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Designing Support for Data-Driven Business Model Innovation in Offline-Established Organizations

DISSERTATION

zur Erlangung des akademischen Grades

Doktor der technischen Wissenschaften

eingereicht an der

Technischen Universität Graz

Betreuerin

Assoc.-Prof.in Dr.in Viktoria Pammer-Schindler

Institute for Interactive Systems and Data Science

Graz, Juni 2024

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Abstract

Advances in data analytics and artificial intelligence, as well as the extensive availability of data, hold the potential for new data-driven business models and services. Nevertheless, this innovation process is perceived as challenging, particularly in traditional organisations. Current literature provides little support for the specific properties of data-driven business models for organisations entering this field. Therefore, this thesis aims to investigate how to design tools, methods and concepts to support data-driven business model innovation in an offline-established organisation.

We adopted a design science research approach in this thesis and conducted a three-year case study with one organisation in the automotive industry. With this approach, three relevant practical and scientific problems (and corresponding research questions) could be identified during data-driven business model innovation: First, how to design a systematic innovation process; second, how to support the idea generation process, particularly how to shape a data-based value proposition; and third, how to support evaluation and decision making, in particular identifying and managing knowledge risks that arise from sharing data. The first question concerns the overarching process and the other two questions concern two steps in a data-driven business model innovation process. Subsequently, we designed, applied and evaluated artefacts that support steps in the process of business model innovation towards a data-driven business model. Other organisations and experts beyond the single case study were also involved in these evaluations.

The above three problems are addressed in the following way in this thesis:

(1) Regarding the overall process, we analysed existing tools and methods supporting data-driven business models via a structured literature review, showed gaps and outlined an agenda for further research. Second, we crafted design principles for a data-driven business model innovation process and showed an exemplary instantiation of a process within our case study.

(2) Regarding idea generation, we designed the Data Product Canvas and showed how such visual collaborative tools support workshops to shape the direction and value proposition of a data-driven business model idea. Further, we proposed a data-based value creation ontology and explored roles and exchanged value objects in a data-driven business model that extends the understanding of data-driven business models.

(3) Regarding evaluation and decision-making, we identified knowledge risks as one relevant risk factor in the design of data-driven business models. We explored how different types of data-related value objects relate to different risks, what contextual factors influence the risk and what measures can be taken to mitigate and manage those risks. Further, we designed a network-based representation of data-driven business models that helps to identify such risks and we explored the business models of data marketplaces – one approach to preventing such risks.

By reflecting and abstracting the results of this thesis, we could make contributions in three directions:

(i) Regarding the design of business model innovation processes, this thesis provides three generic design principles for a business model innovation process: Structure the process along investment decision points; support convergent and divergent thinking within each phase; and enable organisational learning. Further this thesis shows that tools and methods bring the specific aspects of DDBMs into the process.

(ii) Regarding the design of business model tools and methods, DDBM-specific tools are adapted versions of generic business model innovation tools that incorporate the specific knowledge and properties of DDBMs. When designing tools, the underlying theoretical concept must be understood (such as the value-creation logic with data).

(iii) Regarding the understanding and design of data-driven business models, we found that data-driven business models generate customer value by using a data product to support a customer's decision problem. This value-creation logic has to be kept in mind when designing new DDBMs. Further, exchanging data, models and predictions in a DDBM includes the risk of leaking critical knowledge. This risk needs to be considered already during the design of DDBMs. Designing and implementing data-driven business models, therefore, requires a multi-disciplinary approach.

As an outlook for further research, we suggest studying quantitative methods for evaluating DDBMs, implementing IT-based business model tools and processes and designing interventions for introducing business model tools in organisations. Further, we see that the field is moving forward towards AI-based business models. Thus, further research should also study specific characteristics of his kind of DDBM and adapt the tools and processes towards Artificial Intelligence.

Zusammenfassung

Technologische Fortschritte in Data Analytics und Künstlicher Intelligenz sowie die umfassende Verfügbarkeit von Daten beinhalten das Potenzial für neue datengetriebene Geschäftsmodelle. Jedoch wird dieser Innovationsprozess als Herausforderung, insbesondere in traditionellen Organisationen, wahrgenommen. Die wissenschaftliche Literatur bietet für Unternehmen nur wenig Unterstützung für die Analyse und Entwicklung von datengetriebenen Geschäftsmodellen. Das Forschungsziel dieser Arbeit ist daher die Gestaltung von Werkzeugen, Methoden und Konzepten zur Unterstützung datengesteuerter Geschäftsmodellinnovationen in etablierten Organisationen.

Wir haben in dieser Arbeit einen gestaltungsorientierten Forschungsansatz gewählt und eine dreijährige Fallstudie mit einem Unternehmen aus der Automobilindustrie durchgeführt. Dieser Ansatz ermöglichte es uns, drei relevante praktische und wissenschaftliche Problemstellungen (und entsprechende Forschungsfragen) während einer datengetriebenen Geschäftsmodellinnovation zu identifizieren: Erstens, wie muss solch ein systematischer Prozess gestaltet werden? Zweitens, wie kann der Ideenfindungsprozess unterstützt werden, insbesondere die Gestaltung eines datenbasierten Wertversprechens? Drittens, wie kann die Bewertung und Entscheidungsfindung unterstützt werden, insbesondere die Identifizierung und das Management von Wissensrisiken, die durch das Teilen von Daten entstehen? Die erste Frage betrifft den übergreifenden Prozess, die beiden anderen Fragen beziehen sich auf einzelne Aktivitäten im Prozess. In dieser Arbeit wurden Artefakte entworfen, angewandt und evaluiert, die Schritte im Prozess der Geschäftsmodellinnovation hin zu einem datengetriebenen Geschäftsmodell unterstützen. In dieser Evaluierung wurden auch andere Organisationen und Experten über die einzelne Fallstudie hinaus einbezogen.

Die drei oben genannten Fragestellungen werden in dieser Forschungsarbeit auf folgende Weise bearbeitet:

(1) In Bezug auf den Prozess haben wir bestehende Werkzeuge und Methoden zur Unterstützung datengetriebener Geschäftsmodelle mittels einer strukturierten Literaturrecherche bewertet, Lücken aufgezeigt und eine Agenda für weitere Forschung skizziert. Zweitens haben wir Gestaltungsprinzipien für einen datengetriebenen Geschäftsmodell-Innovationsprozess erarbeitet und eine beispielhafte Umsetzung des Prozesses in unserer Fallstudie gezeigt.

(2) In Bezug auf die Ideengenerierung haben wir den Data Product Canvas entwickelt und dabei gezeigt, wie ein visuelles kollaboratives Werkzeug Workshops unterstützt, um die Richtung und das Wertversprechen einer datengetriebenen Geschäftsmodellidee zu gestalten. Darüber hinaus schlagen wir eine Ontologie vor, die die datenbasierte Wertschöpfung beschreibt, und untersuchen Rollen und ausgetauschte Wertobjekte in einem datengetriebenen Geschäftsmodell.

(3) Im Hinblick auf die Bewertung und Entscheidungsfindung haben wir Wissensrisiken als einen relevanten Risikofaktor bei der Entwicklung datengetriebenen Geschäftsmodelle identifiziert. Wir untersuchen, wie verschiedene Arten von datenbezogenen Wertobjekten mit verschiedenen

Risiken zusammenhängen, welche Kontextfaktoren das Risiko beeinflussen und welche Maßnahmen ergriffen werden können, um dieses Risiko zu mindern. Des Weiteren stellen wir eine netzwerkbasierte Darstellung von datengetriebenen Geschäftsmodellen vor, die dabei hilft, solche Risiken zu identifizieren. Weiters untersuchen wir die Geschäftsmodelle von Datenmarktplätzen - einem Ansatz zur Vermeidung solcher Risiken.

Durch Reflexion und Abstraktion der Ergebnisse leistet diese Arbeit Beiträge in drei Richtungen zur wissenschaftlichen Literatur und Praxis:

(i) Im Hinblick auf die Gestaltung von Geschäftsmodell-Innovationsprozessen liefert diese Arbeit drei generische Gestaltungsprinzipien für einen Geschäftsmodell-Innovationsprozess: Strukturierung des Prozesses anhand von Investment Entscheidungen; Unterstützung von konvergentem und divergentem Denken in jeder Phase; Und organisationales Lernen ermöglichen. Weiters zeigt diese Arbeit, dass Werkzeuge und Methoden die spezifischen Aspekte von datengetriebenen Geschäftsmodellen in den Prozess einbringen.

(ii) Hinsichtlich der Gestaltung von Werkzeugen und Methoden sind Geschäftsmodell-spezifische Werkzeuge angepasste Versionen von generischen Geschäftsmodell-Innovationswerkzeugen, die das spezifische Wissen und die Eigenschaften von datengetriebenen Geschäftsmodellen einbeziehen. Weiters muss bei der Gestaltung von solchen spezifischen Werkzeugen das zugrunde liegende theoretische Phänomen verstanden werden, beispielsweise die Logik der datenbasierten Wertschöpfung.

(iii) Hinsichtlich des Verständnisses und der Entwicklung von datengetriebenen Geschäftsmodellen stellen wir in dieser Arbeit fest, dass datengetriebene Geschäftsmodelle einen Mehrwert für den Kunden generieren, indem ein Datenprodukt zur Unterstützung des Entscheidungsproblems bereitgestellt wird. Diese Logik der Wertschöpfung muss bei der Gestaltung neuer Geschäftsmodelle berücksichtigt werden. Außerdem birgt der Austausch von Daten oder Modellen in einem datengetriebenen Geschäftsmodell das Risiko, dass kritisches Wissen nach außen dringen kann. Dieses Risiko muss bereits bei der Konzeption des Geschäftsmodells berücksichtigt werden. Der Entwurf und die Umsetzung datengesteuerter Geschäftsmodelle erfordern daher einen interdisziplinären Ansatz.

Als Ausblick für die weitere Forschung schlagen wir vor, quantitative Methoden für die Bewertung von datengetriebenen Geschäftsmodellen zu untersuchen, die Implementierung IT-gestützter Geschäftsmodell-Tools und -Prozesse voranzutreiben sowie Interventionen für die Einführung von Geschäftsmodell-Tools in Unternehmen zu entwerfen. Außerdem sehen wir, dass sich das Feld in Richtung KI-basierter Geschäftsmodelle bewegt. Daher sollte die weitere Forschung auch die spezifischen Merkmale dieser Art von Geschäftsmodellen untersuchen und die Werkzeuge und Prozesse anpassen.

Acknowledgements

I want to thank the following people, without whom I would not have been able to complete this research and without whom I would not have made it through my PhD degree!

The Data-Driven Business team at the Know-Center GmbH and Graz University of Technology, especially my supervisor Viktoria Pammer-Schindler and my co-supervisor Stefan Thalmann from the University of Graz, whose insights and knowledge into the subject matter steered me through this research.

My former colleague and office neighbour Gert Breitfuß, thank you for our ongoing discussions and exchanges on business model innovation and the company workshops performed together.

Florian Leski, Emina Prlja, and Maximilian Ferstl - thank you for supporting this research endeavour as part of their master's thesis or master's project.

All co-authors of my publications who supported me in the research and paper writing process and by contributed to the respective research chapters of this thesis.

The case company and their employees supported me in this three-year case study, took the time to participate in interviews and workshops and allowed me to participate in many meetings, discussions and innovation initiatives. Without whom, I would have little empirical content for my thesis.

All participants who took part in the study, either in an expert interview or an innovation workshop, enabled this research to be possible.

My family and partner in life - thank you for your patience and encouragement.

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.

Chapters of this Thesis

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List of Abbreviations

AI	Artificial Intelligence
API	Application Programming Interface
BM	Business Model
BMI	Business Model Innovation
CRISP-DM	Cross Industry Standard Process for Data Mining
DDBM	Data-Driven Business Model
DF	Design Feature
DP	Design Principle
DR	Design Requirements
DSR	Design Science Research
GUI	Grafical User Interface
IoT	Internet of Things
ML	Machine Learning
NDA	Non-Disclosure Agreement
RG	Research Goal
RQ	Research Question

Part I
Foundations

Chapter 1

Introduction and Motivation

"Information is the oil of the 21st century, and analytics is the combustion engine."

Peter Sondergaard[1]

1.1 Motivation for this Thesis

The business models of many of today's most valuable firms, such as Google, Amazon, or Facebook, heavily rely on data, analytics and artificial intelligence (Seiberth and Gründinger, 2018). Further, the available data has increased exponentially in recent years, especially due to technologies such as the Internet of Things or autonomous systems. New possibilities in the field of data analytics, machine learning and artificial intelligence also enable traditional organisations to generate value from data and grow their business: The improvement of existing processes as well as the development of new products, services, and overall new business models (Günther *et al.*, 2017; Woerner and Wixom, 2015), so-called data-driven business models (Hartmann *et al.*, 2016; Wiener *et al.*, 2020). But, *"[m]uch less has been written about how, exactly, companies should get started with [using artificial intelligence in business innovation]"* (Agrawal *et al.*, 2018a).

Thus, the question of how to create value from data has gained attention in research (e.g., Günther *et al.*, 2017) and practice (e.g., Bertoncello *et al.*, 2018) likewise. Simultaneously, this field is challenging for traditionally offline established organizations to realize value for their customers and innovate their business model through data and analytics (Schüritz *et al.*, 2017c). Organizations and managers find it difficult to systematically identify relevant opportunities for data as core elements of their business and how to proceed with an evaluation, decision-making, and, ultimately, implementation of a new data-driven business model.

Publicly known cases of data-driven business models are centred to a great extent on American-based and global giants such as Google, Facebook, or Uber. Traditional or offline-established organizations, however, differ from these companies. Any inspiration one may gain from those global giants needs significant re-thinking before it can be usefully applied. The same is true for the existing literature on data-driven business models that emerged from the field of start-ups. Each of these fields is inspirational and important for identifying and developing data-driven business models but needs significant rethinking according to their applied context.

[1] https://gcom.pdodev.aws.gartner.com/en/newsroom, accessed on 2021-11-25 11:25.

Tools and methods support organisations in designing, evaluating and implementing new business models (Schneider and Spieth, 2013). Designing such tools and methods has emerged as an own research field (Bouwman *et al.*, 2020). A wide spectrum of tools and methods exist, with the *Business Model Canvas* (Osterwalder and Pigneur, 2010) as the most prominent example. Nevertheless, little support is available that incorporates the specifics of big data, analytics and artificial intelligence in business model innovation.

1.2 Problem Context: Data-Driven Business Model Innovation in Offline-Established Organisations

This transformation toward a data-driven business model is particularly challenging for offline-established organizations (Fruhwirth *et al.*, 2018; Schüritz *et al.*, 2017c) and is different from start-ups. By offline-established organizations, we mean organizations with an established business model that does not (yet) substantially rely on digital, data analytics, or artificial intelligence-enabled services or products. Schüritz *et al.* (2017c) identified challenges for offline-established organisations structured by ten categories, as Figure 1.1 illustrates.

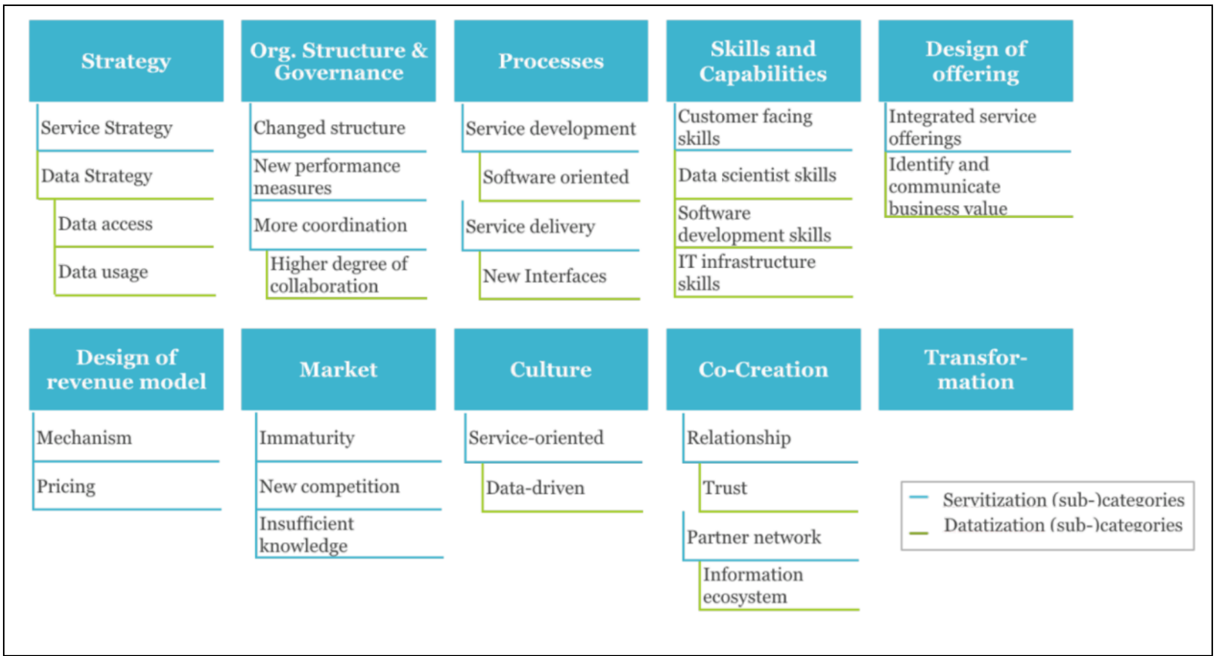

Figure 1.1: Overview of exemplary challenges in transforming to a data-driven business model (Schüritz *et al.*, 2017c).

We decided to focus on organisations with a B2B business model for two reasons. First, business model innovation is more challenging in a B2B setting as there is a limited number of potential customers (compared to B2C business models). Second, less research is available for B2B business model innovation, and existing tools often focus on B2C.

To ensure the practical relevance of our research questions, a large part of this thesis is based on a case study with one automotive company. In this case, we identified practical challenges in data-driven business model innovation in one offline-established organisation that we transformed into meaningful research questions. Further, this case allowed us to demonstrate and evaluate potential solutions for these challenges.

In our case study we identified three practical problems during data-driven business model innovation: First, what is a good design for a data-driven business model that fits to the organisation? This challenge raises the need for supporting the idea generation and design phase. Second, how to evaluate a data-driven business model design to support the decision if it should be implemented? This challenge raises the need for supporting the evaluation and decision-making phase. Third, what would be a good overall approach for developing a data-driven business model? This challenge raises the need for an systematic business model innovation process.

1.3 Research Goal and Leading Research Questions[2]

To address the problem outlined above, we intend to answer the following leading research goal (RG) of this thesis:

RG: *How can we design tools, methods and concepts to support data-driven business model innovation in an offline-established organisation?*

The process of business model innovation is a complex task involving various steps, activities and challenges (Geissdoerfer, 2019; Wirtz and Daiser, 2018). Despite specific activities such as idea generation, evaluation and risk management, organizations also need support over the whole business model innovation activities via a structured management process (Terrenghi, 2019). Up to day, the knowledge on such a holistic process for data-driven business model innovation is still fragmented, missing a sequence of activities and connection of specific tools and methods (Fruhwirth *et al.*, 2020c). In order to provide support for this challenge, we intend to answer the first research question (RQ) of this thesis:

RQ 1: What process design would allow established companies to develop data-driven business models systematically?

This research question will be addressed in Chapter 4. One important activity in business model innovation is generating ideas and formulating a value proposition for a new (data-driven) business model. At the time of starting this thesis, there was no sufficient representation available supporting interdisciplinary collaboration of data science and domain expert stakeholders within organizations to formulate meaningful value propositions based on data and analytics. Thus, we intend to answer the second research question of this thesis:

***RQ 2: How can we support idea generation and design during a data-driven business model innovation*?**

[2] This section represents a summary of the leading research questions. We will derive them latter from the gap in current literature in Chapter 2.3. Table 1.1 in Chapter 1.5 will list the detailed research question of each study of this PhD thesis.

This research question will be addressed in Chapter 5. Despite idea generation, evaluation and decision making are other important tasks in business model innovation (Tesch and Brillinger, 2017; Tesch *et al.*, 2017) that also include the identification of potential risks (Brillinger, 2018; Brillinger *et al.*, 2020). Using data as the main resource and an exchanged value object is creating novel risks that have an impact on the design of data-driven business models. To address this problem, we intend to answer the third research question in this thesis:

RQ 3: How can we support evaluation, decision-making and risk management during a data-driven business model innovation?

This research question will be addressed in Chapter 6. In order to answer these three research questions, this thesis adopts the methodological approaches of Design Science Research (Hevner *et al.*, 2004; Peffers *et al.*, 2007) that are later described in Chapter 3.

1.4 Publications related to this Thesis

Most parts of this PhD thesis have already been published in or are under review in two journals and seven conference proceedings. I was the main contributor to all research studies and the respective paper writing processes. This is also visible in my first authorship of these papers, except for two publications (Breitfuß *et al.*, 2019; Leski *et al.*, 2021): For the former, I substantially extended the paper as part of this PhD thesis. For the latter, I was the operative supervisor of the master's student and first author. The co-authors of these publications are, on the one hand, the two supervisors of this thesis, and on the other hand, colleagues and master students who supported me in data collection and analysis as well as paper writing. My contribution to each study is stated below. The connection of the publications to the chapters of this thesis is later described in the next Chapter 1.5.

Journal publications:

(1) Fruhwirth, M., Ropposch, C. and Pammer-Schindler, V. (2020): “Supporting Data-Driven Business Model Innovations. A structured literature review on tools and methods”, *Journal of Business Models*, Vol. 8 No. 1, 7-25.
   - I conducted the literature search, selection, analysis, and synthesis steps and was the main author during the paper writing. Intermediate results were discussed with my co-authors, who also supported paper writing and, in particular, formulating the discussion and research agenda.

(2) Fruhwirth, M., Pammer-Schindler, V., and Thalmann, S. (xxxx), “Knowledge leaks in data-driven business models? Exploring different types of knowledge risks and protection measures”. Submitted to *Schmalenbach Journal of Business Research.* - **under peer review after minor revision (status April 2024).**
   - I conducted the data collection and analysis (expert interviews and qualitative content analysis) and was the main author of the paper writing. Interim results were

iterated and discussed with the co-authors. The discussion and conclusion section was collectively written with my co-authors.

Conference publications:

(3) 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 *Proceedings of the 32nd Bled eConference, Humanizing Technology for a Sustainable Society*, June 16-19, 2019, pp. 803-820.

- I provided the conceptualisation of differentiating data-driven business model innovations (rows of the matrix) and defined the methodological approach. Further, I substantially extended this paper in Chapter 5.1 of this thesis, particularly an extension of the conceptualisation and the application and evaluation in cases and workshops.

(4) Fruhwirth, M., Breitfuß, G., and Pammer-Schindler, V. (2020): “The Data Product Canvas: A Visual Collaborative Tool for Designing Data-Driven Business Models,” in *Proceedings of the 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.

- I conducted this design science research project and designed the Data Product Canvas, co-facilitated the evaluation workshops with Gert Breitfuß and I was the main author during paper writing.

(5) Fruhwirth, M., Rachinger, M. and Prlja, E. (2020), “Discovering Business Models of Data Marketplaces”. In *Proceedings of the 53rd Hawaii International Conference on Systems Science 2020*, Maui, pp. 5738-5747.

- This publication is based on a master's thesis conducted by Emina Prlja. I co-supervised this thesis together with Michael Rachinger. I was responsible for the research design, guided the data collection and analysis, and was the author responsible for the publication writing.

(6) 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 Hawaii International Conference on System Sciences 2021*, pp. 5218-5227.

- I prepared and conducted the data collection and analysis (interviews and qualitative content analysis) and was the main author during the paper writing process.

(7) Leski, F., Fruhwirth, M., and Pammer-Schindler, V. (2021): “Who Else do You Need for a Data-Driven Business Model? Exploring Roles and Exchanged Values,” in *Proceedings of the 34th Bled eConference Digital Support from Crisis to Progressive Change*, A. Pucihar, M. K. Borštnar, R. Bons, H. Cripps, A. Sheombar and D. Vidmar (eds.). June 27 – 30, 2021, pp. 365-378.

- This publication is based on a master project conducted by Florian Leski. I co-supervised (operative) the master student together with Viktoria Pammer-Schindler. I was responsible for the research study design and supported and supervised data collection, analysis and paper writing.

(8) Fruhwirth, M., and Pammer-Schindler, V. (2023): “Towards Principles for a data-driven business model innovation process – a design science case study” in *Proceedings of the 36th Bled eConference – Digital Economy and Society: The Balancing Act for Digital Innovation in Times of Instability*, A. Pucihar, M. K. Borštnar, R. Bons, G. Ongena, M. Heikkilä, D. Vidmar (eds.). June 25 – 28, 2023, Bled, Slovenia, pp. 545-560. **– awarded with the outstanding paper award.**

- I conducted the case study and collected all data (except for 11 interviews that were performed by the master’s student Maximilian Ferstl, whom I co-supervised), did all the design work and was the main author for paper writing.

Workshop and Research-in-Progress Publications:

(9) Fruhwirth, M., Pammer-Schindler, V., and Thalmann, S. (2019): “To Sell or Not to Sell: Knowledge Risks in Data-Driven Business Models,” *2019 Pre-ICIS SIGDSA Symposium on Inspiring mindset for Innovation with Business Analytics and Data Science*, Munich 2019.

- I conducted the case study presented in this paper and was responsible for writing the paper. The co-authors guided the structuring of the design study in four cycles.

In addition, I have co-authored eight publications that are related to the topic of data-driven business model innovation that are not included in the core of this thesis:

- Armengaud, E., Fruhwirth, M., Rothbart, M., Weinzerl, M., Zembacher, G. (2021), “Digitalization as opportunity for breaking the silos and enabling holistic value creation”. In Hick, H., Küpper, K., Sorger, H. (eds.): *Systems Engineering for Automotive Powertrain Development*. pp. 827-854.
- Breitfuß, G., Fruhwirth, M., Wolf-Brenner, C., Riedl, A., de Reuver, M., Ginthoer, R., Pimas, O. (2020), Data Service Cards - A supporting tool for Data-Driven Business. in *Proceedings of the 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. 599-614.
- Breitfuss, G., Santa-Maria, T., Fruhwirth, M.; Disch, L. (2023): Use Your Data: Design and Evaluation of a Card-Based Ideation Tool for Data-Driven Services. In *Proceedings of the 56th Hawaii International Conference on System Sciences 2023*, pp. 5176-5185.
- Fruhwirth, M., Breitfuß, G. and Pammer-Schindler, V. (2018), “Exploring challenges in data-driven business model innovation from Austrian enterprises”, *in Proceedings of the ISPIM Innovation Conference, Stockholm*, Sweden, June 17-20 2018.

- Fruhwirth, M., Breitfuß, G. and Ropposch, C. (2019), "Mit Daten Wert schaffen. Datengetriebene Geschäftsmodelle als Weg in die Zukunft", *WINGbusiness*, Vol. 52 No. 1, pp. 16–20.
- Fruhwirth, M., Breitfuß, G., Pammer-Schindler, V. and Thalmann, S (2021), "Wissensrisiken beim Design von datenbasierten Geschäftsmodellen identifizieren. Eine Design-Science Research Fallstudie in der Automobilindustrie", In Schallmo, D. (Hrsg.), *Digitale Transformation von Geschäftsmodellen: Grundlagen, Instrumente und Best Practices*, pp. 681–703.
- Kayser, L. Fruhwirth, M., Mueller, R. (2021), Realizing Value with Data and Analytics: A Structured Literature Review on Classification Approaches of Data-Driven Innovations. In *Proceedings of the 54th Hawaii International Conference on System Sciences 2021*, pp. 5686- 5695.

Further, I have co-supervised four Master Thesis and Master Projects that are related to this PhD project, that contributed to publications listed above (1 & 3) and/or supported chapters of this thesis (4):

(1) Prlja, Emina (2019): Discovering Business Models of Data Marketplaces. Master Thesis. Institute for General Management and Organization, Graz University of Technology.
(2) Wagner, Stefan (2019): Market Analysis of Data-Driven Value Propositions in the Automotive Industry. Master Thesis. Institute for General Management and Organization, Graz University of Technology.
(3) Leski, Florian (2020): Network-Based View on Data-Driven Business Models: Developing roles and classes of exchanged entities. Master Project. Institute for Interactive Systems and Data Science, Graz University of Technology.
(4) Ferstl, Maximilian (2021): Validation and Adaptation of a Stage Gate Process for Business Model Innovation. Master Thesis. Institute for General Management and Organization, Graz University of Technology.

During my PhD time I have also served as a reviewer for the following leading Information Systems conferences: eBled 2023, ECIS 2022, ECIS 2021, HICSS 2021, WI 2021, ECIS 2020, DESRIST 2020, AMCIS 2019, ECIS 2019, ICIS 2019 and WI 2019.

Note that the pronoun "we" used in this thesis refers to the author of this thesis and includes both, the colleagues who contributed to parts of the research and co-authored related publications and the readers of this thesis. Therefore, "we" can also be understood as "I".

1.5 Structure of this Thesis

Table 1.1 illustrates how the publications listed in the previous section relate to the outlined research questions from section 1.3. The three research questions form three research streams of this thesis. Each paper relates to one research stream and addresses one sub-research question.

Research Stream	Study	Sub-Research Question	Research Method	Publication Status
Research Question 1: *What process design would allow established companies to develop data-driven business models systematically?* Chapter 4 Systematic Process Design and Toolbox	4.1 A Structured Literature Review on Tools and Methods Supporting Data-Driven Business Model Innovation	What knowledge is available about tools and methods incorporating data as a lens of analysis for business model innovation?	Structured literature review	Published Journal of Business Models
	4.2 Towards Requirements and Principles for a Data-Driven Business Model Innovation Process	What process design allows to systematic develop data-driven business models in offline-established organisations?	Design Science Research, Case Study	Published Proceedings of the 36th eBled Conference 2023 **Awarded with the outstanding paper award**
Research Question 2: *How can we support idea generation and design during a data-driven business model innovation?* Chapter 5 Supporting Tools and Concepts for Idea Generation and Design	5.1 Introductory Study: Classifying Data-Driven Business Model Innovations	How can data-driven business model innovations be classified?	Design Science Research	Partially published[3] Proceedings of the 32nd eBled Conference 2019
	5.2 The Data Product Canvas	How could a visual representation facilitate collaboration and idea generation for data-driven service ideas for non-data experts?	Design Science Research: development of visual canvas and evaluation in four workshop settings	Published Proceedings of the 33rd eBled Conference 2020
	5.3 Towards A Data-Based Value Creation Ontology	How can the logic of value creation with data be described and represented in an ontology?	Ontology development procedure and guidelines	Unpublished
	5.4 A Framework of Actors and Exchanged Values	What roles do exist in a data-driven business model, and how the exchanged values can be categorized?	Structured literature review, evaluation of framework in three cases	Published Proceedings of the 34th eBled Conference 2021
Research Question 3: *How can we support evaluation, decision-*	6.1 Introductory Study: Evaluation and Decision Criteria in Data-Driven Business Model Innovation	What criteria support evaluation and decision making in data-	Design Science Research. Case Study	Unpublished

[3] The corresponding paper was substantially extended in Chapter 5.1 of this thesis.

making and risk management during a data-driven business model innovation? Chapter 6 Supporting Tools and Concepts for Evaluation and Decision-Making		driven business model innovation?		
	6.2 A Network-based Tool for Identifying Knowledge Risks	Can a networked-based representation of business models provide support for identifying and understanding knowledge risks in data-driven business models?	Design Science Research. Case study and evaluation through expert interviews	Published Proceedings ot the 53rd Hawaii International Conference on System Science (HICSS 2021). Earlier version presented at SIG-DSA 2019
	6.3 Exploring Different Types of Knowledge Risks in Data-Driven Business Models	What knowledge risks are associated with sharing different types of data-related value objects in data-driven business models and what are protection measures?	Explorative qualitative research: Interviews with 28 experts; Qualitative Content Analysis	Under review after minor Revision Schmalenbach Journal of Business Research
	6.4 Data Marketplaces as one Solution to Enable Data Sharing and to Prevent Knowledge Risks	What are the characteristic elements of data marketplaces from a business model perspective?	Taxonomy development process	Published Proceedings ot the 52rd Hawaii International Conference on System Science (HICSS 2020).

Table 1.1: Dissertation Overview: Chapters, sub-research questions and related publications

From a readers perspective, this thesis is structured into four parts, as shown in Figure 1.2: *Part I* covers the foundations of this thesis, including an introduction and motivation (Chapter 1), theoretical background (Chapter 2) and the methodological approach of this thesis (Chapter 3). *Part II* subsequently presents the research studies conducted for this thesis, structured along the three research questions: Systematic process design and toolbox (Chapter 4), Supporting tools and concepts for idea generation (Chapter 5) and supporting tools and concepts for evaluation (Chapter 6). *Part III* then denotes contributions of this paper including a discussion of the results, its limitations and insights for further research (Chapter 7). Finally, *Part IV* covers all references (Chapter 9) and appendixes (Chapter 9) of this thesis

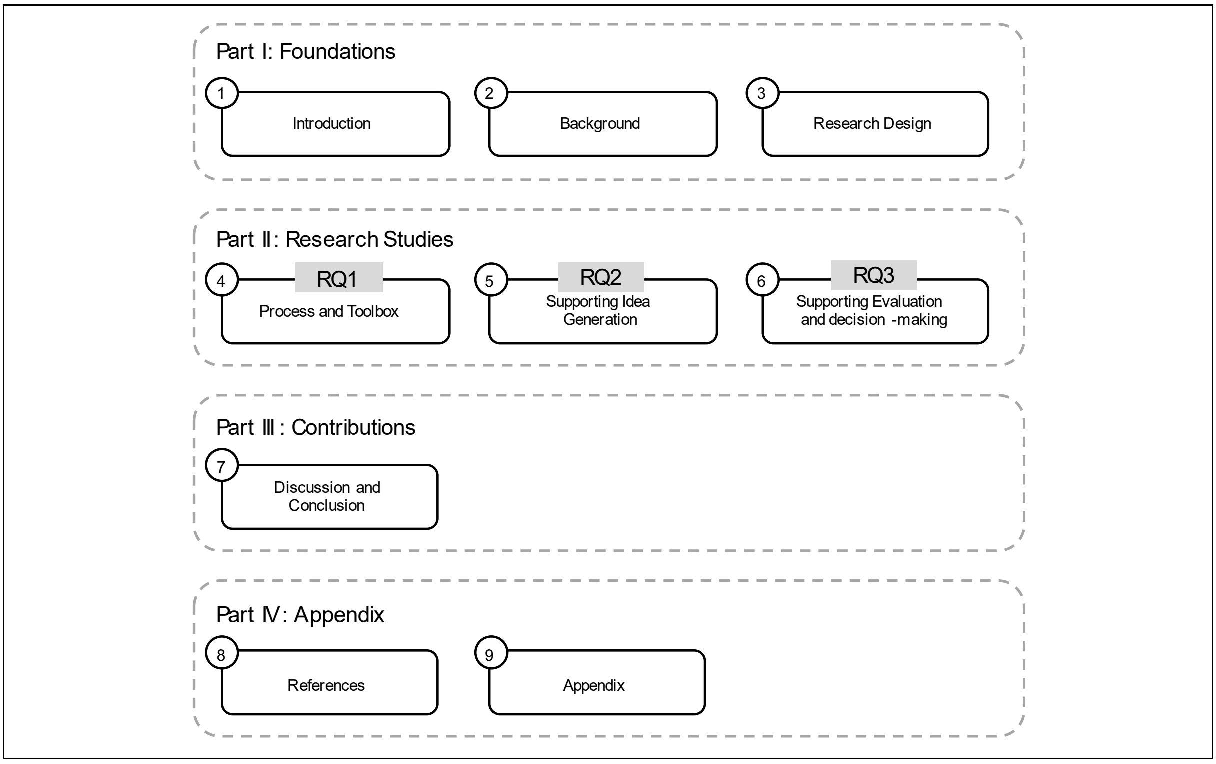

Figure 1.2: Parts and chapters of this PhD thesis.

After the general introduction to this PhD thesis in **Chapter 1** including its motivation, research goal and structure, **Chapter 2** presents the theoretical background and related work relevant for this thesis: business model research in general and data-driven business models in particular. Additional background will be presented in the individual research chapters in part two, if necessary for understanding. **Chapter 3** describes then the general Design Science Research approach of this thesis, the case study setting and how the individual research studies relate to each other. Subsequently, the detailed methodological approach for each research study will be described in the corresponding research chapter in part two (see also Figure 1.3).

Chapter 4 focuses on a systematic process for data-driven business model innovation. First, we will present a toolbox based on a structured literature review in Chapter 4.1. This initial research chapter also highlights two research gaps (i.e., missing support for evaluation and risk management as well as a missing consistent process) that will be addressed in this thesis. Second, we will describe design requirements and principles of a data-driven business model innovation process based on a case study. The outcomes of the subsequent research on supporting design and evaluation are also incorporated in this process design.

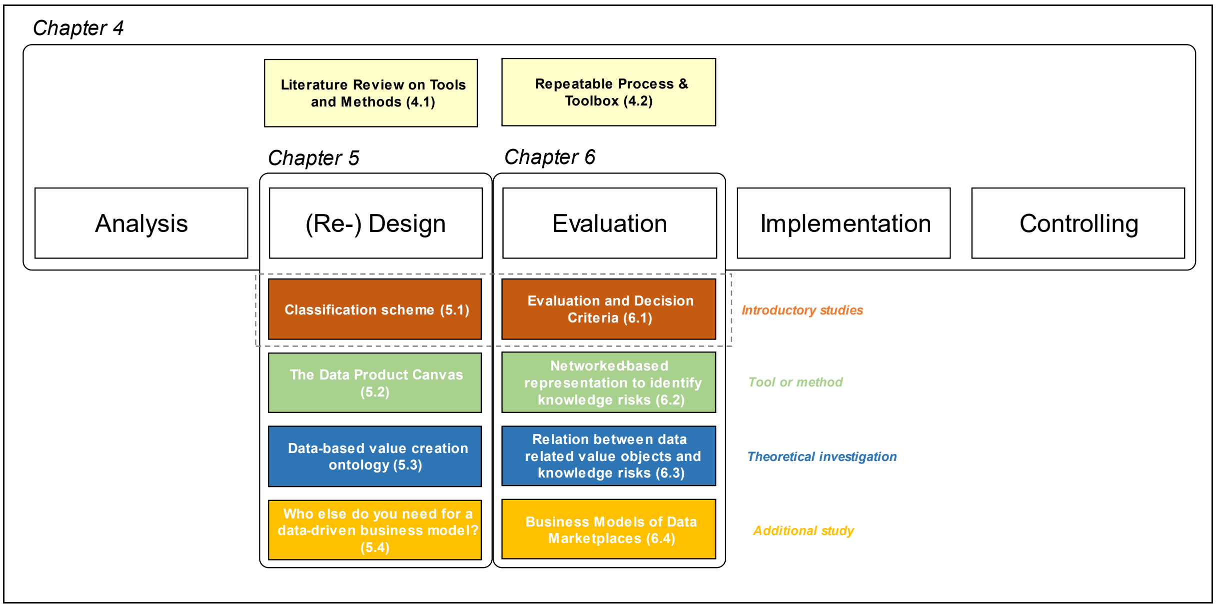

Figure 1.3: Overview of the structure and relation of the research streams and studies in part two of this thesis.

Chapter 5 presents research studies that design support for the idea generation and design phase in a data-driven business model innovation. First, we introduce a classification scheme for data-driven business model as an introductory and unpublished study that guides initiation (Chapter 5.1). Second, we present the data product canvas, a visual collaborative tool that allows a structured description of ideas for data-driven innovations and supports idea generation workshops (Chapter 5.2). Third, we propose an ontology about data-based value creation to explore the value creation mechanism from a theoretical perspective (Chapter 5.3). Forth, Chapter 5 also investigates the question, what other stakeholders are involved in a data-driven business model and what values are exchanged (Chapter 5.4).

Chapter 6 presents the research studies that design support for the evaluation and decision-making phase in data-driven business model. First, we introduce a set of criteria that support evaluation and decision-making in a data-driven business model innovation process as an introductory and unpublished study (Chapter 6.1). Second, we investigate knowledge risks through data exchange as one risk factor in detail by providing a tool that supports the identification of such risks (Chapter 6.2). Furthermore, we explore the relationship between knowledge risks and the type of exchanged value object and potential protection measures from a theoretical perspective (Chapter 6.3). Finally, we explore data marketplaces as one approach to prevent such knowledge risks, from a business model perspective (Chapter 6.4).

The discussion of the results as well as the contributions and limitations of the individual research studies are denoted in the respective chapters in part two. Subsequently, part three denotes the overall results and contributions of this PhD thesis. **Chapter 7** presents a summary of the results in respect to the research goal and gaps (Chapter 7.1), discusses the contributions of this thesis

(Chapter 7.2) and reflects on methodology (Chapter 7.3). Further, it denotes the limitations of our results (Chapter 7.4) and provides additional insights for further research (Chapter 7.5). **Chapter 8** lists all literature references used in this thesis. **Chapter 9** finally provides additional material as appendices for the research Chapters 4 to 6.

Chapter 2
Theoretical Background

"Business models matter. A better business model often will beat a better idea or technology."

Henry Chesbrough[4]

2.1 Business Model Research

2.1.1 Overview and Origin of the Business Model Concept

As this initial quote already highlights, business models have received increased attention in research and practice (Chesbrough, 2010; Wirtz, 2020). From a widespread high-level view, business models describe how organizations create, deliver and capture value (Osterwalder and Pigneur, 2010; Teece, 2010) and explain *"how the pieces of a business fit together"* (Magretta, 2002). Organizations must find an appropriate business model to ensure competitive advantage (Amit and Zott, 2012) and capture value from new technologies (Chesbrough, 2010), such as data analytics or artificial intelligence. Organisations have always run their business compliant with a business model and thus an essential part of economic behaviour (Massa and Tucci, 2013; Teece, 2010). Every organization has a business model independent of if it has explicitly formulated it.

The business model concept has gained significance in research since the mid-90s, as shown by a sharp increase in publications (Zott *et al.*, 2011). Business models are researched in several disciplines, such as information systems (Al-Debei and Avison, 2010; Burkhart *et al.*, 2011; Veit *et al.*, 2014), technology and innovation management (Björkdahl, 2009; Chesbrough and Rosenbloom, 2002; Wirtz *et al.*, 2016a) or strategic management (Magretta, 2002; Wirtz *et al.*, 2016a; Zott and Amit, 2008). This fact is not by chance, as with the internet boom, an increasing number of companies have thought about innovating their business model to keep up with trends such as e-commerce that led to new business logic (Timmers, 1998). Further roots for the importance of the business model concept lie in the pressure for a change in organisations, the increasing globalisation, the deregulation of markets and, in general, more complex and competitive situations (Wirtz, 2020).

The business model emerged from a *vehicle* for innovation to commercialize new technologies (Chesbrough and Rosenbloom, 2002) towards a *source* of innovation, emerging as a source of

[4] Chesbrough (2007, p. 12).

competitive advantage (Morris *et al.*, 2005) (Massa and Tucci, 2013). Independent of the objective of a business model, it can describe both an intended business logic (i.e., a business model idea) or an existing one (i.e., describing and analysing the status quo of a business model) (Terrenghi, 2019).

Business model literature can be classified by taking either a static or a dynamic perspective (Burkhart *et al.*, 2011; Demil and Lecocq, 2010; Wirtz *et al.*, 2016b). The **static business model perspective** (described in Section 2.1.2) sees business models as an "architecture" (Timmers, 1998), a "model" (Baden-Fuller and Morgan, 2010), or an "activity system" (Zott and Amit, 2010) and studies the elements of a business model and their relations and configurations (e.g., Osterwalder, 2004). This perspective allows a description and classification of already existing or hypothetical business models (Terrenghi, 2019). The **dynamic business model perspective** deals with the changes in or of the business model and focuses on innovation with the aid of business model innovation (described in Section 2.1.3). Organizations and individuals are supported in business model innovation with tools and methods (Schneider and Spieth, 2013). Hence, **Business model tooling** emerged as an additional research area itself (Bouwman *et al.*, 2020) (described in Section 2.1.4), complementing the static and dynamic perspective, as it draws from conceptualizations from the static view to facilitating the dynamic (innovation) process in an organisation.

Static Business Model View	Dynamic Business Model View
Business model as a blueprint: description and classification become possible View different business model elements and their configuration and relation	Deals with change and focuses on innovation Change the business model reactive or pro-active (with the aid of business model innovation)
Business Model Tooling	
Designing tools and methods (conceptual models, methods and IT tools) supporting the visualisation, evaluation and implementation of business models	

Table 2.1: Three perspectives and streams of business model research (partially based on Demil and Lecocq, 2010).

The remainder of this chapter on business model research is structured along with those three perspectives, as summarized in Table 2.1 and presents the background literature for these three perspectives.

2.1.2 Static Business Model Research

The static business model perspective allows a description and classification of business models. It thus deals with the definition of a business model, different hierarchies and abstraction levels from which one can look at a business model, and a discussion of what elements belong to it.

2.1.2.1 Definition: What is a Business Model?

Various definitions exist in the literature[5], and no commonly accepted definition exists. Business models can be understood as *"**stories** that explain how enterprises work"* (Magretta, 2002, p. 4) and that describe how organizations create, deliver and capture value (Osterwalder and Pigneur, 2010; Teece, 2010). Thus, the business model as a **conceptual tool** allows "*a simplified description and representation of what value is provided to customers, how this is done and with which financial consequences"* (Osterwalder *et al.*, 2005, p. 5) and aims to express the business logic of a specific organisation (Osterwalder *et al.*, 2005). Business models can also be understood as an *"**architecture** for the product, service and information flows, including a description of the various business actors and their roles; and a description of the potential benefits for the various actors; and description of the sources of revenue"* (Timmers, 1998, p. 4). Theys describe the "*architecture of the value creation, delivery, and capture mechanisms [a firm] employs"* (Teece, 2010, p. 172). Finally, a business model can be understood as *"a **system** of interconnected and interdependent activities that determines the way the company "does business" with its customers, partners and vendors."* (Amit and Zott, 2012, p. 42)

2.1.2.2 Levels of Abstraction and Perspectives in Business Models

Business models are viewed or studied from different hierarchical levels (Osterwalder *et al.*, 2005; Schallmo and Brecht, 2010; Wirtz *et al.*, 2016b), as shown in Figure 2.1. Osterwalder *et al.* (2005) distinguish between conceptual and instance levels.

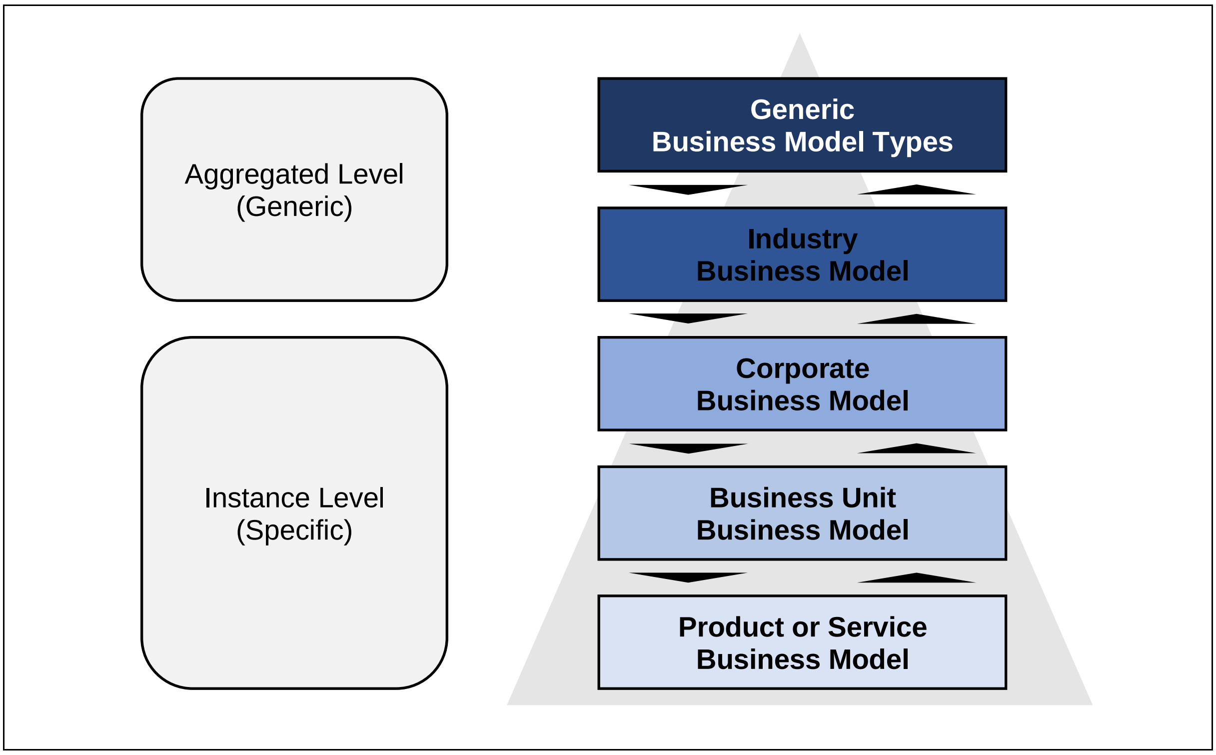

Figure 2.1: Levels of Business Models (adapted from Schallmo and Brecht 2010).

[5] For an overview of business model definitions see for instance Sorescu (2017, p. 3).

On the **conceptual level**, authors provide definitions (i.e., an understanding of what a business model is), define the elements or building blocks that comprise a business model, or provide types and taxonomies of business models that share common characteristics (Osterwalder *et al.*, 2005). Schallmo and Brecht (2010) further distinguish between abstract business model types that are independent of any industry (e.g. generic business model patterns (Csik, 2014; Gassmann *et al.*, 2014; Weking *et al.*, 2018)) and industry business model types (e.g., car-sharing business models (Remane *et al.*, 2016)). The **instance level** deals with describing, representing or conceptualising real-world business models (Osterwalder *et al.*, 2005). According to Wirtz *et al.* (2016b), real-world business models are studied on different abstraction levels of an organization: the company level, such as the business model of Xerox (Chesbrough and Rosenbloom, 2002) or Ryanair (Chesbrough, 2007), the business unit level (e.g., Winterhalter *et al.*, 2017) or product and service level (Bucherer *et al.*, 2012).

Business models can also be studied by adopting either a mono-organizational or a network and ecosystem perspective. The **mono-organizational perspective** puts the company at the centre of the discussion (e.g., Osterwalder and Pigneur, 2010). The **network perspective** has a focus on the value exchanges among actors (e.g., Gordijn and Akkermans, 2001, or Timmers, 1998). They complement each other by providing different perspectives for describing a business model (Gordijn *et al.*, 2005; Terrenghi, 2019).

Business models can be further described by adopting different **levels of abstraction** from reality, as shown in Figure 2.2, varying in depth and complexity (Massa and Tucci, 2013). The highest level of abstraction is the business model as a *narrative* (Perkmann and Spicer, 2010), i.e., a verbal description of how an organization works (Magretta, 2002). The next level of abstraction is the business model as *archetypes*. As already described above, patterns in the structure and configuration of business models can be discovered and serve as an inspiration (Csik, 2014) or as a “role model” (Baden-Fuller and Morgan, 2010). The next abstraction layer is the business model as a *graphical framework*, which describes a business model by enumerating and representing its essential components (Massa and Tucci, 2013). Such business model frameworks (e.g., Al-Debei and Avison, 2010) can also be provided as ontologies (e.g., Osterwalder, 2004) or visual canvases (e.g. Osterwalder and Pigneur, 2010). The next level of abstraction is a *meta-model* to cover also dynamic aspects of a business model, such as adopting system dynamics and describing a business model through causal loop diagrams (Casadesus-Masanell and Ricart, 2010) or focusing on the value exchanges among actors in networks via a conceptual modelling approach (e.g., Gordijn and Akkermans, 2001). On the lowest level of abstraction, a business model can also be viewed as an *activity system* (Zott and Amit, 2010). The business model is described as a system of interrelated activities performed by the focal firm and external stakeholders, such as customers or key partners.

