produced in a strictly structured interview (Myers and Newman 2007). The interviews took between one and three hours and were structured according to three topics value proposition, value creation, and value capturing (Schüritz and Satzger 2016). This structure was chosen because these three topics comprise the main effects on business models reported by the resource data (Schüritz and Satzger 2016). Thereby, the interviewees discussed current initiatives regarding data-driven services and business models. Challenges within development and implementation projects were also outlined. Thus, the interviews both generated valuable data and revealed necessary competencies and, additionally, demonstrated changes within relevant strategies, processes and organizations. Table 1 illustrates the distribution of the experts from the different industries and organizations. Overall, 20 experts from seven different companies and five industries were interviewed. All interviewees were chosen based on extensive experience in digital and data-driven innovations in their organizations.

<table>
<thead>
<tr>
<th>Industry</th>
<th>Number of organizations</th>
<th>Number of experts</th>
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<td>Banking</td>
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*Table 1. Interviewed experts by industry and organization*

All identified criteria for DDBM representations from the expert interviews were collected in one document. The interviews were paraphrased in statements which were data-driven specific. Common statements for all business models, such as management support, were not used for the development of the design principles. All in all, 338 data-specific statements were identified. Afterwards, a structured content analysis according to Mayring (2007) was completed to group the statements into different categories (like data or revenues). These categories were identified after three iteration loops with three researchers. After each statement was sorted into a category, a review of all statements in each category was conducted. During the review, the statements were consolidated into design principles. One design principle contains statements from different interviews. This process was undertaken by two independent researchers. Thus, the design principles were sorted by two researchers independently and were first reviewed by other researchers. The design principles from both researchers were synchronized. The categories and design principles were re-viewed by two other researchers in order to verify the logical derivation of both. This was done to ensure that the deduction of categories and design principles was reasonable and reproducible.

All in all, we deducted 19 design principles from the statements which are specialized for DDBMs; these principles are described in detail in the next section. To provide an overview of the principles, we sorted them into the canvas fields of the BMC. As the BMC is very popular (John and Szopinski 2018) we chose
Design Principles for DDBM Representation

**Key Resources:**  
*R-1: The necessary data should be represented in the business model.* Data are an essential element of the business model. Dependent on the integration of data sources, the company will be able to exploit the potentials of big data (Bulger et al. 2014). Therefore, the company must know which data are needed for the business model (Mathis and Köbler 2016).

In most of the interviews this design principle, i.e. how data should be defined, appeared. One interviewee pointed out that although customer data were available, from a strategic point of view these data alone did not help because they pertained only to the present, not the future. Therefore, these data should be combined with other data to determine how the market and consumer behavior will develop. Another interviewee emphasized it was unknown which data is available in the different departments of the organization in general. All in all, the company’s data assets should be built up which was stressed by another interview partner.

*R-2: Easy, available data, should be highlighted.* If it is clear which data are needed, then these data should also be available. Due to new processes and techniques, it has become increasingly feasible to obtain the necessary data (Chen et al. 2011). Nonetheless, data availability should be less expensive than revenue so that the business model remains profitable.

The interviews highlighted that data access should be provided. Sometimes, there can be a data basis, but the necessary data cannot be found in the available database. Also, customer data cannot be easily accessed if such data are saved on the customer’s side. Furthermore, partners should have access to the data required for their service. This would help one of the interviewed organizations cover resources which they do not have in the company internally. Another interviewee outlined two ways to develop a DDBM. On the one hand, the business model can be constructed first, and the necessary data can be saved afterwards (for example with additional sensors). On the other hand, the company can analyze which data are available first and then develop a new business model based on the obtainable resources.

*R-3: Data quality should be indicated in the business model representation.* It is important not just that the necessary data are available, but also that data quality is guaranteed. Without high data quality, the outcome of the analytics could be false or lead to improper results. All in all, data quality is affected by the degree of data consistency and data completeness (Kwon et al. 2014).

Despite this, one interviewee emphasized a variety of technical challenges regarding data quality. Maintaining high data quality should be the core business activity of the company, but it can take more than one year to reach the desired level. Another organization stated that the quality of customer data can be problematic because these data are not managed by the company. This could be a problem for, e.g. data-driven benchmarking tools.

*R-4: Suitable analysis tools should be represented as a key resource.* Since insufficient tools, such as Microsoft Excel are often used for data analysis, proficient tools and technologies should be utilized for particular tasks. A suitable tool would also guarantee an acceptable output.

The interviews demonstrated how important it is to use the tool efficiently. One project mentioned by an interviewee involved saving energy consumption data in order to expand the predictive maintenance service. This project began as result of high pressure from customers and was undertaken to increase customer loyalty after sales. Currently, such data are saved but not analyzed. For this reason, tools should be developed which can analyze these data. This could in turn lead to a new mobile maintenance service. Another interviewee is offering a benchmarking service. At the moment, the company is using Excel as an analysis tool. In the future, the service should be offered in a self-service portal which is not possible with Excel. Accordingly, more professional tools should be used.

