Towards Principles For a Data-Driven Business Model Innovation Process – A Design Science Case Study

Michael Fruhwirth,[1,3] Viktoria Pammer-Schindler[2]

[1] Know-Center GmbH, Graz, Austria
michael.fruhwirth@silicon-austria.com
[2] Graz University of Technology, Graz, Austria & Know-Center GmbH, Graz, Austria
vpammer@know-center.at
[3] Silicon Austria Labs GmbH, Graz, Austria

Transforming an existing business model into a data-driven one is challenging. Tools, methods and processes can support organisations in that innovation. This paper presents a three-year interventionist case study with an automotive company, where we investigated how an innovation process towards data-driven business models should be designed. We analysed data from interviews, notes from company meetings and workshops, as well as learnings from supporting seven different data initiatives within the organisation. As a result, we present requirements that decision-makers have regarding a process and principles that guide the process design. The principles are not specific to data-driven business model innovation. However, at the level of operationalising the process, activities and actionable tools need to be specific to the goal of a business model innovation: how data and analytics can be used for new services and business models.

Keywords:
business model innovation process, interventionist case study, data-driven business models, design science research, Bled eConference

University of Maribor Press

DOI https://doi.org/10.18690/um.fov.6.2023.35
ISBN 978-961-286-804-8

1 Introduction

Developments in data-driven technologies, as well as the availability of large data sets, hold the opportunity for developing new products, services, and business models (Günther et al. 2017), so-called data-driven business models (DDBMs) (Hartmann et al. 2016). This transformation toward a DDBM is particularly challenging for offline-established organisations (Schüritz et al. 2017b), i.e., organisations with an established business model that does not (yet) substantially rely on data analytics-enabled services or products. Therefore, research has started to design tools and methods as support for developing DDBMs (Fruhwirth et al. 2020b), e.g., supporting idea generation (Kühne and Böhmann 2019), performing financial evaluations (Zolnowski et al. 2017) or identifying risks (Fruhwirth et al. 2021). While these approaches investigate specific aspects of DDBM innovation, such as idea generation, evaluation, or risk management, organisations also need support over the innovation activities via a structured management process (Terrenghi 2019). Further, the knowledge of such a holistic process is still fragmented, specifically missing a sequence of activities and connection of tools (Fruhwirth et al. 2020b). Moreover, there is a lack of knowledge in designing such processes. Research has recently started to develop frameworks to guide the development of a DDBM (e.g., Rashed et al. 2022). Nevertheless, they need to be adapted to the organisational requirements, connected to innovation tools and converted into a structured process. Therefore, we answer the following research question: *What process allows us to develop data-driven business models in offline-established organisations systematically?*

2 Background

Business models can be understood as "stories that explain how enterprises work" (Magretta 2002) and describe how organisations create, deliver and capture value (Osterwalder and Pigneur 2010). Business model innovation (BMI) appears "when two or more elements of a business model are reinvented to deliver value in a new way" (Lindgardt et al. 2009). BMI can be seen as a process, i.e., "the activity of designing – that is, creating, implementing and validating – a new BM [business model]" (Massa and Tucci 2013). Processes serve as a guideline to structure BMI activities in organisations (Wirtz and Daiser 2018). A process comprises idealised phases, such as idea generation or implementation (Wirtz 2011). Each phase is associated with certain activities and generates distinct outcomes (Terrenghi 2019), and tools and methods support these activities (Bouwman et al. 2020). As research often tends to focus on parts of processes, e.g., providing single tools, the knowledge about how phases, activities, and tools are connected is still fragmented (Fruhwirth et al. 2020b). Therefore, research on business model innovation processes increased recently (Andreini et al. 2022), such as a process model to align value creation and value capture in BMI. Nevertheless, little attention has been paid to how to desig such processes. Concretely, we know of only Geissdoerfer (2019) and Simmert et al. (2019), who designed a process for sustainable business model innovation and continuous business model improvement, respectively.

Data-driven business models (DDBMs), in particular, have a conceptual focus on value creation from data (Guggenberger et al. 2020). In a DDBM, data is used as a key resource (Hartmann et al. 2016). Data analytics methods are applied to discover insights from data (Kühne and Böhmann 2019) that are delivered as data-based features, products, or services and support customers in decision-making (Schüritz et al. 2019) and enable the generation of new revenue streams (Schüritz et al. 2017a). Existing literature provides a comprehensive set of typologies of DDBMs (Dehnert et al. 2021), often based on the business models of start-ups (e.g., Hartmann et al. 2016; Schmidt et al. 2018), thus, neglecting offline-established organisations (Fruhwirth et al. 2020b).