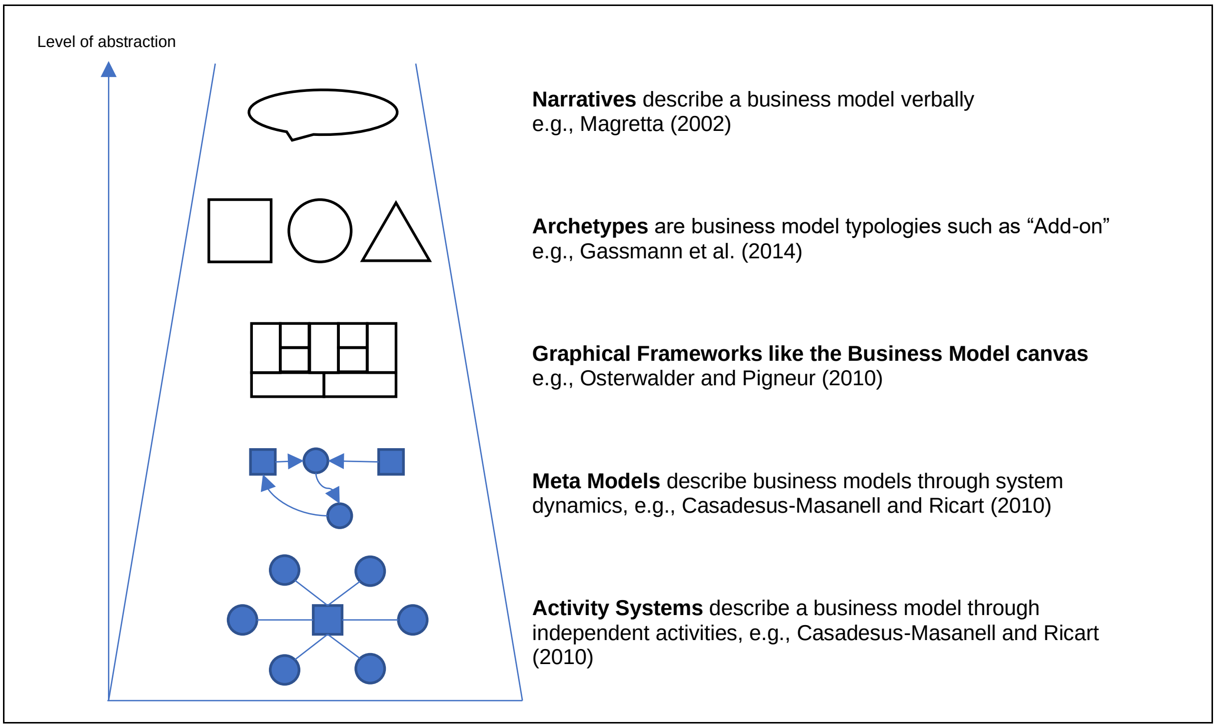

Figure 2.2: Business models are understood as models with different levels of abstraction from reality (adopted from Massa and Tucci, 2013, p. 433).[6]

Note that conceptual models of business models, as mentioned here in the static perspective, can be seen as tools for innovation and will be discussed in detail in Section 2.1.4.

2.1.2.3 Meta-Models: What elements belong to a business model?

Independent of the level of abstraction and perspectives, the extraction and description of the components and elements of a business model is an omnipresent topic in static business model research. The goal is to understand and communicate the business model concept (Demil and Lecocq, 2010; Wirtz *et al.*, 2016b), also referred to as an *"ontological structure"* of the business model (Al-Debei and Avison, 2010). In other words, the business model concept is often characterized by its subordinated elements (Wirtz *et al.*, 2016b).

In the 2000ers, business model research focused on *"decomposing the business model in its fundamental constructs"* (Pateli and Giaglis, 2004). A component-based view is subsequently present in many ways of understanding the term business model (Wirtz *et al.*, 2016b). Several reviews have been conducted to compare and synthesize the business model components (e.g., Al-Debei and Avison, 2010; Krumeich *et al.*, 2012; Wirtz *et al.*, 2016b). From a high-level perspective, the business model concept can be decomposed into the value proposition, the value architecture, the value network and the financial model (Al-Debei and Avison, 2010; Pateli and Giaglis, 2004).

The **value proposition** can be understood as "*the bundle of products and services that create value for a specific customer segment"* (Osterwalder and Pigneur, 2010, p. 22). This business

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[6] The additional text descriptions were inspired by the presentation material of the lecture "Business Model Management" taught by Christiana Ropposch in 2019.

model element focuses on how an organisation satisfies customer needs, solves customers' problems, and shows what services and products are offered (Augenstein *et al.*, 2018).

The **value architecture** sheds light on the technical architecture and organizational infrastructure for a business model that enables the creation and delivery of the value proposition (Al-Debei and Avison, 2010; Timmers, 1998). This value creation view includes the necessary resources, competencies, processes and activities (Krumeich *et al.*, 2012; Osterwalder and Pigneur, 2010)

The **value network** introduces an inter-organizational perspective in the business model and *“enables transactions through coordination and collaboration among parties and multiple companies”* (Al-Debei and Avison, 2010, p. 366). This inter-organizational perspective views stakeholders' relationships by describing the actors and their roles (Timmers, 1998) and the flows of exchanged values (Gordijn and Akkermans, 2001). Actors in a business model include suppliers, key partners, and from a wider perspective also, competitors and customers (Al-Debei and Avison, 2010; Hedman and Kalling, 2003).

The **financial model** deals with all cost-related aspects of the business model and describes how an organization generates revenue (Al-Debei and Avison, 2010). Business model elements of this perspective are the cost structure, the revenue models and pricing mechanisms (Johnson *et al.*, 2008; Osterwalder, 2004).

The nowadays most widely used and accepted decomposition of the business model concept is based on the seminal work of Osterwalder (2004) that was subsequently instantiated in the Business Model Canvas (Osterwalder and Pigneur, 2010). This framework includes the value proposition, the value creation (with key activities, key resources and key partners), the value delivery (with the channels, customer relations and segments) and the value capture (with the revenue streams and cost structure). Other scholars have adopted or criticised these components in their research (e.g., Gordijn *et al.*, 2005). Business model components and their related frameworks also help to understand and support the innovation of a new or the change of an existing business model (dynamic perspective).

2.1.3 Dynamic Business Model Perspective

The business model literature has been *“moving from conceptualizing, characterizing and explaining a business model at a given point in time, towards a more dynamic view”* (Saebi *et al.*, 2017, p. 568). The literature denotes this phenomenon as business model innovation. Organizations can develop new business models with the aid of business model innovation (Chesbrough, 2007), i.e. experimenting with new business model designs (Chesbrough, 2010).

2.1.3.1 Definition: What is Business Model Innovation?

According to Gambardella and McGahan (2010, p. 263), *“business-model innovation occurs when a firm adopts a novel approach to commercializing its underlying assets”*. From a component view of business models, innovation is a business model innovation when two or more elements of a business model are changed or innovated (Lindgardt *et al.*, 2009) to create value for the customer and, at the same time, capture value for the organization (Bereznoi, 2015; Yunus *et al.*, 2010). Business model innovation allows organizations to commercialize new technologies and gain a competitive advantage (Chesbrough and Rosenbloom, 2002).

Business Model innovation is understood in the literature as a subset of *business model design* (or innovation) and *business model development* (or reconfiguration or adaption) (Amit and Zott, 2012; Cortimiglia *et al.*, 2016; Landau *et al.*, 2016; Massa and Tucci, 2013; Saebi *et al.*, 2017; Tesch *et al.*, 2017). Skarzynski and Gibson (2008, p. 111), for instance, distinguish between *"creating fundamentally new kinds of businesses, or about bringing more strategic variety into the business you are already in"* (Skarzynski and Gibson, 2008, p. 111). This can be understood as the creation of a whole new business model or the further development of an existing model (Amit and Zott, 2010; Massa and Tucci, 2013). Other authors differentiate business model innovation between "*the development of fundamentally new and sometimes disruptive models"* (Landau *et al.*, 2016) and the evolution of existing business models in terms of extensions, modifications, reconfigurations and revisions. Business model innovation can be market- or technology-driven (Habtay, 2012) (such as big data, analytics, or artificial intelligence) or driven by internal or external factors (Bucherer *et al.*, 2012). Organizations proactively innovate their business model to shape markets and disrupt industries or actively align their business model to a changing environment (Saebi *et al.*, 2017). Table 2.2 summarises these two approaches based on the definitions of Saebi *et al.* (2017).

	Business Model Reconfiguration	**Business Model Design**
Definition	Business Model Reconfiguration is *"the process by which management actively aligns the firm's business model to a changing environment, for example, changes in the preferences of customers, supplier bargaining power, technological changes, competition."* (Saebi *et al.*, 2017, p. 569)	Business Model Design *"is defined as the process by which management actively innovates the business model to disrupt market conditions"* (Saebi *et al.*, 2017, p. 569)
Motivation	Align the existing business model over time in response to triggers, such as the changing environment	Shape markets or industries by creating typically disruptive innovations using an innovative business model
Other terms in the literature	Business model adaption, business model development	Business model innovation

Table 2.2: Business model reconfiguration vs business model design (based on Saebi *et al.* 2017, pp. 568–569).

In conclusion, a business model innovation can be classified based on the number of elements changed in the business model and their degree of innovation (Spieth and Schneider, 2016). Further, one might consider the innovation based on the abstraction level of the business model (see 2.1.2.2), i.e., if the whole company business model is innovated or only on a lower product or service level. Finally, business model innovation can be distinguished by the time horizon (i.e., a short-term or long-term innovation or evolution). These three perspectives are summarized in Figure 2.3.

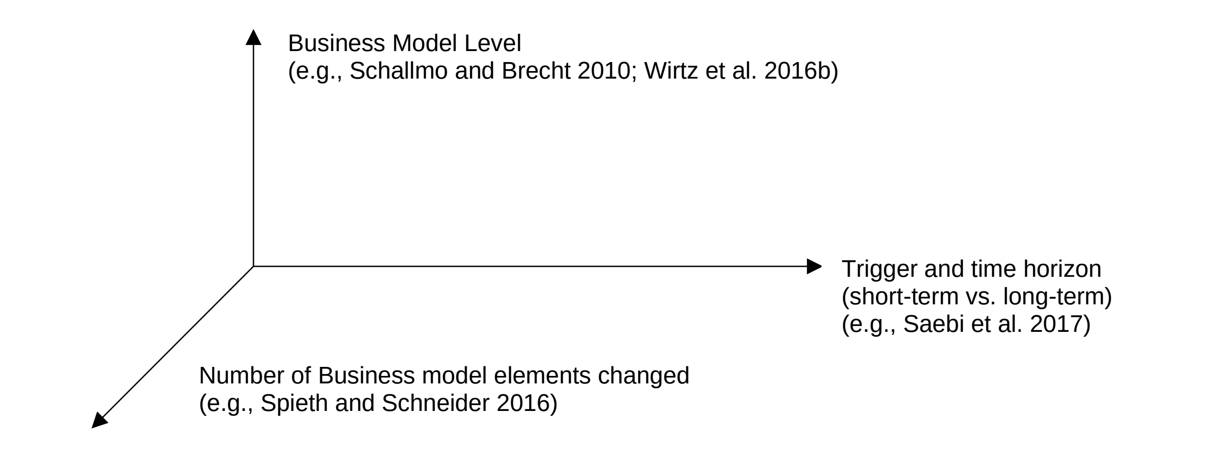


Figure 2.3: Classification of Business Model Innovation (own representation).

After understanding, what business model innovation is, we will describe how a business model innovation is realised in terms of the underlying process.

2.1.3.2 The Process Perspective in Business Model Innovation

As described before, business model innovation is treated as a **result** in the literature, i.e. the replacement or adaption of the existing business model of a company (Mitchell and Coles, 2003). Business model innovation can also be seen as a **process**, i.e. *"the activity of designing - that is, creating, implementing and validating - a new BM"* (Massa and Tucci, 2013, p. 420). Business model innovation processes can serve as a **guideline** to structure business model innovation activities and initiatives in organizations (Wirtz and Daiser, 2018). Successful business model innovations require strong management skills (Osterwalder *et al.*, 2005) and a holistic process (Amit and Zott, 2014), which is referred to as business model management.

Wirtz et al. (2011) described business model management as a process composed of idealized phases such as design (the generation of multiple business model ideas and their selection), implementation (planning and allocation of resources), operation, adaptation, and controlling. Terrenghi (2019) further defines business model management *"as the process, consisting of phases and related activities that are necessary to systematically manage a BM along its complete lifecycle"* (Terrenghi, 2019, p. 73). Business model management requires *"know-how, which is needed to provide for the ongoing orchestration and coordination of activities performed by the various stakeholders, as well as for the continuous adaptation of the entire system to its evolving environment, in order to ensure the business model's sustainability"* (Amit and Zott, 2014, p. 21). This can be reached by discovery-driven and deterministic approaches (Terrenghi, 2019). Managers have to balance their activities in business model innovation between exploration and exploitation (Broekhuizen *et al.*, 2018).

As outlined above, business model management can be decomposed as a sequence of phases with specific activities (Terrenghi, 2019; Wirtz, 2020). Business model innovation processes can serve as a procedural framework or guidance to structure BMI initiatives (Wirtz and Daiser, 2018). Literature provides high-level conceptual phases for a BMI process (Winterhalter *et al.*, 2017). As shown in Figure 2.4, Terrenghi (2019) decomposes business model management into five different activities: analysis, design, evaluation, implementation and controlling. Other researchers arrive with similar decompositions (e.g., Hunke *et al.*, 2017; Wirtz and Daiser, 2018).

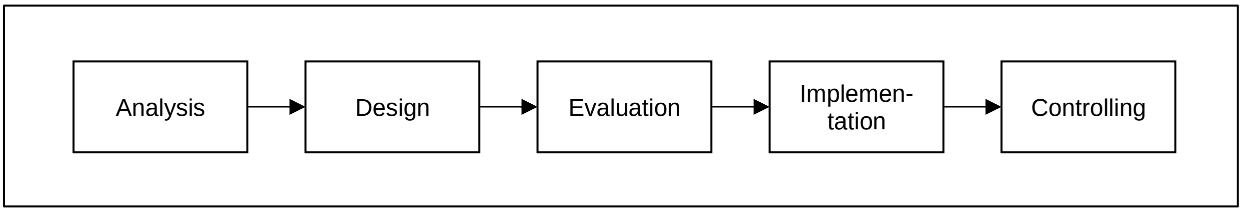


Figure 2.4: Decomposition of Business Model Management into Activities (based on Terrenghi, 2019).

In the **analysis** phase, the organisation's current situation and its ecosystem are analysed (Frankenberger *et al.*, 2013). This phase's activities include a description of the current business model, products and services, and analysing customer needs, the market and competitors (Wirtz and Daiser, 2018). Thie results of the analysis could already show opportunities for new business model designs (Lindgardt *et al.*, 2009). In the **design** phase, organisations generate BM ideas, create a customer value proposition (Johnson *et al.*, 2008) and other elements of a business model design. Further, there is a need to select between business model design alternatives (Wirtz and Daiser, 2018) and to **evaluate** if a business model design should be implemented and, therefore, resources be released (Tesch *et al.*, 2017). To **implement** a new business model and introduce it to markets, it is necessary to make an implementation plan and set up a team (Wirtz and Daiser, 2018). Finally, suppose a business model was successfully implemented and is in operation. In that case, it is important to **control** or monitor the business model (Wirtz and Daiser, 2018) and adapt it to environmental changes (Simmert *et al.*, 2019). As we will have a closer look at the design and evaluation activities in data-driven business model innovation later in the research chapters, we will describe both here shortly.

Business model innovation is a creative and collaborative task (Ebel *et al.*, 2016; Eppler *et al.*, 2011). The goal of the idea generation phase is to come up with many ideas for a viable and innovative business model (Osterwalder and Pigneur, 2010). The challenge in this process is to ignore the status quo and operational difficulties (Osterwalder and Pigneur, 2010), to overcome current business and industry logic, i.e., to “think out-of-the-box”, and to think in business models and not solutions (Frankenberger *et al.*, 2013). One approach to address this challenge is enhancing collaboration (e.g., bringing in external people) and fostering divergent thinking through sketching and brainstorming (Eppler *et al.*, 2011). After arriving with innovative business model ideas, they must be evaluated against their feasibility, viability and desirability (Bland *et al.*, 2020).

Executives must balance estimated return and acceptable risk in their business model design choices (Casadesus-Masanell and Ricart, 2007; Tesch and Brillinger, 2017). Business model designs are subject to uncertainties due to their newness and incomplete information and therefore need to be evaluated. One approach to reducing uncertainties in business model innovation is experimentation (Chesbrough, 2010; Felin et al., 2020) and applying an effectual logic (i.e., action orientation) (Futter et al., 2018; Tesch and Brillinger, 2017). Wirtz and Daiser (2018), for instance, therefore, divide the evaluation phase into "feasibility", "prototyping", and "decision-making" phases. In the feasibility phase, executives identify assumptions in a business model design and test them (Bland *et al.*, 2020). Later in the prototyping phase, they conduct field tests with prototypes or minimal viable products to verify a significant customer demand (Tesch *et al.*, 2017). Decision-making is either seen as a distinct phase (e.g., Wirth and Daiser 2018) or as a certain decision point in the innovation process (Tesch et al., 2017). Identifying relevant risk factors in a business model is one important activity during evaluation and a basis for decision-making, as it enables decision-makers to adopt the business model design or to take proper measures (Brillinger *et al.*, 2020).

Due to the complexity and cognitive effort of these tasks, as well as the increasing relevance of business model innovations, researchers and practitioners likewise have started to develop tools and methods supporting these tasks and activities (Bouwman *et al.*, 2020; Massa and Tucci, 2013; Täuscher and Abdelkafi, 2017).

2.1.4 Business Model Tools and Methods

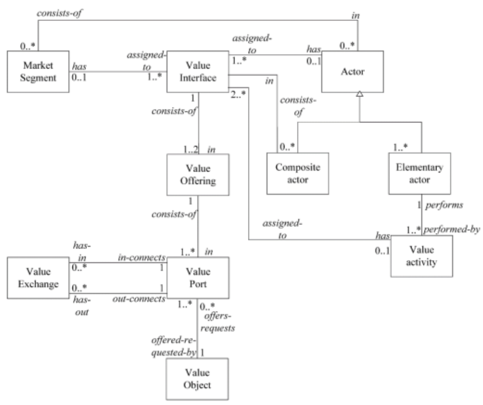
Visualising and exploring opportunities for new business models and their implementation requires much cognitive managerial effort (Massa and Tucci, 2013). Firms can be supported in the activity of business model innovation through tools and methods (Bouwman *et al.*, 2020; Schneider and Spieth, 2013), e.g., through visualizing (Täuscher and Abdelkafi, 2017) or evaluating (Tesch and Brillinger, 2017) business model designs. A **method** is a systematic development approach that follows specific rules, whereas a **tool** supports a part of a development process (Brinkkemper, 1996).

Bouwman *et al.* (2020, p. 413) define **BM Tooling** as *"the use of methods, frameworks or templates (here referred to as tools) to facilitate communication and collaboration regarding Business Model analysis, (re-)design, adoption, implementation and exploitation"* and sees BM Tooling itself as a separate research area. There are already several reviews on BM Tooling synthesizing existing research on visual languages (John *et al.*, 2017), visual representations (Täuscher and Abdelkafi, 2017), or tools and methods for business model evaluation (Tesch and Brillinger, 2017). Business model tools are applied in specific phases (e.g., idea generation) or in all phases of business model innovation. They can take different units of analysis (e.g., the value network or the focal organization) (Bouwman *et al.*, 2020). Existing research streams on business model tools can be divided into *conceptual models*, *methods* for specific tasks and *IT support* (Bouwman *et al.*, 2020; Schwarz and Legner, 2020).

2.1.4.1 Business Model Tools as Conceptual Models

The first research stream deals with **BM tools as conceptual models.** This type of BM tools are shared conceptualizations to model, describe, visualize and discuss business models; by using a "representational formalism" (Pateli and Giaglis, 2004), e.g. through visual languages (John *et al.*, 2017). Conceptual models are instantiated as visual representations of a business model. They can take a *component perspective*, i.e., visually providing several pre-defined business model elements; a *transactional perspective*, i.e., representing actors and model exchanges as flows between actors; and/or a *causal perspective*, i.e., representing causalities between elements of business models (Täuscher and Abdelkafi, 2017).

These visual representations support understanding and communicating a firm's business model (Eppler *et al.*, 2011; Osterwalder, 2004), support generating and developing new business model ideas (Gassmann *et al.*, 2014; Osterwalder and Pigneur, 2010), overcoming organizational innovation barriers (Eppler *et al.*, 2011) or stimulate collaborative innovations (Täuscher and Abdelkafi, 2017). This research stream pursues the component-based view of a business model as presented in the static business model perspective (Section 2.1.2). It describes the relationship between the business model components and aims to organize the information of a business model instance around these elements (Pateli and Giaglis, 2004). The most prominent example of a conceptual model is the Business Model Ontology (Osterwalder, 2004) which was later instantiated in the Business Model Canvas (Osterwalder and Pigneur, 2010). Representative examples for research on conceptual models of business models are illustrated in Table 2.3.

Conceptual Model	**Main Components**	**Visual Representation**
Business Model Ontology (Osterwalder, 2004, p. 44)	➢ Infrastructure management ➢ Customer Interface ➢ Financial aspects ➢ Product	
e3 Value Ontology (Gordijn and Akkermans, 2003, p. 119)	➢ Actors ➢ Market Segments ➢ Value Interface ➢ Value Activity ➢ Value Object ➢ Value Offering ➢ Value Exchange ➢ Value Port ➢ Elementary Actor ➢ Composite Actor	

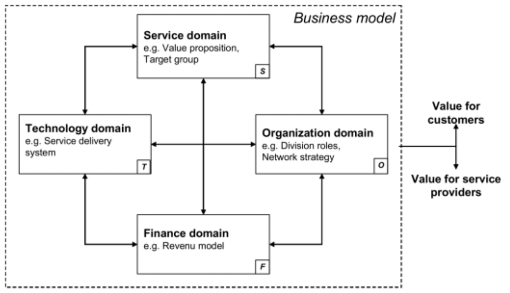
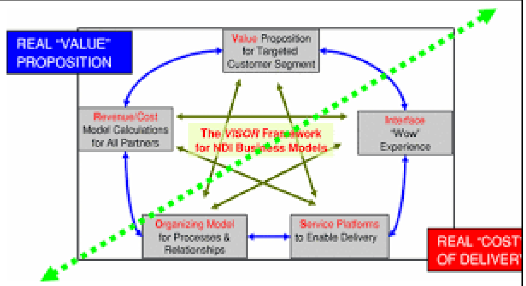
STOF Model (Bouwman *et al.*, 2008, p. 35)	➢ Service ➢ Technology ➢ Organization ➢ Finance	
VISOR Framework (El Sawy and Pereira, 2013, p. 25)	➢ Value Proposition ➢ Interface ➢ Service Platform ➢ Organizing Model ➢ Revenue/Costs	

Table 2.3: Exemplary research on BM Tools as conceptual models (Source: own representation; references of individual images can be found in column 1).

Besides such conceptual models, the business model literature also provides *patterns* (Gassmann *et al.*, 2014; Remane *et al.*, 2017; Weking *et al.*, 2018) and *taxonomies* (e.g., Remane *et al.*, 2016) of business models based on conceptual models. Whereas conceptual models help to describe and communicate a business model, *"actionable answers to how-to questions"* in business model innovation are often lacking (Bouwman *et al.*, 2020). Therefore, researchers and practitioners started to develop methods supporting business model innovation.

2.1.4.2 Business Model Tools as Methods

The second research stream deals with **BM tools as methods** to address specific tasks during business model innovation (Schwarz and Legner, 2020), such as business model exploration (Athanasopoulou and Reuver, 2020) or the evaluation of business models (Tesch and Brillinger, 2017). These tasks relate to specific phases and activities of business model innovation as described in Section 2.1.3.2. In contrast to conceptual models, BM tools as methods also provide a method of use, i.e., actionable knowledge on how to execute a specific task in business model innovation.[7] Examples of such methods from recent research are summarised in Table 2.4.

Method and Reference	Description of Method
Business Model Road Mapping (Reuver *et al.*, 2013)	Business Model Road Mapping is a method to define and visualize the transition in an organization from the current to a future business model. The method helps to define actions and changes in the business model as well as trade-offs between strategic and operational activities.
Scenario Planning as an evaluation methodology (Tesch, 2016)	The author transferred methods from strategic management, such as scenario planning, to business model innovation processes. In a first step, one identifies assumptions in the

[7] Please note that for some conceptual models there exist also methods of use (e.g., for the Business Model Canvas, Osterwalder and Pigneur (2010)) that would also fall under this category of BM Tools.

	business model design and ranks them based on uncertainties and impact, leading to critical uncertainties that can be classified based on the PESTEL framework. Second, one identifies key success factors and builds different scenarios. In the last step, one identifies the impacts of the success factors on the scenarios and crafts strategic implications for the business model.
Business Model Stress Testing (Haaker *et al.*, 2017)	Business Model Stress Testing is a method to evaluate the robustness of a business model and its components against changes in markets, regulations or digital technologies. The method helps visualise challenges and improve the business model's robustness.
Mapping business model risk factors (Brillinger, 2018)	The "mapping business model risk factors" method adopts a value network analysis to identify risk factors within the value network of a business model. This method helps to build a sustainable business model, as risks in a business model need to be identified and managed.
Qualitative evaluation of service-dominant business models (Gilsing *et al.*, 2020)	This method helps to qualitatively evaluate early designs of service business models through guiding questions and corresponding qualitative attributes.

Table 2.4: Exemplary Research on BM Tooling as Methods (Source: own representation).

Beyond these specific methods designed to support business model innovation, there are other tools used in practice, such as the Balance Score Cards, SWOT or PESTEL analysis, that emerged from other fields such as strategic management (Bouwman *et al.*, 2020; Tesch and Brillinger, 2017).

2.1.4.3 Business Model Tools as IT Artefacts

The third research stream deals with **IT support** for developing and managing business models (Hanelt *et al.*, 2015; Osterwalder and Pigneur, 2013; Veit *et al.*, 2014). These BM tools support *digital modelling*, i.e., representing and changing business models (Fritscher and Pigneur, 2014a) by implementing existing modelling languages (Gordijn *et al.*, 2000) and enabling the *collaboration* of business model development in distributed teams (Ebel *et al.*, 2016). Szopinski *et al.* (2019) developed a taxonomy of existing business model development tools available in practice and identified key functions of business model development tools regarding the modelling, collaboration and architecture perspective (Szopinski *et al.*, 2019). Further, Schaffer *et al.* (2020) have derived design requirements and design principles for business model software tools based on a literature review. IT support could be a digital implementation of the Business Model Canvas (Fritscher and Pigneur, 2014a), prefilled business model elements as a creativity support (Athanasopoulu *et al.*, 2018) or support reflecting sustainability in a business model design (Schoormann *et al.*, 2018). Research on designing IT support for BM management also suggests using data-driven methods (Augenstein and Fleig, 2017) or supporting ideation with machine-generated ideas (John, 2016). Further, decision support systems exist to validate business models (Dellermann *et al.*, 2018).

IT support is further important for the whole business model management process, as Terrenghi *et al.* (2017) pointed out: *"Consistent support of the entire BM life-cycle raises the need for adequate*

IT solutions, not only as digital visualization of BMs, where pen-and-paper seems to be sufficient for most practitioners" (Terrenghi *et al.*, 2017, p. 983). They further note that *"IT must support a structured management process, but should not constrain agility in and the iterative nature of the early phases of BM development."* (Terrenghi *et al.*, 2017, p. 983).

2.1.5 Conclusion

Concluding, designing tools and methods for supporting business model innovation has gained attention in recent years in the fields of Information Systems and Innovation Management, following principles of Design Science Research (see Chapter 3). However, most tools and methods have been designed on a conceptual basis and have been evaluated with experts. Nevertheless, they have not been introduced and systematically tested within organisations (Schwarz and Legner, 2020). Further, there is little knowledge available on what role business model tools play in business model innovation processes (Schwarz and Legner, 2020).

Advances in Information Technology, such as Big Data and Data Science, and the digitalization of businesses do not only enable the development of BM tools as IT support, but they are also an opportunity for new digital and data-driven business models (Veit *et al.*, 2014), that will be now discussed in Chapter 2.2. A structured literature review (Fruhwirth *et al.*, 2020c), presented in Chapter 4.1, shows that current research on BM tooling for data-driven business models is still in its infancy, specifically incorporating data and analytics as a central focus or lens of analysis of Business Model tools. The call of Bouwman *et al.* (2020) to bring Design Science Research (see Chapter 3) to BM tooling research motivates this PhD thesis to design tools and methods for supporting data-driven business model innovation.

2.2 Data-Driven Business Models[8]

Tempich and Rieger (2007) were one of the first that mention the term "data-centric business models" in a consulting report (Dorfer, 2016). Chen *et al.* (2011) later connected the concepts "big data" and "business model" in their research article. Hartmann *et al.* (2016) developed the first framework based on business model building blocks and coined the term data-driven business model as a *"business model relying on data as a key resource"* (Hartmann *et al.*, 2016, p. 1385). In the same year, other scholars also started to publish on this topic (e.g., Engelbrecht *et al.*, 2016; Schüritz and Satzger, 2016; Zolnowski *et al.*, 2016). Since then, the concept of data-driven business models has gained attention in the academic field, especially in the Information Systems discipline, as recent literature reviews show (Fruhwirth *et al.*, 2020c; Wiener *et al.*, 2020). Further, data-driven business models have aroused interest among practitioners (e.g., Seiberth and Gründinger, 2018).

2.2.1 Conceptualizing Data-Driven Business Models

Data-driven business models have a conceptual focus on the **value creation from data** (Guggenberger *et al.*, 2020). This focus is the common ground of various definitions in the literature: A business model is data-driven, *"when data are exploited as main resource for innovative service business models"* (Zolnowski *et al.*, 2016), or *"if its core business necessarily requires digital data"* (Engelbrecht *et al.*, 2016, p. 5). The term "data-driven", in general, *"refers to decisions, processes or products that are 'determined by or dependent on the collection or analysis of data' (Oxford Dictionaries 2018)"* (Hartmann, 2020, p. 6). Data *"is required for the value proposition"* (Kühne and Böhmann, 2018, p. 1). But, there is no clear defined threshold of required data in a business model that it can be called a data-driven (Rashed and Drews, 2021; Schüritz and Satzger, 2016). Organisations can improve their existing business with data, enrich their value proposition with data or develop new services and business models based on data (Schüritz and Satzger, 2016; Wiener *et al.*, 2020). Data-driven business models can be conceptualised by their characteristic elements.

2.2.1.1 Characteristic Elements of a Data-Driven Business Model[9]

In a data-driven business model, data is used as a key resource (Engelbrecht *et al.*, 2016; Zolnowski *et al.*, 2016). Value is generated from these data through the generation, aggregation, and processing of data (Hartmann *et al.*, 2016; Schüritz *et al.*, 2017c). Further, data analytics techniques are applied to discover insights from data (Hunke *et al.*, 2019; Kühne and Böhmann, 2019). The results from these value-creation activities are delivered via a data-based value proposition to support customers in their decision-making process (Schüritz *et al.*, 2019b). Such

[8] Note that the topic of data-driven business models has emerged over the time this thesis was written. When we first started investigating this filed in summer 2017 already before this thesis, there were very few publications available. Now, in 2024 data-driven business models are a hot topic in research and a lot is published. This background chapter covers a comprehensive research overview until 12/2022. More recent literature is included in the discussions and outlook sections of this thesis.

[9] A detailed investigation and definition of the characteristic elements of a data-driven business model is presented in Chapter 5.3.

offerings can have different forms, such as data, insights, or actions, depending on the degree of analytics and the depth of involvement in the decision-making process (Hunke *et al.*, 2020a; Schüritz *et al.*, 2019b). These data-driven offerings enable the generation of new revenue streams (Schüritz *et al.*, 2017b). Dehnert *et al.* (2021) developed a consolidated taxonomy of data-driven business models by studying 26 previous taxonomies of data-driven business models and data-driven services and 30 cases.

Meta-Dimension	Building Block	Guiding Question
Value Proposition Model	Value Proposition	What does the company offer to the customer?
	Value Capture	How does the company earn money through the business model?
Value Creation Model	Data Generator	Who or what is generating the data?
	Data Origin	Where does the data come from?
	Data Target	About whom or what is the generated data?
	Data Activity	How is the data handled?
	Data Analytics	How is the data analysed?
	Insight Utilisation	In which form are the insights provided to the customer?
	Cost Structure	How are the costs determined
Customer Interaction Model	Customer Segment	What kind of customer is it?
	Target Customer	Who is the customer group?
	Interaction Type	How does the customer interact with the offering
	Service Flow	When is the service provided?
	Customer Relationship	How is the company supporting the customer?

Table 2.5: Consolidated taxonomy of data-driven business models with guiding questions (adapted from Dehnert *et al.*, 2021).

Data as a Key Resource

Data and information are strategic resources in today's digital businesses (Bock and Wiener, 2017; Mamonov and Triantoro, 2018). Data enables firms to improve processes and decision-making and offer new services and business models (Hartmann *et al.*, 2016; Wixom and Ross, 2017). This leads to the paradigm that data assets and information-based offerings are exchanged for legal tender (Wixom, 2014). Thus, through the emergence of a data ecosystem, data do not only represent an asset that allows companies to improve products or services but have become products in and of themselves (Carnelley *et al.*, 2016; Spiekermann *et al.*, 2018). Data represents in a DDBM both a firm's *resource* (Hartmann *et al.*, 2016) and a *flow* across business actors (Terrenghi *et al.*, 2018). Sources of data for data-driven business models can be *internal* (i.e., obtained from the company's internal IT systems or self-generated sensor data) or *external* (i.e., data purchased from external data providers or obtained for free from publicly available data sources) (Hartmann *et al.*, 2016). There is a trend not only in collecting data from the online world (e.g., social media) but also in the offline world (e.g., sensor data from machines) (Zuboff, 2020). Thus, companies purchase data goods to support their data-driven businesses (e.g., for training machine learning models (Agarwal *et al.*, 2019)). Likewise, companies also have the opportunity to monetize their internal valuable data assets by selling them to other data-driven businesses (Otto and Aier, 2013). One example is to monetise car data for new business models (Sterk *et al.*, 2022).

Data Analytics as Key Activities

Data-driven business models create customer value through **generating, aggregating and analysing** data (Schüritz *et al.*, 2017b). These value-creating activities are described and visualised as a *data value chain* (Curry, 2016). Data analytics is the key activity to generate insights and subsequent value from data. Data analytics refers to methods for automatic recognition of patterns and relations in data sets (BITKOM, 2015). Such methods are taken from statistical learning, machine learning and other fields like descriptive statistics (Kühl *et al.*, 2019). The term data mining describes the process how to apply these methods to solve real-world problems. Artificial intelligence, on the other hand, applies methods from machine learning (Kühl *et al.*, 2019).

Working Definition of Data-Driven Business Models for this Thesis

Building on other definitions and key elements discussed above, we define data-driven business models in the context of this thesis as follows:

A data-driven business model describes how data and analytics are used to deliver value to customers, i.e., to support their decision-making process via data and analytics-based features, and to convert this value into revenue through direct or indirect monetization.

Figure 1.1 illustrates the main components included this definition.

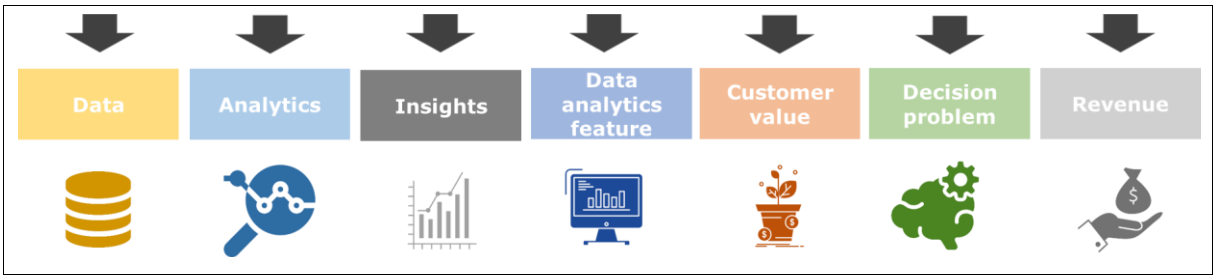


Figure 2.5: Characteristic elements of a data-driven business model (source: own representation, icons made by Freepik, downloaded from flaticon.com)

2.2.1.2 Similar Concepts to Data-Driven Business Models

The phenomenon of creating value from data and developing new products, services and business models from data is also studied in the literature under different names, as Table 2.6 shows. In the understanding of this thesis, those concepts can also be subsumed under the term “data-driven business model”. Some have a conceptual focus on services instead of business models (e.g., “data-driven services”), cover specific types of data-driven business models (e.g., “data wrapping”) or are more historical terms that did not get established in the scientific community (e.g., “data-centric business models”).

Concept	Exemplary Definition	Core Publications
Analytics-based Service	"Analytics-based services (ABS) are a novel type of service which encompasses the application of analytical methods ('analytics') to data." (Hunke *et al.*, 2020a, p. 1035)	(Hunke *et al.*, 2019; Hunke *et al.*, 2020a)
Big Data Business Model	"data can serve as a central component of a business model" (Schroeder, 2016, p. 6)	(Schroeder, 2016; Wiener *et al.*, 2020)
Data-centric Business Models	„Internetbasierte kommerzielle Aktivitäten eines Unternehmens, in denen eine immaterielle Wertschöpfung durch die Sammlung, Aufbereitung und Bereitstellung von Daten zur Befriedigung der Datenbedürfnisse der Kunden vollzogen wird" (Dorfer, 2016, p. 310)	(Dorfer, 2016; Tempich and Rieger, 2007)
Data-Driven Business Model	"business models which use data as a key resource to create new insights for a value proposition for customers." (Kühne and Böhmann, 2019, p. 4)	(Engelbrecht *et al.*, 2016; Hartmann *et al.*, 2016; Kühne and Böhmann, 2019)
Data-Driven Service	"use of data and analytics to support the decision-making process of the customer via data and analytics-based features and experiences in form of a stand-alone offering or bundled with an existing product or service" (Schüritz *et al.*, 2019b, p. 4)	(Azkan *et al.*, 2020; Engel and Ebel, 2019; Rizk *et al.*, 2018; Schüritz *et al.*, 2019b)
Data-infused Business Models	"data and analytics are directly impacting certain components of the business model which we call "infused"" (Schüritz and Satzger, 2016, p. 136)	(Schüritz, 2017; Schüritz and Satzger, 2016)
Data Monetization	"Data monetization is when the intangible value of data is converted into real value, usually by selling it." (Najjar and Kettinger, 2013, p. 213)	(Najjar and Kettinger, 2013; Wixom, 2014)
Data Product	"a data product is defined as the application of data science competences to provide benefit to another entity." (Meierhofer *et al.*, 2019, p. 41)	(Meierhofer *et al.*, 2019; Tempich, 2019)
Data Wrapping	"A wrap is an analytics-based feature or experience – such as a dashboard, a report, an alert, a benchmark, an API, guidance or an automated decision – that is combined with a core product." (Schüritz *et al.*, 2019a, p. 4)	(Schüritz *et al.*, 2019a; Wixom and Schüritz, 2018)
Information-intensive Service	"Information-intensive service (IIS) is a type of service in which information interactions have the most effect on service value creation." (Lim and Kim, 2014, p. 296)	(Lim *et al.*, 2018; Lim and Kim, 2014)
Smart Service	„Dienstleistung, die Daten aus digital vernetzten physischen Objekten (sog. Smart Products) aggregiert, verarbeitet und auf dieser Basis einen Mehrwert erzeugt" DIN SPEC 33453:2019-09 (Deutsches Institut für Normung e.V., 2019, p. 8)	(Beverungen *et al.*, 2019; Wuenderlich *et al.*, 2015)

Table 2.6: Similar concepts related to Data-Driven Business Models

Data-driven business models are understood as a sub-type of *Digital Business Models* (Bock and Wiener, 2017; Guggenberger *et al.*, 2020), explicitly focusing on data as the key resource for value generation (Hartmann *et al.*, 2016). A digital business model uses digital technologies and focuses on digitalising the organisation's business logic (Bärenfänger and Otto, 2015; Veit *et al.*, 2014). Other types of digital business models, such as *IoT Business Models* (e.g., Dijkman *et al.*, 2015; Turber and Smiela, 2014) or *Digital Platform Business Models* (e.g., Shaughnessy, 2016; Täuscher and Laudien, 2018) have a different conceptual focus, but can also be viewed as a data-driven business model with the lens of data-based value creation. Figure 2.6 visualised the relation between data-driven and other digital business models.

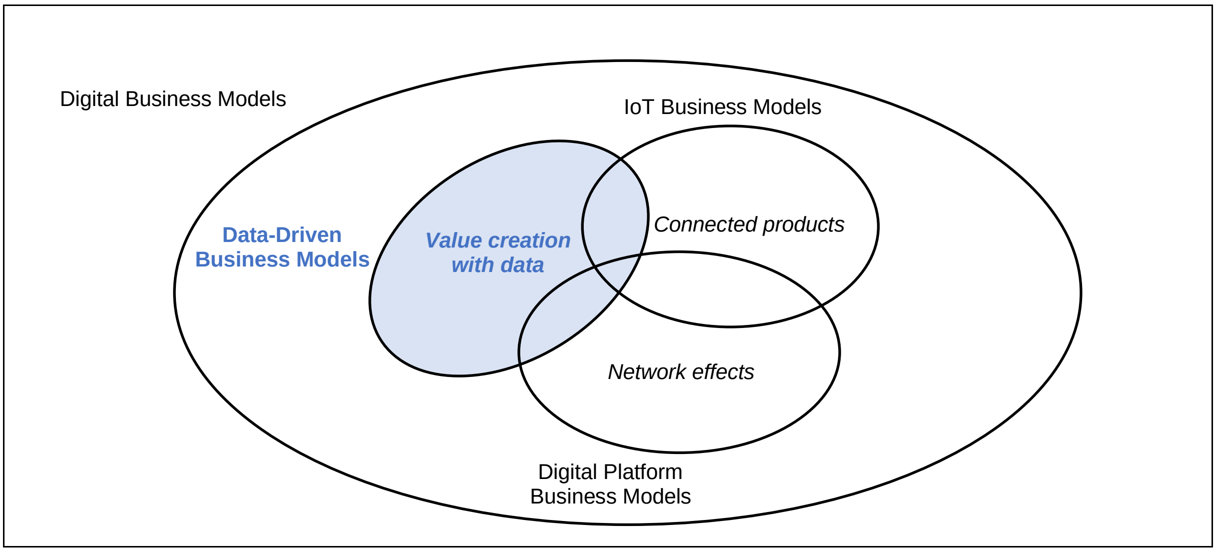


Figure 2.6: Relation of Data-Driven Business Models to other types of Digital Business Models and their conceptual focus (source: own representation).

In this section, we have highlighted the characteristics of a data-driven business model and delimitated it from similar concepts in line with the static business model concept. Nevertheless, the question of how to design and implement data-driven business models remains open. Therefore, we will investigate the dynamic perspective of data-driven business model innovation in the next section, i.e., focusing on the literature on the transformation and process perspective.

2.2.2 Dynamic Perspective: Data-Driven Business Model Innovation

Data-driven business model innovation is understood *"as the process when an organization adopts a novel approach to commercialize data as its new underlying asset to deliver value to existing or new customers"* (Fruhwirth *et al.*, 2020c, 10). In other words, we understand data-driven business model innovation as a change in the value proposition due to the effect of data and analytics (Schüritz *et al.*, 2017c). This process is particularly challenging for offline established organisations with a successful business model. The literature reveals two courses for data-driven business model innovation: refining and improving existing business models with data and designing new business models (Günther *et al.*, 2017; Woerner and Wixom, 2015).

The way toward a data-driven business model is not without **challenges and barriers**. Early studies already investigated such challenges (e.g., Fruhwirth *et al.*, 2018; Schüritz *et al.*, 2017c).

Schüritz *et al.* (2017c) describe organisational challenges in transforming from a service-oriented to a data-oriented business model. Fruhwirth *et al.* (2018) differentiated between organisational, business and technical challenges. Brownlow *et al.* (2015) also mentioned cultural problems as the major inhibitor for realising data-driven business models. Schymanietz *et al.* (2022) noted data privacy and standardisation as two barriers. Mosig *et al.* (2021) investigated regulatory hurdles and aversions in data-driven business model innovation.

One key role in such a transformation process are playing **resources and capabilities**. Hartmann (2020) proposes six different types of resources necessary to realize a data-driven innovation, as shown in Figure 2.7. From a technology perspective, it requires both resources and capabilities. As mentioned above, *data* is one key resource (Hartmann *et al.*, 2016). Data access, collection and ownership are critical here (Schymanietz *et al.*, 2022). Further, successful data-driven business models require *algorithms*, i.e., the "tools" and "machines", to generate insights and subsequently value from data (Agrawal *et al.*, 2018b). Finally, as a technical resource, one also needs *IT infrastructure*, including data analysis software or data storage facilities (Schroeder, 2016).

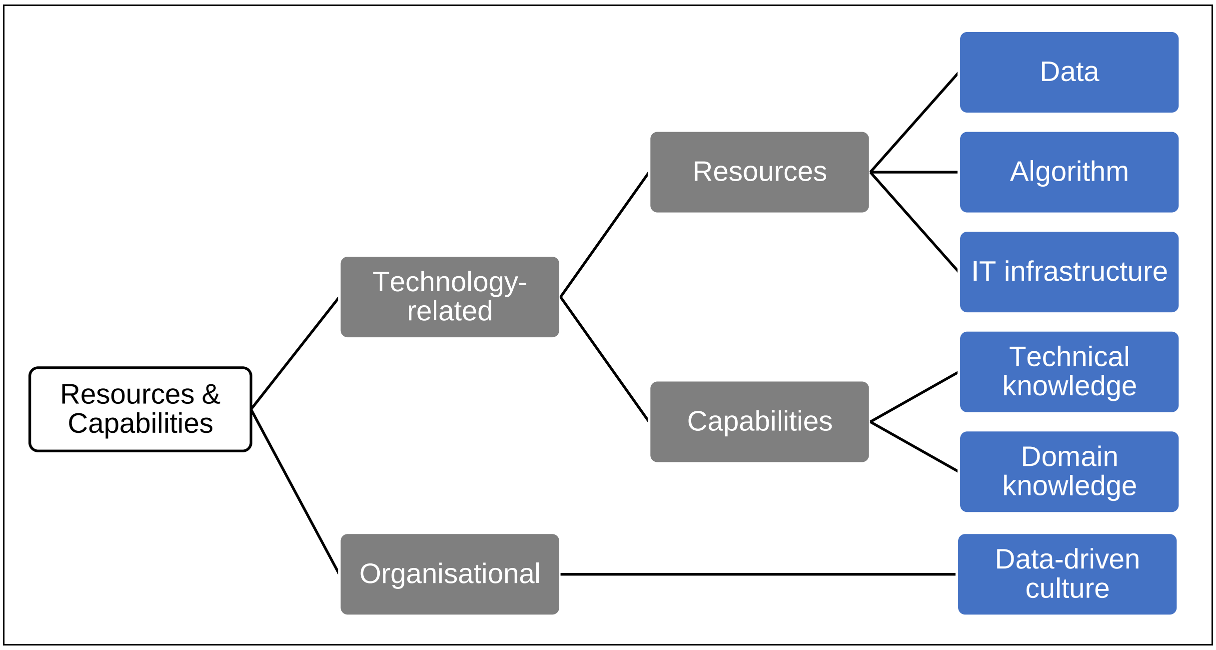


Figure 2.7: Necessary resources for data-driven innovations (adapted from Hartmann, 2020, p. 31).

From a human perspective, a successful data-driven business model requires both *technical knowledge* about data science, machine learning or data governance and *knowledge of the domain* where data science methods are applied (e.g., automotive engineering). Thus, well-trained employees are one further success factor (Schymanietz *et al.*, 2022). From an organizational perspective, this transformation process requires a *data-driven culture,* including customer orientation and collaboration (Schymanietz *et al.*, 2022). Förster *et al.* (2022) identified different employee perspectives as success factors for data-driven business models, such as "data business mediation", where employees balance technical and business requirements to satisfy customer needs.

Scholars structure this process into high-level phases that are based on general business model innovation literature. For instance, Hunke *et al.* (2017) adopted the process layout of Bonakdar and Gassmann (2016) and Lange and Drews (2020) based their process phases on a literature review. Lange *et al.* (2021) later focused their research on realising data-driven business models. They identified four periods: experimentation, developing an MVP, operating a minimum marketable product, and scaling a successful data-driven business model. Rashed *et al.* (2022) provide a reference model for data-driven business model innovation by defining the main activities of each phase. Following existing literature on general BMI, tools and methods support individual activities in a data-driven business model innovation process.

2.2.3 Supporting Data-Driven Business Model Innovation

As the way toward a data-driven business model is challenging, literature has started designing and investigating supporting tools and methods. Existing research predominantly focuses on tools and methods to support idea generation (Fruhwirth *et al.*, 2020c). Literature provides several "canvas" or "maps" to structure ideation workshops or communicate ideas (e.g., Kronsbein and Mueller, 2019 or Kühne and Böhmann, 2019). However, there is a lack of support for decision-making, including risk management, in innovating DDBMs (Fruhwirth *et al.*, 2020c). A detailed overview of supporting tools and methods for data-driven business model innovation based on a structured literature review is presented in Chapter 4.1.

Concluding, data-driven business models have gained attention in the academic world in recent years. There is already a profound understanding of what a data-driven business model is, its main components, and the challenges in this transformation process. Further, first tools and methods are available as support. Nevertheless, little has been written about how a systematic process should be designed in established organisations.

2.3 Synthesis, Research Gap and Research Questions

As we have seen, existing literature on business models provides a solid understanding of a business model and how it can be described and decomposed into its crucial elements. Further, in recent years, the literature also focused on business model innovation, i.e., what (the outcome) and how (the process) a new business model comes into place (Massa and Tucci, 2013). Nevertheless, literature on such processes on business model innovation lacks empirical research (Schneider and Spieth, 2013). Further, literature provides only idealized and conceptual phases of business model innovation (Winterhalter *et al.*, 2017). On the other hand, business model innovation is often unstructured in practice. To support the business model innovation process, researchers and practitioners have designed tools and methods (Bouwman *et al.*, 2020; Schneider and Spieth, 2013), such as the Business Model Canvas (Osterwalder and Pigneur, 2010). However, most of these tools and methods are based on conceptual designs evaluated only by experts; they have not yet been applied and evaluated systematically within (offline-established) organisations (Schwarz and Legner, 2020). Further, the literature lacks a theoretically grounded understanding of business model innovation processes and what role supporting tools and methods play in such a process (Schwarz and Legner, 2020). In general, there is little knowledge available how to design such processes and tools.

Regarding the specific case of data-driven business models, current literature describes the nature of this phenomenon and lacks empirical research (Wiener *et al.*, 2020). Existing literature mainly provides typologies of data-driven business models based on start-ups (e.g., Engelbrecht *et al.*, 2016; Hartmann *et al.*, 2016; Hunke *et al.*, 2019; Schüritz *et al.*, 2017b); thus, neglecting data-driven business model innovation in offline-established organizations. Further, academia has paid little attention to the dynamic aspects of data-driven business models (Wiener et al., 2020), particularly the design and realization (Rashed and Drews, 2021). Furthermore, even less knowledge is available on supporting this dynamic process through tools and methods (Fruhwirth *et al.*, 2020c). Existing tools and methods for business model development (e.g., the Business Model Canvas (Osterwalder and Pigneur, 2010) or the Business Model Patterns (Gassmann *et al.*, 2014)) are too generic for non-data experts as they do not incorporate the specifics of data and analytics in business (Engelbrecht *et al.*, 2016).

This gap in the literature, i.e., a lack of empirical and design research on business model innovation processes and a lack of tool support that take the specifics of data-driven business models into account, raises the need to design supporting tools, methods and processes specifically for data-driven business models in the context of offline established organisations. Therefore, we formulate the following research goal (RG) of this thesis:

RG: *How can we design tools, methods and concepts to support data-driven business model innovation in an offline-established organisation?*

The process of (data-driven) business model innovation is a complex task involving various steps, activities and challenges (Geissdoerfer, 2019; Wirtz and Daiser, 2018). Despite specific activities such as idea generation, evaluation and risk management, organizations also need support over the whole business model innovation activities via a structured management process (Terrenghi, 2019). The knowledge of such a holistic process for data-driven business model innovation is still fragmented, missing a sequence of activities and connection of specific tools and methods (Fruhwirth *et al.*, 2020c). Especially, there is a lack of knowledge on how to design such processes. Existing process models (e.g., Hunke *et al.*, 2017; Lange and Drews, 2020) are based on literature and expert interviews. However, business model innovation processes must be adopted and embedded in an organization's current practices (Winterhalter *et al.*, 2017). To address this gap in the literature, we intend to answer the first research question in this thesis:

RQ 1: What process design would allow established companies to develop data-driven business models systematically?

This research question will be addressed subsequently in Chapter 4. One important task in data-driven business model innovation is generating ideas and formulating a value proposition for a new business model. As stated above, current business model development tools may be too generic, as they do not consider the specific properties of data and analytics (Engelbrecht *et al.*, 2016). Further, as the knowledge and experience about data-driven business models are often scarce in offline-established organisations, there is a need to support the business model design team and the idea generation process with specific approaches. Existing knowledge on characterising DDBMs from taxonomy research needs to be transferred into actionable innovation tools. Currently, there is no sufficient representation that supports the interdisciplinary collaboration of data science and domain expert stakeholders within organizations to formulate meaningful value propositions based on data and analytics (Fruhwirth *et al.*, 2020a). Thus, we intend to answer the second research question of this thesis:

***RQ 2: How can we support idea generation and design during a data-driven business model innovation*?**

This research question will be addressed in Chapter 5. Despite idea generation, evaluation and decision making are other important tasks in (data-driven) business model innovation (Tesch and Brillinger, 2017; Tesch *et al.*, 2017) that also includes the identification of potential risks (Brillinger, 2018; Brillinger *et al.*, 2020). Managers must decide what data-driven business model ideas are most promising to provide investment and resources and proceed with them in the innovation process. Currently, evaluation and risk management is an under-researched field in business model research (Brillinger, 2018). Some evaluation tools and methods exist, as a current literature review shows (Tesch and Brillinger, 2017). Nevertheless, using data as the main resource and an exchanged value object is causing new risks that impact the design of data-driven business models. Up-to-date research on data-driven business models does not consider such specific aspects for evaluation and decision-making (Fruhwirth *et al.*, 2020c). To address this problem, we intend to answer the third research question in this thesis:

RQ 3: How can we support evaluation, decision-making and risk management during a data-driven business model innovation?