*R-5: The ownership of the data should be clearly stated in the representation.* All data need a defined owner. This can be the company, a partner, the customer or another stakeholder. It could be that some data are owned by one party, while other data are owned by a different party. Regardless, the important issue remains that the owner of the data must be clearly defined. Otherwise, ownership can be misleading,
and the company might lose the trust of their customers if they use data which they do not own or are not allowed to use.

In one interview, the owner of the data was not clear. In this case, company machines were equipped with new sensors. These machines are located on the customer side. It is not clear who the owner of the data is because the sensors were not bought from the customer. Therefore, a commitment between the company and the customer should be reached regarding data ownership before the implementation of a new DDBM.

**R-6: The data storage time should be indicated in the business model.** Some interviewees pointed out that a time frame should be defined with respect to data storage and deletion. This concern was raised because organizations must comply with regulations regarding how long data are stored and when the data must be deleted. Additionally, storage space can be saved if unneeded data are deleted, which can in turn free up hat space for more profitable data.

One interviewee stated that customer data are deleted after each project because these data are only relevant during the project’s duration. Nevertheless, some information from the data can be reused in subsequent projects. Thus, the organization has developed methods for extracting knowledge from the data - knowledge which will be retained after project’s end.

**R-7: The representation should include a central data storage.** After the data are captured, it must be defined where the data should be stored. The company must know whether the cloud is being used, whether the data must be kept in a specific country, and whether the data should be stored at the customer site or on its own servers. All in all, the data should be available at one central place - at least a copy of the data. This allows the central analysis of the data, which is faster because there is no need to access external points for the data.

One interviewee emphasized that a central storage point is essential because most digital initiatives are in different departments. With central data storage, data from different departments can be stored at one place, and it is possible to combine data which were not combined before.

**Key Activities: R-8: The purpose and goal of the key data analysis activity should be clear.** A business model should explicitly depict what should be achieved by data usage (Brownlow et al. 2015). Hence, it should provide an answer to the question: “Why?” (Bulger et al. 2014). All in all, data analysis without a goal makes no sense because the outcome is dependent on the aim of the analysis.

One interviewee pointed out that data analytics were conducted for internal use to help estimate risk and define failure quotas. This type of analysis is not only profitable for the company, but also supports the customer, who can benefit by receiving better services and products based on his or her special needs. Another interviewee mentioned the practice of saving ad much data as possible about the customer journey in data-driven projects regardless of whether it was known at the time how or if such data would ultimately be used. It has been shown that this approach does not generate value. The interviewee therefore advised defining the purpose first and identifying the necessary data afterward. Thus, a visualization of the data can help find answers to those questions about the goal of data analysis.

**R-9: The key data analysis activity generates new insights which are reflected in a new value proposition.** To sell the data analysis results, their value must be measured. Doing so requires a quantification of the value positions. All in all, if the data analysis does not generate new insights, it has no benefit to the business model. Thus, the analysis would be senseless and would only incur preventable costs.

One organization wanted to optimize its business processes with data analysis. If internal success occurs, then a service offering for the customer could be deducted. For example, consumption can be planned in advance, and resources can be identified beforehand. Another example is a database project pursued by one of the interviewed companies. This project is aimed at developing a new online shop for customers and involves a proposal mechanism based on forecasts. Furthermore, a new tool was developed to help evaluate website performance. This application combines available data silos in a new way: sales figures and load times are interrelated and compared, which in turn makes optimization of the shop possible.

**R-10: The key activity, data protection, should be represented to safeguard data and prevent data misuse.** Data privacy and protection should be seriously considered by companies. This design principle is
especially important for building trust with customers. The company should comply with local and international data privacy laws. Furthermore, it is important that the data are not misused by employees of the organization. Thus, the company must ensure that all employees are aware of data privacy and protection.

One interviewed organization is developing a platform for technical service employees that permits efficient searches across languages regarding problem descriptions and solutions. In this project, many international data bases have been merged. Although the project has internal uses, the company is unsure about its relationship with data protection laws. Questions have arisen, such as which data can be used by which employee, or whether it is possible to provide international access to data. Another interviewee stressed that their customers are very careful with their data. Although, the customers use the software system of the company on their own machines, they do not allow external access to that system. If some software faults appear, they must be simulated on another machine, one which does not contain the data from the customer’s machine. Data protection laws should be obeyed in each case.

**R-11: Data security must be ensured by representing it in the key activities.** In light of cyber-attacks, data must be protected against unauthorized access, modification, and deletion (Bertino and Sandhu 2005). Otherwise, the company’s image could suffer. Thus, data security is warranted in a DDBM. That said, one interviewee mentioned that security efforts must still be economical.