Further, academia has paid little attention to the dynamic aspects of DDBMs (Wiener et al. 2020), particularly their design and realisation (Rashed and Drews 2021). One exception is the study of Lange et al. (2021), who found that DDBMs are realised iteratively along four periods (experimentation, minimum viable product, minimum marketable product and scaling). Although tools and methods should support organisations along that process (Fruhwirth et al. 2020b), current research mainly focuses on supporting idea generation through canvases (e.g., Hunke et al. 2021; Kayser et al. 2019; Kühne and Böhmann 2019). Further, there is a need for repeatable processes and the connection of tools and methods (Fruhwirth et al. 2020b). Existing high-level process approaches are based on expert interviews (Hunke et al. 2017) or literature reviews (Lange and Drews 2020). Rashed et al. (2022) recently provided a reference framework with six enablers and related activities that guide the design and realisation of DDBMs. Such models guide activities but are not yet embedded in a manageable process and do not connect tools to an overarching procedure (Fruhwirth et al. 2020b).

3 Research Design

Our overarching research approach is an interventionist case study (Korhonen et al. 2021; Yin 2009) with one automotive company (masked due to confidentiality as *Comp*) following principles of design science research. *Comp* is one of the world's leading organisations in engineering and testing of automotive systems, operating in a B2B context, with more than 10.000 employees. *Comp* has a knowledge-intensive business, where innovations are often triggered bottom-up. The automotive industry is undergoing a significant transformation due to data-driven technologies like autonomous driving that offer opportunities for new revenue streams with DDBMs (Seiberth and Gründinger 2018). Thus, the question of *Comp* is how to evolve its profitable business model by leveraging new technologies such as big data analytics and artificial intelligence.

We conducted this case study over three years, from 2018 to 2021. In this case study, we developed individual tools, methods, and an overall process to support *Comp's* DDBM initiatives. Note that the scope of the presented paper is not on the individual stages, activities, or tools but on the overall process and structured support during a DDBM innovation. Further, the scope of this research is on DDBMs on a unit or service level of *Comp* that are proposed in addition to their existing business models. This research can be labelled as an interventionist case study since we actively collaborated with representatives of *Comp* and were involved in different stages of DDBM innovation initiatives. This approach allowed us to access meaningful research data (Korhonen et al. 2021). Aside from 28 semi-structured interviews, this study includes 97 documented meetings and workshops with 73 representatives of *Comp*. Further, one researcher actively participated in seven DDBM initiatives at *Comp*. As design outcomes, we derived design requirements, design principles and design features for such a process.

Design requirements describe what users need and expect from a process. To identify requirements, we conducted 17 interviews with employees responsible for data-driven innovations and 11 interviews with employees responsible for BMI at *Comp*. Further, we collected tacit knowledge about BMI practices and considerations for DDBMs by participating in 97 meetings and workshops over three years. We took notes and had access to additional internal materials (e.g., presentations). We analysed our data following a Qualitative Content Analysis (Mayring 2015): we applied an open coding approach to identify relevant statements, grouped similar statements to codes, and structured the codes to requirements.

Design principles capture the knowledge from the design process and describe salient characteristics of the design that are transferable to other solutions for the same problem (i.e., other business model innovation processes) (Sein et al. 2011). Design principles also show how the requirements link to the specific implementation, i.e., the design features (Meth et al. 2015). We extracted our design principles through reflection and abstraction from our design requirements and features (Gregor et al. 2013).

Design features address specific aspects of the requirements (Maedche et al. 2021) and structure the description of the process design. We crafted design features by addressing the requirements and synthesising best practices at *Comp.* and grounded them in the BMI literature. Further, we conducted a structured literature review (Fruhwirth et al. 2020b), leading to an initial toolbox. One researcher actively participated in DDBM innovations at *Comp*, where we developed DDBM-specific tools. Supporting seven DDBM initiatives in specific activities enabled us to generate learnings on the activity and tool level.

4 Design Requirements

DR1: *A DDBM innovation process should increase the speed of innovation,* i.e., the time to market from an idea to launching a DDBM. Increasing speed is especially important for DDBMs, as they move faster with shorter life cycles compared to traditional product-oriented businesses. One manager at *Comp* mentioned: *"Time to market will be quite important with data. We will only be successful […] if we are really fast in development."* (Manager Data Science). In contrast to traditional products with extensive release and approval processes, DDBMs must go to market with a semi-finished solution – a "minimum marketable product" (Lange et al. 2021). Customer (decision) problems that can be addressed by a data service emerge over time through customer interactions and insights from data analytics.