This research question will be addressed in Chapter 6. In order to reach the research goal and to answer the research questions, we will describe our research approach in the following chapter.

Chapter 3

Research Methodology: Design Science Research

"Designing is learning – with yourself and the world as the teacher."

J.C. Jones[10]

Summing up, the research problems, we identified are design-oriented. Therefore, we decided to adopt the methodological approach of Design Science Research (Hevner *et al.*, 2004; Peffers *et al.*, 2007). As it is necessary to investigate the usage of business model tools also in organisations (Schwarz and Legner, 2020) and to adopt business model innovation processes to the specifics of an organisation (Winterhalter *et al.*, 2017), we embedded the design science research project within a case study with an offline-established organisation. In the next section 3.1, we will introduce the methodology of design science research in general. Afterwards, we will describe in section 3.2 the specific design science research approach of this thesis.

3.1 Design as Science and Research

Design Science Research has been acknowledged as a suitable methodology to address organizational and societal issues (Prat *et al.*, 2015). Design Science Research has been argued to help understand organizational phenomena, and to design artefacts that extend individual and organizational capabilities as well as research by designing and evaluating innovative socio-technical artefacts that solve organizational problems (Gregor and Hevner, 2013; Hevner *et al.*, 2004; Peffers *et al.*, 2007).

3.1.1 Epistemological Considerations[11]

Design Science Research, or more generally speaking, "the science of the artificial" (Simon, 1969) is different to human and natural science and *"and requires different modes of inquiry to reason about the truth of the knowledge created"* (Gregor, 2009). DSR creates knowledge about how to design things through the design process. Therefore, "*statements of truth in DSR do not primarily relate to 'what is' and 'how things are' but to 'what could and what should be' [5] and 'how useful things are expected to be'"* (Sonnenberg and Vom Brocke, 2012). This raises the question: ***What is truth in Design Science Research?***

[10] Design Methods for Everyone. Softopoa (2001)
[11] Parts of this text passage is based on an assignment I have written during the lecture „Wissenschaftliches Arbeiten" at Graz University of Technology in January 2021.

Purao (2013) answer this as *"[d]esign science researchers believe that the proverbial 'truth' is not 'out there' […] instead, they 'dare' to create artifacts intended to change the world"* (Purao, 2013, p. 52). Thus, this worldview differs from that of social or natural science. Doing Design Science Research produces two types of knowledge: **descriptive knowledge** (i.e., describing and predicting what happens as artifacts exists (Gregor, 2009)) and **prescriptive knowledge** (i.e., how to design certain types of artifacts or how to solve certain types of problems) (Hevner *et al.*, 2019). Sonnenberg and Vom Brocke (2012, p. 386) claim that *"the prescriptive knowledge that emerges throughout a DSR process has a truth-like value".* This means, beside from solving a real-world problem - as the practical contribution of a Design Science Research project - DSR also aims **to make truth-like statements about prescriptive knowledge**, i.e., how to design things.

Design Science Research produces project-specific design knowledge (i.e., the design outcome from one project); and through induction, i.e., reasoning and theorizing from several design projects, generating "solution design knowledge" (Drechsler and Hevner, 2018). The aim of Design Science Research is not to verify or falsify theories but to provide good solutions to real-world problems and to contribute prescriptive knowledge (how to design). Thus, in DSR, we want to show that a design was useful under certain conditions in the real world and through induction over several problems and solutions generate prescriptive knowledge that can be seen as truth-like statements. On the other hand Iivari (2015) for instance states that prescriptive knowledge has no truth-like value, as it *follow "the epistemology of utility rather than the epistemology of truth (likeness)"* (Iivari, 2015, p. 108); and only descriptive knowledge (e.g., observations) have a truth value.

3.1.2 Design Science Research Approaches

The literature provides different process- or cycle-based approaches for doing design science research (e.g., Hevner *et al.*, 2004; Peffers *et al.*, 2007; Vaishnavi and Kuechler, 2015). In this thesis, we follow the approach of Hevner *et al.* (2004) with his three-cycle view of relevance, design and rigor (Hevner, 2007). The instantiation of this approach is subsequently described in Chapter 3.2.

Relevance: The relevance cycle provides the requirements for the research (opportunities and problems) in a distinct application context, that contains people, organizational systems and technical system. This problem space consists of *needs* of *stakeholders* that inform the *goals* of the DSR project that are satisfied by *requirements* (Maedche *et al.*, 2019). In addition, the relevance cycle specifies acceptance criteria for the ultimate evaluation of the artefact and allows the introduction of the designed artefacts to the field (Hevner, 2007).

Design: The design cycle represents the iterative activities of constructing and evaluating artefacts (build and evaluate pattern) (March and Smith, 1995). The artefact construction is informed by theory and intends to address issues of the relevant environment; and the artefact evaluation informs theory, and decides whether the artefact indeed addresses issues of the relevant environment (Hevner, 2007; Hevner *et al.*, 2004). The different types of design artifacts are subsequently described in section 3.1.3 and different ways of evaluation are discussed in section 3.1.4.

Rigor: The rigor cycle links the design activities with the knowledge base, to provide past knowledge to the design activities and to eventually extend the knowledge base by adding the results of the research process. The knowledge base includes scientific theories and methods, experience and expertise that define the state-of the art in the application domain and existing artefacts and processes (Hevner, 2007). The knowledge base can be divided into foundations that include previous designed artifacts as well as scientific theories and frameworks; and methodologies as different means for data collection and analysis for the evaluation of artifacts (Dwivedi *et al.*, 2014). Drechsler and Hevner (2018) differentiate in the knowledge base between descriptive (scientific) knowledge and prescriptive (design) knowledge.

3.1.3 Types of Design Outcomes and Knowledge Contributions in Design Science Research

Design science research aims to solve real-world problems of organizations via the creation of innovative artifacts that extend individual and organizational capabilities (Prat *et al.*, 2015; Vom Brocke *et al.*, 2020a). Design science research can generate different types of artifacts. Outcomes can be socio-technical artefacts that have "*both technical and social design features"* (Silver and Markus, 2013, p. 82) or organizational interventions (Romme, 2011). March and Smith (1995) distinguish between four types of artifacts: constructs, models, methods and instantiations. **Constructs** form the language of a domain and conceptualize problems and solution within this domain. **Models** articulate the relationship between concepts. **Methods** are a set of instructions to perform an activity and are based on underlying constructs and models. **Instantiations** are the implementation of artifacts, i.e., constructs, models and methods, in the application context. (Dwivedi *et al.*, 2014; March and Smith, 1995)

Outcomes in design science research not only constitute presenting the situated realization of an artifact (instantiation) and the results from the evaluation, but also providing prescriptive design knowledge, i.e., explanations and instructions how to design artifacts of a certain class (Gregor and Hevner, 2013; Vom Brocke *et al.*, 2020b). There are debates on different types of knowledge contributions in design science research (e.g., Dwivedi *et al.*, 2014).

One type of knowledge contribution generated in design science research are **design theories** (Baskerville and Pries-Heje, 2010). Design theories *"give explicit prescriptions on how to design and develop an artifact, whether it is a technological product or a managerial intervention."* (Gregor and Jones, 2007, p. 313). One example for a design theory in the context of business model tooling is a design theory for visual collaborative tools (Avdiji *et al.*, 2020). Design theories are often understood as principle-based (Baskerville and Pries-Heje, 2010).

Thus, another form of knowledge contribution in design science research are **design principles**. Sein *et al.* (2011) suggests to formalize learnings in action design research into design principles. Design principles *"capture the knowledge gained about the process of building solutions for a given domain, and encompass knowledge about creating other instances that belong to this class (Dasgupta 1996; Purao 2002)"* (Sein *et al.*, 2011, p. 45). Design principles can be further divided into principles of form and function (Gregor *et al.*, 2013). Design principles are generated in advance of the design or extracted subsequent from a design (Möller *et al.*, 2020a). Examples for design principles as knowledge outcomes in the context of business models are for instance design principles of a business model mining system (Augenstein and Maedche, 2017) or design principles for data-driven services in industrial environments (Azkan *et al.*, 2021). Finally, a DSR project can also provide new knowledge about the design process (e.g., Zolnowski, 2015).

3.1.4 Ways of Artifact Evaluation

Design Science Research requires the evaluation of the design output to ensure relevance and rigor of the research. There are different **reasons and goals** for conducting evaluation in design science research (*Why to evaluate?*) (Venable *et al.*, 2016). First, evaluation aims to *"observe and measure how well the artifact supports a solution to the problem. This activity involves comparing the objectives of a solution to actual observed results from use of the artifact in the demonstration"* (Peffers *et al.*, 2007, p. 56). Thus, evaluation aims to determine how well an artifacts achieves its utility in the environment by solving a problem (Venable *et al.*, 2016). Second, an evaluation can also determine if a new artefact makes an improvement to the state of the art from the knowledge base (Venable *et al.*, 2016). This means that an artifact is not evaluated absolutely or relative to the absence of the artifact, but also evaluated relatively to comparable artifacts (Prat *et al.*, 2015). Venable *et al.* (2016) further notes that an evaluation can be conducted to substantiate a design theory, to assess why an artifacts works, if it generates any undesirable impacts (side effects) or also for more complex criteria beyond the artifact's main purpose.

The goal of an evaluation episode is to evaluate the design artifact against several **evaluation criteria** (*What to evaluate?*). The first comprehensive list of 14 evaluation criteria depending on the artifact type was provided by March and Smith (1995). Aier and Fischer (2011) build on that and developed a set of criteria for measuring progress in design theories. Prat *et al.* (2015) presents in his taxonomy a comprehensive list of criteria used by other DSR studies to evaluate an artifact and categorized them along the characteristics of an artifact:. the *goal* of the artifact (e.g., feasibility or effectiveness), the *activities* performed with the aid of the artifact (e.g., performance or accuracy), the *environment* of people (e.g., utility or ease of use), organizations (e.g., alignment with business), and technologies (e.g., absence of side effects) in which the artifact is used, the *evolution* of the artifact (e.g., scalability or robustness), and the *structure* of the artifact (e.g., consistency or completeness) (Prat *et al.*, 2015).

To execute evaluation, one might draw from several **evaluation techniques** or methodologies from the knowledge base (Hevner *et al.*, 2004) (*How to evaluate?*). Prat *et al.* (2015) provide in their taxonomy a comprehensive overview of evaluation techniques, including question-based techniques (e.g., surveys or focus groups), observatory and participatory techniques (e.g., case and field studies), experimental techniques (e.g. controlled experiments or simulations) or descriptive approaches (e.g., informed arguments or illustrative scenarios). Gregor and Hevner (2013) suggest that the an artifacts usefulness is a sufficient criterion for complex artifacts. Executing evaluation can take different **forms**, such as qualitative or quantitative (Cleven *et al.*, 2009) as well as formal proof or logical reasoning (Prat *et al.*, 2015). During evaluation, secondary **participants** are involved that can be researchers, students or practitioners (Prat *et al.*, 2015).

The literature further differentiates the "how" of an evaluation between **naturalistic and artificial evaluation** (Venable *et al.*, 2016). In the former, an artifact is evaluated in its real environment within organizations, whereas in the latter, the artifact is evaluated in an artificial often controlled setting (e.g., with students as target users) that makes the evaluation episode less meaningful but more reliable and repeatable.

The time dimension (*When to evaluate?*) of an evaluation is understood as orthogonal to naturalistic vs. artificial evaluation (Venable *et al.*, 2016). The evaluation can be conducted **ex ante** (i.e., evaluation of an abstract or candidate artifact) or **ex post** (i.e., evaluation of an instantiated artifact), depending on if the artifact was evaluated before or after implementation and instantiation (Prat *et al.*, 2015; Venable *et al.*, 2016). Further, an instantiation of an artifact (e.g., an algorithm) can be applied to a real or fictitious example (Prat *et al.*, 2015; Sun and Kantor, 2006). Other authors suggest following a **continuous** or step-wise **evaluation approach** to also evaluate (incremental) design decisions made in the course of a DSR project (Abraham *et al.*, 2014; Sonnenberg and Vom Brocke, 2012; Venable *et al.*, 2016).

Another distinction in evaluation is made between **formative and summative evaluation**, where the former approach aims to "provide a basis for successful action in improving the characteristics or performance of the evaluand", and the latter aims to "provide a basis for creating shared meanings about the evaluand in the face of different contexts" (Venable *et al.*, 2016, p. 78).

3.1.5 Comparing DSR to other Research Methodologies

Design Science Research is a problem-solving research paradigm, i.e., developing innovative solutions for real-world problems, in contrast to *behavioural research* that aims to develop and verify theories that explain or predict human or organizational behaviour (Hevner *et al.*, 2004). Thus, design science research asks "how" questions, whereas behavioural research asks "why" questions.

The methodology reflects and explains the methods for executing the research, whereas research methods are techniques researchers use to study a certain phenomenon (Goundar 2012). One can use various research methods in Design Science Research, particularly for evaluating artefacts (Hevner *et al.*, 2004; Iivari and Venable, 2009). This thesis will also use various research methods and techniques, particularly for data collection and analysis. For instance, one can use a structured literature review to explore the knowledge base, use established methods for crafting specific types of artefacts (e.g., an ontology or taxonomy), or use interviews and workshops for evaluating artefacts.

The following section will contrast Design Science Research with other research paradigms and approaches, i.e., mixed method research, (canonical) Action Research, and Action Design Research.

Mixed method research combines elements of qualitative and quantitative approaches with the goal of broad and deep understanding and confirmation of certain phenomena (Johnson *et al.*, 2007) and is understood as the third major research approach in the social and behavioural sciences (Johnson and Onwuegbuzie, 2004; Johnson *et al.*, 2007; Venkatesh *et al.*, 2013). Mixed method research is also used to understand phenomena in Information Systems (Venkatesh *et al.*, 2016). Whereas Design Science Research, as mentioned before, in contrast to behavioural research, is a problem-solving research paradigm.

(Canonical) Action Research *“aims to contribute both to the practical concerns of people in an immediate problematic situation and to the goals of social science by joint collaboration within a mutually acceptable ethical framework”* (Rapoport, 1970, p. 499). Canonical Action Research is based on five principles (Davison *et al.*, 2004; Iivari and Venable, 2009): (1) joined collaboration and agreement between researcher and client, (2) following a cyclical process model, (3) the need for a theoretical framework to guide the researchers activities, (4) change through action (i.e., diagnosing the problem, action planning, taking and evaluation) to improve the clients situation, and (5) learning through reflection. Thus, following an Action Research approach aims to understand existing realities, i.e., human behaviour or how organisations work. In contrast, DSR creates new realities by crafting new and innovative artefacts to solve a class of problems (Iivari and Venable, 2009). Iivari and Venable (2009) also state that Action Research is a research method, whereas DSR is more of a research orientation, within which one can use various research methods.

Action Design Research is solving the methodical issue of how to integrate action elements into DSR projects (Maccani *et al.*, 2015). Action Design Research *“is a research method for generating prescriptive design knowledge through building and evaluating ensemble IT artefacts in an organizational setting”* (Sein *et al.*, 2011, p. 40). Action Design Research can be understood as an application of Design Science Research to address an organisational problem (an instance of a class of problems) and to do a highly participatory evaluation (Maccani *et al.*, 2015). Action Design Research considers that the artefact emerges from the interaction with the application context (i.e., the organisation) (Sein *et al.*, 2011). In Action Design Research, the design process is highly participative; thus, the organisation's members involved in the activities to be investigated are part of the research team from an early stage (Maccani *et al.*, 2015). Whereas DSR aims to develop general artefacts that are not only suited for a specific application (organisational) context but also where organisational interventions play a subordinate role (Maccani *et al.*, 2015)[12].

These research approaches have already been compared by other scholars, such as Iivari and Venable (2009), comparing Action Research and Design Science Research; Maccani *et al.* (2015), comparing Action Design Research with Design Science Research and Canonical Action Research; or Dresch *et al.* (2015) who compared Case Study Research, Action Research and Design Science Research.

The following section will describe how we have implemented the Design Science Research methodology in this thesis and the methods and techniques used.

[12] Also quoting Cole *et al.* (2005).

3.2 Research Design of this Thesis[13]

3.2.1 Structuring the Research Process as Design Cycles

The research process documented in this thesis is oriented along with the cycles of Hevner (2007). We identified relevant *problems* while practising data-driven business model innovation within an offline established organisation (*Comp*) as our environment. A detailed description of the case study setting follows in section 3.2.2. Next, for each problem, we consolidated the *knowledge base* for already existing approaches (concepts, tools and methods) to support practitioners with this problem and identified corresponding *research gaps*. As, in every cycle, there was no existing suitable solution available, we crafted an artefact *design* (i.e., a tool, method or concept) informed by theory and requirements from the case. Each of these artefacts is subsequently *evaluated* on a broader basis also with participants and cases outside the organisational boundary of *Comp* (e.g., interviews with experts in business model innovation). By communicating the artefact to the scientific community via publication, we also extend the knowledge base and close the research gap. Finally, each artefact was introduced to and applied in the context of *Comp*. While practising data-driven business model innovation, we identified new problems during this process and started a new design cycle. An overview of the design cycles and corresponding research activities follows in section 3.2.3. Each artifact represents a separate research stream in this thesis.

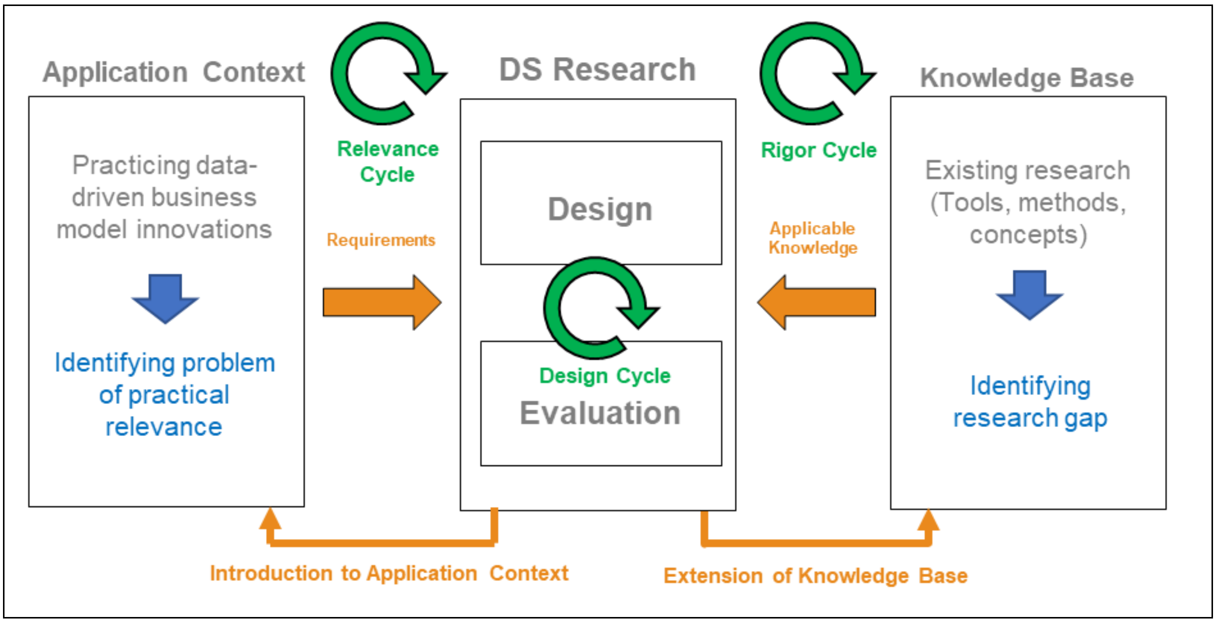


Figure 3.1: The research process in this thesis is structured by the cycles of Hevner (2007).

At some points during this research, we investigated a problem in more detail (i.e., beyond designing a tool or method) from a theoretical perspective. For instance, after designing a visual tool to structure ideas for data-driven business models (see Chapter 5.2), we investigated the phenomenon of data-based value creation in more detail and created a corresponding ontology

[13] Part of this chapter was published as Fruhwirth, M., Pammer-Schindler, V., and Thalmann, S. 2019. “To Sell or Not to Sell: Knowledge Risks in Data-Driven Business Models,” 2019 Pre-ICIS SIGDSA Symposium on Inspiring mindset for Innovation with Business Analytics and Data Science, Munich 2019.

(see Chapter 5.3). Similarly, after designing and evaluating a tool to identify knowledge risks in a business model design (see Chapter 6.2), we investigated the phenomenon of knowledge risks through the exchange of data-related value objects from a theoretical perspective (see Chapter 6.3).

3.2.2 Case Study Setting

As already pointed out, this PhD thesis is embedded in a research project and case study with an automotive organisation. Due to confidentiality, we use the acronym of *Comp*. To assure a high level of anonymity, we provide only minimal information about the case. *Comp* is one of the world's leading companies in engineering and testing of automotive systems. *Comp* has more than 10,000 employees and operates in a B2B context. The automotive industry is a domain that is currently undergoing a significant transformation in its business model logic due to the emergence of data-driven technologies, as examples such as autonomous driving or shared and electric mobility show. These developments threaten existing car sales business but at the same time offer opportunities for new revenue streams with data-driven business models (Seiberth and Gründinger, 2018), thus pressuring automotive companies towards business model innovation. *Comp* therefore also wants to offer new products and services based on data analytics. *Comp* needs a structured approach and supporting tools and methods to achieve that. Concerning design science research, *Comp* constitutes the environment in which research problems are defined and shown to be relevant (Hevner *et al.*, 2004).

We conducted this case study over three years, from 2018 to 2021. As pointed out already, the main goal of this case study was to develop ideas and concepts for new data-driven business models and design support for that process. The case study was structured into four parts. First, we aimed to understand the current business of *Comp* and to get an overview of existing data sources and initiatives. Therefore, we interviewed responsible managers from different departments and business units. Second, we supported *Comp* in generating new data-driven business model ideas through ideation workshops and helped them evaluate them and decide on the most promising ideas. Third, we elaborated on selected DDBMs on a more detailed level, e.g., preparing customer interviews or business model development workshops. Finally, we reflected on the learnings from practising data-driven business model innovation and synthesised them into a systematic process design.

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 data-driven business model innovation initiatives. This approach allowed us to access meaningful research data (Korhonen *et al.*, 2021). Aside from 28 semi-structured interviews, the interventionist case study includes 97 documented meetings and workshops with 73 representatives of Comp. Further, one researcher actively participated in seven data-driven business model initiatives at Comp. In our case study, we observed how data-driven business model innovation is practised in one offline-established organization, what problems arise, and what support is needed. In each phase, we identified problems of practical and scientific relevance and designed and evaluated interventions (i.e., supporting tools and methods). The following section describes these cycles of problem identification, design, and evaluation in detail.

3.2.3 Design Science Research Cycles during the Thesis

We will now describe how we arrived at the different sub-research questions of this thesis and the artefact designs presented in the following chapters. We will structure the research activities again by the design cycles of Hevner (2007). We will start in each cycle with a problem from the environment (i.e., the case study with *Comp*), look into the knowledge base of what is already available, and craft a design to solve this problem. Further, we evaluate and apply the artefact in the context of *Comp* and outside in other organisations. While using the artefact and practising data-driven business model innovation, we identify additional problems addressed in this thesis. At some points, we dig deeper and investigate a problem from a more theoretical perspective ("Theoretical Investigation").

The design and evaluation of individual artefacts is done via sub-DSR projects. For some of them we use specialized methods such as Nickerson *et al.* (2013) for taxonomy development, whereas for others we referred to the generic process models of DSR projects. The detailed research process and applied methods are described in the respective sub-chapters of the results part.

We note here that not all sub-DSR projects have been investigated with the same depth and rigor. Some of them have been important immediate steps that contributed to the identification of later research questions and the overall process design (see here Limitation 3 described in Chapter 7.4).

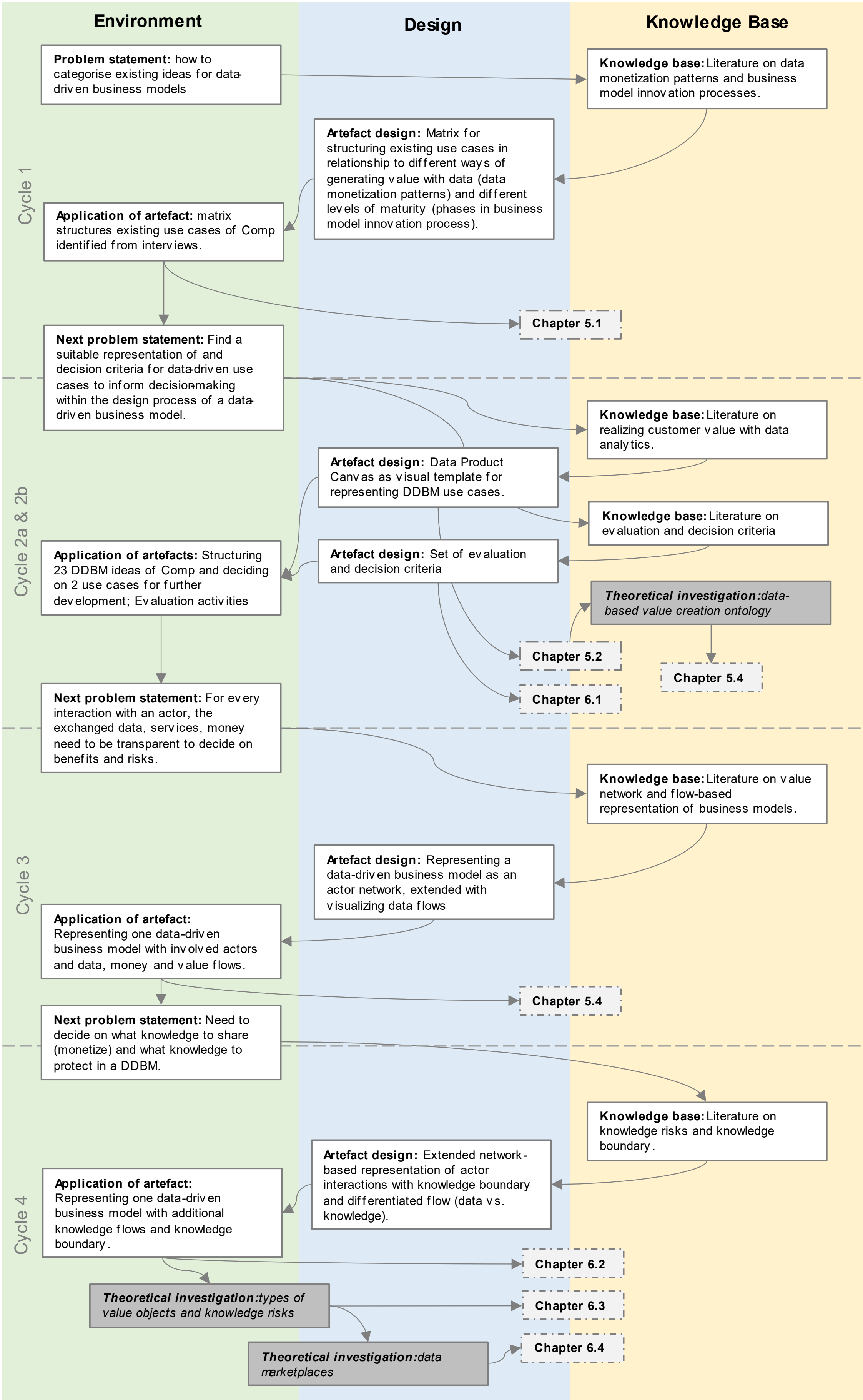


Figure 3.2: Overview of design cycles structured along with the cycles of Hevner (2007) (own representation).

Starting Point: Structured Literature Review

As outlined already in section 1.3, the goal of this thesis is to explore how to design tools, methods and concepts that support organisations in developing data-driven business models, in particular support idea generation and evaluation activities. Therefore, as a first step, we conducted a structured literature review to identify existing tools and methods from the knowledge base (see Chapter 4.1 and Fruhwirth *et al.*, 2020c). We found that little research has been conducted to design support for data-driven business model innovation. Existing work mainly focuses on understanding the phenomenon of data-driven business models in the context of start-ups (e.g. through developing a taxonomy of data-driven business models).

Design Cycle 1: Scoping and Ideation

Problem Statement & Goal: As a first specific problem in the case study, we identified the need for *Comp* to categorise existing ideas for data-driven business models. This analysis is necessary to see the status quo in an organisation that lays the foundation for the direction of innovation. We could not find proper support for that categorisation problem in the structured literature review.

Knowledge Base & Conceptual Perspective: We searched for patterns of data monetisation (i.e., different ways of generating value from data) and phases of business model innovation (i.e., levels of maturity) in the literature. Two dimensions that can help to structure DDBM ideas.

Design Artefact: Based on these two conceptual dimensions we designed an artefact, i.e., a matrix, to structure DDBM ideas and to map a portfolio of ideas. The rows of the matrix encompass different patterns of DDBMs and the rows depict the current phase of a business model innovation (see Chapter 5.1).

Environment: Through 17 interviews with representatives of *Comp*, we identified ideas for data-driven business models and existing data-based offerings in place. We clustered these ideas and offerings by using the artefact described above. The matrix and the result of the clustering were discussed in a half-day workshop with four managers of *Comp* who were specifically responsible for data-driven innovations. Second, we used the matrix to structure the direction of a one-day ideation workshop with 10 participants from product-, business and innovation management of *Comp* (6) and other organizations (4). Later, we also used the categorisation scheme to structure existing data-based offerings at *Comp* for internal training on data-driven business models.

Conclusion for the next cycle: Based on interviews and workshops, we identified (a) the need for a structured representation of data-driven business model ideas (and in particular with a focus on the value proposition) and (b) the need for criteria to evaluate those ideas and to inform decision-making. These new problem statements were addressed in two interconnected cycles 2a and 2b.

Design Cycle 2a: Structured Representation and Idea Generation

Problem Statement & Goal: Building on iteration 1, the goal of iteration 2a was to design a suitable representation of data-driven business model ideas that take the specific aspects of data and analytics into account.

Knowledge Base & Conceptual Perspective: We derived five design requirements for such a representation from the literature. Further, we evaluated existing representations identified in our structured literature review against these design requirements and found that none of these artefacts met all requirements.

Design Artefact: We used these requirements to design a visual tool with a component-based representation of data-driven business models as our design artefact – the *Data Product Canvas* (see Chapter 5.2 and Fruhwirth *et al.*, 2020a).

Environment & Evaluation: We evaluated the artefact in four workshops with 49 representatives of offline-established organisations. As one outcome of this evaluation, some workshop participants did not fully understand or could clearly distinguish all representation elements. Further, we used this artefact to describe 23 data-driven business model ideas of *Comp* (see here design cycle 2b).

Detailed Theoretical Investigation 1: As a results from the workshop evaluation, we decided to develop an ontology about the data-based value creation logic to build the representation on a solid theoretical foundation as a separate detailed theoretical investigation (see Chapter 5.3).

Conclusion for next cycle: Described together with design cycle 2b.

Design Cycle 2b: Evaluation and Decision-Making

Problem Statement: The goal of design cycle 2b was to design support for evaluating data-driven business model ideas. The evaluation aims to select use cases that have the greatest impact on an organisation (e.g., financial returns). The most promising ideas are filtered out of multiple options to use limited resources optimally. This involves balancing estimated returns and risks (Tesch and Brillinger, 2017). Therefore, we refined our current research problem towards a decision problem, such that we understand *"business models [to be] made of concrete choices and the consequences of these choices*" (Casadesus-Masanell and Ricart, 2010, p. 198).

Knowledge Base & Conceptual Perspective: As there was no artefact available in the literature that supports the evaluation of data-driven business models (see our literature review in Chapter 4.1 and Fruhwirth *et al.*, 2020c), we investigated the knowledge base for evaluation and decision criteria in business model innovation and DDBM literature. As guiding conceptualization we used the framework of viability, desirability and feasibility proposed by Bland *et al.* (2020). Further, we enriched our criteria list with insights from the case study.

Design Artefact: As an artefact we developed a set of evaluation and decision criteria. We operationalized the criteria by providing a visualisation including response scales.

Environment & Evaluation: We discussed the criteria with four managers at *Comp* and in a second step, three managers applied it to one of their use cases to assess its maturity. Further, we applied the initial set of criteria to evaluate 23 data-driven business model ideas, represented in the Data Product Canvas (see design cycle 2a), with three decision-makers at *Comp*. We found that a visualisation of the partner network and the associated interactions were missing, as *Comp's* ideas are often based on external data sources from their customers and partners. This information was expected to be additionally necessary to make further informed decisions in the business model innovation process.

Conclusion from design cycle 2a and 2b for next cycle: Following from our workshop with *Comp*, we identified a new problem statement for the next design cycle: For every interaction with an actor, the exchanged data, services and money need to be transparent to decide on benefits and risks.

Design Cycle 3: Network-based Representation of Data-Driven Business Models

Problem Statement & Goal: Building on the insight of iteration 2a and 2b, we found the next problem, that all business interactions with actors and the exchanged values need to be transparent. This is necessary to decide on the benefits and risks in the design process; and the overall feasibility of a data-driven business model idea.

Knowledge Base and Conceptual Perspective: We consolidated the knowledge base (i.e., existing tools and methods for supporting data-driven business models). We found that no research has been conducted with a transactional representation of data-driven business models. Therefore, we conducted a structured literature review to identify types and properties of actors as well as types of exchanged values in a data-driven business model and created a framework of actors and exchanged values.

Design Artefact: We created, as the design artefact within iteration 3, a transaction-based representation of data-driven business models as a value network including actors and exchanged values based on the conceptual framework (see Chapter 5.4 and Leski *et al.*, 2021).

Environment & Evaluation: We evaluated our framework with three experts at *Comp* and aimed to visualise one of their DDBM use cases each. Further, we instantiated the artefact with one selected data-driven business model idea of *Comp*. The data-driven business model was discussed and refined in two two-hour workshops, one with two managers responsible for data-driven innovations and one with six representatives from product management, R&D and engineering. During the first workshop, this representation led to the insight that knowledge is the core asset of *Comp's* data-driven business model idea on which all business model services rely.

Conclusion for next cycle: This immediately triggered the awareness that the knowledge materialized in the prediction model is critical and could, in principle, be at risk in the data-driven business model, especially when it is part of the value proposition, thus leading to unintended knowledge-spill-overs. Thus, this risk needs to be identified and considered in the creation of a data-driven business model.

Design Cycle 4: Knowledge Risks in Data-Driven Business Models

Problem Statement & Goal: Based on the workshop's insight from iteration three that knowledge is the critical asset of a data-driven business model, we frame a more detailed decision problem: Find a trade-off between the benefits of monetizing knowledge (i.e., knowledge as part of the value proposition) and the risk of leaking this knowledge.

Knowledge Base: Again, when consulting the knowledge base, little research was available that considers risks in data-driven business models in general and knowledge risks in particular. Therefore, in design cycle four, we aimed to adopt the artefact from cycle three to support the identification of knowledge risks in a data-driven business model design. Therefore, we investigated the literature on knowledge risks and knowledge boundaries to inform the artefact design.

Design Artefact: We extended our artefact from design cycle 2b with the visualization of the knowledge boundary to support the identification of knowledge risks via exchanging data-related value objects in a data-driven business model.

Environment & Evaluation: We represented one data-driven business model of *Comp* (from iteration 3) in an instantiation of the refined artefact. To evaluate the artefact in terms of usefulness and completeness, we conducted 17 interviews outside comp with experts in business model innovation, data analytics and risk management (see Chapter 6.2 and Fruhwirth *et al.*, 2021b). We found in the evaluation that a more nuanced differentiation of exchanged value objects is necessary to assess the knowledge risk in a DDBM.

Detailed Theoretical Investigation 2: To understand the phenomenon of knowledge risks in data-driven business models in more detail from a theoretical perspective, we conducted an explorative interview study with 23 experts[14]. A qualitative content analysis of the interview transcripts led to the insight that different types of data-based exchanged value objects (i.e., data, models and predictions) lead to different knowledge risks and protection measures (see Chapter 6.3).

Detailed Theoretical Investigation 3: During this study, we found that using *data marketplaces* are one approach to protect knowledge that can be discovered from exchanged value objects. Nevertheless, there is little knowledge available about this new type of actor in the literature. Therefore, we investigated the phenomenon of data marketplaces from a business model perspective by developing a taxonomy and identifying archetypes (see Chapter 6.4 and Fruhwirth *et al.*, 2020b).

Synthesis: Process Design

Apart from the problems identified in the previous design cycles, one need of *Comp* was a systematic approach for identifying, evaluating and implementing data-driven business models in terms of a process model. Up to date, there is little knowledge available about such systematic processes (see Chapter 4.1). We used the collected data from the 3-year case study and the reflections about practising data-driven business model innovation at *Comp* to derive design requirements, features, and principles for a data-driven business model innovation process. During this process, we also aggregated the individual design outcomes from the previous design cycles (see Chapter 4.2 and Fruhwirth and Pammer-Schindler, 2023).

[14] The first 17 interviews were conducted together with the artifact evaluation.

3.2.4 Overview of Research Design and Outcomes of Individual Chapters

Table 3.1 summarises the objective and applied method(s), the collected data, and the design outcome of each research study of this thesis. Each study (research chapter) is also linked to the corresponding design cycle as described in the previous section. The detailed description of the method for each sub-study is described in the respective chapter.

Cycle	Ch.	Objective and Method	Data	Design Outcome
-	4.1	Conducting a structured literature review to identify tools and methods supporting DDBM innovation	33 publications	Toolbox with existing tools and methods structured along with the process phases
1	5.1	Conducting a sub-DSR project to identify an approach to structure DDBM ideas ➢ Reviewing literature ➢ Application in case study	23 DDBM use case ideas (iteration 1) Classifying 4 DDBM offerings at *Comp* (iteration 2)	7 types (patterns) of DDBMs Matrix (visual tool) to structure DDBM ideas
2a	5.2	Conducting a sub-DSR project following Peffers *et al.* (2007) to design a visual collaborative tool that supports idea generation and structured description of DDBMs ➢ Reviewing literature & deriving design requirements ➢ Application in case study ➢ Evaluation in workshops	Qualitative data from 4 evaluation workshops with 49 participants.	The Data Product Canvas (visual collaborative tool)
2a	5.3	Building an ontology for data-based value-creation following existing procedures and guidelines for ontology development	Review of existing literature on DDBMs and value creation 5 use cases at Comp to apply and evaluate the ontology	Ontology with a glossary consisting of 10 key concepts and relations between them
2b	6.1	Sub-DSR project structured by the phases of Vaishnavi and Kuechler (2015) to develop a set of decision criteria that supports evaluation and decision making in DDBM innovation identified from the knowledge base and the case study.	Review of existing literature on evaluation and decision-making in business model innovation Evaluation of completeness through interviews with four managers Applying artefact to three use cases	Set of 28 criteria in 6 categories Instantiation as a visual tool
3	5.4	Conducting a structured literature review to identify actors and exchanged values in a DDBM	33 publications 3 interviews for evaluation (applying tool to cases)	Framework with 8 roles, 2 attributes of actors and 3 types of exchanged values

4	6.2	Conducting a sub-DSR project to design and evaluate a visual artefact to identify knowledge risks in a DDBM ➢ Deriving design requirements in the case study via DSR cycles ➢ Evaluation via expert interviews	Problem identification in one case Evaluation with qualitative data from 17 expert interviews	Network-based tool to identify knowledge risks in a DDBM
4	6.3	Conducting a qualitative explorative study via semi-structured expert interviews to explore knowledge risks in data-driven business models	Qualitative data from 28 expert interviews	Framework with five types of risks, with contextual factors and protection measures
4	6.4	Following the taxonomy creation approach of Nickerson *et al.* (2013) to identify the characteristic elements of data marketplaces from a business model perspective	Qualitative data for 20 data marketplaces from publicly available sources, like company websites or presentations	Taxonomy and four archetypes of data marketplaces business models
-	4.2	Conducting a meta-DSR project embedded in the case study with to craft design knowledge for a business model innovation process ➢ Deriving design requirements from interviews in the case study ➢ Process design via design features ➢ Design principles via reflection and abstraction	Qualitative data from one case study: 28 interviews; 97 documented meetings and workshops; active participation in seven DDBM innovation cases	6 design requirements, 8 design features and 3 design principles for a DDBM innovation process

Table 3.1: Overview of research methods, research data and design outcomes of each research chapter of this thesis (own representation).

After motivating the goal of this thesis, providing the theoretical background on business model innovation and data-driven business models and giving overview presenting the overall research approach of this thesis in Part I of this thesis, Part II will now present the individual research studies and chapters.

Part II
Studies

Chapter 4

Systematic Process Design and Toolbox

"Success is systematic and not automatic."

Kruthika SV[15]

This chapter focuses on a systematic process design supporting data-driven business model innovation. Chapter 4.1 presents a collection of tools and methods structured by phases of business model innovation based on a structured literature review. Chapter 4.2 presents design requirements, features and principles for a business model innovation process based on the case study with *Comp* and a corresponding three-year design science research project.

4.1 A Structured Literature Review on Tools and Methods Supporting Data-Driven Business Model Innovation[16]

4.1.1 Introduction

As the background chapter shows, the literature recognises and researches tools and methods as support for business model innovation processes (Schneider and Spieth, 2013). Several established tools and methods exist, i.e., for designing and evaluating business models (Osterwalder and Pigneur, 2010; Osterwalder *et al.*, 2014; Täuscher and Abdelkafi, 2017; Tesch and Brillinger, 2017). However, developing data-driven business models requires attention to data as a key resource and analytics as key activities. Thus, in addition to such established generic tools and methods, supporting innovation tools and methods that incorporate the perspectives of data and analytics are required to support traditional offline established organizations. Research has already started to develop such tools and methods, but the literature has not been assessed systematically. Consequently, we investigate the following question in this chapter:

What knowledge is available about tools and methods incorporating data as a lens of analysis for business model innovation?

We answer this question through a structured literature review. In this chapter, we structure existing knowledge from previous research on tools and methods with a data focus, identify under-researched fields and provide directions for further research. Concerning existing literature reviews

[15] https://www.yourquote.in/kruthika-sv-dbr4/quotes/success-systematic-not-automatic-45vw accessed on Jan 22nd 2022, 12:41.
[16] This chapter is based on: Fruhwirth, M., Ropposch, C. and Pammer-Schindler, V. (2020), "Supporting Data-Driven Business Model Innovations. A structured literature review on tools and methods", *Journal of Business Models*, Vol. 8 No. 1, 7-25.

on tools and methods in business model innovation in general (for example, visual languages for business models (John *et al.*, 2017), visual tools (Täuscher and Abdelkafi, 2017) or evaluation aspects in business model innovation (Tesch and Brillinger, 2017)), the present literature review takes the complementary perspective of focusing on data as a lens of analysis in business model innovation. Concerning research on data-driven business models, this review complements existing literature reviews such as how to realize value with big data (Günther *et al.*, 2017), digital service innovation enabled by big data analytics (Rizk *et al.*, 2017) or data-driven service innovation (Engel and Ebel, 2019) by focussing on support for the innovation process.

The remainder of this chapter is structured as follows: Section two provides additional background on tools and methods for business model innovation, serving as the conceptual framework for analysis. Section three follows with a description of the process of the structured literature review. The review's findings are structured in section four by the concepts, type of contribution, type of thinking supported and the business model elements studied in each paper. Section five synthesizes existing tools and methods into a toolbox. Subsequently, section six discusses the review and outlines further research. Section seven lists the limitations of this research. This chapter closes with a conclusion and a statement on the implications of this research in section seven.

4.1.2 Additional Background on Tools and Methods in Business Model Innovation

Different tools and methods support individuals and organizations in business model innovation (Schneider and Spieth, 2013). A *method* is a systematic development approach that follows specific rules, whereas a *tool* supports a part of a development process (Brinkkemper, 1996).

Several types of tools and methods are available that support business model innovation. *Visual representations* are one key approach in designing and analysing business models (Täuscher and Abdelkafi, 2017). Visual representations support understanding and communicating a firm's business model (Eppler *et al.*, 2011; Osterwalder, 2004), support generating and developing new business model ideas (Gassmann *et al.*, 2014; Osterwalder and Pigneur, 2010), overcoming organizational innovation barriers (Eppler *et al.*, 2011) or stimulate collaborative innovations (Täuscher and Abdelkafi, 2017). Visual representations can incorporate a transactional, a causal and/or a component-based view (Täuscher and Abdelkafi, 2017). Furthermore, component-based views are based on ontologies or frameworks (Osterwalder, 2004; Osterwalder and Pigneur, 2010). *Taxonomies* and morphological boxes of business models from a certain domain list the most relevant dimensions and characteristics of business models and enable the classification of existing business models (Remane *et al.*, 2016). *Business model patterns* describe recurring configurations of certain business model elements and support idea generation and evaluation via learning from analogies (Gassmann *et al.*, 2014). *Software tools* can also support developing and managing business models (Veit *et al.*, 2014). These tools enable users to represent and change business models digitally, making the process more efficient (Szopinski *et al.*, 2019). Likewise, software tools allow additional actions like collaborative business model development in distributed teams (Ebel *et al.*, 2016). Finally, processes provide distinct phases and activities during business model innovation (Zott and Amit, 2015).

Tools and methods are used in business model innovation for idea generation (Eppler *et al.*, 2011), evaluation and decision-making (Tesch and Brillinger, 2017). These two opposed activities in business model innovation relate to the concepts of *divergent* and *convergent thinking* (Kim and Pierce, 2013) - on the one hand, seeking alternatives and multiple solutions and, on the other hand, deciding on the best possible solution.

Tools and methods can support specific tasks for designing or evaluating specific business model elements or support developing a business model in general. A broad range of tools and methods incorporate all elements of an underlying business model ontology, such as the business model canvas (Osterwalder and Pigneur, 2010). Besides, other tools and methods may also incorporate a view on a specific element of the business model, like the value proposition (Osterwalder *et al.*, 2014) or revenue models (Envision, 2016). A common view in the literature is to divide a business model into value creation, value proposition and value capturing (Gassmann *et al.*, 2014; Johnson *et al.*, 2008; Osterwalder and Pigneur, 2010).

However, besides general tools and methods for business model innovation, organizations require specialized tools that incorporate the specifics of data-driven business models, like data as a key resource or data analytics as a key activity. Knowledge of such specific tools and methods has not been systematically synthesised and discussed; doing so is the overall contribution of this chapter and this thesis in general. The background on tools and methods for business model innovation serves as an analysis framework and different viewpoints for identifying and analysing innovation tools and methods for data-driven business model innovation in this literature review.

4.1.3 Detailed Research Approach

To identify existing literature on supporting data-driven business model innovation, we conducted a structured literature review adopting the general methodology of Webster and Watson (2002) and the rigorous procedure for identifying relevant articles that Vom Brocke *et al.* (2009) proposed. The following subsections describe the search and selection, analysis, and synthesis of relevant literature.

4.1.3.1 Search and Selection Process

To ensure reproducibility and transparency of the process of searching and selecting relevant literature, we describe the five sequential steps in this subsection, summarised in Figure 4.1.

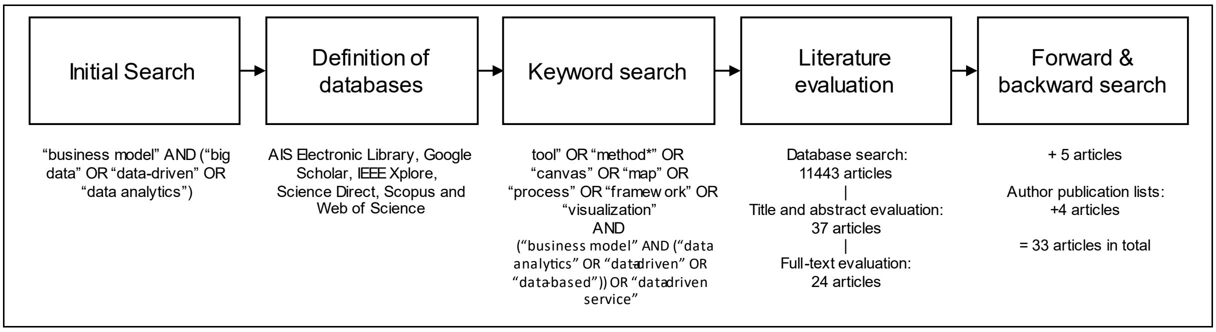


Figure 4.1: Overview of the search and selection process (own representation).

Step 1 - Initial search: We started the initial search within the AIS Electronic Library using the keywords “business model” AND (“big data” OR “data-driven” OR “data analytics”) to gain an overview of the research field from an Information System perspective.

Step 2 - Definition of databases: To identify relevant publications, we conducted a keyword search in the following databases: AIS Electronic Library, Google Scholar, IEEE Xplore, Science Direct, Scopus and Web of Science to cover research from the field of information systems, computer science and innovation and technology management. We did not set a filter by published year due to the infancy of the topic. Publications issued by May 2019 were considered.[17]

Step 3 - Keyword search: The selection of the search strings was initially based on first insights on the topic, as shown in step 1. As the research on data-driven business model innovation is still in its infancy, we extended the search focus to additional keywords to obtain more results, as publications may incorporate data as a central element without directly mentioning the phrase “data-driven business model”. We used a broad range of keywords to identify innovation tools and methods. We defined the first set of search strings as “tool” OR “method*” OR “canvas” OR “map” OR “process” OR “framework” OR “visualization” based on the background literature of this chapter. In addition, to find tools and methods with a business model and data focus, we defined (“business model” AND (“data analytics” OR “data-driven” OR “data-based”)) OR “data-driven service” as the second set of search strings; both combined with the logical operator AND. For the search base Google Scholar, we used the search string “data-driven business model”.

Step 4 - Literature evaluation: The keyword search resulted in a total set of 11443 articles from five databases. To limit the papers to a manageable size, we examined only the first 200 results in each database by sorting the results by the number of citations (or by relevance if sorting by citations was not offered by the individual search database) to capture the most relevant papers. Our selection process involved two stages. In the first stage, papers were judged based on their title, abstracts and keywords. The remaining papers were judged by reading the full text, resulting in 37 articles. We included publications that comply with the following criteria: a publication that has a business model focus or at least one aspect of the business model, like value creation or value proposition; and that has at least a partial focus on data or analytics; and that describes a tool or

[17] We denote not taking into account publications published June 2019 onwards as a general limitation of this chapter (see section 4.1.7). Nevertheless, with our later described research gaps and avenue for future research, we set the path for other parts of this thesis.

method with data as a significant focus on supporting innovation processes; and that are available either in English or German. We restricted the keyword search to peer-reviewed publications. In the forward and backward search and the list of promising authors, we also included non-peer-reviewed publications, such as working papers. In the next stage, numerous duplicates were identified and deleted, leading to 24 relevant articles.

Step 5 - Forward and backward search and reviewing authors' publication lists: A subsequent forward and backward search (Webster and Watson, 2002) performed through Google Scholar and Web of Science provided an additional set of 5 articles using the same evaluation criteria as stated above. Moreover, we looked up publication lists of the authors identified in the previous steps (Schryen, 2015), leading to an additional set of 4 publications. Finally, the search and selection process resulted in a total number of 33 articles.

As shown in Figure 4.2, the final set of papers to review was published between 2015 and 2019. We observed an increasing publication frequency over the years, except for 2019, where we covered publications only for the first five months. Figure 4.3 shows the rating of the selected publications according to VHB-JOURQUAL3[18][19].

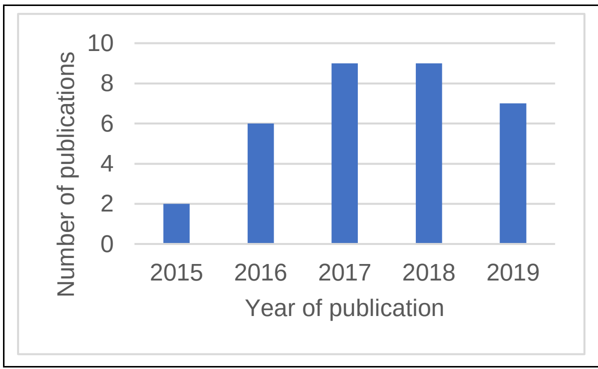


Figure 4.2. Descriptive analysis of selected literature due to the publication year.

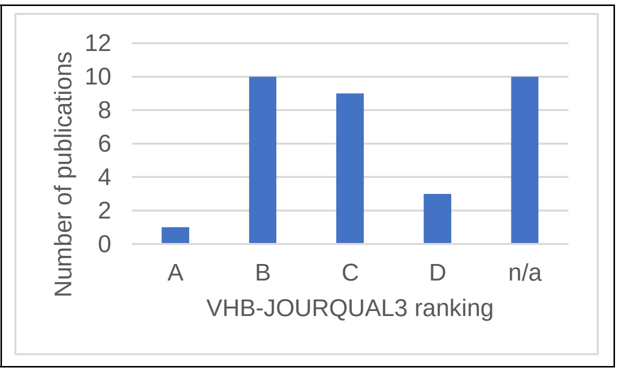


Figure 4.3. Rating of selected publications according to VHB-JOURQUAL3 ranking.