Concerns about data security discourage companies from using cloud services. One interviewee stated that they are skeptical about cloud services. It should be clearly defined which data can be released outside the company itself and which medium should be used. Data security should be guaranteed, especially for sensitive data, such as personal information.

**Channels: R-12: The interfaces for data transmission should be represented in the business model.** There should be common interfaces across which data can be transmitted to different systems. These interfaces can be solely internal to the company or can involve partners, customers or another stakeholder. Without such standard interfaces, it is not possible to gather and analyze all relevant data.

One interviewee emphasized that data transmission is not secure at present, mainly due to substandard communication methods with some machines. Flexible communication is currently not possible because no standardized interfaces exists. The company has not started a project to develop standardized interfaces because doing so is seen as very complicated. Another interviewee referred to the same problems: Wind park operators do not have standards; and even if they did, the operators are under no obligation to use them.

**R-13: The roles and responsibilities should be defined in Service Level Agreements.** A Service Level Agreement (SLA) is a contract which describes the relationship between a service customer and a service provider. Normally, an SLA is a special contract for information technology services (Patel et al. 2009). Thus, these contracts are also important for DDBMs. Due to the large amount of resources and knowledge involved with new technologies, one or more partners with specialized knowledge play an important role in data-driven services. Hence, partners have a special role in such business models and should be managed properly. The interviewees pointed out that it is important to know and define their roles and responsibilities in DDBMs.

**Revenue Models: R-14: The non-monetized value should also be represented in the revenue streams.** This design principle can be a special issue in DDBMs. It is possible that the findings cannot be sold, but that the organization can collect other relevant data which can be sold to other partners.

One example is a free app that collects and sells user data to marketing partners. This can save costs and exert an indirect influence on the business model (Schüritz and Satzger 2016).

**Key Resources and Relationships: R-15: The data used in the representation should be transparent for stakeholders.** Some interviewees explained that it is important that customers know which data are being used for analysis, especially, if these data concern the customer directly. Also, other stakeholders such as employees, organizations, or data privacy specialists, are interested in the data usage. Thus, transparency is important for maintaining trust with stakeholders.

One interview partner discussed a proposed platform that would accompany the customer through the whole life cycle of his or her service system. This platform would be configured by the customer without
additional personal support and software updates would occur automatically. This information could be used as a collaboration tool or be made available over the company boundaries. However, how such data are analyzed should be transparent to the customer. Hence, he or she provides his or her data to the company.

One company in the bank industry pointed out that customer data are saved and analyzed but remain in the company itself. The customers are aware of this, but they nevertheless not know which analyses are being performed. This is, therefore, not transparent to the customer and does not promote trust in the company. Moreover, the interview partner thought that customers are not aware that the bank has knowledge about their consumption.

**R-16: The benefit of sharing customers’ personal data should be clear in the value proposition.** Customers are typically cautious when asked to provide personal or company data. Thus, they must be motivated to share their data by being convinced of the value in doing so, i.e., what they would receive in return. Often, customer data are needed to devise working DDBM. For this reason, it is important to receive data from the customers.

One interview partner remarked that data can be saved, on the one hand, on the customer side, or, on the other hand, locally in the company. Due to the fact that customers generally do not want to provide their data, offering a less expensive service can be more motivating to share their data. If the customer wants to analyze his or her own data, then the company can offer the analysis at a higher cost. Generally, there should be an attractive value proposition with a clear benefit for the customer, which would in turn motivates him or her to provide personal data.

**R-17: The data access rights should be clear in the business model representation to ensure trust from relevant stakeholders.** The access rights for the data should be provided. This is not only relevant for external partners but also for the organization itself (Bulger et al. 2014). Access rights do not just prevent unauthorized access; they also allow everyone to do their jobs. Additionally, they permit the review of data misuse in case if something should happen internally in the organization.

In one interviewed company data-driven projects begin by equipping the products with sensors. However, the access rights to these data have not yet been clarified. At the moment, these data remain on the customer’s side, but commitments with the customer about the necessity of data access have been made. Without these data, the company cannot realize its DDBM.

**Key Activities, Key Resources and Value Proposition:**  

- **R-18: The represented value proposition should be technically feasible given the represented key resources and activities.** According to DDBMs, technical feasibility is important. If the data-driven service cannot be provided with the technical resources, then the organization cannot provide an offering to the customer.

One interviewee pointed out that high dependency in the internal IT infrastructure can lead to corresponding internal challenges. Mostly, the problem is not with the knowledge of the employees or technical problems. Technically, there are already many possibilities to analyze data. Nevertheless, the legal department must examine the changes and a downtime risk should be considered. Another interview partner stated that management should be aware of the technical possibilities. Especially, they should know about the opportunities and challenges that accompany data-driven services.