DR2: *A DDBM innovation process should guide management (investment) decisions.* A successful DDBM innovation requires commitment from management to provide sufficient resources (Rashed et al. 2022). As innovating a DDBM is associated with many uncertainties, resources must be allocated reasonably. Therefore, criteria are needed to inform and objectify decisions, as one manager highlighted: *"It [the process] must support decision-making, it must provide orientation and clear yes/no decisions, provide clear statements."* (Product Manager Data Solutions). One important aspect of decision-making is to identify risks (Tesch and Brillinger 2017), e.g., if critical information could be shared through a data-based value proposition (Fruhwirth et al. 2021).

DR3: *A DDBM innovation process should have an iterative character and follow an effectuation logic* to address the uncertainties in innovating a DDBM. Effectuation focuses on taking action in the market to generate new insights by a trial and error logic (Sosna et al. 2010; Tesch et al. 2017). One common approach for early customer feedback is a Minimum Viable Product (MVP), as one manager reported: *In digital innovations, you have to create an MVP and go into testing at about 50 per cent maturity. Before that, the substance for validation was missing. In the data-driven environment, MVP approaches are much more prominent."* (Manager Digital Services).

DR4: *A DDBM innovation process should be simple and adaptive.* It should focus on the minimal necessary elements that also a prerequisite that the process will be used by all target users, as one manager highlighted: *"It must be simple to make a new topic understandable for a department. Everyone should have the know-how to use the process correctly."* (Project Manager). DDBM innovation requires adaptive approaches (Lange et al. 2021) in contrast to traditional structured processes, e.g., for product development.

DR5: *A DDBM innovation process should educate its users* and establish a mindset (e.g., customer orientation and data thinking). Thus, a process should also provide guidance and how-to instructions and equip its users with the competencies to innovate DDBMs, as one manager exemplary mentioned: *"A process can be supportive if you plan to establish the thinking that is inherent in the process anyway. Keyword: process plus education."* (Project Manager) One example of such educative topics was fostering customer-centricity, which is critical in DDBMs, as value is closely co-created with the customer (Schüritz et al. 2019).

DR6: *A DDBM innovation process should provide actionable how-to instructions for its users.* We found that the how-to of certain activities, such as defining a data product and its potential benefits, is often unclear for non-data domain experts. For instance, one manager mentioned that *"a process should provide a clear roadmap from grasping first ideas up to calculating an ROI with checklists, best practices, examples, and suggestions for business model tools."* (Manager Software).

5 Design Principles and Features

We describe our process design, as shown in Figure 1, guided by our three design principles: structure the process by investment decisions, support cyclic convergent and divergent thinking and enable organisational learning. We implemented the design principles via seven design features.

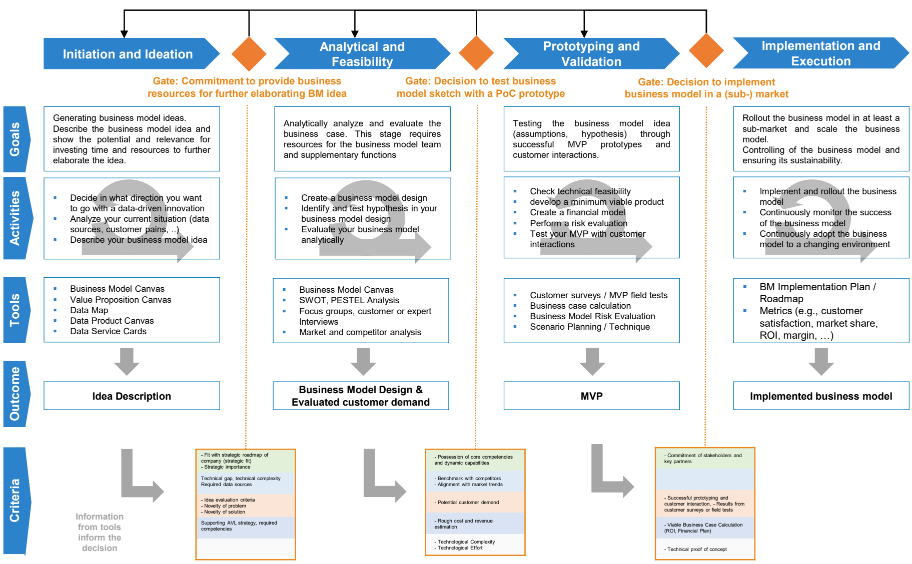

Figure 1: Overview of our process design with instantiated design features (DFs).

5.1 DP1: Structuring the Process by Decision Points

A process should be structured along with management investment decisions that are informed by a set of decision criteria. These criteria determine the information that needs to be collected in each phase to inform the decisions. Based on these criteria, the precedent phase can be defined with its activities and supporting tools. Recommended tools guide and support the data collection process. The following features implement this principle.