4.1.3.2 Analysis and Synthesis Process

The analysis and synthesis step aims to summarize and analyse existing research on tools and methods supporting the process of data-driven business model innovation and to identify gaps in the literature. In this regard, the 33 relevant papers are analysed from a concept-centric perspective, as recommended by Webster and Watson (2002). Concepts serve as the framework of the review to synthesize and discuss the literature in the context of each concept and identify patterns and gaps (Vom Brocke *et al.*, 2009; Webster and Watson, 2002). Thus, a concept matrix is created from the literature search results. The concept matrix contains the identified papers in one dimension and the concepts and their characteristics in the other. The concepts we used are

[18] VHB-JOURQUAL3 is a ranking of journals relevant to business research based on evaluations by the members of the German Academic Association for Business Research. For further information see: https://vhbonline.org/vhb4you/jourqual/vhb-jourqual-3/.
[19] The topic of data-driven business model has gained traction and interest in the literature in the following years. Recent publications are not covered by this literature review but are summarised in the background section of this thesis.

the research question or goal of each paper, the research method of the article, the type of contribution, the type of thinking supported by each tool or method, and the core business model element(s) the article is focusing.

The type of contribution describes the type of tool or method presented in the research. Categories of this concept were developed by an inductive approach informed by the literature on tools and methods for business model innovation (see background section). The type of thinking says what type of cognitive approach in the sense of convergent vs. divergent thinking (Kim and Pierce, 2013) the artefact supports, which relates to the activities of ideation and evaluation in business model innovation. The business model element states the core elements of a business model the article focuses on. The corresponding categories are value creation, value proposition and value capturing, derived by a deductive approach from existing business model research (Gassmann *et al.*, 2014; Johnson *et al.*, 2008; Osterwalder and Pigneur, 2010).

On the one hand, the concept matrix aims to derive distinct perspectives on tools and methods for supporting data-driven business model innovation. On the other hand, sparse parts of the concept matrix demonstrate under-researched fields, thus providing avenues for further research (Vom Brocke *et al.*, 2009). To show directions for future research, we identify missing or neglected themes in what has been researched, which Alvesson and Sandberg (2011) call gap-spotting.

4.1.4 Result 1: Analysis of Existing Literature

Appendix A gives an overview of all 33 publications that are included in this literature review and shows how current work differs significantly across the three concepts of “type of contribution”, “type of thinking supported”, and “element of business model”. The following subsections below synthesize research with respect to the core elements of this concept matrix.

4.1.4.1 Types of contributions

We identified six types different types of contributions in the 33 reviewed papers: “taxonomies and frameworks”, “patterns and types”, “visual tools”, “methods”, “IT tools”, and “processes”. *Taxonomies and frameworks* (Bock and Wiener, 2017; Engelbrecht *et al.*, 2016; Hartmann *et al.*, 2016; Schmidt *et al.*, 2018) represent a “basis for the analysis and clustering of big data-related business models” (Hartmann *et al.*, 2016, p. 1400) and list the main elements and characteristics of data-driven business model innovation.

Business model patterns and types (Förster *et al.*, 2019; Hartmann *et al.*, 2016; Schmidt *et al.*, 2018; Sprenger and Mettler, 2016) “can serve as an inspiration and blueprint” (Hartmann *et al.*, 2016, p. 1400) for organizations. In the context of established organizations, data-enabled business model transformation patterns (Schüritz and Satzger, 2016; Zolnowski *et al.*, 2016) illustrate what business model elements can be affected by data and analytics. *Visual tools* mediate collaboration and support ideation for data-driven innovations. Such visual tools can be divided into a component view (e.g., (Exner *et al.*, 2017; Hunke and Schüritz, 2019; Kühne and Böhmann, 2018, 2019; Nagle and Sammon, 2017)), a transaction view (Brillinger, 2018; Terrenghi *et al.*, 2018) or a causal view

(Förster *et al.*, 2019). Besides such holistic representations of business models, specialized tools emerge (Agrawal *et al.*, 2018a; Hunke and Schüritz, 2019; Hunke and Wambsganß, 2017; Kronsbein and Mueller, 2019; Kühne and Böhmann, 2019; Mathis and Köbler, 2016; Nagle and Sammon, 2017). They support the generalized representation of a business model (Kühne and Böhmann, 2019) by focusing on its central elements, such as key resources, key activities or the value proposition. Transaction- or graph-based representations visualize value networks (Brillinger, 2018; Terrenghi *et al.*, 2018) or data-driven service systems (Kammler *et al.*, 2019). Representations with a causal view visualize the cause-and-effect relations of data in business models (Förster *et al.*, 2019).

We also revealed the *methods* of use for visual tools (Brillinger, 2018; Nagle and Sammon, 2017) or certain types of workshops, like "data discovery sessions" (Schüritz *et al.*, 2017a). Furthermore, we identified the description of how "data thinking workshops" are supported by visual tools (Kronsbein and Mueller, 2019) to generate ideas. Apart from ideation, the methods also support the evaluation of a business model in terms of a "data value assessment" (Wixom and Markus, 2015), a "cost-benefit analysis" (Zolnowski *et al.*, 2017) or the measurement of customer benefit and financial success (Wixom and Schüritz, 2018).

Two publications comprise an *IT-tool*-related contribution. Spiekermann *et al.* (2018) propose a metadata model for data goods as the key resource of data-driven business models. Terrenghi *et al.* (2018) state to implement design elements of a network-based representation via a software-reference model.

Process models in data-driven business model innovation shape the last type of contribution. Such processes describe distinct steps or phases of a data-driven business model innovation, starting with an "Understand" (Benta *et al.*, 2017) or "Initiation" (Hunke *et al.*, 2017) phase, where the current situation of the organization is analysed, and potential data sources are identified. This phase is followed by "Ideation" (Hunke *et al.*, 2017), "Idea generation" (Kayser *et al.*, 2018), "Design" (Benta *et al.*, 2017) or "Use case generation" (Schüritz *et al.*, 2017a) phase, to generate different concepts of and ideas for a business model. Subsequently, a phase of "Proof of concept and evaluation" (Kayser *et al.*, 2018; Schüritz *et al.*, 2017a) or "Prototyping and testing" (Hunke *et al.*, 2017) takes place to test the business model prototype and to evaluate risks. Finally, an "Implementation" (Benta *et al.*, 2017; Schüritz *et al.*, 2017a), "Realization" (Hunke and Wambsganß, 2017) or "Professionalization" (Kayser *et al.*, 2018) phase takes place that aims to implement and operationalize the business model.

4.1.4.2 Types of thinking

We classified existing research also by the type of thinking supported by the artefact for the business model innovation activity of ideating and evaluating. Idea generation for data-driven business model innovation can be supported by frameworks and patterns (Bock and Wiener, 2017; Engelbrecht *et al.*, 2016; Förster *et al.*, 2019; Hartmann *et al.*, 2016; Schmidt *et al.*, 2018; Sprenger and Mettler, 2016), visual tools (Agrawal *et al.*, 2018a; Hunke and Schüritz, 2019; Hunke and

Wambsganß, 2017; Kronsbein and Mueller, 2019; Kühne and Böhmann, 2019; Mathis and Köbler, 2016; Nagle and Sammon, 2017) as well as open questions (Brownlow *et al.*, 2015; Exner *et al.*, 2017) facilitating divergent thinking. Fewer publications focus on evaluation and decision-making, corresponding to convergent thinking. Such activities encompass the analysis of costs and benefits of data and data-driven business model innovation ideas (Wixom and Markus, 2015; Zolnowski *et al.*, 2017); the measurement of created customer value and financial success of a data-driven business model (Wixom and Schüritz, 2018); the reflection on risks (Brillinger, 2018; Wixom and Markus, 2015); influencing factors for decisions on revenue models (Enders *et al.*, 2019) or decision points in the innovation process (Schüritz *et al.*, 2017a).

4.1.4.3 Elements of the business model

Tools and methods incorporate a holistic view or focus on specific business model elements. From the value creation perspective, existing research focuses on elements such as data as the key resource (Mathis and Köbler, 2016; Spiekermann *et al.*, 2018) or data analytics as key activities (Hunke and Wambsganß, 2017). Data-driven services are investigated from a value proposition perspective (Hunke *et al.*, 2019; Hunke and Schüritz, 2019; Kammler *et al.*, 2019; Rizk *et al.*, 2018). Previous research incorporates revenue models and financial evaluation from a value-capturing perspective (Enders *et al.*, 2019; Schüritz *et al.*, 2017b; Wixom and Schüritz, 2018; Zolnowski *et al.*, 2017). Other tools and methods combine two aspects of the business model, such as data as a key resource and the value proposition (Kühne and Böhmann, 2019) or data as the key resource and analytics as key activities (Nagle and Sammon, 2017).

4.1.5 Result 2: Synthesis of tools and methods towards a toolbox

We assigned all identified tools and methods to the corresponding phases and activities of business model innovation, serving as a toolbox, as Table 4.1 shows. On the contrary, the table in **Appendix A** structured the identified papers based on the concept matrix. We have chosen the business model management process in offline-established organizations based on the empirical work of Terrenghi (2019). Table 4.1 shows that most research is available for the design phase of data-driven business model innovation. This implies the current focus of research and the specific need for supporting organizations and individuals in design and idea generation in data-driven business model innovation.

Further, we clustered tools and methods based on different research perspectives. As shown in Table 4.1, tools and methods emerged from different conceptual backgrounds with a diverging focus on the resource data and the business model concept: data-driven business models (i.e., full data and business model focus), digital business models (i.e., partial data and full business model focus) or data-driven innovation (i.e., partial business model and full data focus). This implies that no common wording has been established around data-driven business model innovation and that tools and methods are researched from different perspectives (e.g., business model innovation or service innovation), serving the same purpose for practice.

	Analysis	Design	Evaluation	Implementation	Controlling
Data-driven Innovations *(Partial business model focus)*	Data value assessment[1] Data innovation board[2] Data value map[3] Data discovery sessions[4]	Data innovation board[2] AI canvas[6] Canvas with key factors for analytics-based services[7] Data value map[3] Taxonomy of data-driven /analytics-based services[8]		Graph-based modelling of data-driven service systems[21] Meta data model of data goods[22]	Metrics to reflect data wrapping returns[23]
Data-driven business models *(Data and business model focus)*	Data map[5]	Taxonomy/Framework[9] Patterns/Types[10] Adopted Business Model Canvas[11] Data Insight Generator[12] Ideation tool for key activities[13] Criteria for selecting revenue models[14]	Causal loop-diagrams[18] Cost-benefit analysis [19]		
Digital business models *(Partial data focus)*		Taxonomy/Framework[15] Patterns/Types [16] Design elements for transaction-based representation of cyber-physical systems business models[17]	Mapping business model risk factors[20]		

[1] Wixom and Markus (2015)
[2] Kronsbein and Mueller (2019)
[3] Nagle and Sammon (2017)
[4] Schüritz *et al.* (2017a)
[5] Mathis and Köbler (2016)
[6] Agrawal *et al.* (2018a)
[7] Hunke and Schüritz (2019)
[8] Rizk *et al.* (2018), Hunke *et al.* (2019)
[9] Brownlow *et al.* (2015), Engelbrecht *et al.* (2016), Hartmann *et al.* (2016), Exner *et al.* (2017)
[10] Hartmann *et al.* (2016), Schüritz and Satzger (2016), Zolnowski *et al.* (2016), Schmidt *et al.* (2018), Förster *et al.* (2019)
[11] Benta *et al.* (2017), Kühne and Böhmann (2018)
[12] Kühne and Böhmann (2019)
[13] Hunke and Wambsganß (2017)
[14] Enders *et al.* (2019)
[15] Bock and Wiener (2017)
[16] Sprenger and Mettler (2016)
[17] Terrenghi *et al.* (2018)
[18] Förster *et al.* (2019)
[19] Zolnowski *et al.* (2017)
[20] Brillinger (2018)
[21] Kammler *et al.* (2019)
[22] Spiekermann *et al.* (2018)
[23] Wixom and Schüritz (2018)

Table 4.1: Synthesis of tools and methods for DDBMI across the phases of a business model innovation process.

Nevertheless, some cells of this table and toolbox remain empty: First, we see that most support is available for data-driven innovations. This shows that early gains of big data analytics have been achieved with improving internal processes and systems, but not new business models. Second, with regard to "digital business models", our literature search might not have covered articles on digital business models without an explicit focus on data. Finally, with regard to "data-driven business models" we see that most literature is available for idea generation and that in particular evaluation, implementation and controlling are overlooked by the literature as of 2019.

4.1.6 Discussion and Avenues for Further Research

Our results show that specific tools and methods are available to support innovating a data-driven business model. We have also demonstrated that many tools are available, especially in the design phase of business model innovation. Those tools that are generally used when innovating the business model and common approaches, like the business model canvas or the business model patterns, are transferred to data-driven business models. Below, we discuss gaps and underrepresented facets in existing research fields that highlight avenues for further research on how to support the process of data-driven business model innovation. Table 4.2 summarises the three research streams identified and provides corresponding avenues and recommendations.

Research Field	Research Direction	Recommendations
Overarching perspective on how single tools and methods link together	Designing a toolbox and a repeatable procedure for combining specialized tools and methods towards developing a data-driven business model.	Study interrelation of tools and creation of a toolbox and assignment to business model innovation phases through in-depth case studies Develop a repeatable process design for data-driven business model innovation through design-oriented research
Tools and methods that support convergent thinking (i.e., evaluation and decision-making)	Designing tools and methods for evaluation, decision support and risk management in data-driven business model innovation.	Identifying data and analytics-specific evaluation criteria and success factors through in-depth literature review and expert interviews or surveys Developing decision support tools for data-driven business model innovation through design-oriented research Developing data-specific risk assessment methods for business models
Software tools to support the data-driven business model innovation process	Designing software tools as IT support for developing, evaluating and managing data-driven business models.	Software implementation of data-driven business model representations Combining and integrating tools in software tools to enable data consistency across representations Implementing data-driven methods

Table 4.2. Research fields, research directions and recommendations for further research.

4.1.6.1 Tool chain and overarching methodology for innovating data-driven business models

In the reviewed literature, we see a range of tools and methods for special purposes that are still not related to each other, which is the first research field we identified. Tools and methods either incorporate all elements (e.g., (Exner *et al.*, 2017; Hartmann *et al.*, 2016)) or focus on a distinct element of the business model (e.g., (Mathis and Köbler, 2016; Schüritz *et al.*, 2017b). Thus, several tools and methods proposed are specialized for supporting the innovation process for a certain task, like identifying data sources (Mathis and Köbler, 2016), connecting data with the value proposition (Kühne and Böhmann, 2019) or ideating on analytics key activities (Hunke and Wambsganß, 2017). Specialized tools support the generalized representations of a business model (Kühne and Böhmann, 2019; Mathis and Köbler, 2016; Osterwalder *et al.*, 2014). Likewise, existing research on processes (e.g., (Benta *et al.*, 2017; Hunke *et al.*, 2017)) does not provide information on detailed activities as well as tools in each process phase and lacks empirical evaluation.

To these terms, we frame our first avenue for further research: **designing a toolbox and procedure for combining specialized tools and methods to design and evaluate a data-driven business model.** Further research could study such interrelations between specialized tools to develop a toolbox and toolchain for data-driven business model innovation and assign tools and methods to distinct phases of the innovation process suggested by Hunke *et al.* (2017) with the aid of (in-depth) case studies. We endeavoured to synthesise this literature review in this chapter, as shown in Table 4.1. Second, further research could develop a repeatable process design for developing data-driven business models, e.g. as suggested by Simmert *et al.* (2019) for continuous business model improvements through design-oriented research. Such a clearly defined process with a toolbox assigned to each phase can help managers overcome hurdles when designing and evaluating a data-driven business model due to a lack of structured procedures. This line of future research necessitates integrating research on data-driven business model innovation and innovation management.

- The next chapter (Chapter 4.2) of this thesis addresses this gap. It will investigate how a data-driven business model innovation process looks by presenting design requirements, features and principles.

4.1.6.2 Evaluation and decision-making in data-driven business model innovation

Only a few papers (6 out of 33) investigate convergent thinking compared to divergent thinking, i.e., ideation (20 out of 33), as the table in **Appendix A** shows. Existing research tends to focus on the ideation through taxonomies, patterns or visual tools, thus supporting divergent thinking. Besides divergent thinking, business model innovation also requires evaluation and decision-making (Casadesus-Masanell and Ricart, 2010; Tesch and Brillinger, 2017), for instance, evaluating and selecting ideas for further elaboration or deciding between options and further procedure. Existing research focuses on financial evaluation (Wixom and Schüritz, 2018; Zolnowski *et al.*, 2017). Evaluation of BMs also involves identifying and managing risks (Brillinger, 2018; Tesch and Brillinger, 2017). Wixom and Markus (2015) suggest bringing costs, benefits, and risks to data monetization. Brillinger (2018) identified data as critical value streams and risk factors in value networks of business models. As often pointed out, data ownership, security, privacy, and protection law are challenging factors in data-driven business model innovation (Brownlow *et al.*, 2015; Dremel *et al.*, 2017). Few evaluation methods incorporate such aspects.

In that sense, we frame our second avenue for further research: **designing tools and methods for evaluation, decision support and risk management in data-driven business model innovation**. Through an in-depth literature review and expert interviews or surveys, further research could identify data and analytic-specific decision and evaluation criteria, success factors, and critical elements of data-driven business models. Based on that, further research could develop decision support and evaluation tools to support and inform decision-making. Further research could also develop decision support tools for specific business model elements, e.g., for choosing appropriate revenue models or pricing mechanisms, through design-oriented research in combination with in-depth case studies. Furthermore, decision-makers must balance acceptable risk and estimated return (Tesch and Brillinger, 2017). Further research could investigate methods for identifying and managing novel risk factors in data-driven business model innovations through case studies, expert surveys and design-oriented research. Such evaluation and decision support tools can inform and help managers in their decisions for a particular business model design and balance risks and benefits to ensure the profitability and sustainability of the business model. This line of future research necessitates integrating research on data-driven business model innovation, decision-making and risk analysis in business model innovation and technology-oriented research, such as business analytics.

- Chapter 6 of this thesis will address this research avenue by first providing a set of evaluation and decision criteria and second investigating knowledge risks as one specific type of risk in data-driven business models and how a tool can help identify them.

4.1.6.3 IT support for data-driven business model innovation

The third research field identified is the lack of software tools to support the data-driven business model innovation process. Only two of 33 reviewed research papers involve IT to support data-driven business model innovation. Unlike the digital nature of data-driven business models, the underlying innovation process still appears to be fragmented and paper-based, with very little IT support. Only Terrenghi *et al.* (2018) indicate a software-based reference model for their tool, and the research endeavour of Spiekermann *et al.* (2018) points to an IT-related tool. On the other hand, numerous software tools exist to implement generic business model innovation representations, such as the business model canvas (Szopinski *et al.*, 2019). Much research is also going on in the information systems discipline to develop IT tools for other business models, like the Internet of Things (Athanasopoulu *et al.*, 2018) or sustainable business models (Schoormann *et al.*, 2018).

In that sense, we frame our third research avenue as **designing software tools as IT support for developing, evaluating and managing data-driven business model innovations.** This direction is in line with the call for research for IT support for developing and managing business models (Veit *et al.*, 2014) using methods for information systems design. First, data-driven business model representations can be implemented in software tools to track results and changes digitally. Likewise, combining specialized and generic business model tools within an IT system to enable consistency and information transfer across tools is another fruitful path for further research. In addition, data-related software tools could also be developed, like a meta-database of available data sources within an organization. The business model and the corresponding innovation process could be data-driven to advance the field further. Augenstein and Fleig (2017) suggest using data from organizational information systems to enable the bottom-up creation of a business model, as the underlying process of business model creation is manual and prone to error, time-consuming and subjective. Further research could develop data-driven methods to support business model innovation (Szopinski *et al.*, 2019). For managers, IT tools can support the results of the innovation process in such a way that they are visualized for presentation and communication. Furthermore, IT tools can support the business model design process by delivering important data that is needed. This line of research necessitates further integration between research on data-driven business model innovation, design-oriented research in information systems, and research in business analytics related to the specific characteristics of data and data analytics in business models. This research avenue is out of the scope of this thesis.

- ➢ We will not investigate this research avenue in detail within this thesis. But we will frame implementing IT-based business model innovation tools in the outlook section (*Outlook 2*, Chapter 7.5) and will describe, based on our experience from the case study work promising directions for IT-artefacts supporting data-driven business model innovation.

4.1.7 Conclusion

In this chapter, we have investigated the knowledge base for available tools and methods supporting data-driven business model innovation as of 2019. We clustered existing contributions by the type of contribution, the type of supported thinking and the addressed business model element(s). Further we drafted an initial toolbox clustered by phases of a business model innovation. We identified three gaps in the literature and corresponding avenues for future research – two that we will address in the course of this thesis and one as an outlook.

The major limitation of this research is, that the review reflects the status of 2019. At this point of time, which was also the starting point of this thesis, little support for data-driven business model innovation was available in the literature, this is also reflected in the toolbox of Table 4.1, with many empty cells. Thus, the database search yielded comparatively few results. Some of these were not rated B or above, according to the VHB JOURQUAL3. This fact highlights the emergent character of research supporting the data-driven business model innovation process and the timeliness of providing a structured overview of the knowledge base and synthesis into relevant future research directions at the time of this study.

- We denote this as a general limitation of this thesis (*Limitation 4*, Chapter 7.4): the fast development and advancement in the field of data-driven business models and therefore "older" parts of the thesis might be outdated or need to be updated.

Further, since then the field has developed – supporting tools have been designed also by other researchers and the understanding about data-driven business model has increased. To address the denoted limitation, we have continuously screened the knowledge base for new artefacts and integrated them into the background and/or discussion of other studies in this thesis. Nevertheless, this update is not reflected in this structured literature review. Summing up, building on this toolbox, the next chapter will investigate what such a systematic process design supporting data-driven business model innovation should look like.

4.2 Towards Requirements and Principles for a Data-Driven Business Model Innovation Process[20]

4.2.1 Introduction

As we have seen in the previous chapter, research has started to design tools and methods to support developing data-driven business models more effectively and systematically (Fruhwirth *et al.*, 2020c). Researchers have designed tools supporting the idea-generation phase of data-driven business model innovations (e.g., Hunke *et al.*, 2021b; Kühne and Böhmann, 2019). Further, studies considered financial evaluations (Zolnowski et al. 2017) or identifying risks (Fruhwirth *et al.*, 2021b).

While these approaches investigate specific aspects or steps in DDBM innovation, such as idea generation, evaluation, or risk management, organisations also need support over the whole business model 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 and methods (Fruhwirth *et al.*, 2020c). 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, such frameworks only describe necessary activities. They need to be adapted to the organisational requirements, connected to innovation tools and converted into a structured innovation process. To address this gap, we aim to answer the following question in this chapter:

What process design allows to systematic develop data-driven business models in offline-established organisations?

This chapter based on our three-year interventionist case study with Comp following the principles of design science research. We conducted interviews with involved managers, participated in workshops and meetings and accompanied seven initiatives where the case organisation aimed to develop new data-driven business models. Based on this rich data from the case study and in line with recent literature, we could craft six design requirements (i.e., requirements that a DDBM innovation process must fulfil) and eight design features (i.e., elements that structure a process). We suggest three design principles for a business model innovation process that capture the knowledge gained during our case study work through reflection and abstraction from our requirements and features.

The remainder of this chapter is structured as follows: Section two provides additional background on business model innovation processes. Section three describes the design science and case

[20] This chapter is based on Fruhwirth, M., and Pammer-Schindler, V. (2023): "Towards Principles for a data-driven business model innovation process – a design science case study" in Proceedings of the 36th Bled eConference – Digital Economy and Society: The Balancing Act for Digital Innovation in Times of Instability, A. Pucihar, M. K. Borštnar, R. Bons, G. Ongena, M. Heikkilä, D. Vidmar (eds.). June 25 – 28, 2023, Bled, Slovenia, pp. 545-560. **Awarded with the outstanding paper award**

study approach of this chapter. Subsequently, section four presents the design requirements as our first results and section five presents the design features and principles of a data-driven business model innovation process. The chapter closes with a discussion and a conclusion section.

4.2.2 Additional Background on Business Model Innovation Processes

Business model innovation 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, p. 420). Thus, business model innovation processes can serve as a guideline to structure activities and initiatives in business model innovation in organizations (Wirtz and Daiser, 2018). Such a process consists of idealized phases, such as idea generation or implementation (Wirtz, 2011). Each phase is associated with certain activities triggered by causes and produces distinct outcomes (Terrenghi, 2019). Tools and methods support organizations and individuals in these activities (Bouwman *et al.*, 2020; Schneider and Spieth, 2013; Schwarz and Legner, 2020).

However, existing literature largely provides only idealized conceptual phases for business model innovation (Winterhalter *et al.*, 2017). The process of identifying, designing, and evaluating new business models is still under-researched (Schneider and Spieth, 2013). Few scholars have empirically studied business model innovation processes (e.g., Frankenberger *et al.*, 2013; Sosna *et al.*, 2010; Terrenghi, 2019). Even less attention has been paid to designing such business model innovation processes in the academic literature. Concretely, we know of only Geissdoerfer (2019), who designed a process for sustainable business model innovation, and Simmert *et al.* (2019), who designed a continuous business model improvement process. However, the holistic investigation and design of overarching business model innovation processes are essential, as such a process "need[s] to be structured and embedded in an organization's existing process landscape" (Winterhalter *et al.*, 2017, p. 73). Research tends to focus on parts of overarching processes, and knowledge about how single phases, activities, and tools inter-relate is fragmented (Fruhwirth *et al.*, 2020c).

Current research on supporting data-driven business model innovation mainly focuses on supporting the idea generation phase through visual collaborative tools (e.g., Hunke *et al.*, 2020b; Kayser *et al.*, 2019; Kühne and Böhmann, 2019). Further, there is a need for repeatable processes and the connection of tools and methods for data-driven business model innovation (Fruhwirth *et al.*, 2020c). First high-level process approaches existed on expert interviews (Hunke *et al.*, 2017) or a literature review (Lange and Drews, 2020). Figure 4.4 shows the phases of data-driven business model innovation based on Lange and Drews (2020) and exemplary business model development tools that support the idea generation and design phase of data-driven business model innovation.

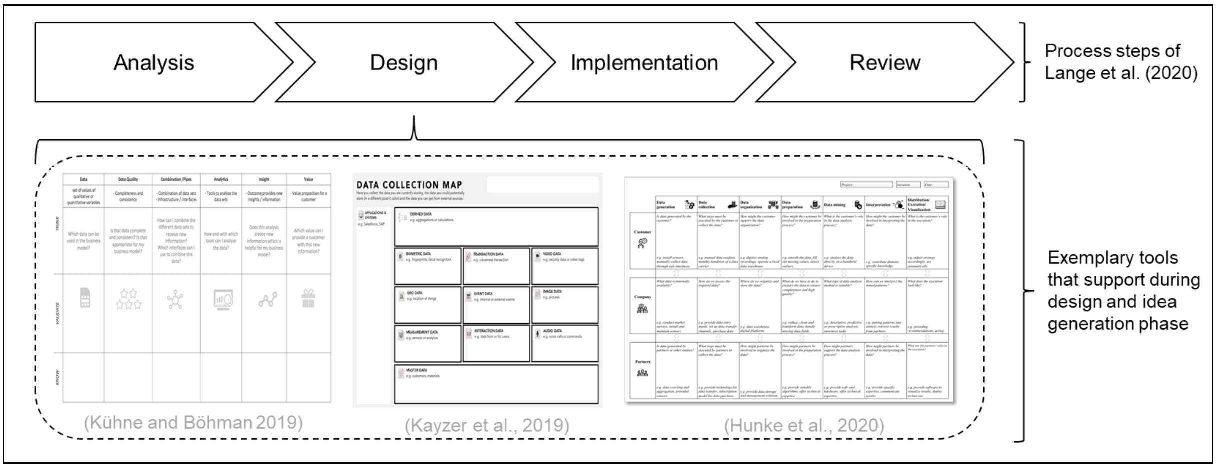


Figure 4.4: Overview of phases and exemplary tools and methods supporting data-driven business model innovation during idea generation.

However, such process models are hardly used in industry as they must be operationalized and adapted to the current organizational practices and specifics. Further, existing tools and methods supporting data-driven business model innovation are not connected to overarching procedures (Fruhwirth *et al.*, 2020c). Current research also overlooks support for evaluation and decision-making (Fruhwirth *et al.*, 2020c). Finally, there is also a lack of design knowledge on how to develop such processes.

4.2.3 Detailed Research Approach

Our overarching research approach is an interventionist case study (Korhonen *et al.*, 2021; Yin, 2009) with *Comp* following principles of design science research. Design science research aims to solve organisations' real-world problems by creating innovative artefacts (Hevner *et al.*, 2004). The research goal of this chapter is to craft design knowledge on how to design such a process.

4.2.3.1 Case Study Setting

We conducted the empirical part of this research chapter as part of the case study with *Comp*, as already outlined in Section 3.2.2 of the method chapter. We conducted this case study over three years, from 2018 to 2021. During this time, *Comp's* expected contribution to practice was defining a DDBM innovation procedure. In this case study, we developed unique tools, methods, and an overall process to support *Comp's* DDBM initiatives. Note that the scope of the presented chapter 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 product/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 data-driven business model innovation initiatives. This approach allowed us to access meaningful research data (Korhonen *et al.*, 2021). Aside from 28 semi-structured interviews, the interventionist case study includes 97 documented meetings and workshops with 73 representatives of *Comp*. Further, one researcher actively participated in seven DDBM initiatives at *Comp*. Our case study observed how DDBM innovation is practised in one offline-established organisation, what problems arise, and what support is needed.

4.2.3.2 Design Activities

We structured our design activities in line with the three interlinked cycles of “relevance”, “design”, and “rigor” (Hevner, 2007; Hevner *et al.*, 2004). The relevance cycle provides the requirements for a distinct application context (*Comp*) and allows the introduction of the investigated artefact (the process). The rigour cycle links the design activities with the knowledge base to add existing knowledge (i.e., literature on business model innovation and DDBMs) to our design and eventually extends the knowledge base by adding research results (i.e., our design knowledge). The design cycle represents the iterative construction and evaluation of an artefact. We generated three outcomes through our design activities: design requirements, principles and features.

Design requirements describe what users need. In this case, design requirements are what decision-makers at *Comp* need and expect from an innovation process. Baskerville and Pries-Heje (2010) define a requirement as “a condition or capability needed by a user to solve a problem or achieve an objective” and must be possessed or met by an artefact design (Baskerville and Pries-Heje, 2010, p. 274). We collected and analysed data from our case study to identify the design requirements. First, we conducted 17 interviews with responsible persons for data-driven innovations at *Comp*. We asked questions, for instance, about the role of data in their business and experiences and challenges with data-driven innovations. Second, we conducted additional 11 interviews[21] with responsible persons for business model innovation at *Comp* and asked questions about their experience and best practices in business model innovation. All interviews were audio-recorded and transcribed. Third, we collected tacit knowledge about business model innovation practices and considerations for DDBMs. Therefore, one researcher participated in 97 meetings and workshops at *Comp* for three years, took notes, and accessed additional internal materials (e.g., presentations). Following a Qualitative Content Analysis approach, we analysed the interview data and meeting notes (Mayring, 2015). We applied an open coding approach to identify relevant statements in the interviews, grouped similar statements to codes, and structured the codes for types of requirements. Finally, we grounded our requirements on the background literature.

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).

[21] These interviews were conducted by Maximilian Ferstl in the course of his Master’s Thesis, which the author of this PhD thesis co-supervised.

Design features address specific aspects of the requirements (Maedche *et al.*, 2021) and structure the description of the process design at *Comp*. We developed design features by addressing the requirements and synthesising best practices at *Comp*. First, we reviewed the literature on business model innovation processes to identify generic phases, activities, and decision points (not specific to DDBMs) as a basis of the process. Further, we conducted a structured literature review (see Chapter 4.1 and Fruhwirth *et al.* (2020c)), leading to an initial toolbox. Second, one researcher actively participated in DDBM innovations at *Comp*. Activities here include the facilitation of idea-generation workshops, where we developed and applied DDBM-specific innovation tools. Further, we supported seven data-driven innovation projects in specific activities, e.g., by preparing customer interviews or conducting competitor analysis. These activities enabled us to generate learnings on the activity and tool levels. Third, we added current best practices from our interviews and meeting notes to the process design. We demonstrated the process via a clickable PowerPoint presentation, interlinked between phases, and discussed it with the managers of *Comp*. The process was presented to and discussed with six managers at *Comp* responsible for data-driven and digital business innovations and incorporated as part of an initiative on digital business innovation.

4.2.4 Result 1: Design Requirements

We retrieved six requirements for a DDBM innovation process from qualitative data from our case study. As Pratt (2008) suggests, we used power quotes for each requirement to underpin our message.

DR1: *A business model 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 in offline-established organisations, as data-driven services move faster with shorter life cycles than traditional product-oriented business models. 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."* (Department Manager)

In contrast to traditional engineering or software 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). This is because customer (decision) problems that can be solved with data and insights that can be generated from data will emerge over time in interaction with the customer and generated data through the operation of data products and services. DDBMs are often co-created with their customers (Schüritz *et al.*, 2019b).

DR2: *A business model innovation process should guide management investment and go-to-market decisions.* We found in our case that successful DDBM innovation requires commitment from management to provide sufficient resources, in line with recent literature (e.g., Rashed *et al.*, 2022). On the other hand, innovating a DDBM is associated with many uncertainties. Thus, resources need to be allocated reasonably. Therefore, a process requires a clear definition of the decision body and criteria 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. Resources must be released in a binding manner."* (Product Manager)

One important aspect of decision-making is to balance estimated returns and associated acceptable risks (Tesch and Brillinger, 2017). A critical activity in DDBM innovation is to evaluate the risks associated with using data, depending on the ownership and characteristics of the data. Another risk aspect is if critical or competitive information could be shared through a data-based value proposition (Fruhwirth *et al.*, 2021b). Another important aspect of decision-making is the alignment of a new DDBM with the company strategy. Data analytics and artificial intelligence open versatile opportunities for business model innovation (Schüritz and Satzger, 2016). Thus, creative ideas for DDBMs and interesting insights from data analytics can go in various directions. One manager at *Comp* reported on his experience with his business model innovation projects:

> *"Projects always have to be in line with the company's strategy. If you propose something that deviates from that, you have to do it very carefully."* (Project Manager)

The alignment of the strategy with a new business model and the aimed market offerings in terms of business goals is an important activity in digital innovation (Turetken *et al.*, 2019).

DR3: *A business model innovation process should have an iterative character and follow an effectuation logic* to address the uncertainties in innovating a DDBM. Following an effectuation approach means that organisations focus on taking actions in the market to generate new insights instead of mainly analytical work, e.g., by analysing the environment (Chesbrough, 2010). In particular, DDBMs are subject to many uncertainties. Developing a (data-driven) business model follows a trial-and-error logic (Sosna *et al.*, 2010; Tesch *et al.*, 2017), where organisations use agile methods such as prototyping, experimentation and piloting (Geissdoerfer *et al.*, 2022). One product manager at *Comp* reported on his experience*:*

> *"Is there a need? Is there a willingness to pay? In the beginning, this question can only be answered in a rough estimate, but this question should accompany you throughout the entire process and be asked again and again."* (Product Manager Software)

The business model literature terms this iterative character and the dealing with uncertainties as experimentation or effectuation (e.g., Chesbrough, 2010). Thus, one common approach for early customer feedback and current practice at *Comp* is Lean Start-Up or a Minimum Viable Product (MVP), in line with recent literature (e.g., Lange *et al.*, 2021). These approaches enable quick verification of customer needs and thus reduce risks during business model innovation. One manager responsible for digital services reported on his experience:

> *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)

Thus, an important activity in DDBM innovation is verifying customer needs and testing the business model design as early as possible. One manager further mentioned that they follow the Lean Start-Up approach. Further, it is important to continuously collect feedback and update the DDBM based on learnings from customer interactions and insights from data analytics.

DR4: *A business model innovation process should be simple and adaptive.* It should focus on the minimal necessary elements, as the process's users' resources are limited. One digital service manager at *Comp* mentioned that filling out templates and lists should not be in the foreground of the process but instead of its supporting character. The simplicity is also a prerequisite that the process can be applied by all target users, as one manager highlighted in the interviews:

> *"It must be simple to make a new topic understandable for a department. Everyone should have the know-how to use the process correctly. Otherwise, it will frustrate them."* (Team Leader)

Further, a process should allow innovators to realise specific tasks or activities. Depending on the degree of innovation, not all phases or activities might be necessary for a business model innovation (Wirtz and Daiser, 2018) or are conducted in different levels of detail. DDBM innovation requires adaptive approaches (Lange *et al.*, 2021) in contrast to traditional structured and predictive processes, e.g., for product development.

DR5: *A business model 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 and establish a new mindset, 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."* (Team Leader)

One example of such educative topics was fostering customer-centricity and early integration of the customer. Involving customers in business model innovation is necessary to align technologies and offerings with current and future customer needs. Customer centricity is critical in DDBMs, as value is closely co-created between the business model owner and the customer (Schüritz *et al.*, 2019b).

DR6: *A business model innovation process should provide actionable how-to instructions for its users*. In our collaboration with *Comp*, we found that tool support for specific problems or the how-to for certain activities, such as a competitor analysis or the evaluation of customer needs, is often unclear for domain experts with little business model innovation background. 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 Solutions)

Further, we found that a process should also advise when certain activities should be performed during the innovation.

4.2.5 Result 2: Design Features and Principles

Design principles (DPs) capture knowledge about designing an artefact and describe the inherent principles of the design. Design features (DFs) address specific aspects of a problem or requirement (Maedche *et al.*, 2021). We structure the description of our process design by our three design principles: structure the process by investment decisions, support cyclic convergent and divergent thinking and enable organisational learning. These design principles are implemented via eight design features. Figure 4.5 shows an overview of the process design at *Comp*. The process is structured by four phases and three intermediate gates triggered by investment decisions. Each phase has a goal, the desired outcome, a list of activities and supporting tools. Each gate defines an investment/termination decision and is informed by decision criteria. The execution of each phase has an iterative character.

4.2.5.1 DP1: Structuring the Process by Decision Points

A process design should be structured along the investment decisions of the management. Each decision point is 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 preceding phase was subsequently defined with its activities and supporting tools. Recommended tools guide and support the data collection process. The following four features implemented this principle.

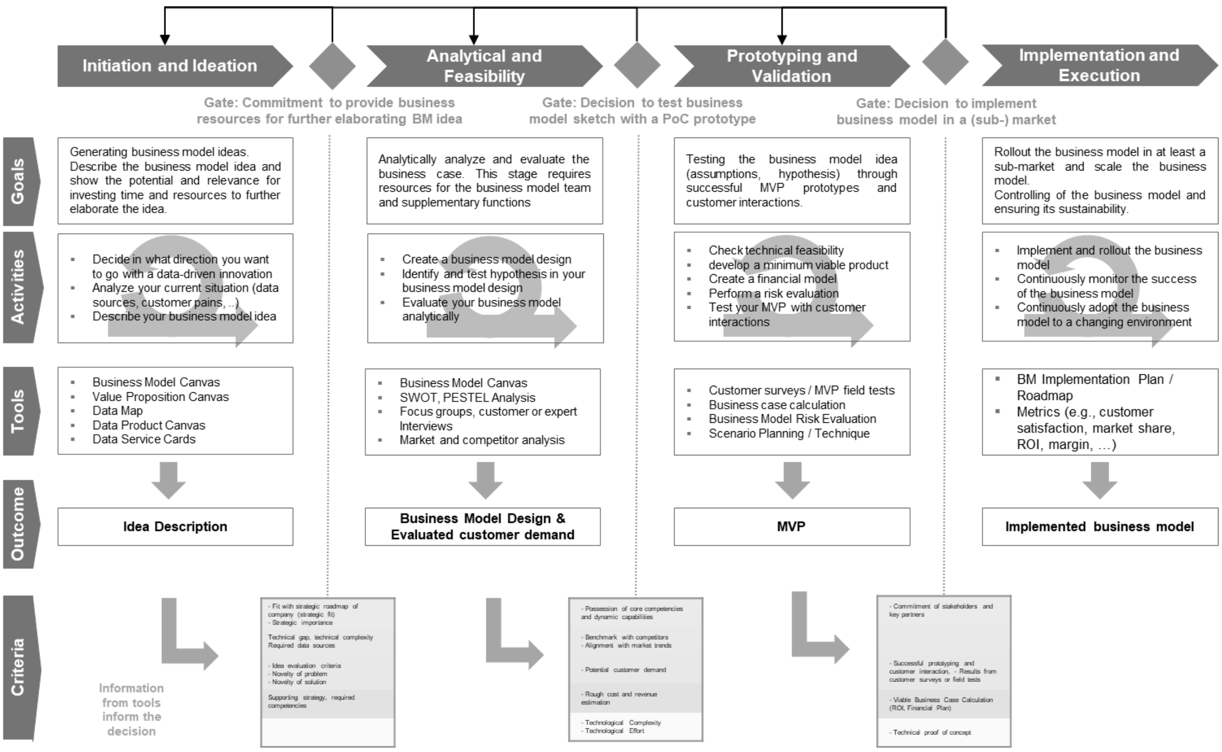


Figure 4.5: Overview of our process design with instantiated design features (DFs).

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 seminal 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 that lay between two gates (i.e., the first and last two phases), dropped the decision-making phase due to our gate structure and adopted the notations to the requirements of *Comp*.

In the *initiation and idea generation* phase, ideas for DDBMs are generated and described by focusing on the addressed customer problems and needs and a vision for the solution. Activities in that stage encompass an analysis of the current state, mapping data sources or investigating customer needs. This phase aims to show the potential and relevance of investing time and resources to further elaborate on the DDBM. At the first gate, the management commits to providing business resources for further analytically elaborating the DDBM.

In the *analytical feasibility* phase, the DDBMs are evaluated analytically by focusing on testing market-related assumptions (e.g., needs, competition, or customers) in the DDBM. This phase includes customer or industry expert interviews and a SWOT or market analysis. In parallel, data sources are exploratively analysed to identify and validate insights as the basis for an offering. The goal is to prepare the investment decision to develop a prototype or minimum viable product. In the second gate, a management decision provides resources for testing the DDBM with a prototype.

In the *prototyping and validation* phase, the DDBM is tested through successful prototypes and customer interactions by focusing on technical and financial assumptions. Activities in this phase encompass proofing the technical feasibility via a minimum viable product and performing business case calculations or a risk assessment. The goal is to prepare the decision to implement and roll out the business model in a sub-market. In the third gate, a decision is made to implement the DDBM and introduce it into a sub-market.

In the *implementation and execution* phase, the DDBM is implemented and rolled out in a (sub-) market and later scaled up. This phase also includes monitoring the business model's execution and ensuring its sustainability with metrics such as customer satisfaction, market share or financial performance. The business model is adapted, if necessary, as a reaction to the changing environment.

DF1.2 - Gate Decision Points: Every gate in the process can lead to four different decision outcomes. First, the management is committed to further investing in DDBM and provides resources for its realisation or gives a go into a (sub-) market. Second, it could be the case that after completing all phase activities, there is still not enough information available, or the DDBM has not yet reached the level of maturity to proceed to the next stage. In this case, management provides additional time and resources to further elaborate on the DDBM in the current phase (e.g., additional tests with customers). The third case is that the phase outcomes did not lead to the expected results, e.g., assumptions in the DDBM, such as the customer demand, could not be validated, and therefore the DDBM initiative must be terminated. In addition to the three decision outcomes, activities in a phase can reveal additional insights about customer problems or new insights from data sources that could lead to a separate DDBM initiative. In this case, a decision is made to proceed with this new DDBM in an earlier stage. A decision body must be defined for each gate, i.e., management with the authorisation and budget for the investment decisions. We also learned from the case that it is important to define a maximal duration for each phase after management must be involved in a decision.

DF1.3 - Supporting decision-making with actionable criteria: A set of evaluation criteria defined by our process informs the decision to invest in or terminate a DDBM. Decision criteria are one approach to qualitatively evaluate a business model (Tesch & Brillinger, 2017) and objectify the management decision if they further invest in a business model idea or prototype (Tesch *et al.*, 2017). We identified decision criteria from six categories based on our case data and the literature: Customer demand, market and competition, organisation and strategy, data and technology, financial rationales, and risks.

Example: The example in Figure 4.6 shows the operationalisation of three criteria informing the decision to proceed to the analytical feasibility phase after ideation. For each criterion, either a binary (yes/no) or Likert scale with labels have been defined. For instance, for the criterion “Clear customer need addressed”, the scale goes from “no specific customer gain/pain identified” to “a significant and meaningful customer problem is identified (and several gains/pains ranked)”.

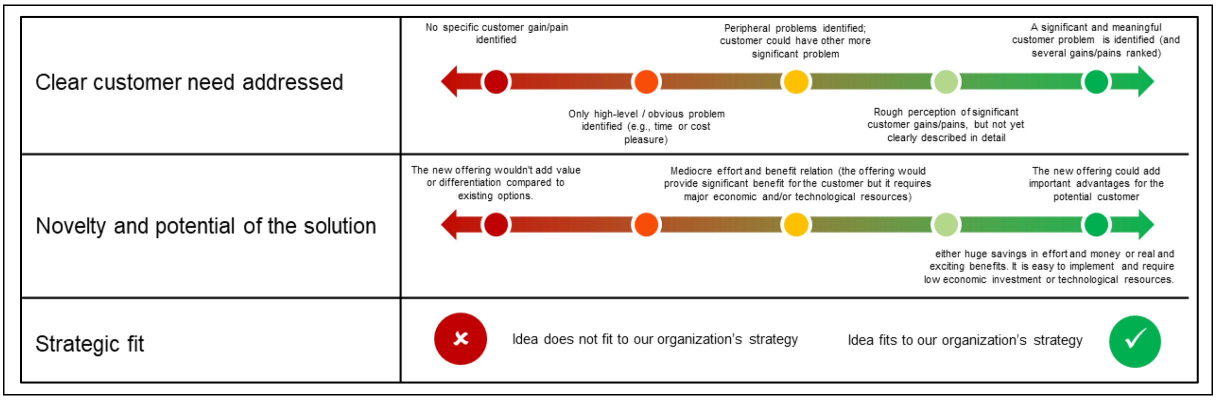


Figure 4.6: Exemplary instantiation of design feature five as evaluation criteria for the idea generation phase (excerpt).

Our case study with *Comp* taught us that the criteria vary across the gates. For instance, to decide if further resources should be provided to evaluate a DDBM idea, criteria such as a clear customer need, the solution's novelty, or a fit to the company’s strategy are considered. Decision-makers at Comp expected an operationalisation of these criteria. This is realised in the process with 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).

DF1.4 – Definition of an outcome for each phase: The process defines the desired outcome and form of documentation that must be generated until the end of each phase.

Example: From our case study and meetings with decision-makers of *Comp,* we learned that it is important to have a clear and defined outcome at the end of each process phase documented in a coherent form. This is particularly 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 for a new DDBM. This includes a description of the customer, the benefits generated, problems addressed, a vision for the data analytics solution and required data sources and data analytics methods and technologies. This outcome is documented in the Data Product Canvas (see t Fruhwirth *et al.* (2020a) and Chapter 5.2).

4.2.5.2 DP2: Support Cyclic Divergent and Convergent Thinking

A process design should support cyclic divergent and convergent thinking in each phase. Every phase in business model innovation has alternating activities that require divergent (i.e., exploring multiple options) and convergent thinking (i.e., deciding and going for one option). These alternating 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). The evaluation phases encompass the cyclic testing and adoption of the DDBM based on customer interactions and market interactions. Both steps encompass divergent thinking (i.e., thinking about approaches how to test a hypothesis in the business model; thinking about what to adapt in the DDBM based on learnings) and convergent thinking (i.e., deciding for and executing one testing approach; deciding for one option for adopting the DDBM). 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 should lead to the defined outcomes without specifying a pre-defined sequence. The activities are iterated and alternated until the target outcome is achieved (e.g., identifying and validating a meaningful customer need).

Example: 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. We identified and prioritised the hypothesis of a DDBM design, selected a suitable testing method (e.g., customer interview, prepared, conducted and analysed them and adopted the DDBM based on the learnings.

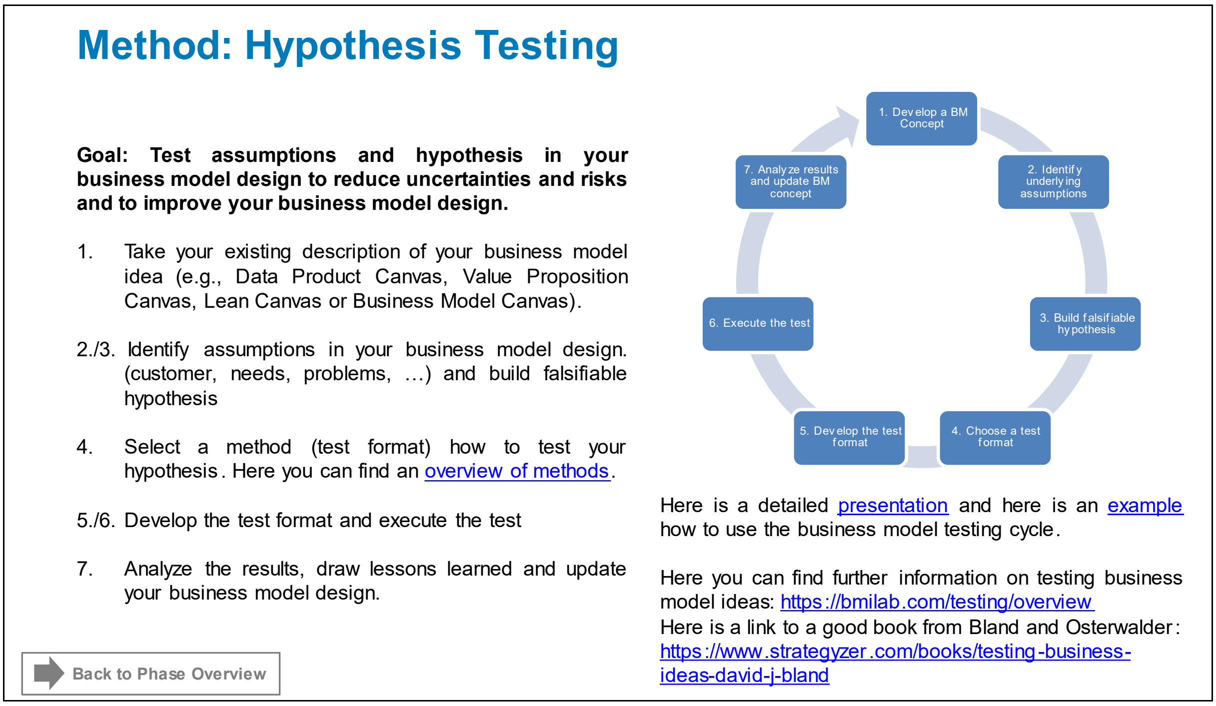


Figure 4.7: Hypothesis testing cycle as an example of an iterative activity within the feasibility and prototyping phases (Source: own representation)

DF2.2 – Suggestions from a toolbox: The activities of a phase are supported by suggestions from a toolbox that can help execute the activity. One or several tools are recommended and visualised for each activity in a phase. The user is routed to a tool description by clicking on the tool preview.

Example: In workshops of our interventionist case study, we combined several existing tools to support generating and describing ideas that are integrated into the process. First, we used a classification matrix (see Chapter 5.1 and Breitfuß *et al.*, 2019) to guide the direction of the idea generation workshops regarding what type of DDBM should be investigated. A *Data Map* then supports identifying, structuring, and documenting potential data sources for a DDBM (e.g., Kayser *et al.*, 2019) as input for idea generation workshops. A card deck – the *Data Service Cards* (Breitfuß *et al.*, 2020; Breitfuß *et al.*, 2023) as an innovation tool provides basic information on DDBMs for non-data experts and supports the creative process in idea-generation workshops. Finally, the idea generation toolbox suggests the Data Product Canvas (see Chapter 5.2; Fruhwirth *et al.*, 2020a) for structuring idea generation workshops and describing and communicating a DDBM idea. Figure 4.8 shows how we implemented the toolbox for the idea generation phase at *Comp*.

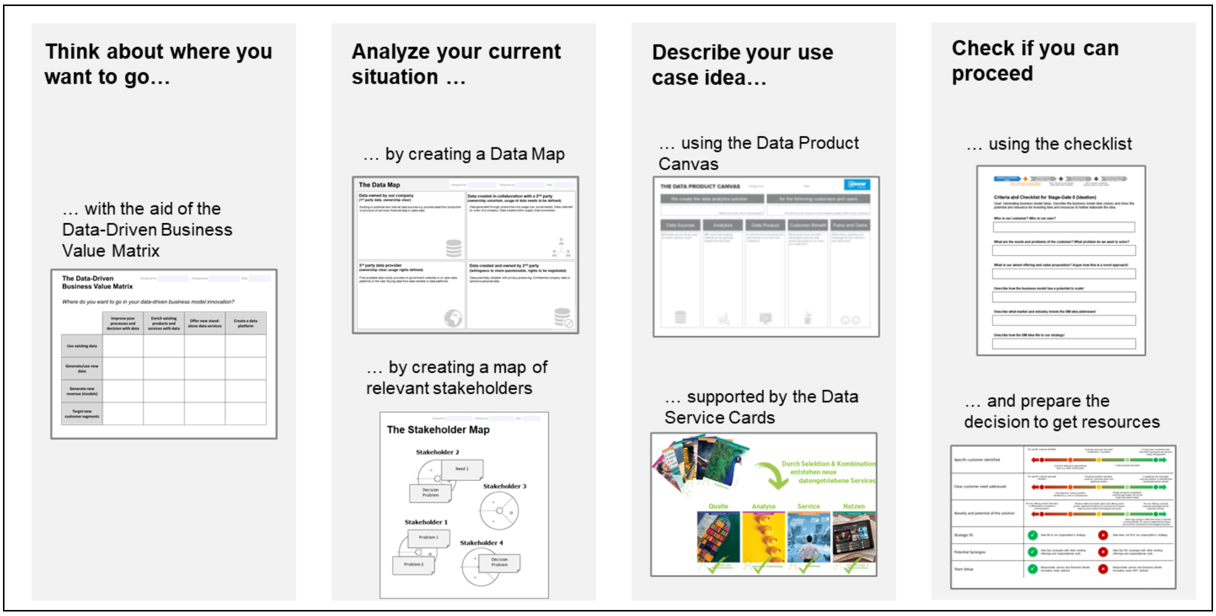


Figure 4.8: Exemplary instantiation of design feature three as an overview of activities and a toolbox for the idea generation phase.