**Customers, Key Partners and Revenue Models:**  

- **R-19: The participation of the customer and partner in the revenue model should be visible.** In a DDBM the partner as well as the customer can have special roles in the revenue model. The customer, for example, gives access to his or her data for access to a service and the company can use these data to offer other services to other customers. Thus, the revenue model in a DDBM can be influenced by partners and customers (Schüritz et al. 2017a).

One example can be found in an interviewed company in which data-driven, usage-dependent service were on offer. Thus, the use of the machine should be paid by the customer only if it is used by him- or herself. The components which measure usage are provided by another partner. It should be clear who should receive how much revenue from the usage-dependent service, because both the company the and partner are involved in the fulfillment of the service.
Discussion

Overall, this research paper highlights specific-data-driven design principles which have not yet been mentioned in existing publications (Brownlow et al. 2015; Hartmann et al. 2014; Kühne and Böhmann 2018). These design principles have also not been presented in the research field of service business models (Zolnowski and Böhmann 2011). Our findings support the existing literature by deepening understanding of DDBMs and adding design principles based on interviews from industry to literature based implications (Kühne and Böhmann 2018). Current research has analyzed DDBM patterns, e.g., Brownlow et al. (2015), Schüritz and Satzger (2016) and Hartmann et al. (2014). Furthermore, scattered frameworks DDBMs exist in the literature; these usually cover one characteristic of the business model, e.g., key resource data (Mathis and Köbler 2016), key activities (Hunke and Wambsganß 2017) and cost structure (Zolnowski et al. 2017). The design principles support the development of such visualized tools and frameworks by deepening understanding of and the demand for DDBM representations. Such design principles are important for building visual representations of a business model because they can be context-specific (John et al. 2017). With your data-driven design principles we provide such a foundation for building these artefacts for DDBM representations. As 19 design principles are too numerous to integrate into one artifact, we recommend building special artifacts for each category. This could be, e.g., plugins for the BMC (Osterwalder and Pigneur 2010) which expand one or more canvas fields with additional artefacts or extending the BMC like Schoormann et al. (2016) suggested.

Most design principles relate to the canvas fields key resources and key activities (R-1-11, R-18). Thus, there is a special focus on these canvas fields in DDBMs. This may hint that research should also focus on these fields in DDBMs, which could in turn lead to two different research directions. First, these two fields should be focused on the BMC, and the questions in these canvas fields should be more specified; that, or another specialized field should be integrated into the BMC. Second, these two fields can be supported by specialized business model representations and frameworks. Such frameworks can be provided additionally and can be integrated with an interface for a general representation like that of the BMC.

Another noticeable issue in the design principles is the coherences between different canvas fields (R-15-19). This might hint at the need for linkages in the business model representation. For example, linkages like in the e3-value (Gordijn 2002) can be added into such a representation.

Conclusion

This paper derives specific DDBM design principles that can serve as assessment criteria for existing business model representations. The design principles were clustered into the fields of the BMC (Osterwalder and Pigneur 2010) in order to structure them. The data-specific design principles emphasized criteria which could be fulfilled with extended DDBM representations.

The contribution of the paper is threefold. First, it contributes to research by providing specific DDBM characteristics that can lead to a deeper understanding of this type of business model. Second, the derived design principles can be used as a foundation for design science research that seek to develop new or improved artefacts for DDBMs. Thus, the design principles act as a foundation for extending artefacts like the BMC (Schoormann et al. 2016) in the special context of DDBMs. Third, practitioners can refer to the design principles when selecting a suitable business model representation tool to visualize and analyze a DDBM.

Our study has some limitations. The design principles were derived by just two researchers. To mitigate this limitation, three other researchers with experience in this field, verified these design principles and adjusted them in iteration loops. In sum, we derived 19 design principles from our interviews. Furthermore, we clustered the data-specific statements in the interviews into categories. Nevertheless, the clustering of the criteria influences the outcome of the research (Innes 1995) regarding the quantity of design principles and the degree of detail. Nonetheless, the design principles were clustered by two different researchers and reviewed by three other researchers. Furthermore, we used the BMC to cluster the design principles. However, the BMC is often used in practice and research for representing business models (Joyce and Paquin 2016; Wallin et al. 2013). Thus, it is a suitable representation for business models.
However, this work points to further research opportunities on DDBMs. First and foremost, this pertains to the development of suitable tools and methods for designing and implementing DDBMs. The design principles proposed in this paper afford the conceptual foundation for a comprehensive analysis of extant artefacts to identify the current state of support for analyzing and generating DDBMs. If the current knowledge base lacks such support, then this paper lays the foundation for the development of new or improved methods and tools for representing DDBMs.

REFERENCES