DF1.1 - Definition of phases and gates: The DDBM innovation process is structured along four phases and intermediate gates: initiation and ideation, analytical feasibility, prototyping and validation, implementation and execution. We based these phases on the review work of Wirtz and Daiser (2018), who identified seven generic phases of a business model innovation process based on a systematic literature review. We merged phases between two gates and dropped the decision-making phase due to our gate structure.

DF1.2 - Support decision-making by actionable criteria: Decision criteria inform and objectify the management decision if they further invest in a business model initiative (Tesch et al. 2017). We identified decision criteria from six categories based on our case and the literature: customer demand, market and competition, organisation and strategy, data and technology, financial rationales, and risks. The criteria are operationalised via evaluation questions and a response scale for each criterion in a closed form (in terms of a binary "yes" or "no", or in the form of Likert items) (Gilsing et al. 2020). Data-specific examples for such criteria are data ownership or risks associated with data sharing.

DF1.3 – Define an outcome for each phase: From our case study, we learned that it is important to have a clearly defined outcome, documented in a coherent form, at the end of each phase. This is, in particular, important when a portfolio of DDBM innovations has to be managed. For instance, the goal for the idea generation phase is to have a fully elaborated idea with a description of the key elements of a DDBM. We used this requirement to develop the Data Product Canvas (Fruhwirth et al. 2020a) as a template. The main elements are a description of the customer, benefits, problems addressed, a vision for the data analytics solution, required data sources and data analytics methods.

5.2 DP2: Support Cyclic Divergent and Convergent Thinking

Every phase in BMI has alternating activities that require divergent (i.e., exploring multiple options) and convergent thinking (i.e., deciding and going for one option). These two types of thinking and related activities are iterated until a target outcome is achieved. For instance, in the idea generation phase, activities encompass generating multiple DDBM ideas (divergent thinking) and filtering and deciding on one promising opportunity (convergent thinking). We implemented this design principle via the following two features.

DF2.1 – Definition of iterative activities for each phase: The process suggests activities for each phase that lead to the defined outcomes. The activities are iterated and alternated until the target outcome is achieved (e.g., identifying and validating a meaningful customer need). In our interventionist case study with *Comp,* we ran through an iterative cycle for testing the hypothesis in a DDBM, as suggested, for instance, by Bland et al. (2020) and added it to the process. This involved alternating activities of identifying potential data sources, generating insights from the data via data analytics and exploring customer needs.

DF2.2 – Suggestions from a toolbox: Each activity of a phase is supported by suggestions from a toolbox. In workshops of our case study, we combined several tools from the literature to support idea generation. First, we used a classification matrix (e.g., Breitfuß et al. 2019) to guide the direction of the ideation workshops (i.e., what type of DDBM should be investigated). A Data Map (e.g., Kayser et al. 2019) then supports identifying, structuring, and documenting data sources as input for idea generation workshops. A card deck (Breitfuß et al. 2023) provides basic information on DDBMs for non-data experts and supports the creative process in idea-generation workshops. Finally, the Data Product Canvas (Fruhwirth et al. 2020a) is used to structure idea generation workshops and describe and communicate a DDBM idea.

5.3 DP3: Enable Organisational Learning

A process should enable organisational learning by providing best practices. A process is based on both generic knowledge from the literature (e.g., phases of BMI) and organisation-specific best practices and tacit knowledge. Further, a process is a vehicle of change to establish desired procedures and ways of thinking. Organisations and their employees can learn by using and continuously updating the process. We implemented this principle based on two features.

DF3.1 – Include best practices: Our process design for DDBM incorporates best practices and learnings from previous DDBM innovations (i.e., critical aspects to consider or how to execute an activity). For instance, for evaluating a DDBM with the help of a SWOT analysis, we added guiding questions that were asked in previous DDBM innovations, such as: Are we too dependent on certain external data sources/providers? What happens if we have no access to the data any more? Are we handling critical customer data where a data breach would have serious consequences (e.g., threatening our reputation)?

DF3.2 – Provide a method of use for tools: For each tool, we defined a goal, an explanation, a template, and suggestions for a combination with other tools. Further we provided an illustrative example of how the tool could be used or was used in a previous initiative. As we found that it was often unclear how a tool should be used, we added step-by-step descriptions of how to use each tool. For instance, for the Data Product Canvas (Fruhwirth et al. 2020a), we found it useful to start with the customer problems, then think about a vision for the data service, consider required data sources and analytics activities, and then iterate.