4.2.5.3 DP3: Enable Organisational Learning

A process design should enable organisational learning on DDBM innovation by providing and taking up best practices and learnings. A process design is based on generic knowledge from the literature (e.g., phases of business model innovation) and organisation-specific best practices and tacit knowledge. Further, a process model is a vehicle of change to establish desired procedures and ways of thinking from a management perspective. Organisations and their employees can learn by using and continuously updating the process model. 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).

Example: 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)?

	Positive	Negative
	Strengths	**Weaknesses**
Internal	Is the data used in the service difficult to replicate, generate or acquire by others? Generating the service requires a large initial data set that is difficult or costly to generate Are the necessary data analytics related key activities and competencies are difficult to copy? (Analysing the data requires specific domain and/or data science knowledge that is rare in the market and that only we have)	Can the data as the fundament of the service be easily copied or generated by others? Do we have the necessary capabilities to build the data-driven service? (e.g., computing power, web service development, analytics, …) Can the necessary data analytics capabilities can be easily copied or are they widely available in the market? (e.g., every data science company can do that) Do we have to continuously check the quality of the data or do manually cure the data? (i.e., it is not scaling)
	Opportunities	**Threads**
External	Can our product or service itself generate valuable data through the usage by the customer? Can we increase our data key resource through product/service usage? Can we improve the quality of our service, algorithm, or predictions through that data? (i.e., can we build a feedback loop that improves the results)	Are we too dependent on certain external data sources/data providers? What happens if we have no access to the data any more? Is there a risk of loosing valuable internal data by technical failures in the service? Is there a risk of leaking critical knowledge by our offering (e.g. providing prediction models)? Are we handling critical customer data, where a data breach would have serious consequences? (e.g., threatening our reputation) Are we handling personal data or data with unclear ownership that could lead to legal consequences?

Figure 4.9: Incorporating best practices from previous DDBM innovations into a SWOT analysis template (source: own representation)

DF3.2 – Provide a method of use for tools: *Our process provides a description and instructions for each supporting tool.* This design feature includes a goal that should be reached by using a tool, an explanation of the tool's usage, a link to a tool template, and suggestions for other tools that could be used in combination. Further, it includes an illustrative example of how the tool or method could be used or was used in a previous DDBM initiative and references to other helpful resources. How-to instructions and examples show best practices and learnings from previous business model innovations and educate the employees via using the process. We found in our case study that it was often unclear how a particular tool should be used, where to start and in what sequence to go through its elements.

Example: Therefore, for instance, as shown in Figure 4.10, we added recommendations for the setting for an idea generation workshop and for using The Data Product Canvas (see Chapter 5.2; Fruhwirth *et al.*, 2020a) based on previous experience with the tool. Further, the process provides a step-by-step approach to using the tool, i.e., with what building blocks to start, what questions to ask and how to fill each building block. We found it useful to start with the customer problems, think about a vision for the data product or service, consider required data sources and analytics activities, and then iterate.

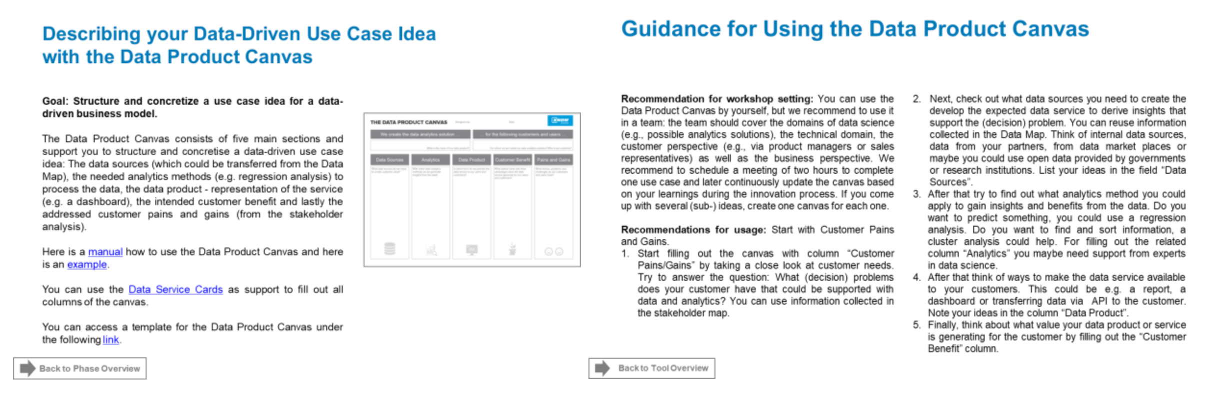


Figure 4.10: Exemplary instantiation of design feature 4 showing description and instructions for the Data Product Canvas.[22]

4.2.6 Discussion

We generated design knowledge for a DDBM innovation process through a three-year interventionist case study with *Comp* guided by principles of design science research. We derived eight requirements for a DDBM innovation process and implemented them via eight design features. Through reflection and abstraction from the specific case of DDBM innovation at *Comp*, we crafted three design principles not specific to DDBM that can be applied to other business model innovation processes. Table 4.3 summarises how the design principles link the design requirements and features.

Design Requirements	Design Principles	Design Features
DR1 Increase speed DR2 Support decision-making DR3 Iterative and effectuation DR4 Simple and adaptive DR5 Educate users DR6 Actionable how-to instructions	DP1 Structure along investment decisions	DF1.1 Description of phases DF1.2 Definition of gates DF1.3 Decision criteria DF1.4 Definition of outcomes
	DP2 Support cyclic convergent and divergent thinking	DF2.1 Activities DF2.2 Toolbox
	DP3 Enable organisational learning	DF3.1 Best practices & feedback DF3.2 Method of use

Table 4.3: Overview of design requirements, principles, and features of our DDBM innovation process.

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 organisations with a B2B business model (Rummel *et al.*, 2022). Support cyclic convergent and divergent thinking reflects digital innovations' agile and iterative nature (Ghezzi and Cavallo, 2020). Finally, enabling organisational learning reflects the

[22] The Data Product Canvas will be discussed in detail in chapter 5.1 of this thesis.

need for a knowledge-intensive business where innovations often happen decentralised and bottom-up (Burnes *et al.*, 2003). Thus, our results show that the principles are not specific to DDBMs. They can be transferred to processes for other types of business models in similar contextual settings. On a more specific level, regarding the configuration of its features - the activities and tools – the process is very specific for DDBMs, as the tools and activities bring in necessary knowledge for DDBMs. In line with previous work (e.g., Hunke *et al.*, 2017; Rashed and Drews, 2021), the tools and activity level shape the specific characteristics of DDBMs.

We showed that a process design should be structured along with management (investment) decision points and criteria that inform these decisions. This principle follows a structured innovation approach (Wirtz et al., 2016) and reflects traditional organisations' management steering and hierarchical control structure (Rummel et al. 2022). Phases predominantly structure existing process designs from the literature (e.g., Geissdoerfer, 2019; Hunke *et al.*, 2017; Rashed *et al.*, 2022). However, specific decision points are missing in current business model innovation processes. Only Tesch *et al.* (2017) empirically investigated decision points and decision criteria in business model innovation. Lange *et al.* (2021) further add that incumbent organisations use Stage-gates for a stop-or-go decision during DDBM innovation. Also, Geissdoerfer (2019) found evidence that "milestones" and "gates" are used to structure business model innovation in practice. Overall, business model innovation processes have not yet reached the level of maturity with stages and gates compared to product innovation processes (Winterhalter *et al.*, 2017).

Further, a process design should support cyclic convergent and divergent thinking within each phase. This principle reflects the iterative and agile nature of digital innovations in general (Ghezzi and Cavallo, 2020; Rummel *et al.*, 2022) and DDBM innovation in particular. 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 parts in their process structure. Fruhwirth *et al.* (2020c) also suggest structuring tools and methods supporting DDBMs by convergent and divergent thinking. Cyclic divergent and convergent thinking relate to topical approaches such as Design Thinking and Lean Start-Up for business model innovation (Brown, 2008; Ries, 2011; Rummel *et al.*, 2022).

Nevertheless, there is a tension between these two design principles, i.e., the required iterative and flexible character (within each phase) with alternating divergent and convergent activities and the strict stage-gate logic (at the gates between the phases) to release further resources or terminate a DDBM innovation. Digital start-ups use agile methods for business model innovation, known as Lean Start-up approaches (Ghezzi and Cavallo, 2020). Cooper and Sommer (2016) addressed this issue. They found that IT and manufacturing firms recently combined agile development methodologies and Stage-Gate approaches for software or physical 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 business model innovation process in digital transformation. Furthermore, Thus, these empirical studies underpin the relevance of this study's design principles. Hence, we see a fruitful direction for further research to investigate detailed design principles for how strict stage-gate logic and agile approaches are combined in business model innovation processes.

A business model innovation process design should also enable organisational learning, as our third design principle states. This principle reflects that innovation often happens bottom-up in knowledge-intensive organisations, such as *Comp*, and that knowledge about such new business models is just emerging in organisations. Existing process designs in the literature are informed by expert interviews, i.e., formalising their experiences and knowledge into the process (e.g., Hunke *et al.*, 2017; Rashed *et al.*, 2022; Simmert *et al.*, 2019). Geissdoerfer (2019) further conducted participatory action research by applying and refining his process in two real-world cases. In our case study with *Comp,* we observed that DDBM innovations often happen bottom-up in the departments with customer interactions, as domain experts are often close to the (decision) problem that can be addressed with a data analytics solution. Therefore, they generate learnings and insights about DDBM innovation that need to be transferred to the organisational system. These domain experts also need the skills and tools for business model innovation to develop new DDBMs successfully. Thus, by incorporating best practices and learnings, a business model innovation process can be the vehicle for 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. According to Berends *et al.* (2016), business model innovation emerges through a combination of different learning mechanisms, in particular, cognitive search via business model design (e.g., Osterwalder and Pigneur, 2010) and experimental processes via experimentation and effectuation (e.g., Sosna *et al.*, 2010). Thus, this literature stream underpins the relevance of our third design principle and, vice versa, our results confirm recent literature. Hence, we see a fruitful direction for further research to explore design principles of how a business model innovation process can enable organizational learning, particularly, support cognitive search and experimentation activities.

On a tools and methods level, our process is very specific for DDBMs. Tools and methods support the activities within each phase and bring in the knowledge and specifics for a type of business model, such as DDBMs. By suggesting DDBM-specific activities, tools and methods, organisations and individuals can learn about this new type of business model's characteristics. Recent literature has investigated DDBM-specific activities during business model innovation (Lange and Drews, 2020; Rashed and Drews, 2021). This chapter showed how different innovation tools link together to support idea-generation activities. Our case and a recent literature review also showed that many tools are available for idea generation (Fruhwirth *et al.*, 2020c). Nevertheless, we found in our case study that there is a need for further research in several areas of designing tool support for DDBMs. First, further research should design support for supporting decision-making and evaluating risks in DDBM innovation, particularly identifying DDBM-specific decision criteria. Second, the literature lacks tools and methods supporting the realisation of DDBMs. Research recently started empirically investigating the realisation (i.e., prototyping and implementation) of DDBMs (e.g., Lange *et al.*, 2021; Rashed and Drews, 2021) that now needs to be transferred to business model innovation tools. In particular, there is little support available for testing and evaluating DDBMs.

4.2.7 Conclusion

In this chapter, we have presented requirements, features and principles of a data-driven business model innovation process based on the case study with *Comp* following the principles of Design Science Research. Previous research has studied business model innovation processes empirically (e.g., Terrenghi, 2019; Tesch *et al.*, 2017), theoretically (e.g., Lange and Drews, 2020; Wirtz and Daiser, 2018), or through design studies (e.g., Geissdoerfer, 2019; Hunke *et al.*, 2017; Simmert *et al.*, 2019). To the best of our knowledge, this study is the first to explicitly provide design knowledge for business model innovation processes based on empirical design work with one real-world organisation, exemplarily shown in the case of data-driven business models. Our work complements existing data-driven business model research on frameworks and processes (e.g., Lange *et al.*, 2021; Rashed *et al.*, 2022) that mainly focus on activities in data-driven business model innovation by presenting a structured management process.

This chapter provides two contributions to the literature. First, we showed in this case study that a business model innovation 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 results are in line with recent literature, for instance, regarding the stage gate logic in business model innovation (Rummel *et al.*, 2022; Tesch *et al.*, 2017). Our principles point to other disciplines, such as psychology (with convergent and divergent thinking) and (organisational) learning. Our principles are not specific to DDBMs and can be transferred to other types of business models in a similar organisational context.

- ➢ The three design principles are also one overall contribution of this thesis (*Contribution 1*, Chapter 7.2).

Second, our results show that the activity and tool level bring in the specifics of DDBMs to a business model innovation process. We showed how different tools and methods are interlinked, and there are still gaps in the literature regarding business model tooling.

- ➢ The insight that tools and methods bring the specific aspects of data-driven business models into the process is also one overall contribution of this thesis (*Contribution 2,* Chapter 7.2).

4.3 Conclusion on a Systematic Process Design and Toolbox

Summary: In this first results chapter, we looked at how a process and corresponding toolbox supporting data-driven business model innovation should look. First, we conducted a structured literature review to identify and classify existing tools and methods from the literature and defined three gaps and avenues for further research. Second, we conducted a three-year case study with an automotive company to identify requirements, features and principles of a data-driven business model innovation process.

Learnings from Chapter 4.1: Supporting tools and methods can be classified based on different approaches: (I) Different types of innovation tools and methods, majority of research papers until 2020 focused on DDBM taxonomies, (II) Innovation tools can cover distinct business model elements (e.g., revenue models) or cover all business model elements; (III) Innovation tools can be assigned to different BMI phases, and (IV) business model tools can support convergent and divergent thinking. There is a lack of structured processes connecting distinct activities, tools and methods, one gap we will address in Chapter 4.2. We have also seen little available supporting evaluation and decision-making, which we will address in Chapter 6. Finally, we found that the literature misses proper IT support for a data-driven business model, one gap we propose in this thesis as an avenue for further research (see section 7.5.2).

Learnings from Chapter 4.2: When designing a data-driven business model innovation process, two questions need to be answered: (1) What are the requirements from the management that such a process must fulfil? (2) What are the principles for designing such a process? The first principle (structuring a process along gates and investment decision points) reflects the hierarchical control structures and the need for investment steering of traditional organisations with a B2B business model. We will investigate supporting tools and methods for this question in Chapter 6. The second principle (support cyclic convergent and divergent thinking) reflects the agile and iterative nature of digital innovations. The next two chapters will focus on tools and methods supporting idea generation (convergent thinking) and evaluation (divergent thinking). Nevertheless, tensions between these two design principles need to be resolved. Finally, the third principle (enabling organisational learning) reflects the need for a knowledge-intensive business where innovations often happen decentralised and bottom-up.

Overall contribution and outlook: The overall contribution of this chapter is that a process requires support for convergent and divergent thinking, needs to have both iterative and stage-gate character and that the specifics of data-driven business models come with the specialized toolbox and activities. Convergent and divergent thinking will structure the remainder of the results in this thesis. In the following chapters, we will focus on idea generation and evaluation. For each phase, we will investigate in detail different tools and concepts that support organisations in designing and evaluating DDBMs.

Chapter 5

Supporting Tools and Concepts for Idea Generation and Design

"Everything begins with an idea."

Earl Nightingale[23]

This chapter deals with the design of tools and methods that support idea generation, design and formal representation of data-driven business models. As an introduction, we present a guiding classification scheme for data-driven (business model) innovations in Chapter 5.1. Subsequently, Chapter 5.2 presents the Data Product Canvas. This visual tool supports the collaborative design of the value proposition of a data-driven business model, focusing on the data-based value co-creation dimension between the customer and the business model owner. Chapter 5.3 then investigates the phenomenon of value creation with data in more detail and suggests a "data-based value creation ontology". Finally, Chapter 5.4 introduces a network-based representation and analysis of data-driven business models, focusing on the ecosystem perspective of value creation in data-driven business models with actors and exchange values.

5.1 Introductory Study: Classifying Data-Driven Business Model Innovations[24]

5.1.1 Introduction

Big data, analytics and artificial intelligence offer offline-established organizations endless options for business model innovation (Schüritz and Satzger, 2016). Thus, before organizations start a new data-driven business model innovation initiative, they must decide what direction their innovation should lead. Existing literature provides different frameworks on how data-driven business model innovations can be classified (Fruhwirth *et al.*, 2020c; Kayser *et al.*, 2021). Nevertheless, there is

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[23] Robert C. Worstell, Earl Nightingale (2017): "How to Change Your Life in 30 Seconds - Compleat". Midwest Journal Press, p. 98. Retrieved from books.google.com on 02.10.2022 10:10

[24] This chapter is partially published; parts of this chapter are based on one publication I have co-authored: 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 Proceedings of the 32nd Bled eConference, Humanizing Technology for a Sustainable Society, June 16-19, 2019. This paper was substantially extended by me in this thesis. I reworked and extended the conceptionalization and applied and evaluated it in several cases and workshops.

no comprehensive overview or actionable innovation support for practitioners. Thus, in this introductory chapter, we address the following question:

How can data-driven business model innovations be classified?

Therefore, we adopted a design science research approach. We reviewed existing literature on data-driven business model innovation, developed a comprehensive classification scheme and instantiated it in a visual tool. We demonstrated and evaluated the classification scheme and visual tool in our case study with *Comp*.

The rest of this chapter is structured as follows: First, we overview existing classification schemes for data-driven business models in section 5.1.2. Second, we describe our methodological approach in section 5.1.3. We then present our classification scheme and visual tool in section 5.1.4. Next, we demonstrate and evaluate our artefact within the context of *Comp* in section 5.1.5. Finally, we close this chapter with a discussion and conclusion in section 5.1.6.

5.1.2 Additional Background on Classification Schemes for Data-Driven (Business Model) Innovations[25]

Literature provides different approaches for classifying data-driven business models, such as frameworks, taxonomies, patterns and archetypes (Kayser *et al.*, 2021). One example of a framework is the BITKOM matrix (BITKOM, 2013), which aims to classify big data projects along two dimensions: first, if “existing data” or “new data” is used, and second if it supports the “existing business” or enables “new business”. Taxonomies (e.g., Azkan *et al.*, 2020; Hartmann *et al.*, 2016; Schmidt *et al.*, 2018) decompose data-driven business models into dimensions and characteristics as their distinctive features. For instance, Hartmann *et al.* (2016) provide a five-dimension taxonomy with “data sources”, “key activity”, “offering”, “target customer”, “revenue model”, and “specific cost advantage” as the characteristic business model dimensions. Patterns and (arche-)types of data-driven business models can be derived from such a taxonomy (e.g., Hartmann *et al.*, 2016; Schmidt *et al.*, 2018). Prominent examples of such patterns are “Data-as-a-Service” or “Analytics-as-a-Service” (Chen *et al.*, 2011).

Data-driven innovations can also be classified along with the elements of the business models that are affected by the innovation (Kayser *et al.*, 2021). Schüritz and Satzger (2016) studied 115 cases of data-driven innovations and how each innovation affects the value creation, value capture or value proposition of the business model, leading to “five patterns of data-infused business model innovation”. Wixom and Ross (2017) suggest three ways in which big data and analytics can affect a business model: First, data can be used to improve internal processes and decisions; second,

[25] For a detailed investigation of classification approaches of data-driven innovations through a structured literature review read the following publication: (7) Kayser, L. Fruhwirth, M., Mueller, R. (2021), Realizing Value with Data and Analytics: A Structured Literature Review on Classification Approaches of Data-Driven Innovations. In Proceedings of the 54th Hawaii International Conference on System Sciences 2021, pp. 5686- 5695.

data can extend existing products and services; and third, data can lead to totally new stand-alone services.

Although several classification approaches exist in the literature, little research has been conducted to synthesise them (Kayser *et al.*, 2021). Further, none of these approaches has been transferred into hands-on, actionable tools practitioners can apply to classify their data-driven business model ideas. Thus, this chapter aims to design a tool informed by the literature and demonstrated in our case study.

5.1.3 Research Approach

We follow our design science research approach to develop a classification scheme for data-driven business model innovations (Hevner *et al.*, 2004; Vaishnavi and Kuechler, 2015) embedded in the case study with *Comp* (see Chapter 3.2) in our case study. After being aware of the problem (classifying DDBM ideas to guide further innovation), we consulted the knowledge base for literature on such classification schemes. We identified five patterns distinguished by the type of value proposition. We suggested classifying DDBMs along with these patterns and the level of maturity and subsequently developing a visual tool. We demonstrated and evaluated this tool in the context of *Comp*, where we structured 23 data-driven innovations identified through 17 interviews (see **Appendix C**) and discussed it in a workshop with four managers at *Comp* responsible for data-driven innovations in 2018. Based on the insights of this workshop, we adopted the classification scheme. We applied the revised artefact to structure five running DDBMs of *Comp* and two from the automotive industry as part of a company-internal training on data-driven business model innovation in 2020. As we have denoted this chapter as an “introductory study” it has as a limitation not the same depth and rigor as other chapters of this thesis.

5.1.4 Result 1: Artifact Design Description

Based on the literature, we initially identified five different classification patterns of data-driven business model innovations, as shown in Table 5.1: “Data-enabled improvements”, “Data-enriched products and services”, “Data-driven Services”, “Data-as-a-Service”, and “Auxiliary big data services. We added two patterns in the second design iteration: “Analytics-as-a-Service” and “Data Platform”. The former was separated from the auxiliary pattern; the latter emerged as an important phenomenon for the automotive industry during our case study.

Data-enabled improvements: Organisations use data and analytics to improve their existing business. Thus, this does not affect the value proposition. Improvements can be made in value creation (e.g., optimising production processes with data analytics to achieve higher efficiency) or value capture (i.e., customer-specific or location-based pricing enabled by data) (Schüritz and Satzger, 2016). Another way to optimise a business is through better decision-making based on fine-grained data (Schroeder, 2016; Wixom and Ross, 2017).

Pattern	Description	Value Proposition
Data-enabled Improvements	Leverage data and analytics to optimise organisation-internal processes and decisions.	The value proposition is not affected.
Data-as-a-Service	Sell data similar to other goods. Activities in this pattern also include aggregating or storing data. The goal of this pattern is to provide valuable data to other actors.	Data
Data-enriched Products and Services	Enhance existing products and services with data and analytics to create additional benefits. The goal is to achieve a competitive advantage or to increase the price or sales volume of the core product or service.	Product/service with data/information as an add-on
Data-driven Services	Offer stand-alone data-driven services based on internal data or external data. The goal here is to solve new customer problems with data.	Information, recommendations or answers
Auxiliary data services	Support data and analytics activities of other organisations. This pattern is applied when they do not have the necessary competencies (e.g., providing consulting services or computation and storage infrastructure)	Non-data product or service
Analytics as-a-Service	Analyse data for the customer and provide the results or even the analytics solution. This pattern is applied when the customer does not have the competencies or resources to build an analytics solution by himself.	Analytics solution
Data Platforms	Provide a platform where others can upload, store, visualise or analyse their data.	Access to data

Table 5.1: Classifying data-driven business model innovation in five patterns (adopted and extended from Breitfuß *et al.*, 2019).

Data-as-a-Service: Organisations can sell data generated by themselves or acquired and aggregated from third-party data providers (Chen *et al.*, 2011; Otto and Aier, 2013). This acquired data is usually cleaned, aggregated or anonymised and transformed into a product (Van't Spijker, 2014). One challenge in the Data-as-a-Service pattern is to estimate the value of the data to determine a price (Breitfuß *et al.*, 2019).

Data-enriched products and services: Organizations can use data and analytics to enrich their core products and services (Wixom and Ross, 2017). This practice is also called “data wrapping” (e.g., Wixom and Schüritz, 2018). Based on such add-on data-driven services, organisations can escape commoditisation, increase customer satisfaction and generate additional revenues (Schüritz *et al.*, 2017c).

Data-driven services: Organisations can use data and analytics to offer new services independently of their existing core offering (Schüritz *et al.*, 2017c; Wixom and Ross, 2017). Data-driven services support customers' decision-making with data, insights or actions (Azkan *et al.*, 2020; Schüritz *et al.*, 2019b). Compared to data-enriched products, this requires a new business model (Wixom and Ross, 2017).

Auxiliary data services: Organisations can support other firms in realising a data-driven business model, especially if they lack the necessary competencies and resources. Examples of auxiliary services are big data infrastructure-as-a-service, software-as-a-service or consulting and advisement services (Schroeder, 2016).

Analytics-as-a-Service: A special case of auxiliary data services is Analytics-as-a-Service. In this pattern, the business model owner has the analytics competencies and technical components (e.g., algorithms, models or software codes) for solving data analytics-specific problems (e.g., for specific types of data, like time series or textual data). These components are combined into a customer-specific solution (Chen *et al.*, 2011) that is applied to the customer's data (Hartmann *et al.*, 2016). Compared to the data-driven service pattern that represents standardised offerings (products), Analytics-as-a-Service offerings are customised to the requirements and needs of a single customer.

Data Platforms: Organisations can also aim to build a data platform to provide other organisations access to data. A special type of data platform is a data marketplace that matches data providers and consumers and fosters secure data exchange with a pricing mechanism (see Chapter 6.4 and Fruhwirth *et al.*, 2020b). Such a data platform can also be designed as a multi-sided platform, where other organisations are using the data platform to offer additional data-driven services (Otto and Jarke, 2019; Reuver *et al.*, 2017). One possible source of revenue is a brokerage fee for each transaction (Schüritz *et al.*, 2017b)

We selected “maturity” as our second dimension to classify data-driven business model innovations in offline-established organisations. Therefore, we adopted in the first design iteration the six phases of a data-driven business model innovation process suggested by Hunke *et al.* (2017): “Mobilisation”, “Initiation”, “Ideation”, “Integration”, “Realisation”, and “Administration”.[26] The mobilisation phase aims to set up a team and project for the data-driven business model innovation. The current situation (e.g., identifying available data sources) and customer needs are subsequently analysed in the initiation phase. The idea generation phase aims to develop different concepts for a data-driven business model. These concepts are tested and refined in the integration phase (e.g., through prototyping). The realisation phase aims to bring the DDBM to operation. Finally, the DDBM is monitored and managed in the administration phase after market introduction (Hunke *et al.*, 2017).

Subsequently, we instantiated the DDBM classification patterns and phases of maturity into a visual tool that is demonstrated in the next section.

[26] After investigating data-driven business model innovation processes in detail (research presented in Chapter 4.2 was mostly conducted after the research presented in this chapter), we ended up in slightly different phases. The example presented here includes the initial phases from the first iteration.

5.1.5 Result 2: Artifact Demonstration in the Case Setting

We applied and demonstrated the visual tool in the case setting with Comp. We used the tool to classify 23 data-driven innovations identified through 17 interviews with managers at *Comp* in 2018 (see **Appendix C**).

The outcome of this classification, as presented in anonymised form in Figure 5.1, was discussed in a half-day workshop with four managers of *Comp*. They are specifically responsible for data-driven innovations. It made clear that most of the cases were still in the mobilisation or initiation stage, that the number of ideas was lower than expected, and that support for idea generation is needed (and will be addressed in the other studies of this chapter).

Further, the discussion with the managers made clear that the category "Auxiliary Data Services" was too unspecific and needed to be refined and that a category referring to the emerging topic of data platforms was missing (and also not covered by the literature at this point of the research in 2018).

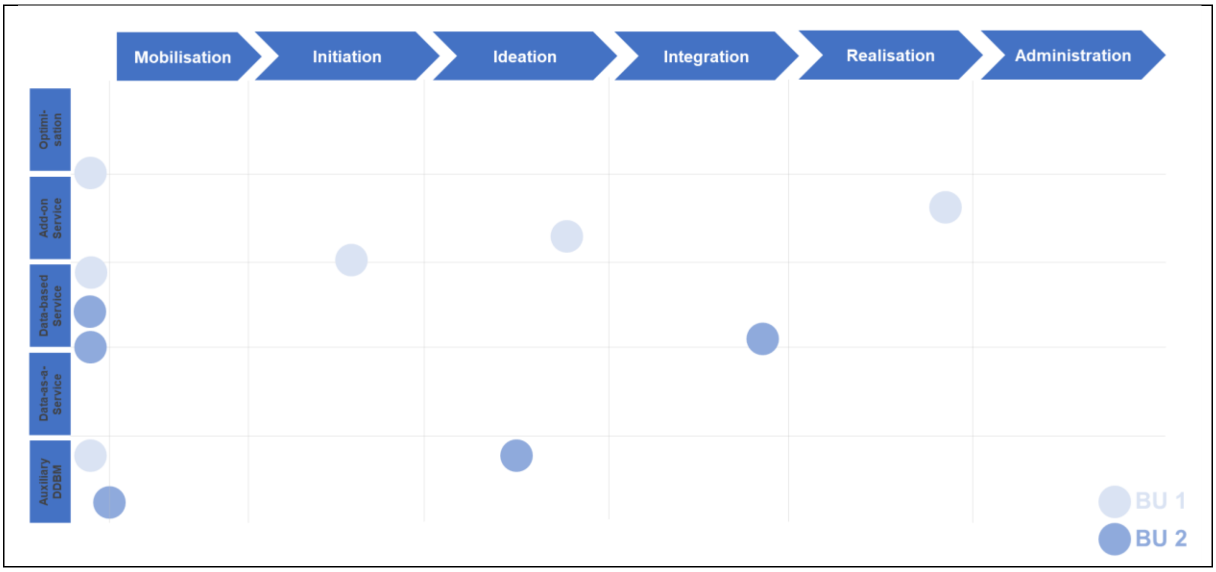


Figure 5.1: Application of the visual tool for classifying data-driven business model innovations in one automotive organization (anonymized, adapted from Fruhwirth *et al.*, 2021a).

Thus, we refined the category system by adding the patterns "Analytics-as-a-Service" and "Data Platform". Later in the case study, we used this adapted category scheme to classify existing data-driven innovations at *Comp* (with real offerings and customers) in a company training on data-driven business model innovation. Figure 5.2 below shows an anonymised excerpt of the lecture material.

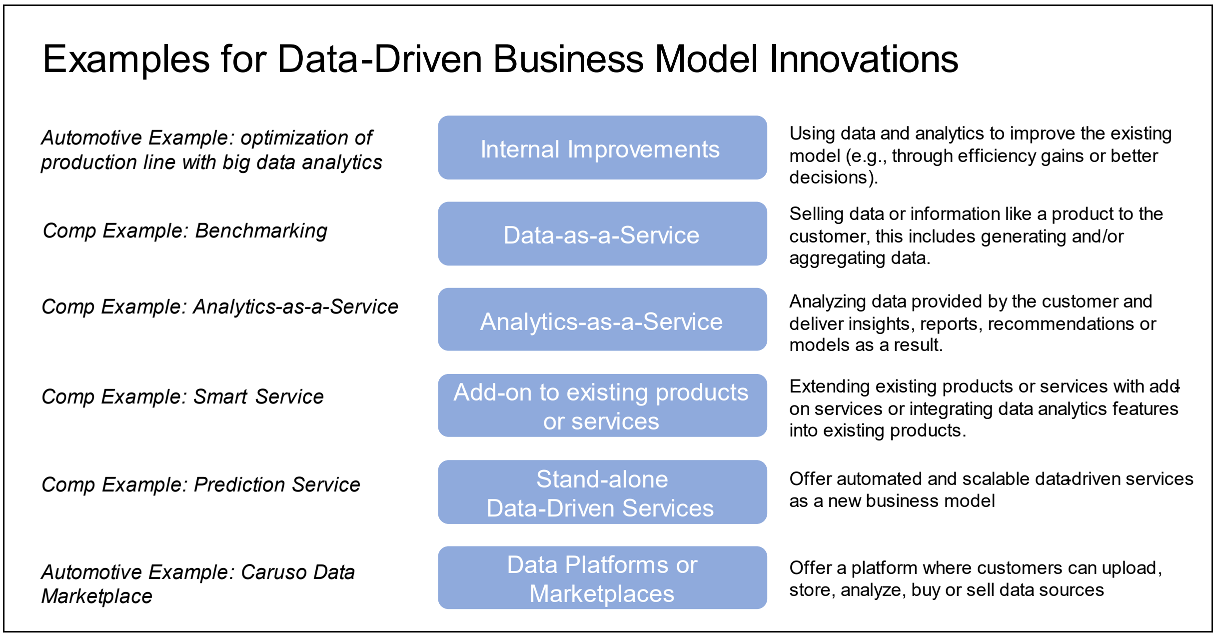


Figure 5.2: Applying the adapted categorisation scheme in a company training (anonymised, excerpt).

5.1.6 Discussion and Conclusion

In this chapter, we have developed a categorisation scheme for data-driven innovations that we instantiated as a visual tool and demonstrated in our case organisation. Our classification scheme suggests that different types of data-driven business model innovations slightly differ in development and thus require different or adopted versions of supporting tools and methods. Focusing on the value proposition, it makes sense to divide DDBMs into three types: *DDBMs in a broader sense* (including data-enabled improvements, auxiliary data services and data platforms) where data and analytics are a central part of the business model but not directly part of the value proposition; *DDBMs in a narrow sense* (including Data-as-a-Service, Analytics-as-a-Service, Data-enriched Products and Services), where data is part of the value proposition; and *pure DDBMs*, where novel data-driven services are created to support customers in their decision and automation problems. In the rest of this thesis, we will focus on the pure DDBM pattern of “Data-driven service”. Only Chapter 6.4 investigates data marketplaces, a special type of data platform and by that a DDBM in a broader sense.

- Thus, with this work we contribute to the further understanding of data-driven business models (see contributions in section 7.2.3 of this thesis).

As we developed the classification scheme of this chapter before the overall process design presented in Chapter 4.2, we now aim to synchronise these two models, as shown in Figure 5.3. The “Initiation and Ideation” phase of the process described in Chapter 4.2 corresponds to the first three phases of the classification scheme (“Mobilisation”, “Initiation”, and “Ideation”). The “Analytical Feasibility” phase (i.e., testing and evaluating a DDBM concept before any implementation and prototyping) and the “Prototyping and Validation” phase (i.e., testing and evaluating a DDBM concept after the development of a prototype) correspond to the “Integration phase” of the classification scheme. Finally, the “Implementation and Execution” phase of the BMI process corresponds to the “Realisation” and “Administration” phases of the classification scheme, as it covers both the implementation and market introduction as well as the ongoing monitoring and management of the operating business model. We visualise this mapping between the two studies in Figure 5.3.

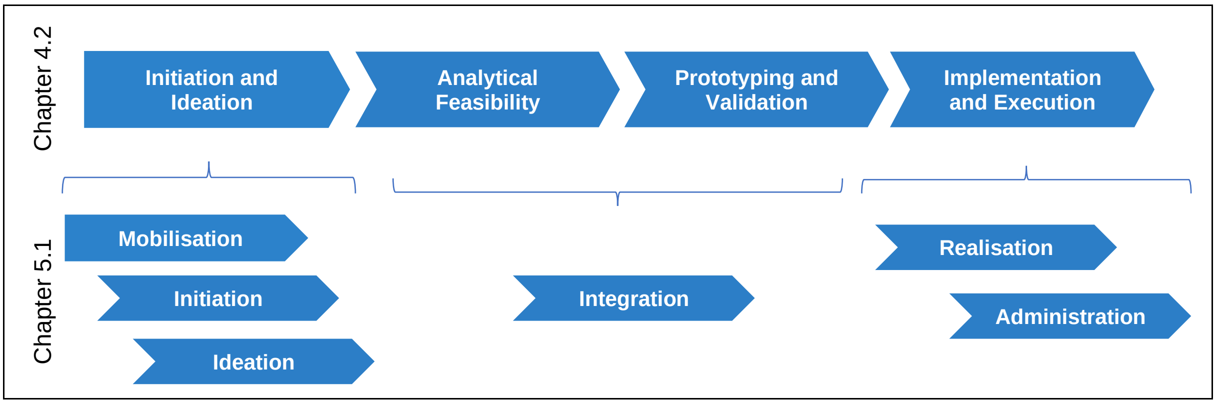


Figure 5.3: Aligning the maturity levels of the classification scheme with the business model innovation process presented in Chapter 4.2.

Following up on this classification of the level of maturity of a data-driven business model initiative, one avenue for further research addressed in this thesis is to develop a set of criteria that support classifying data-driven innovations to the right level of maturity. Chapter 6.1 takes this up where we developed evaluation and decision criteria for pre-defined gates for the overall business model innovation process. These criteria can be used to assign a use case to a certain phase: When all criteria of the previous gate are fulfilled, and not all gates from the next gate are fulfilled, an innovation is classified to this stage.

Furthermore, our results have a certain limitation due to the fast advancement of the research field and technology, and major parts of this chapter were conducted between 2018 and 2020. We have already addressed this issue, as described, by updating the classification scheme in 2021, e.g. by adding the emerging area of data platforms as an additional pattern. In 2024, one could add more patterns due to the increased usage of machine learning and the in-depth integration of data services and artificial intelligence into organisational information systems (Hopf *et al.*, 2023; Shollo *et al.*, 2022), leading to the automation of decisions and actions.

➢ We address this issue as a general limitation (*Limitation 4*, Chapter 7.4) and an overall outlook (*Outlook 4*, Chapter 7.5) of this thesis.

Finally, the demonstration of our artefact in the context of *Comp* pointed to the direction that further support for idea generation was needed. The next chapter will take this up and aims to develop a tool that supports idea generation for data-driven services – particularly defining the value proposition with a visual collaborative tool, the Data Product Canvas.

5.2 The Data Product Canvas[27]

5.2.1 Introduction and Problem Description

One difficulty for offline-established organisations that want to pivot to a data-driven business model is the lack of knowledge about data-based value propositions and a limited understanding of customer problems inside the organization (Bertoncello *et al.*, 2018). Thus, before building a data-driven business model, organisations must identify a data product that meets market needs (Davenport and Kudyba, 2016). Furthermore, developing data-driven business models is a collaborative task involving knowledge and stakeholders from different disciplines, such as data scientists, domain experts and business people. Bridging this gap is challenging. As we will show in this chapter, we encountered both problems in our case study with *Comp*. Finally, only a few data-focused tools and methods have been available to support the innovation process, as chapter 4.1 showed. Thus, we address the following question in this chapter:

How could a visual representation facilitate collaboration and idea generation for data-driven service ideas for non-data experts?

In this chapter, we propose the Data Product Canvas, a visual artefact that intends to support the development of a data-driven business model, particularly considers the development of a structured value proposition and understanding of customer needs and aims to support the necessary interdisciplinary communication. We have developed the Data Product Canvas in a sub-DSR project and evaluated it in four workshops with practitioners from established organizations. In the evaluation, we studied the (perceived) usefulness and acceptance of the Data Product Canvas, its actual usage, and the generated outcome.

5.2.2 Additional Background on Data Products and Visual Collaborative Tools

One central dimension of a business model is the value proposition. Osterwalder and Pigneur (2010, p. 22) describe the value proposition as *"the bundle of products and services that create value for a specific customer segment"*. This business model element focuses on how an organization satisfies customer needs, solves customers' problems, and shows what services and products are offered (Augenstein *et al.*, 2018). The value proposition of a business model can be infused by data and analytics (Schüritz and Satzger, 2016), leading to new data-driven services. Data-driven services use *"data and analytics to support the decision-making process of the customer via data and analytics-based features and experiences in form of a stand-alone offering or bundled with an existing product or service"* (Schüritz *et al.*, 2019b, p. 4). Next to data-driven

[27] This chapter is based on the publication: Fruhwirth, M., Breitfuß, G., and Pammer-Schindler, V. 2020. "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.

services also the concept of “data products” emerged by practitioners (e.g., Glassberg Sands, 2018), as a subset of services. Specifically, data products help users make better decisions and formulate customer benefits (Tempich, 2019). The users of a data product can be internal or external customers. Delivering economic value for the product owner requires a proper business model. The bottom line of those concepts, which we further refer to as data products, is that a service provider uses data and analytics to deliver value to an (internal or external) customer to solve a customer problem, specifically supporting his decision-making process via a data product.

Individuals and organisations can be supported in this process of developing new services and business models through tools and methods (Schneider and Spieth, 2013). Visual tools help to communicate a firm’s business model or stimulate collaborative innovation and idea generation (Osterwalder and Pigneur, 2010). Various generic tools exist, such as the Business Model Canvas (Osterwalder and Pigneur, 2010). Furthermore, specialized representations exist for specific business model elements, such as the Value Proposition Canvas (Osterwalder *et al.*, 2014). Such representations also exist for specific types of business models (e.g., characterized by the type of key resource), supporting general representations of business models (Kühne and Böhmann, 2019). There is a lack of tools supporting the development of products and services based on data and analytics (Fruhwirth *et al.*, 2020c; see Chapter 4.1). Existing tools do not meet the requirements for developing data products, as we will see in the following sections.

5.2.3 Detailed Research Approach

To develop the Data Product Canvas, we carried out a sub-DSR project to develop a new and innovative artefact that helps to solve the real-world problem of generating ideas for data products. We followed the sequential process of Peffers *et al.* (2007), consisting of six phases, as shown in Figure 5.4: problem identification and motivation; objectives of a solution; design and development; demonstration; evaluation; and communication.

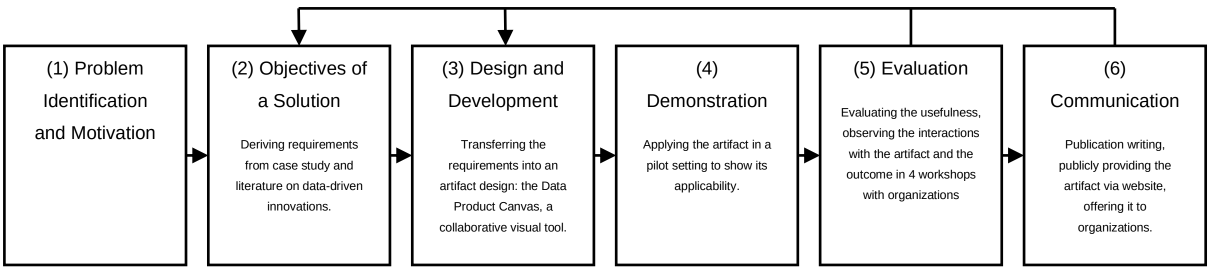


Figure 5.4: The DSR approach employed in this study (adapted from Peffers *et al.*, 2007).

The introduction section of this chapter and section 5.2.4.1 address the “problem identification and motivation phase”. The second phase, “objectives of a solution”, determines the requirements for developing data products from literature and our case study with *Comp* (section 5.2.4). The third phase, “design and development”, focuses on transferring the requirements into a visual representation (section 5.2.5). In the fourth phase of the process, “demonstration”, we apply our artefact within a pilot setting at *Comp* (i.e., a workshop with four managers) to demonstrate its applicability. In the fifth phase, “evaluation”, we evaluate the artefact for its usefulness and ease of use within workshops of different organizations (5.2.6). The last phase, “communication”, is accomplished via the referenced publication (Fruhwirth *et al.*, 2020a) and this thesis. An adapted canvas version was also published on the Safe-DEED EU project website.[28]

5.2.4 Result 1: Requirements

5.2.4.1 Practical Requirements and Problem Motivation

We have identified the problem within the design cycle one of our overall case study with *Comp* (see Chapter 3.2.2), where the goal was to support *Comp* in innovating new data-driven business models. A one-day workshop with an external consultant organization and 12 participants, where the author of this thesis also participated, was conducted in 2018 to generate new business ideas based on data. Participants had positions in product management, research management or business development. During the workshop, we observed the need for a visual representation to structure and communicate data-related business ideas. After three rounds of open ideation sessions with sticky notes, a generic template was used further to elaborate selected ideas in detail in small groups. The outcome of the workshop was a broad range of digital business ideas. Reflecting on the process and the outcome made it clear that traditional organizations that now want to go in the direction of data business need clear and structured guidance at the beginning of the innovation process to formulate and communicate business ideas with data. This observation was the motivation and starting point for this research to develop a visual tool supporting idea generation. After the design phase of this design science research project, the tool was used to structure 21 data-related ideas from the case company. The analysis revealed that the user pains and benefits were unclear in most existing ideas, underpinning the need for such a collaborative visual tool supporting idea generation for data-driven services.

5.2.4.2 Theoretical Requirements for Developing Data-Driven Services

To elaborate on design requirements for an artefact that aims to solve the problem of collaboratively developing ideas for data products, we reviewed existing literature on developing data-driven services, products and business models and identified five design requirements.

Identifying the required data sources is one crucial step within the exploration phase of data-driven innovations (Davenport and Kudyba, 2016; Kayser *et al.*, 2019; Kronsbein and Mueller, 2019). Data can originate from different sources: on the one hand, from internal information systems (e.g., CRM); on the other hand, data from external sources, such as free available sources (Hartmann et al. 2016), data provided by customers (Hunke *et al.*, 2019) or purchased data assets from data marketplaces (Fruhwirth et al. 2020). Despite their origin, there are different types of data sources, describing what the data is about (e.g., customers, objects or processes; (Hunke et al. 2019)) or the format of the data (e.g., video, audio or image; (Kayser et al. 2019)). Beyond the diversity of

[28] https://businessmakeover.eu/tools/safe-deed-data-driven-business-canvas, accessed on 02.10.2022 13:15. As of April 2024 tools not available any more on the platform.

data sources, there is also the challenge of insufficient shared data understanding within an organization when different roles and departments interact or work with the same data (Kayser *et al.*, 2019; Mathis and Köbler, 2016). Making data visible is one approach to address this issue to facilitate discussions for data-driven innovations (Kayser *et al.*, 2019; Kühne *et al.*, 2019). Winter (2019) argues that when IT-related concepts are "black-boxed", data becomes understandable and usable for non-data experts, such as stakeholders with domain expertise or business background. Thus, we frame the first design requirement (DR) for our artifact as follows:

DR-1: The necessary data sources for the data service should be visualized on a conceptual level to facilitate a shared understanding.

Data itself often has no value for the user. Value is derived from data by applying analytical methods to generate insights. Different analytics methods exist for data products (Hunke *et al.*, 2019); such methods can cluster, correlate, recommend, or search data to create meaningful insights that have potential value for data users. The organization should know which tools and methods are appropriate and necessary to generate insights from the data and how to interpret the data (Dremel *et al.*, 2017; Kühne and Böhmann, 2019). Data analysis activities are related to one key activity in data-driven business models (Hartmann et al. 2016). Therefore, we articulate the second design requirement:

DR-2: The required data analytics methods and activities to generate insights from data should be visible in the artefact representation.

The service provider uses data and analytics to support the data users' decision-making process to create value for the customer (Schüritz *et al.*, 2019b). Therefore, a proper fit between available data sources and user needs is vital for a compelling value proposition (Mathis and Köbler, 2016). Thus, beyond data analytics, data product development also requires customer intimacy and customer understanding (Wixom and Schüritz, 2017). Service design, in general, starts from the user perspective, meaning understanding the tasks (the "job-to-be-done" cp. Christensen *et al.*, 2016b), challenges and wishes of the user and map them to the value offering (Osterwalder *et al.*, 2014). Specifically, developing data products requires bringing together the business (customer understanding) and data world (Glassberg Sands, 2018; Mathis and Köbler, 2016) to create a meaningful solution. Thus, we articulate the third design requirement:

DR-3: The pains, wishes and needs of data users that the data product could address should be visualized to create a meaningful solution.

The goal of designing data products is to solve the user's problems and address his wishes and needs. However, the provider alone only creates potential value through the data service. The provider, jointly with the customer, create real value (Schüritz *et al.*, 2019b) by using the data product in the user's decision-making process. This relates to the concept that information has no value; value results only from its usage (Moody and Walsh, 1999). As the user is at the centre of the innovation process, the aspired value for the user should be described (Kronsbein and Mueller, 2019). To understand, as an innovation team, how the data product creates what value for the customer through its usage, we articulate the fourth design requirement:

DR-4: The resulting value-in-use of the data product for the user should be conceptualized.

Davenport and Kudyba's (2016) development model also covers the presentation of the data product. The presentation can have different forms, depending on the level of co-creation between provider and user: In the simplest form, a provider can deliver data through reports, dashboards or APIs, or in more sophisticated form through alerts, benchmarks or even automated decisions (Schüritz *et al.*, 2019b). A visual representation should also incorporate that view, i.e., to specify what is exchanged between the provider and the user. Thus, we articulate our fifth design requirement:

DR-5: The type of presentation of the data product should be visualized to conceptualize the data product.

5.2.4.3 Existing Visual Representations for Developing Data Products

After deriving a set of requirements for an artefact that aims to provide a solution to the given problem, we checked the requirements against existing visual representations to justify that there is an actual need for a new artefact. We conducted a structured literature review (see chapter 4.1 and Fruhwirth *et al.*, 2020c) to identify existing visual representations for data-driven innovations in the literature. We added two more representations (5, 9) that were published after our search and selection process.

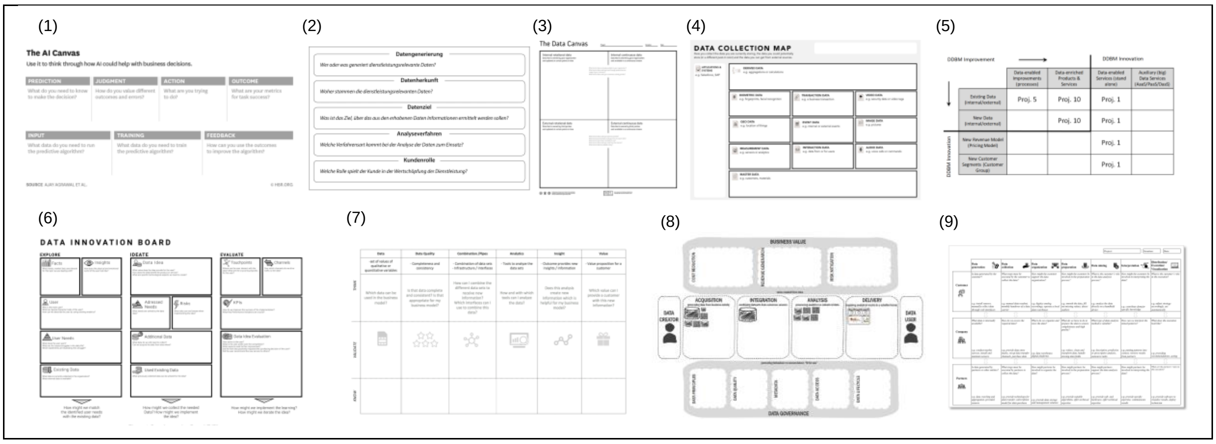


Figure 5.5: Existing visual templates supporting data-driven business model innovation as of 2020: (1) AI Canvas (Agrawal *et al.*, 2018a), (2) Analytics-based Service Canvas (Hunke and Schüritz, 2019), (3) Data Canvas (Mathis and Köbler, 2016), (4) Data Collection Map (Kayser *et al.*, 2019), (5) Data-Driven Business Value Matrix (Breitfuß *et al.*, 2019), (6) Data Innovation Board (Kronsbein and Mueller, 2019), (7) Data Insight Generator (Kühne and Böhmann, 2019), (8) Data Value Map (Nagle and Sammon, 2017), (9) Key Activity Canvas (Hunke *et al.*, 2020b).

We checked for each visual representation to see if it meets the five derived requirements of this chapter, as shown in Table 5.2.

Existing visual tools with data as a lens of analysis	DR-1: Data Sources	DR-2: Analytics Methods	DR-3 User Problems	DR-4: User Benefits	DR-5: Data Product
(1) AI Canvas (Agrawal et al., 2018)	✓	✓	(✓)	-	-
(2) Analytics-based Service Canvas (Hunke and Schüritz 2019)	✓	✓	-	-	-
(3) Data Canvas (Mathis and Köbler 2016)	✓	-	-	-	-
(4) Data Collection Map (Kayser et al., 2019)	✓	-	-	-	-
(5) Data-Driven Business Value Matrix (Breitfuß et al., 2019)	(✓)	-	-	-	-
(6) Data Innovation Board (Kronsbein and Mueller 2019)	✓	-	✓	✓	-
(7) Data Insight Generator (Kühne and Böhmann 2019)	✓	✓	-	✓	-
(8) Data Value Map (Nagle and Sammon 2017)	✓	✓	-	-	✓
(9) Key Activity Canvas (Hunke et al., 2020)[29]	-	✓	-	-	-

Table 5.2: Comparison of existing tools based on the identified requirements (as of February 2020).

The *AI Canvas* (Agrawal et al. 2018) helps to organize and evaluate how artificial intelligence helps with business decisions. It includes, on the one hand, the main elements of decision-making (prediction, judgement, action and outcome) and the main elements of machine learning (input, training and feedback). With this logic, it addresses DR-1 (data sources), DR-2 (analytics methods) and DR-3 (user problem).

Hunke and Schüritz (2019) developed a framework (the *Analytics-based Service Canvas*) to conceptualize analytics-based services along the dimensions of the data generator, the origin of the data, what the data is about, the applied analytics methods and the role of the customer, herby addressing DR-1 (data sources) and DR-2 (analytics methods).

The *Data Canvas* (Mathis and Köbler 2016) helps to identify and organize data sources across the perspectives of data origin (internal vs. external) and refresh rate of the data (regular vs. sequential), by that fulfilling DR-1 (data sources).

Similarly, Kayser et al. (2019) developed the *Data Collection Map* to structure data sources across 11 types of data sources within an organization to facilitate a shared understanding and identify key data stakeholders within an organization, also fulfilling DR-1 (data sources). Though both visualizations do not consider value creation with data, neither tool can help solve the identified challenge.

[29] This tool was initially published as Hunke and Wambsganß (2017) during our literature search phase.

Breitfuß et al. (2019) introduced the *Data-Driven Business Value Matrix* to classify data-driven innovations based on different strategic options for innovating an organization's business model with data and analytics. The authors partially address DR-1 (data sources) with their framework.

The *Data Innovation Board* (Kronsbein and Mueller 2019) facilitates developing and ideating data-driven products and services for non-data experts. The canvas provides elements about the data sources (DR-1), the user needs (DR-3) and the idea or user benefit (DR-4), among others. Despite the various elements in its underlying ontology, the artefact misses a conceptualization of the data product (DR-5) and the analytical methods (DR-3), thus not fulfilling all requirements.

The *Data Insight Generator* (Kühne and Böhmann 2019) aims to connect data as a specific resource type and the value proposition for a data-driven business model. This artefact provides support to ideate about several activities that are required to craft a proper value proposition based on data as the key resource (namely data quality, combination, analytics, insights), herby addressing DR-1 (data sources) and DR-2 (analytics methods).

The *Data Value Map* (Nagle and Sammon 2017) tackles the problem of a lack of shared understanding and misalignment between data stakeholders. It includes data sources (DR-1), analytics methods (DR-2), and the conceptualisation of the data product (DR-5).

Hunke *et al.* (2020b) introduced a framework (the *Key Activity Canvas*) that supports structuring data-related key activities within a data-driven business model and assigning those activities to stakeholders (partners, customers, and the service provider), herby addressing DR-2 (analytics methods).

As our review of previous research shows, no artefact has sufficiently solved the problem by fulfilling all five identified requirements. Specifically, few visual tools incorporate the perspective of connecting data with the user problems and benefits and conceptualising the data product's presentation.

5.2.5 Result 2: Artifact Description – The Data Product Canvas

To overcome the gap between previous visual tools with data as a specific lens to support the collaborative development of data products, we developed the Data Product Canvas, visualised in Figure 5.6. The five main fields (columns) of the canvas address the design requirements identified in section 5.2.4.2: elements "data sources", "data analytics", and "data product" in the provider sphere and "user benefits" and "pains and gains". Table 5.3 shows this mapping between design requirements and elements of the Canvas. Two additional elements have been added that describe the data product's name and the customer's address. These two elements highlight the dyadic view of the provider and customer sphere.

Sphere	Design Requirement	Canvas Field	Example
Provider Sphere	DR-1: The necessary data sources for the data service should be visualized on a conceptual level to facilitate a shared understanding.	Data Sources	Weather data
	DR-2: The required data analytics methods and activities to generate insights from data should be visible in the artefact representation.	Analytics	Correlation analysis
	DR-5: The type of presentation of the data product should be visualized to conceptualize the data product.	Data Product	Dashboard
Customer Sphere	DR-4: The resulting value-in-use of the data product for the user should be conceptualized.	Customer Benefit	Cost Optimization
	DR-3: The pains, wishes and needs of data users that the data product could address should be visualized to create a meaningful solution.	Pains and Gains	Too many expired goods

Table 5.3: Mapping of design requirements to the canvas fields with an illustrative example

An icon, trigger question, and illustrative examples are provided for each element. The Data Product Canvas should be used in the initiation and ideation phase when an organisation aims to develop the first ideas for a data product. The canvas can be used in a workshop with an interdisciplinary team of data scientists, domain experts and management. Further, it can be used as structured documentation of ideas.

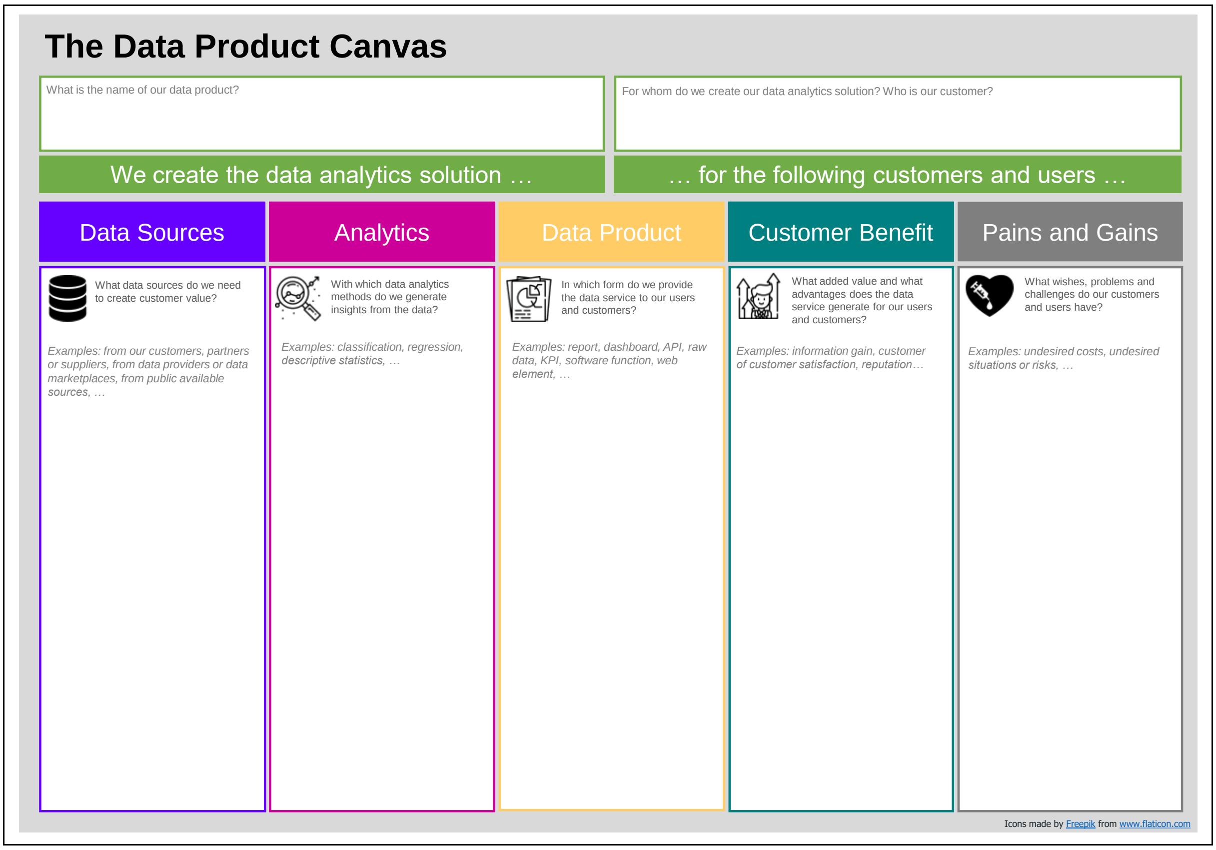


Figure 5.6: Instantiation of the Data Product Canvas (Revision 1).[30]

[30] Between evaluation case C and D we changed the visual appearance (the colours) of the canvas.

5.2.6 Result 3: Artifact Evaluation through Participatory Ideation Workshops

To complete our sub-DSR project, we had to "observe and measure" (Peffers *et al.*, 2007, p. 56) how well our artefact supports the design of data products. This involves comparing the objectives of our solution with the observed results from using the artefact (Peffers *et al.*, 2007). We used workshops as an evaluation method. Workshops are a common and appropriate method to evaluate visual collaborative tools (i.e., our canvas) with target users (i.e., practitioners responsible for innovations) in a naturalistic setting (i.e., with participants develop a DDBM for their organisation during the workshop) (e.g., Avdiji *et al.*, 2020; Kühne and Böhmann, 2019). Workshops also allow multiple evaluation goals and data collection (Thoring *et al.*, 2020), such as observing interactions with the artefact, evaluating the idea as a result of the activities in the workshop (i.e., the developed idea) or collecting qualitative feedback about the usefulness, usability, etc. of the artefact. In contrast to other evaluation methods, such as experiments requiring more participants, workshops allow evaluation with target users in a naturalistic setting. We performed an ex-post evaluation in a (semi-) naturalistic setting.

5.2.6.1 Description of the Evaluation Method and Workshop Setup

For designing our workshops as an evaluation method, we followed the principles Thoring *et al.* (2020) suggested, including defining the focus and goals, role allocations, data triangulation, transparency and reflection. We ensure transparency by describing the workshop setting, i.e., the evaluation goals, methods, details about the cases and participants, and the workshop's sequence. The two involved researchers reflected on the evaluation procedure after each workshop. The focus of the workshops was to observe the artefact's usage in idea-generation activities for data-driven business models.

Case descriptions: We have carried out four workshops with company representatives involved in ongoing processes of identifying and concretizing opportunities for data-driven business in their respective companies. Workshop attendance was between 6 and 18 participants; group work in workshops was carried out in groups of 3-6 participants. Each workshop is a case for studying the Data Product Canvas. Table 5.4 gives an overview of the evaluation settings, describing the participants and the duration and date of each workshop.

Case B and C represent a fully naturalistic setting, as the participants were from the same organisation, workshops were carried out on-site, and participants developed ideas for their respective departments. Cases A and D represent a semi-naturalistic setting, as participants were still practitioners but were recruited from multiple organisations and formed mixed groups. Workshops were carried out at a neutral place (i.e., neither on-site of the company nor at the research organisation). Participants developed use cases for one company within the group.

Case	Description of Participants	Number of Participants	Duration	Date
A	Representatives from green technology firms (e.g., general managers, engineers, innovation managers)	14 participants (4 groups of 3-4 participants each)	~60 min	Mar. 2019
B	Product, innovation, R&D manager and data scientist from an engineering company	6 participants (one group)	~120 min	Aug. 2019
C	IT manager, data scientist and domain experts from a manufacturing company (e.g., quality, supply chain management or manufacturing)	11 participants (3 groups of 4-6 participants each)[31]	~60 min	Oct. 2019
D	Representatives from green technology firms (e.g., innovation, engineering, management)	18 participants (3 groups of 6 people)	~120 min	Feb. 2020

Table 5.4: Overview of evaluation settings for the Data Product Canvas.

Workshop goal, sequence and role allocation: The outcome goal of each workshop setting was to conceptualize an idea for a data product. Furthermore, from a research perspective, the goal was to evaluate the Data Product Canvas as a workshop facilitation artefact. The organisation already provided an initial rough idea in each case beforehand. The available data sources were already collected in a prior workshop in cases A, B and C. In each case, one researcher acted as a workshop facilitator, introduced the canvas and gave initial instructions, whereas a second researcher observed the participants and took notes. By separating coaching and data collection, we aimed to minimize the risk of research bias (Thoring *et al.*, 2020). The workshops were carried out in the following sequence: (1) introduction to DDBMs & explanation of the canvas by one of the researchers, (2) provision and/or collection of existing data sources (in separate data map) as input, (3) participants got the task to think about a new data product or service for their organisation and to describe the idea in the elements of the canvas with the help of sticky notes (Avdiji *et al.*, 2020). The workshop facilitator assisted when questions popped up. (4) After task completion, the team presented their outcome and expressed their experience while using the canvas. (5) The researchers asked basic feedback questions, such as

Triangulation – multiple data sources: To increase the validity of the evaluation, we used data from different evaluation methods within the workshops, thus facilitating data triangulation. (i) *Observations and notes*: We took field notes during each workshop, observing and documenting the participants' behaviour and interaction with the artefact. For confidentiality reasons, the workshops have not been recorded, particularly as some have been carried out on-site at the company, developing new business ideas. Further, no notes have been taken regarding their thoughts about business problems and ideas. (ii) *Interviews and group discussion*: Participants were asked feedback questions directly after the workshop about the usefulness and ease of use.

[31] Workshops were conducted consecutively; two participants of the company participated in all three workshops.

(iii) *Pictures*: We have documented each workshop's outcome (i.e., the filled canvas) through pictures, thus enabling a content analysis of the developed ideas.

We structured the evaluation results along with three evaluation goals: the acceptance and perceived usefulness, the actual usage and interactions with the artefact, and the outcome of each workshop (generated idea with the canvas).

5.2.6.2 Perceived usefulness and acceptance

Overall, all groups and participants perceived the Data Product Canvas as useful. An IT manager in evaluation case C stated that the canvas effectively describes a data use case within a one-hour meeting. He didn't expect to be so fast. A participant in case A mentioned that this representation helps to organize the problem: *"You see very quickly where to focus: What do you want? What does the customer want?"* (Participant in case A, group 2). Furthermore, identifying the user was perceived as a necessary but challenging task: "*It took us quite a long time to figure out who our customers were. Only then could we continue with the right elements [of the canvas]"* (participant in case A, group 2). Another workshop participant highlighted the usefulness of the canvas elements: *"It's very good that you think about all the steps"* (Participant in case A, group 3). Focusing on the customer was particularly important, as another participant mentioned: *"For whom are we doing this for? That was good to make that explicit"* (Participant in case C, group 1).

The need to focus on the user perspective was also observed. For instance, in case C, group 3, the participants were discussing the user benefit of the initial idea (introduced by one domain expert). It emerged that the benefit was unclear, and thus, it was hard for the participants to develop a meaningful data product idea. A participating manager of case C decided not to continue working on this idea after the workshop. On the contrary, the manager in case C decided to implement a proof-of-concept of the developed data product ideas of groups 1 and 2, thus highlighting the usefulness of the Data Product Canvas.

A data scientist in case C reported after the workshop that they are already using the canvas in their daily work in collaboration with other departments. Similarly, the organization of case B is considering including the canvas in its portfolio of innovation tools**. Thus, based on the results from four evaluation cases, we have evidence for our artefact's perceived usefulness and acceptance.**

5.2.6.3 Usage and interaction with the artefact

We observed different sequences and how the participants filled out the canvas fields. For instance, one group in case A started with the data sources and ended with thinking about what they must analyse (referring to the "Analytics" column). Participants also noted that it was difficult to decide what column to start. Most groups started from the left ("Data Sources"). This approach of using the canvas seems intuitive, although no specific starting point was intended through the design. On the other hand, we observed that participants found it easier to generate a data product idea when starting from the user's perspective. A participant in case A stated that they should have started with the right columns of the canvas (“Pains and Gains” and “Benefit”), as they realized only later while filling out the right columns what they wanted to develop (a digital twin solution).

Reflecting on all four evaluation settings, we hypothesised that thinking about pains and benefits should be one of the first steps. **Thus, a further improved canvas and workshop format version should guide where to start.**

We have also observed some termination problems: The difference between the category »Benefit« and the category “Pains and Gains” was not clear for several participants in all four cases. There was, for instance, the feedback from one participant that it was not clear what to fill into the column “Benefit”, as the information was, in their perception, already included in “Data Product” or “Pains and Gains”. Furthermore, participants in case D misinterpreted the “Benefit” column as the benefit for the provider, i.e., they were thinking about how they could make money with the service idea. **Thus, a further improved version of the canvas and workshop format should further clarify the concepts of benefits and pains/gains.**

Furthermore, we have observed that detailing an idea based on the degree of maturity is sometimes needed. For instance, participants in case C questioned what data is required to build the data product (e.g., using existing archival data to identify influencing factors of the model) and what data sources are later required for the running system (i.e., integrated in the current working process of the user with “life data”). Thus, it may be required to differentiate those perspectives, e.g., via filling out several canvases. Similarly, we have observed that sometimes the participants put many (sub-) ideas for a data product in one canvas (e.g., delivering the results via different data products). For instance, in case B, the participants came up with different ideas for the “Data Product” column (e.g., providing KPIs, providing a report, selling aggregated data, integrating a function to an existing software tool or providing the data analysis as-a-Service) all addressing the same customer pains and gains. Another interesting observation was that group 1 in case A also added a sketch of the data visualization to the “Data Product” field. The artefact design initially did not intend this but was perceived as helpful.

5.2.6.4 Exemplary Data Product Ideas from the workshops

The last source of evaluation data was the outcomes of each workshop, i.e., the generated idea. Figure 5.7 shows two documented data product ideas using the Data Product Canvas and post-its in a workshop setting. The first idea (left) describes a data product supporting one process step of a manufacturing company. With the help of data, factors influencing product quality that lead to transparency, less rework, and higher product quality can be identified. The second idea (right) describes a data product for street operators: data should help support investment decisions for renewing street infrastructure, leading to more efficiency and fewer accidents. For confidentiality reasons, not all information is visible.

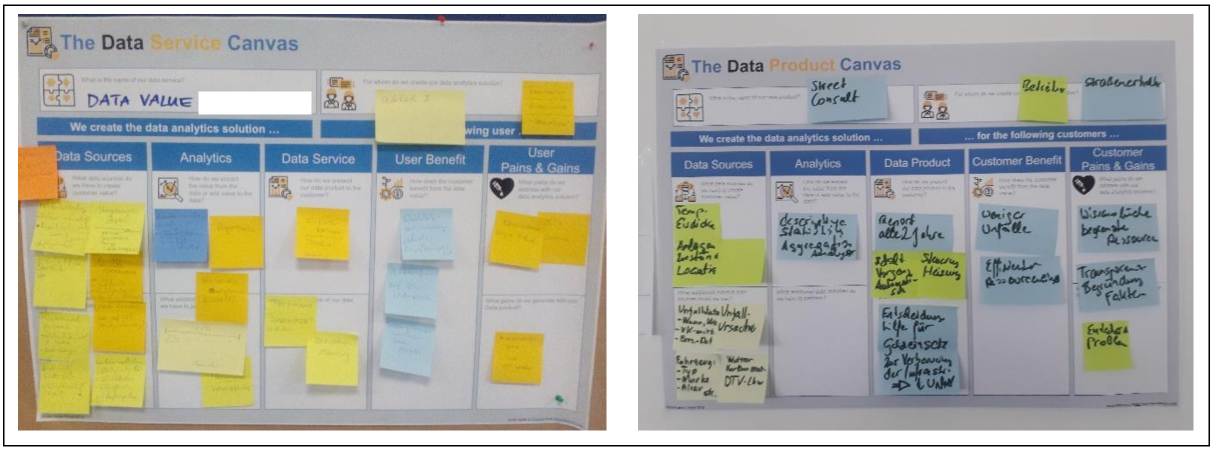


Figure 5.7: Two exemplary ideas of workshops using the Data Product Canvas (partly anonymized).

Concluding from our evaluation episodes, the Data Product Canvas was perceived as useful for supporting idea generation and facilitating workshops and interdisciplinary discussions. Nevertheless, the main recommendations for improvement are a method of use (guidance on how to use the canvas) and to elaborate more on the underlying ontology to clarify the elements (in particular, “Customer Benefits” and “User Pains & Gains”.

5.2.7 Discussion and Conclusion

In this chapter, we described the developed of the Data Product Canvas, a visual-collaborative tool that aims to support idea-generation workshops and enables a structured description of data-driven business model ideas. We evaluated the usefulness and ease of use through workshops with organizations and target-users. Overall, our evaluations show that the Data Product Canvas was perceived as usable and beneficial for organizations and interdisciplinary teams initiating a data-driven innovation. Furthermore, the presented artefact contributes to research question two of this thesis. From a practical perspective, an adapted version of the canvas was applied in the EU project *Safe-DEED*[32] and was added to the toolbox of the *businessmakeover* platform[33]. In the following, we will discuss our results concerning further activities, such as a method of use, the combination with cards as an innovation tool, the interplay of the canvas with other innovation tools and the shortcomings of the canvas.

Despite this practical relevance, we found in our evaluation that guidance on where to start is needed. Therefore, based on our learnings from the evaluation, workshops and usage of the Data Product Canvas, we suggest a method of use as described in Figure 5.8. The method of use includes a description of the workshop setting (participants, schedule) and recommended steps how to fill the canvas. Start with the customer needs (pains and gains) and, in particular, to focus on the decision problem that the customer could have (Schüritz *et al.*, 2019b). As a second step, the data sources necessary to derive insights that inform the decision problem need to be identified

[32] https://safe-deed.eu/ accessed on 21.10.2022, 20:47
[33] https://businessmakeover.eu/tools/safe-deed-data-driven-business-canvas accessed on 21.10.2022, 20:49.

and analysed to create a data-need fit (Mathis and Köbler, 2016). In the third step, the necessary analytics methods and key activities need to be explored (Hunke *et al.*, 2020b).

Recommendation for workshop setting: You can use the Data Product Canvas by yourself, but we recommend using it in a team: the team should cover the domains of data science (e.g., possible analytics solutions), the application domain (e.g., construction), the customer perspective (e.g., via product managers or sales representatives) as well as the business perspective. We recommend scheduling a meeting of two hours to complete one use case and later continuously update the canvas based on your learnings during the innovation process. If you come up with several (sub-) ideas, create one canvas for each.

Recommendations for usage: Start with Customer Pains and Gains.

1. Start filling out the canvas with the column "Customer Pains/Gains" by closely examining customer needs. Try to answer the question: What (decision) problems does your customer have that could be supported with data and analytics? You can use information collected in the stakeholder map.
2. Next, check out what data sources you need to develop the expected data service to derive insights that support the (decision) problem. You can reuse information collected in the Data Map. Think of internal data sources, data from your partners, from data marketplaces, or maybe you could use open data provided by governments or research institutions. List your ideas in the field "Data Sources".
3. After that, try to find out what analytics method you could apply to gain insights and benefits from the data. If you want to predict something, you could use a regression analysis. If you want to find and sort information, a cluster analysis could help. For filling out the related column "Analytics" you maybe need support from experts in data science.
4. After that, consider ways to make the data service available to your customers. This could be, e.g., a report, a dashboard or transferring data via an API to the customer. Note your ideas in the column "Data Product".
5. Finally, consider what value your data product or service generates for the customer by filling out the "Customer Benefit" column.

Figure 5.8: Method of Use for the Data Product Canvas.

Building on the outcomes of this chapter and the corresponding publication (Fruhwirth *et al.*, 2020a), a set of cards with potential variables for each category of the canvas was developed (Breitfuß *et al.*, 2020). The cards serve as examples and creativity support for filling out an adapted version of the canvas during exploration and ideation workshops in addition to the usage of sticky notes (Avdiji *et al.*, 2020), as an evaluation study showed (Breitfuß *et al.*, 2023). In this study, the canvas and the cards were instantiated as an online tool[34] that is publicly available. This digital version of the canvas also addresses the need for IT support in data-driven business model innovation as outlined in Chapter 4.1.

➢ We will discuss IT-support as a general outlook of this thesis (*Outlook 2,* Chapter 7.5).

Furthermore, the Data Product Canvas can be used in combination with other visual representations. On the one hand, the Data Product Canvas provides valuable input for other tools, such as the Business Model Canvas (Osterwalder and Pigneur, 2010). On the other hand, other tools can provide information and input for the Data Product Canvas, such as the Data Collection Map (Kayser *et al.*, 2019). Furthermore, the Data Product Canvas can be seen as a specialized

[34] https://dataservicecards.at/ accessed on 21.10.2022, 20:53.

version or the Value Proposition Canvas (Osterwalder *et al.*, 2014). The Value Proposition Canvas aims to connect the customer and his needs with the value proposition. The Data Product Canvas aims to connect the customer and his needs (in particular, a decision problem) with the Data Product (a data-based value proposition).

- Thus, DDBM-specific tools can be seen as a specialized representation of general business model tools – one overall contribution of this thesis (*Contribution 3,* Chapter 7.2).
- Overall, with this discussion, we also contribute to the research direction for a toolbox and the connection of tools, as outlined in Chapter 4.1.

Nevertheless, we see a limitation concerning the evaluation that will be discussed in the overall limitation of this thesis (*Limitation 2*) in Chapter 7.4. Second, we found in our evaluation that the concepts of benefits and pains/gains need further clarification. To address this issue, we will develop an ontology that describes the data-based value creation logic to further clarify the elements and concepts. The ontology can serve as the basis for a revised canvas version in the following chapter of this thesis. Third, the canvas has been developed and evaluated in 2019 and 2020. Since then, rapid technological advances, particularly in Machine Learning and Artificial Intelligence, have also led to the emergence of AI-based business models (e.g. Åström *et al.*, 2022; Weber *et al.*, 2022). Thus, a further version of the canvas also needs to consider this development.

- We see this direction as an overall limitation of this thesis (*Limitation 4*, Chapter 7.4) and an overall direction for future research (*Outlook 4*, Chapter 7.5).

5.3 Towards A Data-Based Value Creation Ontology[35]

5.3.1 Introduction

As already pointed out in the previous chapter, one challenge in data-driven business model innovation is to bridge the gap between the business and data domains. Value creation approaches have been developed for each discipline, such as Jobs-to-be-Done (Ulwick, 2016) to identify significant customer problems or the CRISP-DM[36] framework (Shearer, 2000) for conducting data science projects. Nevertheless, little research has been conducted to build a bridge between those disciplines. Further, contemporary research lacks clarity of the terms and concepts used and a detailed analysis of the value proposition and benefits perspective of data-driven services and business models that build the conceptual foundation for innovation tools. Existing research on classification approaches for data-driven business models includes frameworks (e.g., Hartmann *et al.*, 2016), taxonomies (e.g., Azkan *et al.*, 2020; Hunke *et al.*, 2019), archetypes (e.g., Hunke *et al.*, 2020a) or patterns (e.g., Schüritz and Satzger, 2016) but lacks of ontologies (Kayser *et al.*, 2021).

An ontology is an artefact consisting of concepts and their relations to describe a certain phenomenon (Blaschke *et al.*, 2018). It is the foundation for visual inquiry tools (Avdiji *et al.*, 2020) supporting the innovation process. The general problem is that there are different, similar, but not unified conceptualizations of value creation with data that use different concepts and terms for the same phenomenon (Kayser *et al.*, 2021). What is missing is a shared conceptualisation in the data-driven business model literature that integrates existing seminal work on value creation from business research. Therefore, existing tools and methods lack a conceptual foundation in ontologies. Few papers provide an ontology for specific aspects of data-based value creation, but they are not rigorously developed (e.g., Kayser *et al.*, 2019; Kronsbein and Mueller, 2019). Therefore, we address this chapter's research question:

How can the logic of value creation with data be described and represented in an ontology?

To answer this research question, we adopted the approach of Blaschke *et al.* (2018) by following the *Methontology* approach of Fernández-López *et al.* (1997) and the guidelines of Kishore *et al.* (2004). Based on the literature, we created a glossary of concepts in the data-based value creation logic and formalised their relations in a diagram. We further applied the ontology to a real-world use case and used it as a basis for four training workshops with *Comp*.

[35] This chapter has not been published.
[36] CRoss Industry Standard Process for Data Mining

5.3.2 Additional Background on Customer Value Creation and Ontologies

We ground our ontology development process on three closely related theoretical concepts of customer value creation: The *Job-to-be-Done* theory, the *Value Proposition*, and the *Service-Dominant Logic*.

The **Job-to-be-done Theory** shaped by Ulwick and Christensen provides a solution for the innovator's dilemma in disruptive innovation (Christensen *et al.*, 2016a; Ulwick, 2016). The basic idea behind this theory is that customers hire a product or service to get a job done (Christensen *et al.*, 2007; Ulwick, 2016). A job *"is the fundamental problem a customer needs to resolve in a given situation"* (Christensen *et al.*, 2007, p. 38) and describes *"the progress that a customer desires to make in a particular circumstance*." (Christensen *et al.*, 2016a, p. 45). Jobs not only have a functional but also an emotional and social component (Christensen *et al.*, 2007; Christensen *et al.*, 2016b) and comprise a set of process steps (Bettencourt and Ulwick, 2008). Jobs differ from solutions, as customers can hire different solutions for the same job (Bettencourt and Ulwick, 2008). Thus, the job-to-be-done theory aims to design products and services around poorly performed jobs (Christensen *et al.*, 2016b) and to create customer value by improving the execution of specific job steps (Bettencourt and Ulwick, 2008). This improvement of the execution of the job can be described and quantified by a desired outcome statement that describes the metric of how a customer measures the success of the product or service in improving the execution of the job (e.g., faster, cheaper or more predictable) (Ulwick, 2016; Ulwick and Bettencourt, 2008).

The Job to be done Theory motivated and influenced the design and development of the **Value Proposition** Canvas (Ulwick, 2016). Osterwalder and Pigneur (2010, p. 22) define the Value Proposition as *"the bundle of products and services that create value for a specific Customer Segment"*. The value proposition is a strategic tool enabling the communication of value packages (Payne *et al.*, 2017). It focuses on the perspectives of benefits and values (Augenstein *et al.*, 2018) and can be divided into distinct offerings (Gordijn *et al.*, 2005). Anderson *et al.* (2006) differentiate a value proposition statement between "all benefits" of an offering, "favourable points of difference" compared to the next best offering and "resonating focus", describing the most important aspects that generate the greatest customer value. A value proposition can further be divided into quantitative and qualitative values (Augenstein *et al.*, 2018; Osterwalder and Pigneur, 2010) and should be analysed across its life cycle (Osterwalder, 2004).

According to **service-dominant logic**, customers participate in the (co-) creation of value by integrating resources and knowledge from suppliers (Vargo and Lusch, 2004). Only the customer can determine and realise the value (Mathis and Köbler, 2016), the "value-in-use" (Vargo and Lusch, 2004). This means that firms provide "value propositions", which are determined by the value perceived by the user and not the features of the offering (Schüritz *et al.*, 2019b; Vargo and

Lusch, 2004). Providers can also influence the fulfilment of the value and create value in the interaction with the customer (Grönroos and Voima, 2013).

Several ontologies have already been developed in this context of value proposition and value creation, as Figure 5.9 shows. An ontology is the pragmatic approach to structure and codifies knowledge about concepts, relationships and constraints regarding a domain (e.g., business models or value creation) (Blaschke *et al.*, 2018; Kishore *et al.*, 2004). An ontology *“enable[s] a shared understanding of the structure of information among people”* (Noy and McGuinnss, 2002)[37]. An ontology is also the conceptual foundation for visual collaborative tools (Avdiji *et al.*, 2020). Osterwalder (2004) developed in his PhD Thesis the *Business Model Ontology*, a generic conceptual model of business models. It consists of four related parts: the product with its value proposition, the customer interface, the infrastructure and the financial aspects of a business model. Later, the ontology was instantiated in the Business Model Canvas (Osterwalder and Pigneur, 2010).

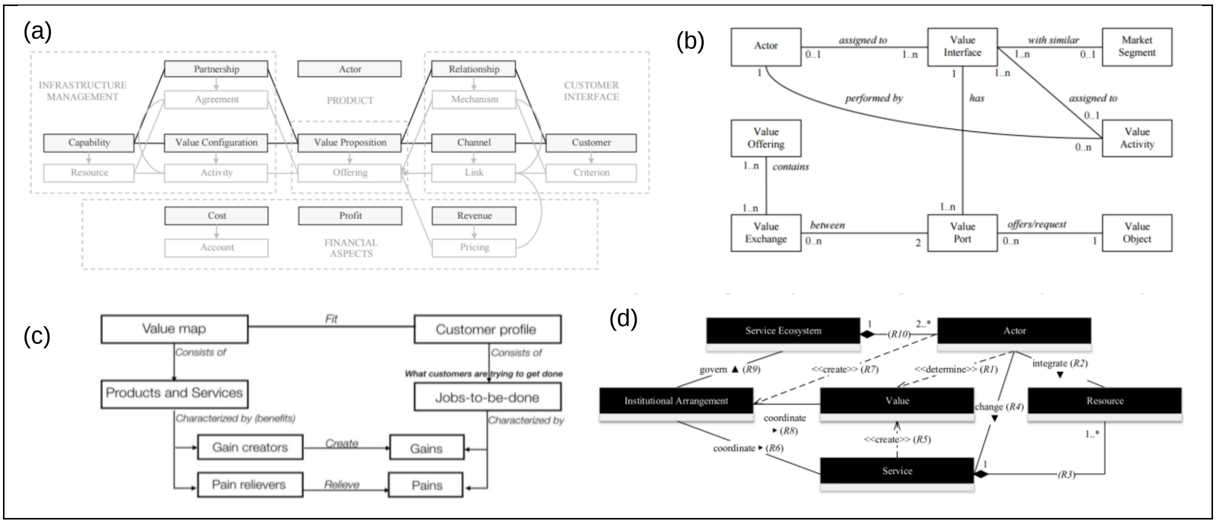


Figure 5.9: Examples of existing ontologies: (a) Business Model Ontology (Osterwalder, 2004), (b) e3 Value Ontology (Gordijn and Akkermans, 2001; Gordijn and Akkermans, 2003), (c) Ontology for the Value Proposition Canvas (Avdiji *et al.*, 2020), and (d) Value Co-Creation Ontology in Service-Dominant Logic (Blaschke *et al.*, 2018).

Gordijn and Akkermans (2003) proposed an alternative *e3-value ontology* for business models by putting the actors and exchanged values through value interfaces and ports into the centre of discussion. On a more granular level of the business model, Osterwalder *et al.* (2014) introduced the Value Proposition Canvas to describe the relationship between the customer (problems) and the offering and its features. Avdiji *et al.* (2020) later described and analysed the underlying implicit ontology: the company's value (proposition) map should fit the customer profile, who has several Jobs-to-be-done with its pains and gains addressed by pain relievers and gain creators of the offering. Blaschke *et al.* (2018) created a *Value Co-Creation Ontology* in the Service-Dominant Logic by extending existing ontologies and following a comprehensive ontology-building process.

[37] cited after Kishore *et al.* (2004).

Understanding the underlying structure of value creation with data by an ontology supports generating ideas and recognising design considerations (Lim *et al.*, 2018). From this perspective, only Zeleti and Ojo (2017) presented an open data business model ontology. To the best of our knowledge, no other has been developed in the context of value creation with data, as a recent literature review showed (Kayser *et al.*, 2021). Therefore, this chapter aims to develop a data-based value creation ontology that should support the design and evaluation of data-driven business models.

5.3.3 Detailed Research Approach

To develop our ontology for data-based value creation, we adopt the approach of Blaschke *et al.* (2018), using the steps of *Methontology* (Fernández-López *et al.*, 1997) as well as suggested guidelines for ontology development of Kishore *et al.* (2004). As Figure 5.10 shows, phases I to III of *Methontology* and guideline 1 to 5 focus on this chapter, as we aim to synthesise concepts and relationships in data-based value creation.

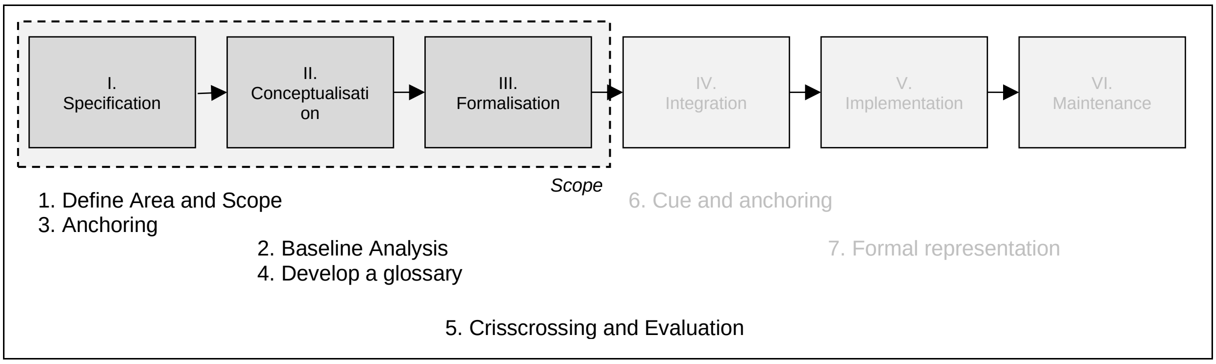


Figure 5.10: Overview of the applied research process following the phases of Fernández-López *et al.* (1997) and the guidelines of Kishore *et al.* (2004).

Step I – Specification: The goal of this phase is to craft and document the purpose and scope of the ontology in natural language (Blaschke *et al.*, 2018; Fernández-López *et al.*, 1997).

Guideline 1 - Define areas and scope: This ontology's purpose is to conceptualise the data-based value creation logic (see introduction section). Such a conceptualization is needed as a basis for visual inquiry tools, i.e., canvases (Avdiji *et al.*, 2020) that support organizations and individuals in data-driven business model innovation (Fruhwirth *et al.*, 2020c). Further, we aim to extend existing value creation ontologies, as shown in the background section. The goal is further to develop a generic ontology, not for one specific application domain of data-driven business models, such as Fintech (Schmidt *et al.*, 2018), Manufacturing (Azkan *et al.*, 2020) or Logistics (Möller *et al.*, 2020b).

Guideline 3 - Anchoring: We derive anchor points from ideas of existing theoretical frameworks, such as Jobs-to-be-done and predominant components of data-driven business model taxonomies. The main anchor points are the spheres of *provider* and *user* (e.g., Grönroos and Voima, 2013), an *offering* that supports a *customer job* (e.g., Ulwick, 2016); and data as a *key resource* and data analytics as *key activities* that are used for value creation (e.g., Hartmann *et al.*, 2016). These anchor points ground the ontology and guide the development process (Blaschke *et al.*, 2018; Kishore *et al.*, 2004).

Step II - Conceptualisation: The goal of this phase is to capture existing domain knowledge in a conceptual model by crafting a vocabulary (Blaschke *et al.*, 2018; Fernández-López *et al.*, 1997).

Guideline 2 - Perform a baseline analysis: In this step, we draw from existing knowledge from the literature on value creation, data-driven business models, and existing ontologies (see background section). In this task, we also reused previous literature reviews from Fruhwirth *et al.* (2020c) and Kayser *et al.* (2021). Further, this step included brainstorming activities to identify initial concepts, relationships and examples.

Guideline 4 - Develop a glossary of terms: Based on the literature and material identified in the baseline analysis, we applied a qualitative content analysis (Mayring, 2015) and did cart sorting with characteristics and dimensions of existing taxonomic approaches. The outcome of this step is a table of concepts (glossary) with explanations and examples.

Step III – Formalisation: The goal of this phase is to craft a specifiable ontology in a formal language through crisscrossing and to evaluate the ontology for completeness (Blaschke *et al.*, 2018; Fernández-López *et al.*, 1997)

Guideline 5 - Formalise ontology using crisscrossing: We used a crisscrossing strategy to extract relationships from the concepts of our glossary and structure them using a formal language (UML). This includes general relations, such as "is-a" or "has-a", as well as class properties.

Evaluation and demonstration: Finally, we aim to evaluate the ontology against its completeness by applying it to a representative real-world data-driven use case. In the second step, we used this case as a basis to develop a data-driven business model during four training workshops within *Comp*. Further, we used the ontology to describe another four use cases at *Comp* with the same notations and discussed them with the responsible managers.

5.3.4 Results

5.3.4.1 Description of Key Concepts (Glossary)

Data represents the key operant resource for co-creating value (Engel and Ebel, 2019) and a key resource in the business model (Hartmann *et al.*, 2016). How data sources can be classified is extensively discussed in the literature: Data can have different s*ources of origin* associated with different data ownership: own internal data (Hartmann *et al.*, 2016), data provided by the customer (Azkan *et al.*, 2020), data generated through using the data product (Rizk et al., 2018) and third-party external data, e.g., from data marketplaces (Fruhwirth *et al.*, 2020b). Further, data is generated differently: by humans (customers), machines (objects) or processes (Hunke *et al.*, 2019). Different data types influence the analytics methods, like structured data from databases, time series, text or image data (Kayser *et al.*, 2019).

Concept	Description	Example
Provider	The provider is the owner of the data-driven business model and offers a data product to gain revenues in return.	Meteolytix
User	The user or customer is using the data product to get support in his decision problems or to automate one of his tasks or actions (Schüritz *et al.*, 2019b).	Bakery chain production planner
Data Source	Data represents the key operant resource for co-creating value (Engel and Ebel, 2019) and a key resource in the business model (Hartmann *et al.*, 2016).	Weather data, sales data
Data Activities	*Data activities* or *"value creation oriented data processing"* (Guggenberger *et al.*, 2020) represent the *"process of turning data into value"* (Fielt *et al.*, 2019).	Correlation analysis, predictive analytics
Insights	*Insights* or information created from data activities "*reveals interesting facts about the original data source"* (Lim *et al.*, 2018) that could be *"useful and hidden patterns and relationships"* in the data (Rizk *et al.*, 2018). These insights inform decisions or form the basis for the automation of actions.	Bread sales correlate with weather
Data Product	The *data product,* also denoted as *"data and analytics-based features and experiences"* (Schüritz *et al.*, 2019b), constitutes the form of how the insights are delivered to the user (Azkan *et al.*, 2020; Lim *et al.*, 2018). There are different delivery mechanisms (e.g., download, app, web interface) and interfaces (e.g., GUI, API) for a data product (Möller *et al.*, 2020b).	Prediction module in the production planning software
Proposed Value	The *proposed value* describes the value proposition behind the offered data product (Azkan *et al.*, 2020). A data product can, for instance, support or enable quality control, condition monitoring, or decisions. Therefore, the proposed value describes the function of the data product.	Predicting the sales of pastries based on weather data
Decision Problem or Action	The goal of a data product is to support *decisions* and automate *actions* (Schüritz *et al.*, 2019b), or in general, support customers in achieving their *goals* (Lim *et al.*, 2018).	How much bread shall we produce tomorrow?
Value-in-use	The *value-in-use* describes the actual value gain for the user through using the data product in a specific context (Azkan *et al.*, 2020; Blaschke *et al.*, 2018). Value is only created when the user uses the received insights from the data product for a specific purpose (i.e., his decision problem) (Lim *et al.*, 2018). The idea is that insights (information) only have value through usage (Moody and Walsh, 1999).	Monthly cost savings of a specific bakery chain
Value-in-exchange	The *value-in-exchange* describes the negotiated value for the data product, i.e., the monetarization possibilities of the provider in return for offering the data product (Azkan *et al.*, 2020; Blaschke *et al.*, 2018).	Monthly subscription fee

Table 5.5: Description of key concepts in data-based value creation.

The **provider** or the owner of a data-driven business model utilises data as a resource to create value for the user (Kaiser *et al.*, 2019; Schüritz *et al.*, 2019b), for instance, by adding data-driven services to a physical product (Wixom and Ross, 2017).

The **user** is receiving and using the data product to address one of his needs (i.e., a decision problem or a task to automate). The user creates value-in-use by utilizing the proposed value of the data product defined by the provider (Schüritz *et al.*, 2019b).

Data Activities or *"value creation oriented data processing"* (Guggenberger *et al.*, 2020) represent the *"process of turning data into value"* (Fielt *et al.*, 2019). Data activities also refer to tools and methods applied to sources to extract useful and hidden patterns (Rizk *et al.*, 2018). Data activities can be described along the value chain, from data generation to distribution (Hartmann *et al.*, 2016).

One main activity is data analytics which is performed in different degrees: descriptive, diagnostic, predictive and prescriptive analytics (Hunke *et al.*, 2019). In more advanced analytics, this also involves the training of machine learning models (Agrawal *et al.*, 2018b). Data activities can be divided among actors, i.e., the provider, customer and partners (Hunke *et al.*, 2020b; Zolnowski *et al.*, 2016). Further, there are prerequisites, like ensuring data quality or aggregating and preparing data sources for successful insights creation.

Insights or information created from data activities "*reveals interesting facts about the original data source"* (Lim *et al.*, 2018) that could be *"useful and hidden patterns and relationships"* in the data (Rizk *et al.*, 2018). These insights inform decisions or form the basis for automating actions.

The **Data Product** constitutes how insights are delivered to the user (Azkan *et al.*, 2020; Lim *et al.*, 2018). Data products are features and experiences based on data analytics (Schüritz *et al.*, 2019b). There are different *delivery mechanisms*, how the data product is provided to the customer and how the customer interacts with the data product, such as specialised software, web interface, cloud platform, downloads, smartphone applications, e-mails or displays on a physical product (Möller *et al.*, 2020b). Further, there are different interfaces how for transferring data or insights, like APIs (Application Programming Interfaces), dashboards, GUIs (Graphical User Interfaces), or reports (Möller *et al.*, 2020b). The data product is also integrated into existing (non-data) products and services: as a by-product, add-on or stand-alone product (Hunke *et al.*, 2019; Möller *et al.*, 2020b; Wixom and Ross, 2017).

The **Proposed Value** describes the function of the data product and the value proposition behind the offering (Azkan *et al.*, 2020). In particular, it is the benefit of the data product and its features proposed by the provider. A data product can, for instance, support or enable quality control and condition monitoring or inform decisions. The data product can take different forms (e.g., data, insights or actions) that involve different value-creation activities of the user: A data product can be the delivery of data via aggregated reports, dashboards or APIs. In this case, the user has to generate insights from the data for decisions or actions on his own. A data product can also be insights, like benchmarks, alerts, or identification of aberrational activities. In this case, the user must make sense of this information for decisions or actions. A data product can also be recommendations for actions or decisions: like the suggestion of the next steps in a task or the recommendation of products in an online shop. Finally, a data product can also encompass actions and automated decisions, like performing predictive maintenance, including manual interventions. It is important to focus the proposed value and the offering on the support for the user in executing the steps in a job (Bettencourt and Ulwick, 2008). Summing up, the goal of a data product is to support decisions, automate *actions* (Schüritz *et al.*, 2019b), or generally support customers in achieving their *goals* (Lim *et al.*, 2018). Thus, data products help users with certain decision- or automation problems during their jobs-to-be-done (Bettencourt and Ulwick, 2008). Therefore, a certain information base is necessary.

The **value-in-use** describes the value gained for the user by using the data product (Azkan *et al.*, 2020). Value is only created when the user uses the received insights from the data product for a specific purpose, i.e., his decision problem (Lim *et al.*, 2018). The idea behind that is that insights (information) only have value through their usage (Moody and Walsh, 1999) and that the value is not determined by the features of a data product but by the value perceived by the user (Vargo and Lusch, 2004). Schüritz *et al.* (2019b) noted that the provider alone creates potential value (i.e., the proposed value), and together with the user, they are creating real value. Value-in-use describes the value gain for the user in a specific context, e.g., the cost savings in a particular month of a bakery chain due to using a data product (Blaschke *et al.*, 2018). Further, there is a difference between information creation and value creation (Lim *et al.*, 2018). Examples of value in use for the customer are efficiency gains (cost reductions, time savings, or flexibility), improved quality, and improved human-based operations and decision-making (Azkan *et al.*, 2020).

Value-in-return describes the negotiated (monetary) exchange for the data product (Blaschke *et al.*, 2018; Leski *et al.*, 2021). There are two approaches: direct and indirect monetarization. In direct monetarization, money is exchanged against the data product via revenue and pricing models (Enders *et al.*, 2019). In the indirect monetarization approach, monetary value is generated through cost savings for the provider, increases in sales volume or higher prices for the core (non-data) products that are enriched with a data product (Wixom and Schüritz, 2018). In multi-sided revenue models, monetary value is generated through data-driven tailored advertisement and paying with data (Schüritz *et al.*, 2017b).

5.3.4.2 Relationships and UML Diagram

In phase III, we identified relationships between these concepts and visualised them in a UML class diagram, as Figure 5.11 shows.

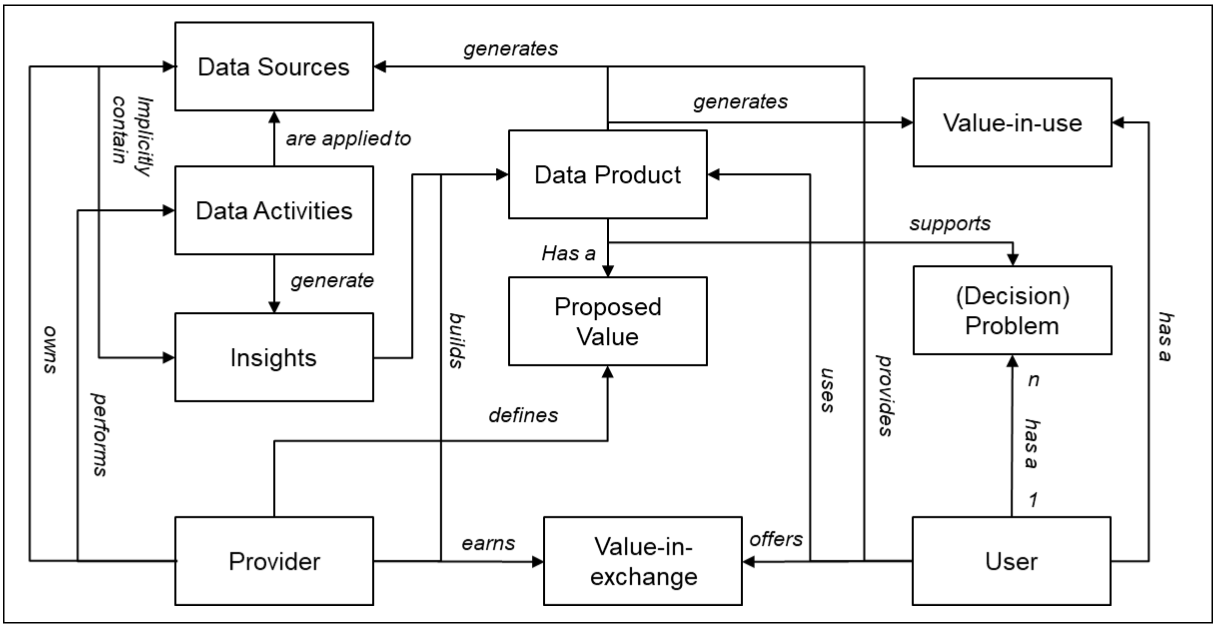


Figure 5.11: Visualising the relationships between concepts of the data-based value creation ontology (own representation).

5.3.4.3 Demonstration: The Case of Meteolytix

We demonstrate our ontology by applying it to one real-world data-driven use case. We selected the data product "*meteolytix intelligent bakery suite"* of the company *Meteolytix*[38], as it is both illustrative and appropriate for a data-driven business model. The company is addressing two decision problems of bakery chains: How many pastries will I sell tomorrow/next month? And how many pastries shall I produce today/next week? The company identified correlations between weather and sales numbers of specific products to inform these decision problems of bakery managers. For instance, customers buy more sweet pastries on days with cold and rainy weather and dark bread on days with hot weather. Thus, the company generated a sales prediction model with more than 400 influencing factors. Based on these valuable insights, *Meteolytix* built a data product (sales forecasts) as a function for the software product *meteolytix intelligent bakery suite".* Bakery chains can save costs due to reduced waste and product returns, increase revenue due to fewer sell-outs, and increase customer satisfaction of their end-customers by using the data product and supporting their decision problem. In return, bakery chains pay *Meteolytix* a periodic fee. Figure 5.12 illustrates this value creation logic using our ontology's concepts. Further, we have added this example of *Meteolytix* to the glossary table.

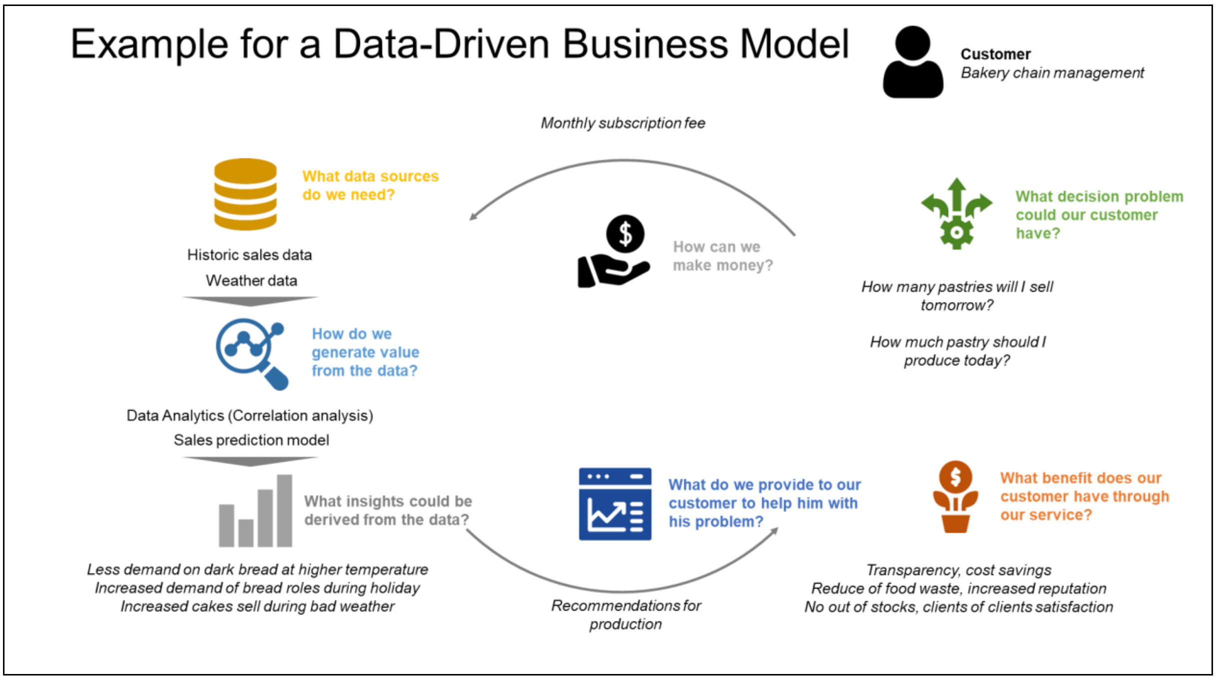


Figure 5.12: Illustrating the value creation logic of *meteolytix* bakery prediction service by applying the main concepts of our ontology (Symbols made by freepik, downloaded from www.flaticon.com).