6 Discussion

In this study, we investigated a DDBM innovation process through a case study from two perspectives: First, what are the requirements and expectations of the management regarding a process? And second, what are the inherent principles that guide the design of such a process? We found three salient principles that map to the characteristics of our case study. Structuring a process along gates and investment decision points reflects the hierarchical control structures and the need for investment steering of traditional B2B organisations (Rummel et al. 2022). Support cyclic convergent and divergent thinking reflect the agile and iterative nature of digital innovations (Ghezzi and Cavallo 2020). Enabling organisational learning reflects the need for a knowledge-intensive business where innovations often happen decentralised and bottom-up (Burnes et al. 2003). Thus, our principles are not specific to DDBMs; they can be transferred to other types of business models in similar contextual settings. Nevertheless, on the activities and tools level, the process is very specific for DDBMs, as the tools and activities bring in the necessary knowledge and specifics of DDBMs.

We showed that a process design should be structured along with (investment) decision points and informing criteria. This principle relates to a linear BMI process approach (Andreini et al. 2022) and reflects traditional organisations' management steering and hierarchical control structure (Rummel et al. 2022). However, specific decision points are missing in current BMI processes. Tesch et al. (2017) empirically investigated decision points and decision criteria, Lange et al. (2021) further add that incumbent organisations use Stage-Gates for a stop-or-go decision during DDBM innovation.

Further, a process design should support cyclic convergent and divergent thinking within each phase. This principle relates to the recursive BMI process approach (Andreini et al. 2022) and reflects the iterative and agile nature of digital innovations in general (Ghezzi and Cavallo 2020; Rummel et al. 2022). This principle relates to topical approaches such as Design Thinking and Lean Start-Up for BMI (Brown 2008; Ries 2011; Rummel et al. 2022). Existing process designs from the literature do not explicitly differentiate between convergent and divergent thinking. However, Hunke et al. (2017) already visualise convergent and divergent thinking aspects in their process. Fruhwirth et al. (2020b) also suggest structuring BMI tools by convergent and divergent thinking.

Nevertheless, there is a tension between these two design principles, i.e., the required iterative and flexible character (within each phase) with iterative divergent and convergent activities and the strict Stage-Gate logic (at the gates between the phases). Cooper and Sommer (2016) found that IT and manufacturing firms recently combined agile development and Stage-Gate approaches for product development, the so-called Agile-Stage-Gate hybrid model. Rummel et al. (2022) further found that manufacturing firms with a B2B business model use hybrid agile and Stage-Gate models for their BMI process. Thus, these empirical studies underpin the relevance of this two design principles.

A BMI process should also enable organisational learning. This principle reflects that innovations in knowledge-intensive organisations (such as *Comp*) often happen bottom-up and that knowledge about new business models is emerging over time in organisations. In our case study, we observed that DDBM innovations happen bottom-up in the units based on customer interactions, as domain experts are closer to the customer problem that can be addressed with data analytics. Therefore, generated learnings and insights about DDBMs need to be transferred to the organisational system. The domain experts also need the skills and tools to develop DDBMs successfully. Thus, by incorporating best practices and learning, a process can be the vehicle of knowledge transfer from individuals to the organisation and vice-versa (Sosna et al. 2010). The need for a high level of learning is crucial in fast-moving environments based on digital technologies (Burnes et al. 2003), such as data analytics. Thus, this literature stream underpins the relevance of our third design principle.

On a tools and activity level, our process is very specific to DDBMs. Tools and methods support the activities within each phase and bring in the knowledge and specifics for DDBMs. By suggesting DDBM-specific activities, tools and methods – and showing how they are interlinked - organisations and individuals can learn about the characteristics of this new type of business model. Recent literature has investigated DDBM-specific activities during BMI (Lange and Drews 2020; Rashed and Drews 2021). Nevertheless, there is a need for further research in several areas of tool support for DDBMs. First, further research should identify DDBM-specific decision criteria and evaluate DDBM-specific risks. Second, as research recently started to empirically investigate the realisation of DDBMs (i.e., prototyping and implementation; e.g., Lange et al. 2021; Rashed and Drews 2021), these insights should be transferred to tools and processes.

Finally, our research is not without limitations. All our design outcomes are based on a single case. While we aimed to generalise our results through design principles and reflected in the discussion how these appear in other, similar processes, future research should build on the principles and reflect on their usefulness in helping design a DDBM innovation process. Second, we did not rigorously evaluate the process. Future research could conduct interviews to evaluate our design principles. It should also investigate how comparative and experimental research complement case study work. This could show how our process improves the performance and outcome of DDBM innovations in organisations. It could further measure the effectiveness of the process in terms of velocity (i.e., time from the first idea to the execution of the DDBM) and economic impact (i.e., the success rate of innovations).

7 Conclusion

This paper provides three contributions to the literature: First, we showed that the design of a BMI process could be viewed from two perspectives: what the users expect from a process (requirements) and how to design such a process (principles and features). Our principles align with recent literature and point to other disciplines, such as psychology (with convergent and divergent thinking) and (organisational) learning. Second, we showed that a BMI process can be operationalised by defining outcomes, activities and tools for each phase, as shown in Figure 1. Third, our results show that the activity and tool level bring the specifics of DDBMs to a BMI process. Further, we provide an integrated perspective on how different tools and methods are interlinked.

Acknowledgements

This work was supported by the COMET — Competence Centers for Excellent Technologies Program, funded by the Austrian Federal Ministry (BMK and BMDW), the Austrian Research Promotion Agency (FFG), the province of Styria (SFG) and partners from industry and academia. The COMET Program is managed by FFG. In addition, we thank Maximilian Ferstl for conducting part of the interviews.

References

Andreini, D., Bettinelli, C., Foss, N. J., and Mismetti, M. 2022. "Business model innovation: a review of the process-based literature," *Journal of Management and Governance* (26:4), pp. 1089-1121 (doi: 10.1007/s10997-021-09590-w).

Bland, D. J., Osterwalder, A., Smith, A., and Papadakos, T. 2020. *Testing business ideas*: *Strategyzer.com/test*, Hoboken, New Jersey: John Wiley & Sons, Inc.

Bouwman, H., Reuver, M. de, Heikkilä, M., and Fielt, E. 2020. "Business model tooling: where research and practice meet," *Electronic Markets* (30:3), pp. 413-419 (doi: 10.1007/s12525-020-00424-5).

Breitfuß, G., Fruhwirth, M., Pammer-Schindler, V., Stern, H., and Dennerlein, S. 2019. "The Data-Driven Business Value Matrix: A Classification Scheme for Data-Driven Business Models," in *32nd Bled eConference Humanizing Technology for a Sustainable Society*, A. Pucihar (ed.), pp. 803-820.

Breitfuß, G., Santa-Maria, T., Fruhwirth, M., and Disch, L. 2023. "Use Your Data: Design and Evaluation of a Card-Based Ideation Tool for Data-Driven Services," *Proceedings of the 56th Hawaii International Conference on System Sciences*, pp. 5176-5185.

Brown, T. 2008. "Design Thinking," *Harvard Business Review* (56:4).

Burnes, B., Cooper, C., and West, P. 2003. "Organisational learning: the new management paradigm?" *Management Decision* (41:5), pp. 452-464 (doi: 10.1108/00251740310479304]).

Cooper, R. G., and Sommer, A. F. 2016. "Agile-Stage-Gate: New idea-to-launch method for manufactured new products is faster, more responsive," *Industrial Marketing Management* (59), pp. 167-180 (doi: 10.1016/j.indmarman.2016.10.006).

Dehnert, M., Gleiss, A., and Frederik, R. 2021. "What makes a data-driven business model? A consolidated taxonomy," *Proceedings of the Twenty-Ninth European Conference on Information Systems (ECIS 2021).*

Fruhwirth, M., Breitfuß, G., and Pammer-Schindler, V. 2020a. "The Data Product Canvas: A Visual Collaborative Tool for Designing Data-Driven Business Models," in *33rd Bled eConference Enabling Technology for a Sustainable Society*, A. Pucihar, M. K. Borštnar, R. Bons, H. Cripps, A. Sheombar and D. Vidmar (eds.), Online. June 28-29 2020, pp. 515-528.

Fruhwirth, M., Pammer-Schindler, V., and Thalmann, S. 2021. "A Network-based Tool for Identifying Knowledge Risks in Data-Driven Business Models," in *Proceedings of the 54th Annual Hawaii International Conference on System Sciences*, T. Bui (ed.), pp. 5218-5227.

Fruhwirth, M., Ropposch, C., and Pammer-Schindler, V. 2020b. "Supporting Data-Driven Business Model Innovations: A structured literature review on tools and methods," *Journal of Business Models* (8:1), 7-25.

Geissdoerfer, M. 2019. *Sustainable business model innovation: Process, challenges and implementation.*

Ghezzi, A., and Cavallo, A. 2020. "Agile Business Model Innovation in Digital Entrepreneurship: Lean Startup Approaches," *Journal of Business Research* (110), pp. 519-537 (doi: 10.1016/j.jbusres.2018.06.013).