In the second step, we used this case as an illustrative example in four training lectures on data-driven business models. The goal was to interactively develop a data product for bakery chains with the participants step-by-step based on the concepts of our ontology. The practitioners perceived the concepts as sufficient and clear to understand and build a data product.

[38] https://meteolytix.de/baeckereiservices/

In addition, we have evaluated our ontology by representing five data products of *Comp* using the ontology. We had access to company-internal material for each use case, such as sales presentations or product information sheets. Further, we presented the cases described with the ontology to the responsible business managers and asked if anything was missing and if the use case was presented clearly. These cases were also part of the training lecture. Figure 5.13 illustrates three anonymised (pixelated) examples for data products of *Comp* using our ontology.

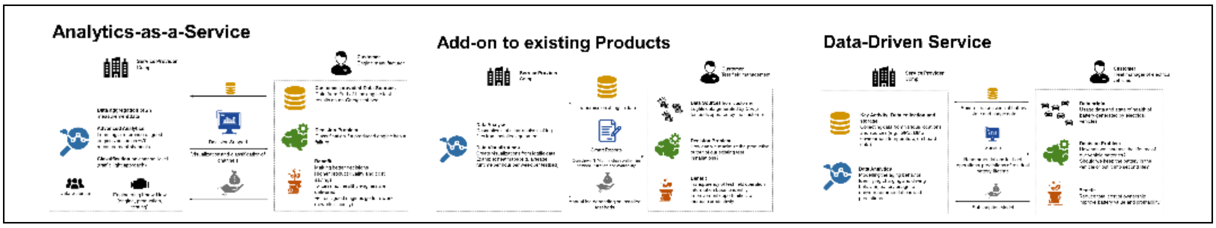


Figure 5.13: Application of the ontology to three data-driven use cases at *Comp* (anonymised, pixelated).

5.3.5 Discussion

With our ontology, we have aimed to bridge the gap between the data and the business sphere. Currently, very little research in the field of DDBM has been focusing on customer problems and values. Existing literature is mainly focusing the value architecture (i.e., data sources, analytics key activities, interfaces), as also one recent literature review showed (Kayser *et al.*, 2021). Further data science literature focuses on information creation, not customer value creation. The concepts and viewpoints about customer jobs, needs and benefits emerged from and are well-defined in the innovation and marketing disciplines, as the service-dominant logic or the jobs-to-be-done theory show. Little has been written about that in the DDBM literature. Lim *et al.* (2018) and Schüritz *et al.* (2019b) started investigating the value-in-use concepts of data products. Other conceptualisations remain vague regarding customer value. What was missing in the literature was a bridge between those two worlds (data science and customer value). To the best of our knowledge, this chapter is the first that provides a comprehensive investigation.

5.3.5.1 Questions for your data-driven business model

The concepts from our ontology lead to questions for designing a data product (or a data-based value proposition). Job-to-be-done theory argues for starting with the customer jobs and related problems that are supported by the offering (Ulwick, 2016). In the context of data products and data-driven business models, jobs to get done are supporting decisions and automating actions (Schüritz *et al.*, 2019b). Therefore, the first question should be: **(1) What decision problems could our customers have? What jobs or actions could be automated?**

We need specific insights derived from data sources through data analytics activities to inform such a decision problem or automate a job. Therefore, the next questions should be asked iteratively: **(2) What data sources do we need? (3) What insights could be derived from the data? (4) How do we extract information and insights from the data? What are the main activities and methods?**

To deliver insights to the user and to generate value, we need to conceptualise a data product in terms of form of delivery and function (i.e., the proposed value). Therefore, data product managers should ask the following two questions: **(5) In what form do we provide to our customer to support him in his decision problem or automate his jobs (actions)? (6) What benefit or value gain for the user do we propose for our data product?**

The customer is then using the data product during his job execution, which should help him get the job done by informing decisions or automating actions. Therefore, data product managers should ask themselves: **(7) What value makes one specific customer gain in his context by using our data product?** To earn something in return and to build a sustainable business, the last question based on the ontology should be: **(8) What do we get in return for offering the data product? How can we make money?** Figure 5.14 summarises these eight questions.

(1) What decision problems could our customers have? What jobs or actions could be automated?
(2) What data sources do we need?
(3) What insights could be derived from the data?
(4) How do we extract information and insights from the data? What are the main activities and methods?
(5) In what form do we provide to our customer to support him in his decision problem or automate his jobs (actions)? What benefit or value gain for the user do we propose for our data product?
(6) What benefit does our customer have by using the data product?
(7) What do we get in return for offering the data product? How can we make money?

Figure 5.14: Eight questions for your data product (own representation).

5.3.6 Conclusion

In this chapter, we have investigated the data-based value creation logic and developed an ontology. We provided a glossary of key concepts and visualised their relations in a diagram. We demonstrated our ontology by applying it to a real-world data product and used it as a central element in a lecture series at *Comp*. From a practitioner's perspective, our ontology helps to design data-based value propositions, supports visualising and communicating ideas and clarifies the concepts often confusedly used in practice.

Our results contribute to the understanding data-driven business models as we investigated the value creation and value proposition perspective that is still under-researched (Kayser *et al.*, 2021). We found that data-driven business models generate customer value by using a data product to support a customer's decision problem. This value creation logic needs to be kept in mind when designing a new DDBM.

- This insight relates to one general contribution of this thesis with regard to understanding and designing data-driven business models: Data-driven business models generate customer value by using a data product to support a customer's decision problem. (see *Contribution 5*, Chapter 7.2).

Secondly, our ontology serves as the foundation for designing visual collaborative tools (Avdiji *et al.*, 2020) that provide a conceptualization for a shared understanding of the value creation with data.

- ➢ This connects to one general contribution of this thesis that the underlying concept needs to be understood when designing supporting tools and methods (*Contribution 4*, Chapter 7.2).

The research design of this chapter is not without limitations. Although we followed a rigorous approach to build our ontology, the evaluation was shoaly. We only demonstrated our ontology in one real-world use case and applied it to five cases at *Comp*.

- ➢ We denote this limitation regarding evaluation as a general limitation of this thesis (*Limitation 2*, Chapter 7.4).

Another limitation of this chapter is that we focused on data analytics and excluded artificial intelligence. Another fruitful direction for further research would be to extend the ontology specifically to value creation with Artificial Intelligence, as AI has regained attention in academia (Feuerriegel *et al.*, 2024; Sjödin *et al.*, 2021) and industry (Bughin *et al.*, 2017) likewise for business innovation.

- ➢ We denote this as a general limitation of this thesis (*Limitation 4*, Chapter 7.4) and a direction for further research (*Outlook 4*, Chapter 7.5).

Finally, as we have focused on the (customer) value creation logic in this chapter, the ontology has not investigated other central elements of a data-driven business model, such as competencies, key partners or the value architecture. Therefore, we will look closely at the partner and exchanged values perspective in the following chapter of this thesis.

5.4 A Framework of Actors and Exchanged Values[39]

5.4.1 Introduction

It is crucial to understand its environment and the involved stakeholders to successfully design a data-driven business model, as companies will collaborate more and increase their dependencies (Hunke *et al.*, 2017). Each actor in a business model has to understand his own role and the overall configuration (Bettencourt *et al.*, 2014). Typically, traditional firms rely on new external partners for their data-driven business models, such as a data marketplace or analytics service providers. Thus, it is important to know the roles that need to be fulfilled by actors in their business model already during the business model design phase. Business model representations with a transactional focus are useful for understanding, developing, and modelling business models (Täuscher and Laudien, 2017). There, types of actors and exchanged values support modelling a business model (Terrenghi *et al.*, 2018). Despite this, research on data-driven business models mostly overlooks the partner and ecosystem perspective. Accordingly, we ask the following research question in this chapter:

What roles exist in a data-driven business model, and how can the exchanged values be categorized?

To answer this question, we conducted a structured literature review and derived a framework with a set of eight roles and two attributes that can be assigned to actors and three classes of exchanged values. We evaluated the framework by applying it to three use cases from one company in the automotive industry.

The rest of this chapter is structured as follows: 5.4.2 provides additional background on actors in business ecosystems. Next, we describe our methodological approach in section 5.4.3. We present our results in section 5.4.4 (artefact) and 5.4.5 (evaluation). Finally, this chapter closes with a discussion and conclusion in section 5.4.6.

5.4.2 Additional Background on Actors in Business Ecosystems

As we already noted, a business model can be understood as "*an architecture of the product, service and information flows, including a description of the various business actors and their roles; a description of the potential benefits for the various business actors; a description of the sources of revenues*" (Timmers, 1998, p. 4). These actors are independent economic entities and "*exchange value objects, which are services, products, money, or even consumer experiences. A value object is valuable to one or more actors"* (Gordijn and Akkermans, 2001, p. 13). A business

[39] This chapter is based on the publication: Leski, F., Fruhwirth, M., and Pammer-Schindler, V. 2021. "Who Else do You Need for a Data-Driven Business Model? Exploring Roles and Exchanged Values," in 34th Bled eConference Digital Support from Crisis to Progressive Change, A. Pucihar, M. K. Borštnar, R. Bons, H. Cripps, A. Sheombar and D. Vidmar (eds.). June 27 – 30, 2021, pp. 365-378. The publication itself is based on a master project conducted by Florian Leski, where the author of this thesis served in a supervisory role. The empirical part and also part of the writing of this chapter is based on the work of the Master student.

model can also be seen as a set of activities performed by the focal organization itself, its customers, suppliers, and/or partners (Zott and Amit, 2010). Thus, every actor has one or more roles that describe an actor's activities, functions, or contributions to the business model (Terrenghi *et al.*, 2018). This understanding of business models takes a network-centric and transactional view, focusing on value exchange among actors. Similar concepts have been established, such as the value network (Allee, 2008) or the business ecosystem (Jacobides *et al.*, 2018).

5.4.3 Detailed Research Approach

To identify types of actors and classes of exchanged values in data-driven business models, we conducted a literature search and adopted an inductive category formation approach to analyse and synthesise the literature. Finally, we evaluated the framework in three data-driven business models from our case study with *Comp*.

We based the **search and selection process** on the guidelines and recommendations of Vom Brocke *et al.* (2009) and Webster and Watson (2002). We started with a database search, as summarised in Table 5.6. Our search strings were informed by previous literature denoted in the background section. We searched separately for papers dealing with actors and exchanged values in ecosystems. By applying the stated logical search terms in the respective databases[40], we found 2513 articles; 917 for actors, 1496 regarding exchanged values. Further, we searched Google Scholar by the two search terms "data-driven business model" and "data value chain", and the first five pages adding up to 50 results for each query, were reviewed.

Search string			**AISel**	**IEEE Xplore**	**Science Direct**	**Scopus**	**Web of Science**	**ACM**	**SUM**
("digital" OR "data-driven" OR "data-infused" OR "data-based") AND ("business model" OR "service")	AND	(role" OR "actor" OR "partner")	300	22	230	162	118	85	**917**
		("network" OR "ecosystem" OR "value chain")	281	214	258	306	193	244	**1496**

Table 5.6: Summary of search strings and database search results.

Further, we applied a three-step selection process: First, we selected 119 relevant articles based on their titles. Second, we scanned the abstracts of these selected papers for relevance, limiting them to 62 articles. Third, we read the full text of the remaining papers and made a final selection of 26 articles that were relevant to our research. We also conducted a forward and backward search (Webster and Watson, 2002), leading to an additional set of 11 publications. Therefore, we arrived

[40] Search strings were applied to title, abstract, keywords and/or full text depending on the database to retrieve a manageable number of articles per query. The specific application of the search strings varied for each database.

at a final sample of 38 articles (17 for actors and 21 for exchanged values), whereas five articles were present in both categories, resulting in 33 articles[41] without overlaps.

After the search and selection process, we **analysed and synthesized** the selected literature following an inductive category formation approach (Mayring, 2015). We examined the papers' content to define distinct roles for actors and classes of exchanged values present in data-driven business models. Initially, we specified that the level of abstraction of the resulting classes must be generic to be applied to a broad spectrum of industries. We analyzed the material focusing on the results, findings, conclusions, figures, and tables and summarized the essential parts of the material for both actors and exchanged values. Subsequently, we synthesized this interim outcome into a generic set of categories, consisting of ten roles and two attributes that can be assigned to actors and three classes of exchanged values. After the evaluation, two roles were dropped or merged with other roles.

The framework was **evaluated** and refined in three use cases from the automotive industry. Therefore, we conducted three semi-structured interviews with managers from *Comp* (as shown in Table 5.7), each responsible for developing a business model for data-driven innovation. We selected only cases where a data-driven service was provided to external B2B customers. All names and specific information were anonymised to ensure the confidentiality of the company, interviewees, and use cases. In the beginning, we introduced the framework of roles and classes of exchanged values. We asked the interviewees to apply the framework to their use cases, particularly the involved actors and exchanged values. The outcome of each interview was a visual network-based representation of the business model. Further, we asked how understandable, useful and comprehensive the framework is and if some roles were missing or unnecessary.

Interviewee	Position	Use Case	Duration
A	Product Manager	Service in the field of autonomous driving	45 min
B	Product Manager	Providing end-customer insights as a service	30 min
C	Project Manager	Fleet monitoring service for electric vehicles	45 min

Table 5.7: Overview of conducted interviews for evaluating our framework.

5.4.4 Result 1: A Framework of Roles and Exchanged Values

In the following, we present our framework, as shown in Figure 5.15, by introducing eight roles and two attributes that can be assigned to an actor and three classes of values that are exchanged between actors. Note that we describe here for simplicity only the final framework after performing the initial evaluation described later in section 5.4.5. The initial framework can be found in **Appendix I**.

[41] The full list of identified articles can be found in Appendix H.

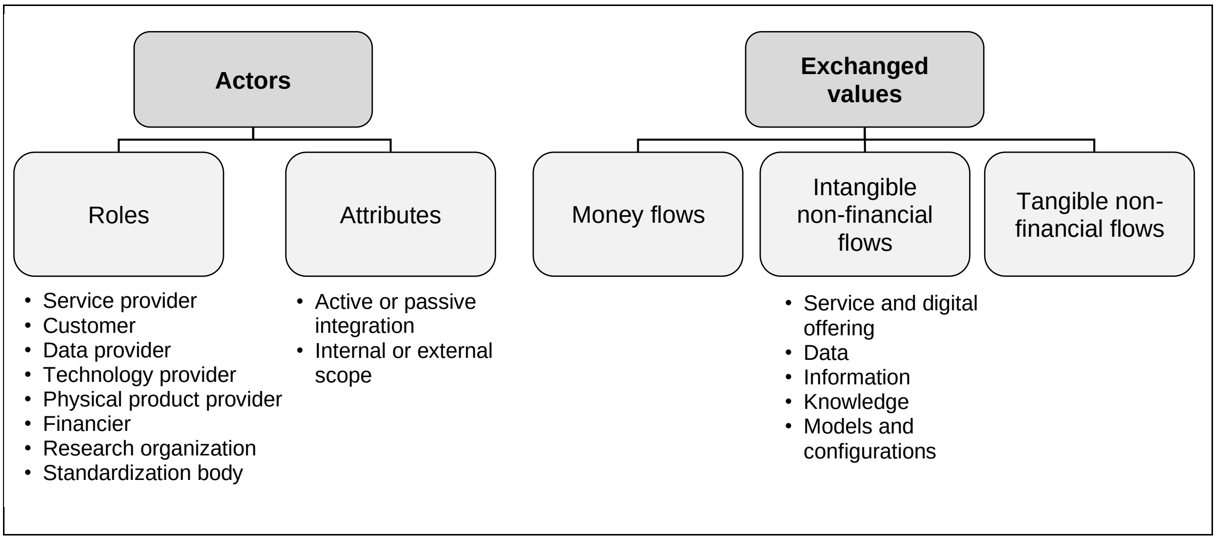


Figure 5.15: Classification of actors and exchanged values in data-driven business models.

5.4.4.1 Roles of Actors in Data-Driven Business Models

We have identified eight different roles that can be assigned to an actor in a DDBM:

A **service provider** is an actor who utilizes data as a resource to create or co-create value for other actors (Immonen *et al.*, 2014; Kaiser *et al.*, 2019; Schüritz *et al.*, 2019b), for instance, by adding data-driven services to a physical product (Terrenghi *et al.*, 2018).

A **customer** is a recipient of the offering who also has a need. The customer initiates the value generation process triggered by his needs (Terrenghi *et al.*, 2018), can actively participate in the value (co-)creation (Cova and Salle, 2008), or acts just as a passive receiver. A customer creates real value by utilizing the potential value of the data-driven service offered by the service provider (Schüritz *et al.*, 2019b).

A **data provider** is an actor who collects and aggregates data from public or private sources, performs the necessary preprocessing steps, and provides it to other actors who request data (Curry, 2016). This role includes collecting data about a physical object's conditions in a cyber-physical system (Terrenghi *et al.*, 2018).

A **technology provider** is an actor who provides the necessary technical infrastructure, platforms, and tools to the business model owner, such as data management solutions or cloud technology (e.g., Curry, 2016; Immonen *et al.*, 2014).

A **physical product provider** is an actor who manufactures and sells a physical core product equipped with data-collecting devices, such as sensors, that should be enriched with a data-driven service (Kaiser *et al.*, 2019; Papert and Pflaum, 2017; Terrenghi *et al.*, 2018).

A **financier** provides financial resources for the business model innovation, such as a pre-financing investor, an incubator, or a venture capitalist (Curry, 2016; Papert and Pflaum, 2017).

A **research organization**, such as a university, a research partner, or an internal research and development department, is an actor that engages with other actors in the business model to support the value-generation process (Kindström *et al.*, 2015; Schymanietz and Jonas, 2020).

A **standardization body** is responsible for introducing common standards and controlling the economy by addressing topics such as transparency or data privacy in the ecosystem (Curry, 2016; Terrenghi *et al.*, 2018).

5.4.4.2 Actor Attributes

We further found two attributes that can be assigned to each actor describing their interaction in the business model: the level of integration into the business model (i.e., active or passive) and the scope (i.e., internal or external).

The **integration** of an actor into the business model can be either active or passive. An actively integrated actor can benefit from working with other actors in the business model (Zolnowski *et al.*, 2016). Turetken *et al.* (2019) distinguish between core partners actively engaged in the value-creation process and enriching partners. The focal organization oversees the business model and takes an active role. Also, a customer can play an active role in the value co-creation process of a data-driven service (Schüritz *et al.*, 2019b) or stay passive by just receiving an offering.

The **scope** describes the internal or external relation relative to the focal business model that is currently analyzed. A service ecosystem consists of internal and external roles (Sklyar *et al.*, 2019). All actors that are clustered within the same organizational unit of the focal business model are considered internal. The business model owner cannot run the business alone and is usually supported by external and internal actors (Schymanietz and Jonas, 2020). For instance, a data-driven business model can rely on internal, external data sources, or both (Hartmann *et al.*, 2016), thus often involving external data providers.

5.4.4.3 Exchanged Values between Actors

Actors are exchanging values in a data-driven business model that we clustered into three classes: money flows, intangible non-financial flows, and tangible non-financial flows.

The class of **money flows** summarizes all exchanged values of financial nature. Money enables negotiating and trading between economic actors (Allee, 2008). Money flows can occur in different forms, denoted as revenue models, such as subscription fees or a pay-per-use model (Terrenghi *et al.*, 2018). The choice of one model is influenced by several factors, such as capabilities and the characteristic of the service (Enders *et al.*, 2019).

The class of **intangible non-financial flows** summarizes all exchanged values between actors that are non-monetary and intangible, meaning that it "*cannot be seen, felt, tasted or touched"* (Chowdhury and Åkesson, 2011, p. 4). Such values are generally denoted as **services** (e.g., Immonen *et al.*, 2014; Täuscher and Laudien, 2017) and **digital offerings** (Sklyar *et al.*, 2019; Täuscher and Laudien, 2017). On a more granular level, flows can be divided into **data** (e.g., Engelbrecht *et al.*, 2016; Terrenghi *et al.*, 2018), **information** (e.g., Curry, 2016; Schüritz *et al.*, 2019b), **knowledge** (e.g., Brownlow *et al.*, 2015; Schüritz *et al.*, 2019b), and **models** or configuration of models (Hirt and Kühl, 2018).

The class of **tangible non-financial flows** summarizes all exchanged values between actors that are non-monetary and tangible, such as physical products, raw materials, or other physical resources (e.g., Allee, 2008; Täuscher and Laudien, 2017). DDBMs can also rely on hardware as a key resource, such as measurement instruments, data transmission devices, or data-generating products.

5.4.5 Result 2: Light Evaluation and Discussion in three Cases

We evaluated the initial framework from the literature synthesis by interviewing three managers of *Comp*. We discussed one real-world data-driven use case in each interview. Together with the interviewee, we applied each case to the framework and delineated the DDBM as a network-based representation by using our framework as a model kit. We evaluated our artefact regarding the completeness, discriminability, and understandability of the individual elements and the usefulness of the overall framework.

The framework was sufficient to describe and analyze the cases: all roles, attributes, and values of the framework appeared in the cases, and no additional ones that were not included in the framework emerged through the data collection process. When analyzing the content of our cases, we found that in two of three cases, one actor in the business model fulfilled both roles of the customer and a data provider, because the business model relied on data provided by the customer. Further, the business models relied on partners with the role of a technology provider (e.g., providing a platform for data analysis), and a physical product provider (e.g., providing measurement hardware for data acquisition and devices for storage and transmission). Also, the attribute scope has helped distinguish between roles that are fulfilled internally and by external partners in the business model. Regarding the completeness of the framework, one interviewee mentioned that *"it is quite comprehensive. I can't think of an actor that is missing"* (Interviewee A). Interviewee C mentioned that he missed the user role, as in the B2B context, the user and buying customer are often separate actors within one organization.

Regarding the definition of roles, we found that the initial roles of data supplier and data collector were difficult to distinguish, as one interviewee mentioned: "T*he differentiation between the collector and supplier is diffuse for me. It might make more sense for other use cases*" (Interviewee A). Therefore, we decided to merge both under a new "data provider" role. Similarly, distinguishing the initial roles of resource integrator, service provider and technology provider was challenging. We decided to drop the role of resource integrator and refined the definition of a technology provider, in the sense that a technology provider only offers the resource without supporting the application compared to a service provider. Further, the interviewees found it beneficial to have a more nuanced level of integration. We found that it is necessary to elaborate a more granular differentiation of exchanged intangible values, for instance, what distinct type of exchanged data in a data-driven business model is essential.

Regarding the framework's usefulness, it could help to understand complex environments by illustrating all involved actors. Interviewee B, for instance, mentioned that a visual representation with this framework could be beneficial in complex and multi-layered business models and ”*where there are no flows on both sides, it is critical because only one actor can benefit from the setting”* (Interviewee B).

Figure 5.16 shows an exemplary network-based visualization of one data-driven business model: The business model owner (service provider) provides a data-driven service to the customer in exchange for a subscription fee. The data-driven service is developed with the aid of internal and external partners, who provide Analytics-as-a-Service, cloud technology and raw data. An external physical product provider provides measurement hardware to the customer that is needed to collect additional data to use the data-driven service. An internal financier provides the necessary financial resources for developing the business model.

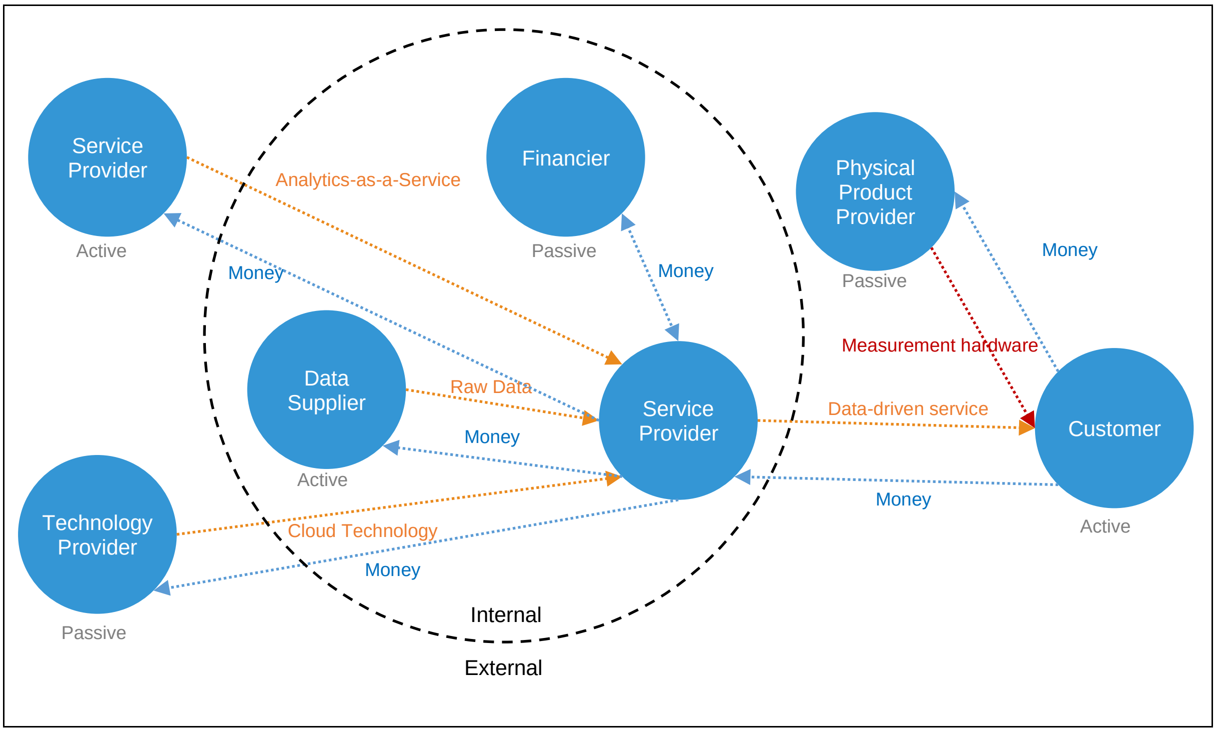


Figure 5.16: Exemplary application of our framework as a network-based visualization of a data-driven business model from *Comp* (anonymised).

5.4.6 Conclusion

Summing up, we developed in this chapter a framework with roles and attributes that can be assigned to actors and classes of values exchanged between actors in data-driven business models. With this framework, we contribute to the general understanding of data-driven business models (see section 7.2.3 in the overall discussion of this thesis) by structuring actors, and exchanged values. This is in particular important, as key activities need to be orchestrated in a

DDBM (Hunke *et al.*, 2020b). This adds the focus on data as a major type of exchanged value to flow-based business model representations (e.g. Gordijn and Akkermans, 2001).

The main limitation of this chapter is the sparse evaluation of the framework only via three experts from one company (our case company) by applying the framework to one case each.

- We denote this sometimes sparse or light evaluation as a general limitation of this thesis (*Limitation 2*, Chapter 7.4).

A more general limitation of this study is that the level of detail and methodological rigor is significant lower compared to other parts of this thesis.

- We see this as a general limitation of this thesis (*Limitation 3*, Chapter 7.4).

Nevertheless, this "light" study served as a starting point for future research: This framework served as a basis for developing a network-based representation of data-driven business models for identifying and then visualizing relevant actors and value flows that supports identifying certain risks (see Chapter 6.2). Further, we will investigate data-related value exchanges and associated risks, protection measures and contextual factors in Chapter 6.3. Finally, we will study one particular type service and technology providers – data marketplaces – in Chapter 6.4.

5.5 Conclusion on Supporting Idea Generation and Design

Summary: Chapter 5 focused on the value and benefit dimension during idea generation and the design of data-driven business models. First, we have provided an overview of different types of data-driven business models and presented a matrix that guides the direction for the idea generation process at an early stage. Second, we have provided a visual collaborative tool, i.e., the Data Product Canvas, that supports idea generation workshops to generate, describe and communicate data products. Third, we have investigated the data-based value creation logic from a theoretical viewpoint and provided a data-based value creation ontology. Finally, we considered involved actors and exchanged values in a data-driven business model.

Learnings from Chapter 5.1: In this chapter, we have developed a categorisation scheme for data-driven innovations that we instantiated as a visual tool and demonstrated in the case study with *Comp*. We suggest that different types of data-driven business model innovations slightly differ in development and thus require different or adopted versions of supporting tools and methods. Second, by focusing on the value proposition, DDBMs can be divided into three types: DDBMs in a broader sense, DDBMs in a narrow sense and pure DDBMs. All further studies of this thesis focus on the pure DDBM pattern of “Data-driven service” (except for Chapter 6.4, where data marketplaces are studied as one actor in “pure DDBMs”).

Learnings from Chapter 5.2: In this chapter, we developed the Data Product Canvas based on requirements derived from literature focusing on five core elements of a data-driven business model. Our evaluation via workshops with practitioners from the industry showed that this canvas is a useful and effective tool to generate and document ideas for data-driven business models at an early stage and to structure idea-generation workshops. Further, this study highlighted that generating ideas for DDBMs should be interdisciplinary between “business” and “data” people. Further, we showed in this chapter how the canvas is connected to other tools.

Learnings from Chapter 5.3: To understand the mechanism of customer value generation with data and analytics in data-driven business models, we crafted an ontology on data-based value creation logic. This ontology showed that a data product aims to support a customer decision problem via data-generated insights. Further, we distinguished between the provider's proposed value and the customer's value-in-use by using the service. Understanding this value creation logic is crucial for practitioners to design meaningful offerings as part of a DDBM. Further, this ontology can inform further tool design.

Learnings from Chapter 5.4: In this chapter, we developed a framework with roles (e.g., technology providers) and attributes (e.g., internal vs. external) that can be assigned to actors and classes of exchanged values between actors in data-driven business models. One important learning of this chapter was that actors can have an active or passive role in a business model and that not only data but also other types of values are exchanged, such as models or their configuration. Overall, our typology of actors and exchanged values support visualizing a DDBM from a network perspective and allowing a differentiated analysis of the business model compared to component-based representations (e.g., analysing risks from exchanged values).

Overall Contribution of this Chapter: The contribution of Chapter 5 is that both a structure for representing a DDBM (e.g., a canvas with major elements of a DDBM) and examples for potential variants of each element (characteristics) (e.g., a list of potential actors in a DDBM) both support idea generation. These elements and characteristics bring the specific knowledge of DDBMs to non-DDBM experts. This knowledge can be either retrieved from the knowledge base (literature) or by empirical studies and builds the foundation for the design of supporting tools and methods.

Outlook: When designing new business models, decision-makers must find an optimal balance between estimated returns and acceptable risks (Casadesus-Masanell and Ricart, 2010; Tesch and Brillinger, 2017). Therefore, decision-makers use certain criteria to decide whether to provide resources for a business model idea or not. The following research chapter will investigate the general question: What criteria support decision-making during data-driven business model innovation? Identifying and managing risk is important in business model innovation (Brillinger, 2018) and data-driven business models (Tebernun *et al.*, 2018). In a data-driven business model, one critical aspect is: **What risks are connected with the exchange of data flows with other actors?** Now in Chapter 6 we will investigate the questions from four perspectives.

Chapter 6

Supporting Tools and Concepts for Evaluation and Decision-Making

"Risk comes from not knowing what you are doing."

Warren Buffet[42]

This chapter deals with designing tools, methods and concepts that support evaluating data-driven business models. A general gap in current data-driven business model literature that we pointed out in our literature review in Chapter 4.1. As an introductory study, we present first in Chapter 6.1 an operationalised set of evaluation and decision criteria. One important aspect of such decisions are risks. Data-driven business models can lead to new risks due to the nature of data as a key resource and exchange value. In particular, one risk is the potential spillover of competitive knowledge due to data exchange. Therefore, we present in Chapter 6.2 a tool that supports the identification of so-called knowledge risks in the design phase of a data-driven business model. Subsequently, Chapter 6.3 will examine these risks in detail by exploring different risks depending on the exchanged value object, contextual factors and protection measures. Finally, in Chapter 6.4, we will investigate data marketplaces - one architectural approach to prevent knowledge risks from a business model perspective.

6.1 Introductory Study: Evaluation and Decision Criteria in Data-Driven Business Model Innovation

6.1.1 Introduction

Innovating a data-driven business model does not only require support during idea generation. Managers also need support to decide whether to invest further in a data-driven business model innovation. We identified this need also at the end of design cycle one of our case study with *Comp*. After a design iteration of a business model, an evaluation step is needed to assess the business model design and guide further direction (Wirtz and Daiser, 2018; Zott and Amit, 2015). Stage-gate processes are a *de facto* standard in similar problem domains, such as technology or product

[42] Robert G. Hagstrom Jr. (1994): The Warren Buffett Way: Investment Strategies of the World's Greatest Investor. John Wiley & Sons, New York. pp 94-95. Indirect quote from https://quoteinvestigator.com/2018/03/18/risk/ accessed on 12.09.2022 10:45.

innovation (Cooper, 2008). In contrast, business model innovation is not practised at this level of maturity (Winterhalter *et al.*, 2017). Further, evaluation and decision support are underrepresented in the literature (Fruhwirth *et al.*, 2020c; Tesch and Brillinger, 2017). Therefore, we address the following question in this chapter:

What criteria support evaluation and decision-making in data-driven business model innovation?

We conducted a sub-DSR project presented in this chapter to answer this question that relates to design cycle 2b of this thesis. After becoming aware of this problem, we conducted a literature review and derived a set of evaluation and decision criteria with a qualitative content analysis approach. We instantiated and demonstrated our decision criteria in the context of *Comp* and contributed to the overarching business model innovation process (as described in Chapter 4.2). The rest of this chapter is structured as follows: Section 6.1.2 provides additional background on evaluation and decision-making in business model innovation. Subsequently, our methodological approach is described in section 6.1.3. Section 6.1.4 presents our set of evaluation and decision criteria that we subsequently instantiate and demonstrate in the context of *Comp* in Section 6.1.5. This chapter closes with a discussion and conclusion in Section 6.1.6.

6.1.2 Additional Background on Evaluation and Decision-Making in Business Model Innovation

Evaluating a business model is the activity of assessing the performance of a business model (Brea-Solís *et al.*, 2015; Gilsing *et al.*, 2020). This activity is important as *“responsible managers have to decide, whether and in which form the proposed BMI is going to be implemented”* (Wirtz and Daiser, 2018, p. 48). Selecting a business model design is a multi-criteria decision-making problem (Kumar *et al.*, 2017). Nevertheless, evaluation and decision-making in business model innovation is under-researched (Fruhwirth *et al.*, 2020c; Tesch and Brillinger, 2017). However, such criteria have been long researched in similar fields such as business angles investment decisions (e.g., Mason and Harrison, 2003; Maxwell *et al.*, 2011) or product portfolio and innovation management (e.g., Cooper and Edgett, 2001; Hart *et al.*, 2003).

A business model can be evaluated during its design (ex-ante) or execution (ex-post) (Gilsing *et al.*, 2020). This chapter focuses on the first approach. We can find three types of evaluation during ex-ante business model innovation: Firstly, continuously improve the business model design through questions and criteria (Osterwalder and Pigneur, 2010; Tesch and Brillinger, 2017). Secondly, select one business model design from a pool of options (Hunke *et al.*, 2017). Thirdly, inform a decision on whether to proceed with and invest in a certain business model idea in a stage-gate logic (Tesch *et al.*, 2017). Further, managers apply two decision approaches in business model innovation: effectual and causal (Tesch and Brillinger, 2017; Tesch *et al.*, 2017). Following an effectuation logic, organisations take a trial-and-error approach to generate new insights (i.e., prototyping) in the market (Chesbrough, 2010; Sosna *et al.*, 2010). In causal logic, organisations analyse and evaluate their business models analytically (e.g., through a SWOT analysis or market research) (Tesch *et al.*, 2017).

Recent literature reviews show that few publications provide tools and methods supporting evaluation (Steinhöfel *et al.*, 2018; Tesch and Brillinger, 2017). Casadesus-Masanell and Ricart (2007) and Teece (2010) were some of the first who suggested criteria for evaluating a business model. Heikkilä *et al.* (2016) provided a repository of metrics related to business model elements aiming to focus the design on the desired strategic outcomes of the management. Mateu and Escribá-Esteve (2019) and Gilsing *et al.* (2020) designed evaluation methods with operationalised evaluation criteria (e.g., through Likert scales). Tesch *et al.* (2017) identified two decision points in digital business model innovation informed by a set of criteria from an empirical study. Simmert *et al.* (2019) used metrics from creativity research to assess business model ideas generated with the aid of their method. Osterwalder and Pigneur (2010) suggested evaluating a business model design through a SWOT analysis, where a set of criteria assesses each building block of the business model. Bland *et al.* (2020) finally provided hypotheses for each building block of a business model and a set of evaluation methods.

Concluding, existing research provides conceptual criteria that need to be operationalised for specific points in business model innovation (i.e., evaluating ideas or business model designs). Literature provides no comprehensive overview of decision criteria for all phases of a business model innovation. Thus, they are not connected to business model innovation processes except in the work of Tesch *et al.* (2017). Finally, no research is available on evaluation and decision criteria that address the specifics of data-driven business models (Fruhwirth *et al.*, 2020c; see also section 4.1.6.2). Thus, the research presented in this chapter aims to develop a set of criteria that support the decision-making process on whether to continue with a data-driven business model innovation connected to the business model innovation process presented in Chapter 4.2.

6.1.3 Detailed Research Approach

To develop an artefact that supports evaluation and decision-making in data-driven business model innovation, we conducted a sub-DSR project with two iterations, structured by the phases of Vaishnavi and Kuechler (2015), as summarized in Table 6.1. In the introduction section, we described the problem (need for evaluation and decision support during a business model innovation). We described the research gap at the end of the background chapter.

We first consolidated the knowledge base in **iteration one** to identify existing research on evaluation and decision criteria in business model innovation (see background section on page 135). As little research was available, we also considered similar fields such as product innovation and portfolio management (e.g., Cooper and Edgett, 2001) or business angle investment decisions (e.g., Maxwell *et al.*, 2011) to draw criteria. Second, to ensure practical relevance, we could also identify decision and evaluation criteria from the case study with *Comp* while practising data-driven business model innovation and participating in meetings. Third, we generated a set of decision criteria (see result section on page 138) as the first output of this chapter by applying a Qualitative Content Analysis approach (Mayring, 2015) to the data from the first two steps. We collected all criteria in a database, applied inductive coding, and ended up with six categories and 28 criteria. In the second step, we matched the criteria categories with the three dimensions (desirability, feasibility and viability) that Bland *et al.* (2020) suggested. Finally, we performed a "light" evaluation by discussing the criteria with four managers at *Comp* responsible for and practising data-driven business model innovation. We addressed the *completeness* of our criteria catalogue by asking questions such as "Have you encountered any other decision or evaluation criteria in your data-driven business model innovation?". We took notes for each criterion during the interview. Due to confidentiality, the meetings were not audio recorded.

In **iteration two**, we first assigned the criteria to each phase of the business model innovation process discussed in Chapter 4.2 (see **Appendix J**) based on the defined phases and gates. We iterated the assignment with representatives at *Comp* during the case study. Second, we instantiated and operationalised the criteria by developing a scale (e.g., binary or Likert) for each criterion and generated a visual tool. Finally, three managers at *Comp* used the visual tool to retrospectively evaluate one data-driven business model innovation they were responsible for (see Figure 6.2 for an illustrative example). Based on this second "light" evaluation, we could collect initial evidence for our artefact's usefulness and ease of use and recommendations to improve it further in some details.

	First Design Cycle	**Second Design Cycle**
Problem Awareness	After a design iteration of a business model, an evaluation step is needed to assess the business model design and guide further direction (Wirtz and Daiser, 2018; Zott and Amit, 2015). The case study confirmed this need and the practical relevance of the problem. Literature provides no comprehensive overview of and actionable decision criteria for all phases of a business model innovation.	
Suggestion	Conducted a literature review on existing decision criteria and identified criteria from the case study with Comp.	Assignment of each criterion to a phase/decision point of a business model innovation process
Development	A set of 28 evaluation and decision criteria structured by six categories and three themes	Operationalizing the criteria by instantiating them in open-ended questions and visual tools, including Likert scales and binary items
Evaluation	Discussion the decision criteria with four managers at Comp regarding their completeness	Three managers evaluated the artefact for its usefulness by applying it to one DDBM innovation retrospectively.
Conclusion	Each process phase focuses on a different criteria category; thus, specific aspects are more important at specific stages. The information for each criterion gets more detailed and precise over time. The category of risks is a complementary dimension to all other categories, as uncertainties in the other categories (e.g., financials or customer demand) can represent potential risks for the business model.	

Table 6.1: Mapping our research activities to the phases suggested by Vaishnavi and Kuechler (2015).

6.1.4 Result 1: A Set of Evaluation and Decision Criteria

We structured our evaluation and decision criteria along with three themes (desirability, feasibility and viability suggested by Bland *et al.*, 2020) and six categories (customer demand, market and competition, organisation and strategy, data and technology, financial rationale and risks) based on our bottom-up analysis of the literature and the learnings from the case study with *Comp*. *Desirability* addresses whether the customers want the aimed offering of the business model and what the market is already offering and demanding. *Feasibility* addresses whether the organisation can develop and operate the business model and if the desired solution is technically feasible. *Viability* addresses whether the organisation should implement the new business model based on estimated returns and expected risks. Table 6.2 summarises the identified criteria and respective themes and categories.

Themes	Categories	Criteria
Desirability	Customer Demand	Meaningful customer problem Ease of value communication Unique value proposition Lead customers identified Successful interactions with prototypes Customer adoption Willingness to pay
	Market and Competition	Alignment with market and industry trends Market size and growth rate Competitive intensity Available alternatives Imitation and protection Time-to-market vs. window of opportunity
Feasibility	Organisation and Strategy	Strategic fit Strategic importance Possession of core competencies Influences on processes and required changes Potential internal synergies Commitment of key partners Team and industry experience
	Data and Technology	Technological feasibility Data feasibility (ownership, protection, quality, …)
Viability	Financial Rationale	Cost-benefit estimation (ROI) Affordable Loss Cost factors Certainty of revenues Cash flows Scalability
	Risks	Uncertainties in the other five categories are potential risks in the business model design

Table 6.2: Overview of evaluation and decision criteria structured along with six categories.

6.1.4.1 The Desirability of the Business Model: “Do they want this?”

Criteria in the desirability theme investigate whether customers want the aimed value proposition and if there is an attractive market (Bland *et al.*, 2020). We further divided this view into the categories of “customer needs”, which look at the individual customer level, and “market and competition”, which takes a high-level perspective on the needs and activities in the industry.

The most important question initially is if a **meaningful customer problem** was identified and addressed by the desired solution (Maxwell *et al.*, 2011; Tesch *et al.*, 2017). One evidence of customer value is how easy it is to communicate the value proposition (Mateu and March-Chorda, 2016) (**ease of value communication**). Ideas for a data-driven offering are discussed with other stakeholders (e.g., industry experts or potential customers). If the aimed value proposition is easily understood, it indicates that a meaningful customer need is addressed. One criterion regarding customer demand is the solution's novelty (Simmert *et al.*, 2019). The question here is if it offers unique value and meets customer needs better (Cooper and Edgett, 2001) and if it provides important advantages to existing solutions (Mateu and March-Chorda, 2016) (**unique value proposition**).

Another evidence for potential customer value is lead customers (Maxwell et al., 2011) that are already identified and/or contacted. We learned from our case with *Comp* that new data-driven offerings are often co-developed with a lead customer through projects and later turned into a standardised product or service. Such projects already provide initial funding for development and are an opportunity to learn about customer problems and needs. Customer needs are verified through field tests, **successful prototypes,** and customer **interactions** (Tesch *et al.*, 2017). Another question that needs to be considered is how easily the customers will adapt to the new offering (Maxwell *et al.*, 2011) (**customer adoption**). From our case study, we learned that using data products often required changes in the processes and practices of the customer to buy or use them. For instance, a data-driven service requires new purchase processes for the customer by buying via credit card instead of wire transfer and by using a pay-per-use model instead of an annual payment. Further, a data-driven service might require changes in existing work processes (e.g., engineering methods) before using the service. Finally, it is important to evaluate the **willingness to pay** of the customer (Cooper and Edgett, 2001). Customers must be willing to adopt the data-driven service for a successful business model. They also should want to pay for it, which is an important input for financial evaluations of the business model (see below).

The second perspective of the business model desirability is market and competition to ensure the long-term success of the business model. The data-driven business model should be **aligned with market and industry trends** (Tesch *et al.*, 2017). One important criterion for investing in a business model idea is a sufficient **market size** (Mateu and Escribá-Esteve, 2019) or a growing market (Cooper and Edgett, 2001; Maxwell *et al.*, 2011). Decision-makers must also consider how **competitive** the market is and what **alternatives** are available (Cooper and Edgett, 2001; Mateu and March-Chorda, 2016; Maxwell *et al.*, 2011). Thus, it is important to benchmark the business model with competitors (Tesch *et al.*, 2017). One aspect that guarantees the long-term success of a business model is how easily competitors can copy the offering (Maxwell *et al.*, 2011) and if there are any protection mechanisms in the business model design (Mateu and March-Chorda, 2016) (**imitation and protection**). For instance, if an organisation is aggregating data from public sources or data providers and, based on this, providing a data product, this might be easily copied by other players in the market if there are no protection mechanisms, such as internal data sources. From our case study, we learned that it is important to balance the **time-to-market** (i.e., how long it takes from an idea to market launch) with the **window of opportunity** (i.e., during what time window our solution is attractive for the market before it is outdated by other technologies or offered by competitors).

6.1.4.2 Feasibility of the Business Model: "Can we do this?"

Criteria in the feasibility theme address the question of whether the organization is capable of developing the new data-driven business model in terms of key resources (e.g., technologies or competencies), key activities (e.g., changes in processes) and key partners (Bland *et al.*, 2020). From the organizational perspective, this encompasses the fit with the company's strategy and its importance, the possession of necessary competencies and effects on existing processes, potential synergies, the commitment of key stakeholders and experiences in that field.

A business model idea must fit to or be aligned with the "strategy" (Cooper and Edgett, 2001), "strategic roadmap" (Tesch *et al.*, 2017) or "objectives" (Casadesus-Masanell and Ricart, 2007) of the organisation (**strategic fit**). This criterion is also an important aspect of *Comp*. One project manager mentioned that getting management support (regarding budget and resources) is easier if the data-driven innovation is aligned with the company strategy. Another product manager at *Comp* also mentioned that it is hard to determine this strategic fit and that he discusses this fit for new ideas with the strategy manager. Like the strategic fit, the **strategic importance** (Cooper and Edgett, 2001) of an innovation (field) informs decision-making. One product manager at *Comp* mentioned that data-driven innovation addresses a strategic goal of his general manager (e.g., revenue growth of x% in one business segment). Next to strategy, possessing the necessary **core competencies** (Tesch *et al.*, 2017) to build and operate the business model is also important. One business development manager at *Comp* mentioned the question he asks for every new idea: Do we leverage our core competencies in the new business model? Leveraging core competencies can be a competitive advantage. Like the competencies, decision-makers consider any required changes or negative effects on existing **business processes**. For instance, a new data-driven service requires online payment via credit card, whereas existing sales processes at the organisation run via traditional invoices and wire transfers. Other criteria affecting management investment decisions are potential synergies with existing technologies, offerings and processes (Cooper and Edgett, 2001). We also learned from the case study that this could be existing (software) solutions other departments have developed. On the other hand, a new data-driven business model could cannibalise existing businesses and lead to conflicts with other departments or business units. Therefore, it is important to be aligned with other internal stakeholders. The **commitment of key partners** and internal stakeholders (Tesch *et al.*, 2017) can be a stop-or-go criterion, especially as data-driven business models require collaboration with new partners (Leski *et al.*, 2021), often Start-Ups. One product manager reported on one innovation case where they collaborated with a data marketplace and found it difficult to set up all the contractual agreements for collaboration. The **experience** of the innovation team and the industry (Maxwell *et al.*, 2011) plays another important role in investment decisions for a new business idea. For instance, having one team member on board with experience with a new industry targeted by the data-driven business model (e.g., the construction industry for an automotive company) is important.

From a technological perspective, decision-makers consider if it is feasible to implement the business model if there are any obstacles. Literature denotes development and **technology** risks (Maxwell *et al.*, 2011), including the gap, complexity and degree of uncertainty (Cooper and Edgett, 2001). We identified several factors regarding data from the case study (**data feasibility**). The first factor addresses the origin of the data. When the business model is mainly based on a single *external* source of data (e.g., from data providers or publicly available data), the business model might depend on this source, which could be a risk if this external data source is not accessible anymore. If the business model is based on *internal* data, there might be the risk of leaking this internal (and valuable) data through a technical fault in the data service. Another risk arises with handling sensitive customer or personal data (data protection law), especially if the ownership is unclear. One more critical factor is having the required data quality and controlling and ensuring this quality. Further, there is the question of how easy it is for other organisations to generate this valuable data by themselves. For some services, an initial critical volume of data is needed (Förster *et al.*, 2019), and there is the question of how resource-intensive it is to generate or acquire it. Finally, a data-driven service can generate valuable data through its usage, leading to a self-enforcing loop where the service quality is increased by the volume of data (Förster *et al.*, 2019).

6.1.4.3 Viability of the Business Model: “Shall we do this?”

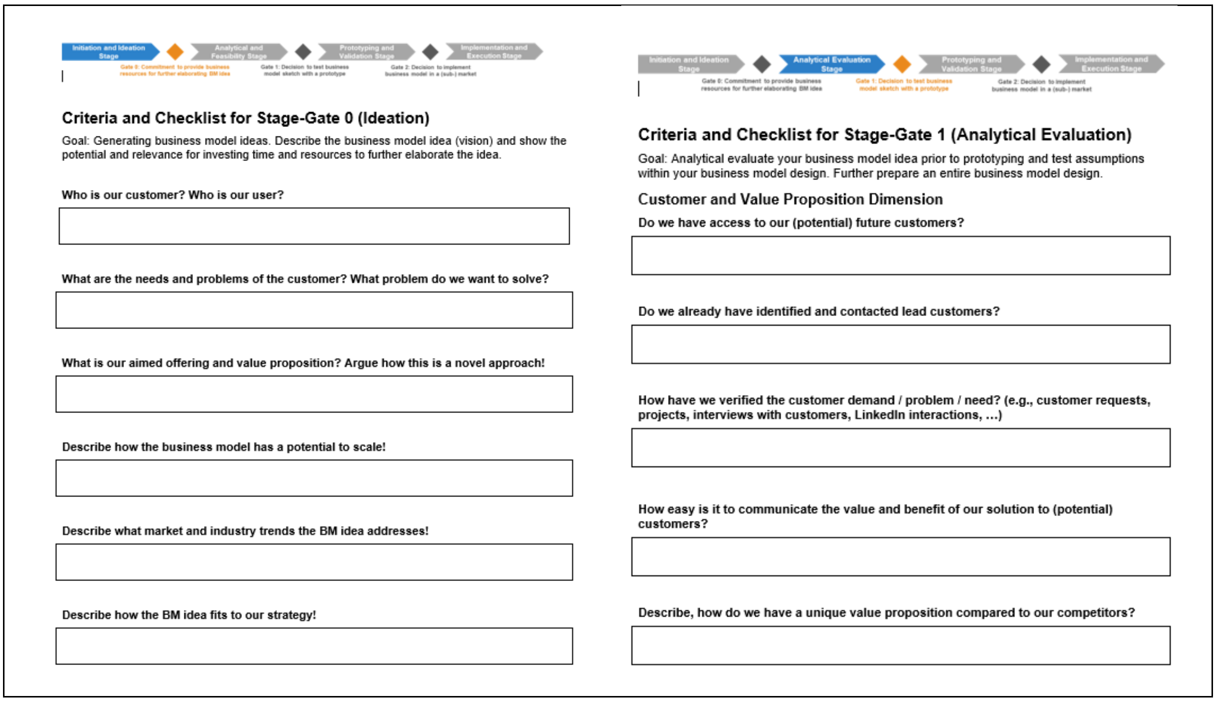
Criteria in the viability theme address the question of whether the business model can generate more revenues than costs (Bland *et al.*, 2020) and if the expected returns (financial rationale) are balanced with acceptable risks (Casadesus-Masanell and Ricart, 2007).

During the design phase, only a rough **cost-benefit estimation** can be performed (Zolnowski *et al.*, 2017). Thus, it is better to base the decisions on **affordable losses** than estimated returns (Bilgeri *et al.*, 2015). When more information is available through prototyping and testing, a viable business case calculation should be performed (Tesch *et al.*, 2017). There are different methods and metrics to determine the financial viability of the business model, such as the return on investment (ROI), cash flows, certainty of returns or the payback period (Cooper and Edgett, 2001; Maxwell *et al.*, 2011). **Cost factors** in a data-driven business model can be split into initial (development) costs (e.g., software development effort, purchasing data, data preparation and cleaning, algorithm development) and running costs (e.g., data infrastructure, maintenance, or ensuring data quality). From a revenue perspective, it is also important to have **predictable revenues** and proper **cash flows** (Osterwalder and Pigneur, 2010). One manager at *Comp* also mentioned that the **scalability** of a business model is an important decision criterion, i.e., how easy it is to scale a solution (offering) from one customer to many.