Gilsing, R., Turetken, O., Ozkan, Baris, Adali, Onat Ege, and Grefen, P. 2020. "A method for qualitative evaluation of service-dominant business models," *Proceedings of the Twenty-Eight European Conference on Information Systems (ECIS) - A Virtual AIS Conference.*

Guggenberger, M. T., Möller, F., Boualouch, K., and Otto, B. 2020. "Towards a Unifying Understanding of Digital Business Models," *Twenty-Third Pacific Asia Conference on Information Systems, Dubai, UAE, 2020.*

Günther, W. A., Rezazade Mehrizi, M. H., Huysman, M., and Feldberg, F. 2017. "Debating big data: A literature review on realizing value from big data," *The Journal of Strategic Information Systems* (26:3), pp. 191-209 (doi: 10.1016/j.jsis.2017.07.003).

Hartmann, P. M., Zaki, M., Feldmann, N., and Neely, A. 2016. "Capturing value from big data – a taxonomy of data-driven business models used by start-up firms," *International Journal of Operations & Production Management* (36:10), pp. 1382-1406 (doi: 10.1108/IJOPM-02-2014-0098).

Hunke, F., Seebacher, S., Schüritz, R., and Illi, A. 2017. "Towards a Process Model for Data-Driven Business Model Innovation," *Proceedings of the 19th IEEE Conference on Business Informatics (CBI)*, pp. 150-157.

Hunke, F., Thomsen, H., and Satzger, G. 2021. "Investigating Modular Reuse as an Underlying Mechanism of Conceptualization during Service Design – the Case of Key Activity Orchestration," in *Proceedings of the 54th Annual Hawaii International Conference on System Sciences*, T. Bui (ed.).

Kayser, L., Mueller, R. M., and Kronsbein, T. 2019. "Data Collection Map: A Canvas for Shared Data Awareness in Data-Driven Innovation Projects," *2019 Pre-ICIS SIGDSA Symposium on Inspiring mindset for Innovation with Business Analytics and Data Science, Munich 2019.*

Korhonen, T., Selos, E., Laine, T., and Suomala, P. 2021. "Exploring the programmability of management accounting work for increasing automation: an interventionist case study," *Accounting, Auditing & Accountability Journal* (34:2), pp. 253-280 (doi: 10.1108/AAAJ-12-2016-2809).

Kühne, B., and Böhmann, T. 2019. "Data-Driven Business Models: Building the Bridge Between Data and Value," in *Proceedings of the 27th European Conference on Information Systems - Information Systems for a Sharing Society*, J. Vom Brocke, S. Gregor and O. Müller (eds.), Stockholm and Uppsala, Sweden.

Lange, H. E., and Drews, P. 2020. "From Ideation to Realization: Essential Steps and Activities for Realizing Data-Driven Business Models," *22nd IEEE International Conference on Business Informatics (CBI) Workshops, Antwerp, 2020*.

Lange, H. E., Drews, P., and Höft, M. 2021. "Realization of Data-Driven Business Models in Incumbent Companies: An Exploratory Study Based on the Resource-Based View," *Proceedings of the Forty-Second International Conference on Information Systems, Austin 2021*.

Lindgardt, Z., Reeves, M., Stalk, G., and Deimler, M. S. 2009. "Business Model Innovation: When the Game Gets Tough, Change the Game," Boston Consulting Group.

Maedche, A., Gregor, S., and Parsons, J. 2021. "Mapping Design Contributions in Information Systems Research: The Design Research Activity Framework.," *Communications of the Association for Information Systems* ((forthcoming), in Press).

Magretta, J. 2002. "Why Business Models Matter," *Harvard Business Review* (80:5), pp. 86-92.

Massa, L., and Tucci, C. L. 2013. "Business model innovation," in *The Oxford handbook of innovation management*, M. Dodgson, D. M. Gann and N. Phillips (eds.), Oxford: Oxford Univ. Press, pp. 420-441.

Mayring, P. 2015. *Qualitative Inhaltsanalyse*: *Grundlagen und Techniken*, Weinheim: Beltz.

Meth, H., Mueller, B., and Maedche, A. 2015. "Designing a Requirement Mining System," *Journal of the Association for Information Systems* (16:9), pp. 799-837 (doi: 10.17705/1jais.00408).

Osterwalder, A., and Pigneur, Y. 2010. *Business Model Generation*: *A Handbook for Visionaries, Game Changers, and Challengers*, Hoboken, New Jersey: John Wiley & Sons.

Rashed, F., and Drews, P. 2021. "Pathways of Data-driven Business Model Design and Realization: A Qualitative Research Study," in *Proceedings of the 54th Annual Hawaii International Conference on System Sciences*, T. Bui (ed.), 5676-5685 (doi: 10.24251/HICSS.2021.689).

Rashed, F., Drews, P., and Zaki, M. 2022. "A Reference Model for Data-Driven Business Model Innovation Initiatives in Incumbent Firms," *Proceedings of the Thirtieth European Conference on Information Systems (ECIS 2022), Timişoara, Romania.*

Ries. 2011. *The lean startup*: *How today's entrepreneurs use continuous innovation to create radically successful business*, New York: Currency.

Rummel, F., Hüsig, S., and Steinhauser, S. 2022. "Two archetypes of business model innovation processes for manufacturing firms in the context of digital transformation," *R&D Management* (52:4), pp. 685-703 (doi: 10.1111/radm.12514).

Schmidt, J., Drews, P., and Schirmer, I. 2018. "Charting the Emerging Financial Services Ecosystem of Fintechs and Banks: Six Types of Data-Driven Business Models in the Fintech Sector," *Proceedings of the 51st Hawaii International Conference on System Sciences*, pp. 5004-5013.

Schüritz, R., Farrell, K., Wixom, B. H., and Satzger, G. 2019. "Value Co-Creation in Data-Driven Services: Towards a Deeper Understanding of the Joint Sphere," *Proceedings of the Fortieth International Conference on Information Systems (ICIS), Munich.*

Schüritz, R., Seebacher, S., and Dorner, R. 2017a. "Capturing Value from Data: Revenue Models for Data-Driven Services," in *Proceedings of the 50th Hawaii International Conference on System Sciences*, T. Bui (ed.), Waikoloa Village, Hawaii, USA, pp. 5348-5357.

Schüritz, R., Seebacher, S., Satzger, G., and Schwarz, L. 2017b. "Datatization as the Next Frontier of Servitization: Understanding the Challenges for Transforming Organizations," *Proceedings of the Thirty-Eighth International Conference on Information Systems (ICIS), Seoul.*

Seiberth, G., and Gründinger, W. 2018. "Data-driven business models in connected cars, mobility services and beyond," *BVDW Research*, available at https://bvdw.org/datadrivenbusinessmodels/.

Sein, M. K., Henfridsson, O., Purao, S., Rossi, M., Lindgren, R., Sein, Henfridsson, Purao, Rossi, and Lindgren. 2011. "Action Design Research," *Management Information Systems Quarterly* (35:1), pp. 37-56 (doi: 10.2307/23043488).

Simmert, B., Ebel, P. A., Peters, C., Bittner, E. A. C., and Leimeister, J. M. 2019. "Conquering the Challenge of Continuous Business Model Improvement," *Business & Information Systems Engineering* (61:4), pp. 451-468 (doi: 10.1007/s12599-018-0556-y).

Sosna, M., Trevinyo-Rodríguez, R. N., and Velamuri, S. R. 2010. "Business Model Innovation through Trial-and-Error Learning," *Long Range Planning* (43:2-3), pp. 383-407 (doi: 10.1016/j.lrp.2010.02.003).

Terrenghi, N. 2019. *Design, Implement, Repeat: Essays on Business Model Management in Offline-Born Organizations*.

Tesch, J., and Brillinger, A.-S. 2017. "The Evaluation Aspect of Digital Business Model Innovation: A Literature Review on Tools and Methodologies," in *Proceedings of the 25th European Conference on Information Systems*, I. Ramos, V. Tuunainen and H. Krcmar (eds.), Guimarães, Portugal, pp. 2250-2268.

Tesch, J., Brillinger, A.-S., and Bilgeri, D. 2017. "Internet of Things Business Model Innovation and the Stage-Gate Process: An Exploratory Analysis," *International Journal of Innovation Management* (21:5), 1740002-1 - 1740002-17 (doi: 10.1142/S1363919617400023).

Wiener, M., Saunders, C., and Marabelli, M. 2020. "Big-data business models: A critical literature review and multiperspective research framework: A Critical Literature Review and Multi-Perspective Research Framework," *Journal of Information Technology* (35:1), pp. 66-91 (doi: 10.1177/0268396219896811).

Winterhalter, S., Weiblen, T., Wecht, C. H., and Gassmann, O. 2017. "Business model innovation processes in large corporations: Insights from BASF," *Journal of Business Strategy* (38:2), pp. 62-75 (doi: 10.1108/JBS-10-2016-0116).

Wirtz, B. W. 2011. *Business Model Management: Design - Instruments - Success Factors*, Gabler.

Wirtz, B. W., and Daiser, P. 2018. "Business Model Innovation Processes: A Systematic Literature Review," *Journal of Business Models* (6:1), pp. 40-58.

Yin, R. K. 2009. *Case study research: Design and methods*, Los Angeles: SAGE.

Zolnowski, A., Anke, J., and Gudat, J. 2017. "Towards a Cost-Benefit-Analysis of Data-Driven Business Models," in *Proceedings der 13. Internationalen Tagung Wirtschafstinformatik (WI 2017)*, J. M. Leimeister and W. Brenner (eds.), pp. 181-195.