However, the evaluation of business models should focus on estimating returns and identifying relevant **risk** factors in a business model (Brillinger *et al.*, 2020; Casadesus-Masanell and Ricart, 2007), such as knowledge risks (see Chapters 6.2 and 6.3). Brillinger (2018) and Brillinger *et al.* (2020) already provide a comprehensive list of risk factors structured by the business model elements. In the context of this chapter, uncertainties in the other five categories are potential risks in the business model design.

6.1.5 Result 2: Instantiation and Demonstration in an offline-established Organization

After developing the set of decision and evaluation criteria based on the literature and the learnings from the case study in the previous section, we operationalised them and demonstrated the artefact in the context of *Comp*. First, we assigned each criterion to one gate of the business model innovation process presented in Chapter 4.2 (see **Appendix J**).


Initiation and Ideation Stage
Gate 0: Commitment to provide business resources for further elaborating BM idea
Analytical and Feasibility Stage
Gate 1: Decision to test business model sketch with a prototype
Prototyping and Validation Stage
Gate 2: Decision to implement business model in a (sub-) market
Implementation and Execution Stage

Criteria and Checklist for Stage-Gate 0 (Ideation)

Goal: Generating business model ideas. Describe the business model idea (vision) and show the potential and relevance for investing time and resources to further elaborate the idea.

Who is our customer? Who is our user?

What are the needs and problems of the customer? What problem do we want to solve?

What is our aimed offering and value proposition? Argue how this is a novel approach!

Describe how the business model has a potential to scale!

Describe what market and industry trends the BM idea addresses!

Describe how the BM idea fits to our strategy!

Initiation and Ideation Stage
Gate 0: Commitment to provide business resources for further elaborating BM idea
Analytical Evaluation Stage
Gate 1: Decision to test business model sketch with a prototype
Prototyping and Validation Stage
Gate 2: Decision to implement business model in a (sub-) market
Implementation and Execution Stage

Criteria and Checklist for Stage-Gate 1 (Analytical Evaluation)

Goal: Analytical evaluate your business model idea prior to prototyping and test assumptions within your business model design. Further prepare an entire business model design.

Customer and Value Proposition Dimension

Do we have access to our (potential) future customers?

Do we already have identified and contacted lead customers?

How have we verified the customer demand / problem / need? (e.g., customer requests, projects, interviews with customers, LinkedIn interactions, …)

How easy is it to communicate the value and benefit of our solution to (potential) customers?

Describe, how do we have a unique value proposition compared to our competitors?

Figure 6.1: Exemplary instantiation of the criteria in a questionnaire (own representation, anonymised).

Second, we operationalised the criteria by instantiating them in open-ended questions. We collected all criteria for one gate in a questionnaire, as shown in Figure 6.1. This questionnaire should help innovators improve their business model design and guide them during each phase. Further, this questionnaire helps structure the information collected during the activities in the phase and informs the decision-maker's gate evaluation. We used this questionnaire in three use cases at *Comp* while participating in data-driven business model innovation and could improve the structure and formulations while practising.

Third, we operationalised the criteria for quantification through Likert scales and binary items if applicable. We used existing elements from the literature (e.g., Mateu and March-Chorda, 2016 or Maxwell *et al.*, 2011). Where no scales were available, we developed them and discussed them with representatives of *Comp*. Further, we visualised the scales and used colours. We performed a "light" evaluation approach: We presented the final artefact to three managers at *Comp*. They retrospectively evaluated one DDBM case they are responsible for each gate. Figure 6.2 shows an exemplary instantiation and application of evaluation criteria for gate two after the prototyping phase. This excerpt shows that the use case is not ready for passing gate two, and further work is necessary, for instance, in the technical proof of concept and the protection mechanism.

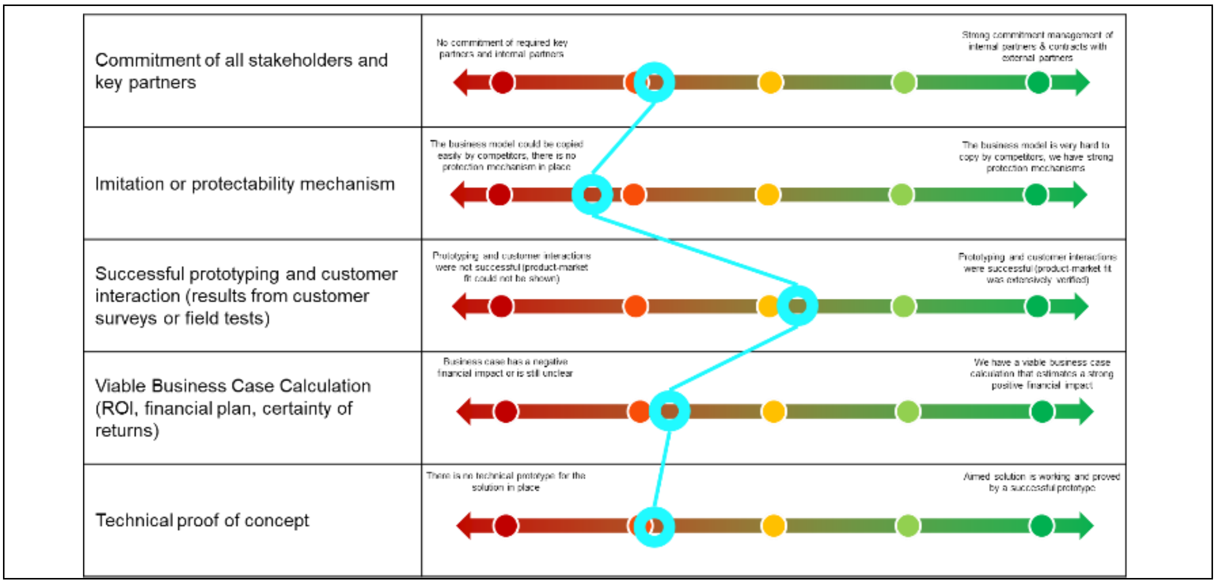


Figure 6.2: Exemplary demonstration of the operationalised criteria of the feasibility and prototyping stage applied by practitioners to one use case (own representation, excerpt, anonymised).

6.1.6 Discussion and Conclusion

In this introductory chapter, we have presented a set of evaluation and decision criteria for data-driven business model innovation, connected it to a business model innovation process and showed an exemplary instantiation in the context of *Comp*. Regarding the connection to a stage-gate process, we see a focus on specific categories in each phase of business model innovation. The early phases ("Initiation and Ideation") focus on the market and customer demand to evaluate if there is a market for the offering. Later, an evaluation of whether the business model can be implemented is performed through a proof of concept ("Prototyping and Validation" phase). Thus, performing a detailed business case calculation with an estimated ROI makes no sense when the customer demand is still not verified. Although the other categories are also considered in each phase, decision-makers focus less on them. For instance, it makes sense to have a rough cost-benefit estimation at an early stage if the business model could be, in principle, profitable. Further, our case study work found that information about one category or criterion becomes more precise over time as more evidence is available from learning through interactions with customers and the market. For instance, the financial rationale evolves from a rough cost and return estimation early on to a detailed and viable business case calculation after successful prototyping and interactions with customers (see, e.g., Tesch *et al.*, 2017).

The results of this chapter address the need for more research on evaluation and decision-making in data-driven business model innovation (as pointed out in our literature review in Chapter 4.1 and Fruhwirth *et al.*, 2020c). Further, the results contribute our process described in Chapter 4.2 and Fruhwirth and Pammer-Schindler (2023) and, particularly, the stage-gate model. Further, the criteria can be used to categorise data-driven business model innovations to maturity levels, as suggested in Chapter 5.1. From a practitioner's perspective, this chapter provides hands-on criteria for managers. Although the criteria were developed specifically for *Comp* based on the literature, the six categories are generic and can be applied to every business model and organisation.

The research presented in this chapter is not without limitations. Regarding the *completeness* of the criteria, limited literature was available on decision criteria in business model innovation and the practical insights were drawn only from one case study.

- This relates to one general limitation of this thesis, that parts are relying on a single case study with Comp (*Limitation 1*, Chapter 7.4).

One major limitation of this chapter concerns the evaluation. Regarding our artefact's understandability and ease of use, we conducted only a light evaluation by applying the tool to three use cases at *Comp*. Although they already perceived it as useful and easy to use, more empirical evidence is necessary for a complete evaluation. Regarding the effectiveness of our artefact, we have not made any proof to what extent it improves the evaluation investment decision quality in data-driven business model innovation.

- Thus, the limitation regarding evaluation is also a general limitation of this thesis (*Limitation 2*, Chapter 7.4).
- Overall, these mentioned issues in the discussion also relate to another general limitation of this thesis that not all studies have been conducted in the same depth with the same rigor (*Limitation 3*, Chapter 7.4). As already pointed out in the beginning of this chapter, we presented here an introductory study for the next chapters.

Summing up, this chapter provided an overview of evaluation and decision criteria during data-driven business model innovation and an exemplary instantiation of the case organisation. It is important to note that unfulfilled criteria can lead to uncertainties and risks in the business model. Therefore, the following chapters will detail one risk factor specific to data-driven business models, i.e., the knowledge risk through sharing data-related value objects.

- We will present one tool that supports identifying and discussing knowledge risks while designing data-driven business models in the next Chapter 6.2.

6.2 A Network-based Tool for Identifying Knowledge Risks[43]

6.2.1 Introduction

Data-driven business models not only hold the opportunity for business growth and new revenues for organizations, but they might also cause new types of risks concerning data. Exchanging data across organisations can lead to unwanted knowledge spill-overs (Ilvonen *et al.*, 2018) and so-called knowledge risks (Durst and Zieba, 2017). Thus, from a risk management perspective, managers need support to identify and manage such risks in designing a (data-driven) business model (Brillinger *et al.*, 2020). Nevertheless, current research on tool support for innovating data-driven business models mainly focuses on supporting idea generation and the design process (Fruhwirth *et al.*, 2020c; see chapter 4.1). Likewise, risk management in business model innovation is an under-researched field (Brillinger *et al.*, 2020). Further, novel risks evolving from business models based on digital technologies make new risk management frameworks and tools necessary (Dellermann *et al.*, 2017). To address this gap, in line with the call for more research on managing knowledge risks in strategic Information Systems (IS) settings (Loebbecke *et al.*, 2016) and the call for research in IS on tooling for risk management in business model innovation based on digital technologies (Tesch and Brillinger, 2017), we aim to answer the following question in this chapter:

Can a networked-based representation of business models support identifying and understanding knowledge risks in data-driven business models?

In this chapter, we follow our Design Science Research approach (Hevner et al. 2004) and split our research endeavour into two parts. The first part is embedded in the case study with *Comp*. There, we identified the knowledge risks problem while participating in developing a data-driven business model and designed an artefact (i.e., a network-based business model representation). We found the artefact useful in discussing and identifying knowledge risks. In the second part, we evaluated this artefact to generalize our design results. Therefore, we conducted an interview study with 17 experts from industry and academia to evaluate the ease of use in terms of structure and understandability and the perceived benefit and problem fit of our artefact.

This chapter is structured as follows: Section 6.2.2 provides additional background on knowledge risk management and risk management in business model innovation. A detailed description of the method and approach, including the problem identification, initial artefact design and the applied interview evaluation method, follows in section 6.2.3. Subsequently, section 6.2.4 presents the problem identification and artefact design from the case study and section 6.2.5 presents the

[43] This chapter is based on: Fruhwirth, M., Pammer-Schindler, V., and Thalmann, S. (2019): "To Sell or Not to Sell: Knowledge Risks in Data-Driven Business Models," 2019 Pre-ICIS SIGDSA Symposium on Inspiring mindset for Innovation with Business Analytics and Data Science, Munich 2019.; and 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 Hawaii International Conference on System Sciences (HICSS), pp. 5218-5227.

artefact evaluation via expert interviews. This chapter closes with a discussion and outlook in section 6.2.6.

6.2.2 Additional Background on Knowledge Risks and Risk Management in Business Model Innovation

Developing (data-driven) business models can be understood as a set *"of concrete choices and the consequences of these choices"* (Casadesus-Masanell and Ricart, 2010, p. 198). Managers must balance acceptable risks and estimated returns when deciding between different business model design options (Casadesus-Masanell and Ricart, 2010; Tesch and Brillinger, 2017). Risks in business models can threaten the profitability or sustainability of the business model or even the firm's value (Brillinger, 2018), making it necessary to manage the risks of a business model. Risk management generally involves identifying, assessing, measuring, and monitoring risks (Brillinger *et al.*, 2020; Hallikas *et al.*, 2004). Risks are usually evaluated by assessing the probability of a risk event and the impact on the business model (Brillinger *et al.*, 2020; Hallikas *et al.*, 2004). Business model risks can also be analysed for each business model building block (Brillinger, 2018; Brillinger *et al.*, 2020; Osterwalder and Pigneur, 2010), like risks related to the offering or risks related to the infrastructure of the business model.

Risk management concerning business models is particularly important in business model innovation, i.e., updating an existing business model or creating a new one. Innovating new business models comprises risks due to their uncertainties and complexity (Brillinger *et al.*, 2020; Euchner and Ganguly, 2014; Taran *et al.*, 2013). Thus, many business model innovations fail (Christensen *et al;* Taran *et al.*, 2015) or imply financial losses or image loss (Brillinger *et al.*, 2020). Therefore, risk management should be integrated into the business model innovation process to reduce *"the risks related to the uncertainty and complexity of developing and implementing a new business model"* (Taran *et al.*, 2013, p. 44). However, there is a lack of risk management in business model innovation in practice (Taran *et al.*, 2015) and research (Waitzinger, 2015). One risk management method in business model innovation is experimentation, i.e., testing hypotheses of a business model design through business experiments to reduce uncertainties (Bland *et al.*, 2020; Ganguly and Euchner, 2018). Another approach is considering risks in the business model design (Girotra and Netessine, 2011). After identifying and being aware of risks, managers can adapt the business model design as a risk management measure (Brillinger *et al.*, 2020). One approach for identifying risks in business models is to use lists of risk factors, such as the drainage of intellectual property and knowledge (Brillinger *et al.*, 2020). Knowledge protection literature refers to such risks as knowledge risks (Durst and Zieba, 2018), and the growing exchange of data sets increases such risks.

Data-driven business models involve new types of risks. On the one hand, such new business models imply increased interactions between various actors in the business model (Dellermann *et al.*, 2017). On the other hand, risks also emerge from the increased usage of Information

Technology, especially with data as a key resource and exchanged value object. Birkel *et al.* (2019) list such risks in the context of Industry 4.0, including risks related to cyberattacks, data ownership, data security, data handling, and cloud computing. Brillinger *et al.* (2020) list data-related risk factors, such as data security, data ownership, data privacy, or data quality. Tebernun *et al.* (2018) consider risks in data networks, such as the contingency risk of data sources. Fernández-Manzano and González-Vasco (2018) examine risks regarding data privacy, especially in using personal data in DDBMs. One type of such risk in business models is the drainage of intellectual property or know-how from the business model owner (Brillinger *et al.*, 2020), in particular through the exchange of data (Ilvonen *et al.*, 2018; Zeiringer, 2021). Knowledge management literature denotes such events as knowledge risks (Durst, 2019; Manhart and Thalmann, 2015).

This diversity of (knowledge) risks requires a set of tools and methods *"to identify, prevent or manage them"* (Durst and Zieba, 2018, p. 7). In the wider context of business models based on digital technologies that don't specifically focus on exchanging data or data-derived value objects, only a few studies explicitly provide tools and methods for risk management. Dellermann *et al.* (2017) provide a 4-steps risk management framework for innovation risks in digital business models. Brillinger (2018) provides an adopted method of the Value Network Analysis to identify risks in ecosystems of Internet of Things business models. Brillinger *et al.* (2020) provide a list of business model risk categories, such as data or intellectual property risks, that decision-makers can use as a checklist to identify risk and uncertainty factors in their business models to adapt the business model design further.

Nevertheless, knowledge risks are missing in current literature reviews on business model innovation (e.g., Schneider and Spieth, 2013 or Tesch and Brillinger, 2017). Knowledge management literature provides several tools and methods to manage knowledge risks, such as a knowledge risk management framework (Massingham, 2010), a proactive process for managing knowledge security risks (Ilvonen *et al.*, 2015) or mapping information and knowledge assets for security risk assessment (Padyab *et al.*, 2014). However, such tools are scarce in the context of DDBMs (Fruhwirth *et al.*, 2020c).

6.2.3 Detailed Research Approach

To address this literature gap and answer the research question of this chapter, we follow our Design Science Research approach of this thesis by conducting a sub-DSR project. The first part of the study presented in this chapter was conducted in the case study with *Comp,* where we identified the problem of knowledge risks while designing a data-driven business model and designed an artefact, i.e., a network-based business model representation (published as Fruhwirth *et al.*, 2019). In the second part, we conducted an interview study with experts to evaluate our artefact (published as Fruhwirth *et al.*, 2021b). We will describe the detailed methodological steps for both parts in the following.

6.2.3.1 Problem Identification and Artifact Design in the Case Study

As already described in the method chapter of this thesis (see section 3.2.3), our research approach in the case study has been iterative, with each iteration having elements of (i) identifying and answering problem statements from the environment of relevance (*Comp*), (ii) elements of design and evaluation, with design artefacts supporting decision making, and (iii) elements of rigour, with additional background from research on DDBM innovation, and decision support artefacts (cp. Fruhwirth *et al.*, 2019). Iterations one and two describe the background work that was necessary to arrive at the problem of knowledge risks. We have presented the research output of these two iterations in previous chapters of this thesis. Iterations three and four now illustrate the relevance of the research question, the developed design artefacts, and the relationship of the designed artefact with our background literature.

6.2.3.2 Formative Evaluation through Expert Interviews

To qualitatively evaluate our artefact's structure, understandability, and perceived benefit, we have chosen expert interviews as our evaluation method. This approach enabled us to collect descriptive justificatory knowledge on the artefact design from experts who have experience in the domain (Sonnenberg and Vom Brocke, 2012). Via snowball sampling, we selected 17 experts in the domains of Business Models, Data Science, and/or Knowledge Management from academia and industry to collect feedback for our artefact from those related perspectives. Academic experts held positions as professors or senior researchers. Practitioners were working in the Automotive, Information Technology or Consulting industry and held technical or management positions. Table 6.3 gives an overview of the interview participants.

Institution		**Position**		**Background**[44]	
Academic (R0-R8)[45]	8	Professor	6	Business Models	7
		Senior Researcher	2	Data Science	9
Practitioners (I1-I9)	9	CEO/Director	4	Knowledge Management	6
		Senior Manager	3		
		Consultant/Data Scientist	2		

Table 6.3: Description of recruited participants in this interview evaluation study.

We divided the semi-structured interviews into two parts: in the first part, we explored and discussed the problem of knowledge risks in DDBMs to provide the application context and background for the innovation tool (see Chapter 6.3). In the second part, we first presented the artefact and an exemplary case, as described in section 6.2.4, and asked the experts questions regarding the artefact's structure, applicability and usefulness. The evaluation of our artefact based on a single exemplary use case induced some **limitations** on the generalisability of our results: one might argue that findings are specific to the use case we have instantiated. Two characteristics

[44] Not mutually exclusive. One expert might have a background in more than one domain.
[45] R0 was one PhD student that also acted as a pre-test for the first part of the interview guideline related to Chapter 6.3.

of our study mitigate this limit: *Firstly*, we interviewed experts with various backgrounds. Hence, the exemplary case served as a grounding and starting point for the discussion; interviewees also gave feedback based on their own experiences. *Secondly*, the exemplary use case corresponds to the anonymised version of a real business case. This approach implies, on the one hand, a realistic example and, on the other hand, through anonymisation, one that isn't domain-specific. However, our approach is limited to use cases in the B2B environment.

We conducted the interviews between November 2019 and May 2020 via face-to-face meetings or digital communication software (such as Skype or GoToMeeting) in German or English. All interviews were audio-recorded and transcribed. To further analyse the text material, we applied the Qualitative Content Analysis approach suggested by (Mayring, 2015). As a starting point, themes were defined corresponding to the goals of the evaluation and the questions asked in the interviews (e.g., the problem relevance, the structure, understandability, or expected benefit of the artefact). We built our categories inductively within these themes by coding the interview material. We cleaned the text, dropped passages without relevant content, and consolidated codes belonging to the same subject under new categories. Quotes from interviews conducted in German were translated into English, overlooked by a second researcher and marked with a (*) in this chapter. Pseudonyms replaced names of persons or organisations to maintain anonymity.

6.2.4 Result 1: Problem Identification, Artefact Design and Demonstration through four Design Iterations

We arrived at the problem of knowledge risks through four design iterations in our case study. We report here only shortly on iterations one and two, as we have presented their results already in previous chapters. Iterations three and four then focus on the problem of knowledge risks and the network-based representation as the designed artefact. We map here also the iterations with our overall Design Cycles presented in section 3.2.3.

Iteration 1: Scoping and Ideation (Design Cycle 1)

During scoping and ideation for DDBM at *Comp*, decision-makers were challenged to find methods and tools supporting the DDBM process. We designed a matrix that maps ideas for DDBM to these categories (see Chapter 5.1). This matrix (the design artefact of iteration 1) was discussed and used to structure two workshops at *Comp*. Based on the workshops, we identified as a requirement the need for a structured representation of DDBM that can structure discussions and ideation by focusing on data analytics-related value propositions and identifying relevant decision criteria for evaluating ideas.

Iteration 2: Framing the Problem Statement as a Decision Problem (Design Cycle 2b)

Building on iteration 1, the goal of iteration 2 was to identify decision criteria and a suitable representation for DDBM that takes aspects from data and analytics into account. Therefore, we refined our research problem towards a decision problem, such that we understand *"business* *models [to be] made of concrete choices and the consequences of these choices*" (Casadesus-Masanell and Ricart, 2010, p. 198). Subsequently, we employ Behavioural Decision Theory (Simon, 1959) as a guiding theory. Behavioural Decision Theory aims to understand decision-making patterns and tendencies of humans, e.g., to design appropriate decision support tackling these tendencies. BM frameworks and evaluation criteria serve as decision support (Osterwalder and Pigneur, 2010; Tesch and Brillinger, 2017) via structuring the required decision inputs, ensuring data completeness in line with Behavioural Decision Theory. Based on this background from Behavioural Decision Theory, and the relevance identified within *Comp* for the need of a structured representation of DDBMs, we articulate the first design requirement for an artefact that supports decision-making as part of the DDBM design process:

Design Requirement: A DDBM representation needs to focus on the main elements of a DDBM, particularly data analytics, value proposition and customer needs.

Within iteration 2, we developed the Data Product Canvas, a component-based representation of DDBM, as a design artefact (see Chapter 5.2 and Fruhwirth *et al.*, 2020a). We applied this artefact in the context of *Comp* to structure the representation and evaluation of 23 DDBM ideas. The ideas were discussed in a workshop with four managers directly responsible for data-driven innovations. The artefact informed the decision to elaborate further and explore two of the 23 DDBM ideas. One was prioritised and worked on in iterations 3 and 4. As *Comp's* DDBM ideas largely rely on external data sources from their customers and other actors, it became clear in this workshop that a visualization of the partner network and interactions was missing in the current artefact, and it was expected that this would be necessary to inform further decision-making.

Iteration 3: Refining the Decision Problem – Problem Identification (within Design Cycle 3)

Based on the insight of iteration 2, we found that the exchanged data, services and money need to be transparent for every business interaction with an actor. This information is necessary to decide on expected benefits and risks in the design process and the overall feasibility of a DDBM idea. We understand this activity as visualising a value network's roles, deliverables and transactions (Alee, 2008).

Analysing the partner network in a business model is an important step for improving the decision base (Brillinger, 2018), especially for *Comp,* as the selected data-driven business model idea contains external data sources and provides data products in exchange with different stakeholders. Transaction-based representations of BM (Gordijn and Akkermans, 2001) have already emerged to visualize the flow of business values for BM, e.g., based on Cyber-Physical Systems (Terrenghi *et al.*, 2018). From the view of Behavioural Decision Theory, we identified further decision inputs as actors, the exchanges between actors and the balance of the value exchanges (Brillinger, 2018). Based on this background and the relevance identified within *Comp* to represent business interactions and networks, we articulate the second design requirement:

Design Requirement: A transaction-based representation of BMs and data as an additional value flow is required to inform the decision on value network with actors and to balance benefits and risks.

We, therefore, created, as a design artefact within iteration 3, a representation of DDBMs as value networks, including actors, value exchanges, and customer needs as the main elements (for an overview of actors and exchanged values, see Chapter 5.4 and Leski *et al.*, 2021). An actor is *"an independent economic (and often legal) entity"* (Gordijn and Akkermans, 2001, p. 13) and has one or several roles in the network, like customer, data provider, end user or key partner. Actors are exchanging value objects like data, money, services, products or other benefits. Customer needs trigger exchanges.

We instantiated this representation with the selected DDBM use case within *Comp*. The DDBM was discussed and refined in two two-hour workshops, one with two managers responsible for data-driven innovations and one with six representatives from product management, R&D and engineering. *Comp* generates and refines data-driven ageing models of physical components based on data from different data sources. Based on this model, *Comp* can sell predictions for residual lifetime and value, as well as usage recommendations. During the first workshop, this representation led to the insight that knowledge is the core asset of *Comp's* DDBM on which all other data-driven services of the business model rely. This immediately triggered the awareness that the knowledge materialized in the data-driven model is critical and could, in principle, be at risk in the DDBM, especially when it is part of the value proposition, thus leading to unintended knowledge-spill-overs. Therefore, we frame the problem of knowledge risks in data-driven business models as follows:

> *Knowledge risks in data-driven business models occur when valuable knowledge of a company is materialised in data-related value objects and used as the basis of an offering. Through the exchange of such objects, critical knowledge may leak the organization's boundary and put the company's competitive advantage at risk.*

Iteration 4: Focus on core knowledge asset and knowledge risks – Artefact Design (Design Cycle 4)

Based on the workshop's insight from iteration 3 that knowledge is the critical asset of a DDBM, we frame a more specific decision problem: Find a trade-off between the benefits of monetizing knowledge (i.e., knowledge as part of the value proposition (Hartmann *et al.*, 2016)) and the risk of exposing this knowledge. To take this decision seriously, decision-makers need transparency about the knowledge contained in the exchanged data sets or digital value objects. This is also a relevant question for *Comp* as their business heavily relies on engineering know-how; for instance, one business area manager stated during the interviews: *"How can we build new* [data-driven] *services around our engineering know-how without fully giving the knowledge away?".*

In DDBM, knowledge of real-world phenomena is materialized in knowledge-related assets, like algorithms, predictions or models that can easily be transferred across actors and may be part of the value proposition of the business model. *"Value creation and capture require that companies choose between knowledge sharing and protection, or try to find some way of incorporating these two alternatives"* (Olander *et al.*, 2009, p. 352). This leads to a risk/benefit decision between sharing or protecting knowledge-related assets (Manhart *et al.*, 2015). With the lens of Behavioral Decision Theory, these knowledge-related flows serve as an additional decision input to ensure information completeness. In addition, the potential risk of unintended knowledge spillover should be visualized in our artefact to support decision processes. Prior research on knowledge risks found that making the knowledge boundary explicit enhances the decision quality (Lee *et al.*, 2015). Based on this insight and proposal to visualize knowledge boundaries by Lifshitz-Assaf (2017), we articulate the next design requirement for our artefact:

Design Requirement: To consider knowledge risks while designing DDBM data- and knowledge-related flows together with their knowledge boundaries, need to be represented.

The artefact from iteration four consists of actors (e.g., business model owner, data provider, customer segment), value flows (e.g., goods, data, knowledge, money) and the visualization of knowledge boundaries as dashed circles. An **actor** is *"an independent economic (and often legal) entity"* (Gordijn and Akkermans, 2001). It has one or several roles in the network, like the business model owner, a customer, a data provider, or another key partner. Actors exchange tangible and intangible **value objects** like money, data, knowledge, services, products, or other benefits. Further, a visual **knowledge boundary** makes the potential knowledge transfer visible. The artefact design was informed by previous research on business models (like network-based representations of business models (Brillinger, 2018; Gordijn and Akkermans, 2001; Terrenghi *et al.*, 2018) and knowledge risks (Lee *et al.*, 2015).

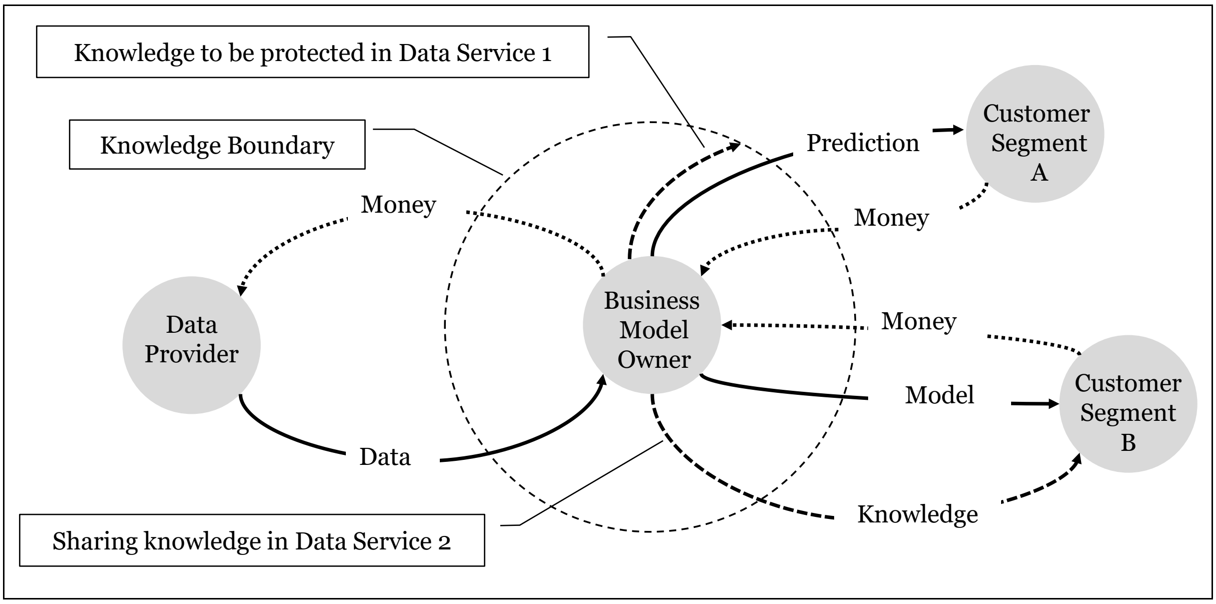


Figure 6.3: A network-based business model representation to identify and discuss knowledge risks.

We represented the DDBM of *Comp* (from iteration 3) as an instantiation of the refined artefact. To ensure anonymity, Figure 6.3 shows a fictitious DDBM as an illustrative example. The actor "*Business Model Owner"* is acquiring data from a "*Data Provider"* in exchange for money to develop a model of a real-world phenomenon (i.e., predicting the residual lifetime of a novel technical component). Therefore, the business model owner exploits his engineering knowledge, data from research projects, and data from a *Data Provider*. Thus, the *Business Model Owner* is materializing his core engineering knowledge in this data-driven (prediction) model. This model enables several options for offerings by the *Business Model Owner* for *Customers A* from Industry 1 and *Customers B* from Industry 2. In case one, the *Business Model Owner* is offering the model as a service to *Customer Segment A* and is sharing only predictions and, therefore, can protect the knowledge materialized in the model. In case 2, the *Business Model Owner* is selling the model to *Customer Segment B* from another industry and thus also sharing his core knowledge. We have presented here only the types of labels for simplification and retaining the anonymity of the original use case. In the real-world case, we have precisely named the flows and actors as suggested by (Allee, 2008).

6.2.5 Result 2: Artifact Evaluation through Expert Interviews

Now we present our findings of the artefact evaluation regarding the relevance of the use case (tool support for identifying knowledge risks during a DDBM innovation), the ease of use of the network-based representation in the sense of structure and understandability and the fit of our solution to the problem of knowledge risks.

6.2.5.1 General Relevance of Use Case

The challenge of knowledge risks in DDBMs was generally perceived as a novel and relevant problem by the interviewed experts, as one consultant mentioned:

> *"Fundamentally, I do believe this is a risk. It's just that reconstructing knowledge is currently not a discipline that is often or prominent published. Because reverse engineering is in the European, Western world not a prominent engineering discipline. I'm pretty sure that companies are doing it."* (I1* - Consultant Data Analytics)

Further, the interviewee highlighted that this reverse engineering of knowledge is hidden. In this context, the interviewees mentioned their need for tool support to make the (potential) reverse engineering more transparent. It makes sense to consider such potential risks already during the design process of business models, which was the intention of the tool, as one industry consultant (I3) stated:

> *"If I initiate an innovation process to identify new business areas from data, it makes sense as a second step that I immediately go with such a tool and assess the business model not only from a business perspective, because that's what you usually do anyway, but also to accompany the risk [assessment] with such a tool. And to do that as part of the process and not at the end."* (I3* - CEO Cyber Security Start-Up)

Overall, the wish to perform the risk assessment as part of the design process seems important. One academic expert (R4) reported from one company that analysing risks was part of their strategy development process and thus in front of business model innovation. However, currently, knowledge risks are assessed quite traditionally, as one interviewee described:

> *"Risk management is actually more like simply working with lists. We calculate business cases on the basis of experience and of course we have assumptions regarding profitability; and the more sensitive the assumptions are on a business case, the higher we estimate the risk. And then we track that risk more or less with lists."* (I7* - Manager Business Model Innovation, Automotive Company A)

This "hands-on" approach has limitations regarding complex settings and hidden knowledge risks in big data sets. The interviewees are aware of this limitation and lack proper guidelines and tool support:

> *"If you ask me, what sets of rules do we have to make sure when we develop and sell models to our customers, that they are not somehow misused. There's still little available."* (I4* - Manager, Automotive Company B)

Our interviewees showed awareness of knowledge risks and articulated a need for systematically identifying and managing such risks arising from the exchange of data-related value objects. However, currently, there is a lack of guidance and tool support.

6.2.5.2 Structure and Understandability of the Artifact (Ease of Use)

We presented our artefact to our experts via a synthetic case based on our experience from the case study with *Comp* (i.e., abstracted from a real company but still reasonable; see Section 6.2.4 and Fruhwirth *et al.*, 2019). Generally, interviewees perceived the network-based approach as understandable and appropriate. The representation was sufficient to communicate the example and to discuss the knowledge risks with the experts. One director for digital services brought up the suitability of the network-based representation:

> *"I think exactly this kind of network makes it clear that you have risks that differ from those that you have traditionally. And that's what it's all about. To say, you have to look at the data topic separately because the nature of these risks is somewhat different compared to selling a classic product"* (I5* - Director Digital Services)

The interviewee acknowledged the novelty of risks arising from data-driven collaborations and appreciated the additional perspective. Another manager for business model innovation highlighted the benefit of extending the common representation with the dimension of data to identify and assess the impact of knowledge risks:

> *"Yes, all in all, such network models are already established tools for representing business models. Therefore, it* [this artefact] *can be seen as an extension of the already existing network tools with data, as one of various aspects, what it makes sense in any case to consider additionally to develop business models iteratively. And I think the language you're using* [...] *is definitely appropriate."* (I7* - Manager Business Model Innovation, Automotive Company A)

Our interviewees confirmed that the main elements of the artefact (the actors and flows of data, knowledge, money and benefits) are sufficient and easy to understand to describe, communicate and discuss the business model. The flow of money, for instance, was mentioned as a necessary element to balance the estimated benefit with the expected risks.

However, several comments and recommendations were made to subdivide the main elements further more granularly. Table 6.4 summarises the results structured by the category of design element and with exemplary evidence from the interviews, which are further discussed.

We found that the different types of data-related value objects that are currently subsumed under data flows should be specified on a detailed level in the representation to identify and discuss potential knowledge risks. One professor for digital platforms (R1) pointed out that knowledge risks may arise from data transfer or access to data (e.g., single queries), which are different kinds of data-related value objects. In this regard, a list of sub-elements could be helpful. One director for digital services (I5) underpins that, as he mentioned, it is hard for people in practice to type elements in such network-based representations.

Artefact Element	**Expert recommendation**	**Exemplary evidence**
Types of data flow	Subdivision of data flows into different types of data-related value objects	I1, I2, I5, R2
Types of knowledge	Specification and visualization of the different types of knowledge	I6, R4
Bi-directional flows	Visualize bi-directional flows of data and knowledge	R2,RA4, R6, I1, I2
Intensity of flows	Add the intensity of flows (quantification) to balance the acceptable risks with expected returns	I7, I8
Visualization of Knowledge Risks	Potential knowledge risks should be visually marked for decision-makers when identified.	R6, I7, I8
Knowledge Boundary	Clarify if the visualisation of the knowledge boundary is a security measure or an awareness measure.	R2, I1, I7, I9

Table 6.4: Identified recommendations for improvements of the artefact's structure.

The type of knowledge should also be visualised in the representation. Types of knowledge could be expert knowledge from engineers, knowledge on the development of the algorithms or training of the model, or knowledge of the application context. A representation should specify what knowledge is critical or confidential and what knowledge flow is uncritical or necessary for the business model.

Our interviewees also mentioned that there are bidirectional knowledge flows between actors that should be visualised, i.e., knowledge flows from other actors (e.g., customers) to the business model owner. One professor for business administration and an expert in knowledge risks (R6), for instance, said:

> *"And what is missing here, you have one-sided flows of information and knowledge. [...] we expect exactly that in a modern company that learns from the customers, who also send information to me. And knowledge as well. So, I would make bilateral flows".* (R6* - Professor for Business Administration)

Thus, a DDBM could also create a knowledge risk for a customer or partner when they transfer data to the business model owner. One data science consultant (I1), for instance, mentioned that if the business model owner wants to calculate a prediction for the customer, the customer has to transfer data to the business model owner that forms the input for the prediction and thus could create a knowledge risk for the customer.

The exchanged value should be quantified to conceive the trade-off between the potential risks and the estimated returns for management decisions or actions from the visualization. One DDBM startup CEO (I8), for instance, mentioned as a manager, he needs more information, not only about the labels but also the intensity of the flows. One director of digital services (I7) further mentioned the approach to visualize this through the strength of the flow.

When identified, the potential knowledge risks should be visualized within the business model representation. As pointed out by experts I7 or I8, only the results of such an analysis are presented to executive management for decision. Thus, the visualization of the risks should be clear and easy to understand. I8; for instance, suggested:

> *"I think it* [the artefact] *needs some more colour. Risk is for me always associated with danger, which means I need something red somewhere."* (P8* - CEO DDBM Start-Up A)

The interviewees controversially discussed the visualization of the knowledge boundary: One data science consultant (I1) mentioned that this approach is interesting to get this barrier into people's heads. On the contrary, one professor for business model innovation (R2), for instance, mentioned that such a barrier could assume that such a barrier could be technically possible. Two interviewees, I7 and I9, questioned the utility of the knowledge boundary and mentioned that the drain of knowledge could have been identified just by the flow elements.

6.2.5.3 Expected benefit and fit of our solution to the problem

The representation was found to be appropriate for discussing the different types of potential knowledge risks with the interviewed experts, extending the model presented in Section 6.2.4 and to think about other potential risks. The interviewees stated that they perceive the artefact in its current version as helpful in visualising and communicating knowledge risks and creating awareness of this problem. Table 6.5 provides some statements as evidence for those expected benefits.

Expected Benefit	Exemplary Statements
Visualisation	*“Yeah, I think it is good. Because you can visualize and see ok, this are the situations, I can exchange, data and money and these are the dynamics, the wall. I think that is more easily to see, visualize and think about these relationships.”* (R3 – Professor Business Analytics) *"This is some kind of flow modelling, of flows of data, knowledge, money. I think it's pretty good for visualization."* (I6* - Senior Manager Data Analytics Consulting)
Communication	*"What is the value of the tool? For me, it is, at this point, a pure communication of the service. Where are the streams of data? If that is the purpose, then it has value. Would I use it in practice? Yes, I could imagine if the network is complex enough. if I have many data streams that I find difficult to communicate. Then it can be a good communication tool."* (I9* - CEO DDBM Start-Up B) *"[...] if it's really about doing this as a core business, then I should think about how I'm giving the information to the outside world; and that the different aspects you should think about, that they'll come up for discussion, I think that's good.”* (I2* - Data Scientist Automotive Company C)
Awareness Rising	*"Yes, it creates this awareness. [...] the warning sign, to be aware of the fact of having the distinction, to whom I offer the service and to whom not. I imagine that this can help.”* (I1* - Consultant Data Analytics) *"And it definitely makes sense to create awareness that I need to think about it [the risks]."* (I3*- CEO Cyber Security Start-Up) *"I believe that this is already helpful for companies if they are aware of how knowledge can leak from their own company borders, i.e., how knowledge can leak and where the problem is perhaps somewhat higher and where the problem is perhaps not so high.”* (R4* - Professor Data Science)

Table 6.5: Exemplary statements to the expected benefit of the artifact.

Further, our interviewees pointed out that in addition to the benefit of visualization, communication, and rising awareness, managing knowledge risks in DDBMs also requires **providing actionable information** to the management. Decision makers need clear and easy-to-understand conclusions and recommendations for decisions. One manager for business model innovation, for instance, reported on his experience in a large organization:

> *"Often, this practically fails because it is challenging to discuss very abstract relationships in practice. COMP works in such a way that decisions are made straight top down by senior management. [...] In the end, you should have a result that points to a very clear recommendation for action. That is the most important thing, also a learning that I had myself. [...] The important thing is that you have a statement afterwards that you can write down in three sentences. Otherwise, all the tools and methods are worthless because it does not influence the main decision because the main decision makers cannot grasp it"* (I7* - Manager Business Model Innovation Automotive Company A).

As this interviewee stated, there is a demand for a low visualisation complexity. Still, on the other hand, interviewees request many details which should be included, such as weights or probabilities.

Such details should include the assessment and quantification of the risk in terms of probability and impact; for instance, interviewee one CEO of a DDBM start-up noted:

> *"For me, the risk always has something to do with probability. Thus, to add weighting somewhere, a risk weighting."* (I8* - CEO DDBM Start-Up A)

In particular, the experts desired the estimation of the impact as this is very important for balancing between potential risks and estimated return as one manager from the industry mentioned:

> *"I think it's great if I can see at a glance where are the risks, and how serious they are, because I want to be able to identify any management decisions at the end of the day."* (I8* - CEO DDBM Start-Up A)

In this regard, our interviewees request quantifications of all measures regarding the risk:

> *"However, it [the tool] doesn't quantify the risk of data loss or the importance of the data in your company. Hence, the quantification is missing."* (I1* - Consultant Data Science)

Identifying and evaluating knowledge risk requires information on a more detailed level of granularity in addition to the abstract modelling of the flows and actors in the business model, particularly the detailed description of the flows of data and knowledge. The quantification of the exchanged value and the value of the knowledge needed for balancing the risk is extremely challenging as one interviewee resonates:

> *"And there you would need some understanding of how to measure money against data, how to measure the value of data, or the value of knowledge, or the value of predictions. This is, of course, very difficult."* (I7* - Manager Business Model Innovation Automotive Company A).

Our interviewees finally suggested questions to collect the required information. Table 6.6 presents such exemplary questions mentioned by our interviewees.

Category	**Exemplary Questions**
Valuation of data-related value objects	*"Which data, which algorithms, which actions are especially worth protecting, especially important to me as a company?"* (I6* - Senior Manager Data Analytics Consulting) *"Is the algorithm proprietary, so how valuable is it? Can it be developed easily in the beginning? Because he may or may not also have the engineering skills."* (I6* - Senior Manager Data Analytics Consulting))
Data-related questions	*"Do I have any contractual obligations in this data that I'm not allowed to give away?"* (I9* - CEO DDBM Start-Up B) *„Does the data give any inference to something else of my company, like the metadata, the meta-information of the data?"* (P9* - CEO DDBM Start-Up B) *"Do only I have this data? Can the data be generated or approximated by someone else?"* (I6* - Senior Manager Data Analytics Consulting))

Model-related questions	*„At the model level I have to evaluate, is such a model inversion possible, what information does my model reveal, in what form does it reveal it?“* (I9* - CEO DDBM Start-Up B)

Table 6.6: Exemplary questions to assess knowledge risks from the interviewed experts.

6.2.6 Discussion and Conclusion

In this chapter, we have identified the problem of knowledge risks in data-driven business models through exchanging data-related value objects in one case study with *Comp* and designed an artefact to support identifying such risks during business model design. Second, we evaluated this artefact with experts.

The main contribution of this chapter is twofold: First, we identified that knowledge risks are a **relevant decision parameter in the design process of DDBM**. Based on the behavioural decision theory, we framed this insight as a decision problem and collected the first piece of evidence for its relevance. We found this to be a specific aspect of DDBM, contrasting with non-data-driven business models and complementing existing research on business model risk factors (Brillinger, 2018). This finding is grounded on empirical evidence from *Comp* (Iteration 3 - identification of value objects in actor interactions; Iteration 4 - identification of associated knowledge risks and the necessity for a knowledge boundary). Knowledge risks are especially relevant for a knowledge-intensive service company, as these have valuable core knowledge. In this regard, *Comp* is a typical case as it offers services and products based on its expert know-how in automotive engineering.

- ➢ With these findings we contribute to the understanding of DDBMs, in particular via *Contribution 6* of this thesis (see Chapter 7.2): Exchanging data, models and predictions in a DDBM induce the risk of leaking critical knowledge. This risk needs to be considered already during the design of a DDBM.

Our second contribution are the **design requirements for providing practical decision support**. Based on an analysis of the decision process, we identified the need to represent the flow of data and knowledge as value objects and the need to represent the knowledge boundary. We crafted a prototype of our design requirements and collected initial evidence that those representations support the decision-making during the DDBM design process. A baseline proposition for further research in the field is that considering knowledge risks in the design process of DDBM enhances the decision quality of the design process and, thus, the success of a DDBM.

- ➢ With these findings we contribute to the knowledge on designing DDBM tools and methods, one direction of contributions of this thesis (see section 7.2.2).

Our evaluation highlights that practitioners and researchers in business models, data science and knowledge management are aware of knowledge risks arising from data-centric collaborations in DDBMs. Further, they agree on the **potential usefulness of systematic support** for assessing and monitoring such risks from the start of developing a DDBM. Such tool support doesn’t exist so far. Experts also mentioned that knowledge risks could be an important factor when deciding to establish or withhold a new DDBM. Thus, the present work contributes to the call for research on managing knowledge risks in strategic settings (Loebbecke *et al.*, 2016) and the call for risk management tools in business model innovation (Tesch and Brillinger, 2017). We further contribute to the literature on business model innovation (Amit and Zott, 2012; Chesbrough, 2007, 2010) by suggesting considering knowledge risks already in the business model design supported by our artefact. It complements existing research on technical and organisational measures to manage knowledge risks in data-centric collaborations (Kaiser *et al.*, 2021; Zeiringer and Thalmann, 2020) as well as general methods for managing knowledge risks (Ilvonen *et al.*, 2015; Padyab *et al.*, 2014).

Our evaluation study further showed that the network-based representation of data-driven business models was **easy to understand** and was perceived as useful for discussing knowledge risks in a given DDBM. It was perceived as helpful as it visualises the different flows of knowledge, money, and data between actors in the network. Thus, it enables DDBM designers to identify unwanted outflows of knowledge and balance them with the exchanged benefits. *Knowledge* refers to an expert judgement on what knowledge could be embedded in exchanged data. Regarding *money*, we focused only on business models with money-related flows in a B2B environment. We acknowledge that non-monetary returns also exist in multi-sided revenue models of DDBMs (e.g., advertising or paying with data) (Schüritz *et al.*, 2017b). Further research could adopt the artefact to such types of revenue models. *Data* refers to a type of exchange between actors in business models that needs to be described as concretely as possible in the representation of each case.

Further, the discussions with our interviewees and the derived design recommendations highlight two elements of particular importance in the studied network-based representation, namely the quantification of risks and different types of value objects. Both elements are a recommendation for us to re-design the artefact in further iterations. Specifically, these design recommendations call for clarification on what the key conceptual elements are in considering risks in DDBM. We see both as valuable starting points for future research.

Risk quantification: The evaluation interviews revealed that managing knowledge risks in DDBMs also requires an estimation of the probability (i.e., how easy it is to retrieve the knowledge) and the impact (i.e., what is the value of the leaked knowledge) of such risks as a decision input for the members of the DDBM design team. For such an estimation, relevant data needs to be collected. On the one hand, our interviewees expressed their desire for comprehensive and quantifiable indicators. On the other hand, they also see the practical challenges and efforts to collect the required data for such a decision-support tool. Hence, a suitable balance needs to be found, and tool support could help lower the efforts to collect the required data. Hence, research on how to best collect the required data for our proposed network-based representation seems an interesting research topic and a practical prerequisite for deployment in practice.

- Thus, this direction for future research relates to one general outlook topic of this thesis, i.e., using quantitative methods for evaluating business models (see *Outlook 1*, Chapter 7.5).

Different types of value objects: Existing transaction-based representations of business models encompass flows of data (Terrenghi *et al.*, 2018) or flows of knowledge (Solaimani *et al.*, 2015). In DDBMs, data-related value objects, such as raw data streams, models or predictions are exchanged. Thus, design recommendations from our interviews show that such nuanced differentiation of data-related value objects should be included as different types of exchanged entities in a network-based representation, as they have different characteristics regarding knowledge risks. Thus, it is necessary to examine how the types of exchanged value objects are associated with different types of knowledge risks. A nuanced distinction of exchanged values would be needed to discuss two fundamental questions of risk management: In what sense does this value object contain critical knowledge of an organisation, and how easy is it to retrieve the knowledge from the shared value object? For instance, current computer science research shows that machine learning models could be retrieved from sharing predictions via an API (Tramèr *et al.*, 2016). Such technical knowledge needs to be translated into risk assessment for DDBMs.

- Chapter 6.3 will now take up this direction for future research and will investigate three types of data-related value objects in detail. We will explore how different types of value objects are associated to different types of risks, what are the contextual factors and potential protection mechanisms.

6.3 Exploring Different Types of Knowledge Risks in Data-Driven Business Models[46]

6.3.1 Introduction

As discussed in the previous chapters, DDBMs imply exchanging data and similar data-related value objects. Further, in such business models, sensitive information and competitive knowledge are materialised in such value objects. At the same time, data science methods allow extracting information or knowledge from fine-granular, heterogeneous data, leading to potential risks when data is shared. Whereas before, knowledge needed to be represented in a much more explicit manner. Thus, it is challenging for organisations to evaluate what knowledge could be discovered from shared data sets (Zeiringer and Thalmann, 2020). For instance, simply "looking at the data" (i.e., at the headers of a database or descriptive statistics over a single dataset) is not enough to assess which knowledge could be drawn from the data. Sharing data implies the risk - which we refer to as knowledge risks - that competitive knowledge could leak and spill over to other organisations.

For example, we found such potential risks in our case study with *Comp* (see Fruhwirth *et al.*, 2019 and section 6.2.4). In this case, novel knowledge of a real-world physical phenomenon (i.e., predicting the residual lifetime of a physical component) was generated from data and materialised in a model. Building new DDBMs around this model (i.e., offering the model) could imply the risk of leaking core knowledge, as one workshop with managers of this company showed. Further, the willingness to share data is often a prerequisite for a DDBM, but potential knowledge leakages negatively influence this willingness. Thus, DDBMs require balancing between sharing and protecting knowledge. Further, IP might be shared or could be re-engineered when offering machine learning models through an API (Application Programming Interface) (Hanzlik *et al.*, 2021).

Knowledge risks have been studied in strategic alliances (Hernandez *et al.*, 2015; Jiang *et al.*, 2016; Kale *et al.*, 2000) and traditional business models (Al-Aali and Teece, 2013). However, as shown above, DDBMs imply new risks, particularly that knowledge may spill over to competitors via sharing data and similar value objects. Although such risks exist, little has been written about how different types of offerings of DDBMs, or exchanged value objects in particular, relate to potential knowledge risks. Therefore, we address this chapter's research question: **What knowledge risks are associated with sharing different types of data-related value objects in data-driven business models and what are protection measures?**

[46] This chapter is based on Fruhwirth, M., Pammer-Schindler, V., and Thalmann, S. (xxxx), "Knowledge leaks in data-driven business models? Exploring different types of knowledge risks and protection measures". Submitted to Schmalenbach Journal of Business Research (under peer review after minor revision as of April 2024).

To answer this research question, we interviewed 28 experts from industry and academia to explore cases of potential knowledge risks. We structured different types of risks, contextual factors and protection measures based on the three basic types of value objects: data, models and predictions. Based on our findings, we suggest three fields of action to mitigate knowledge risks in DDBMs: using technology, adjusting the business model design and building trustful relationships and contractual regulations. Managing knowledge risks in DDBMs requires a balanced view and interdisciplinary approach during the design of a DDBM.

6.3.2 Additional Background

6.3.2.1 Value Objects in Data-Driven Business Models

As data intermediation is the central value proposition (Dorfer, 2016), it is worthwhile to analyze DDBMs based on the type of value proposition and offerings. For instance, Schüritz *et al.* (2019b) differentiate between data, insights, and actions as offerings. Dehnert *et al.* (2021) further differentiate between data, information/knowledge, actions and non-data products and services in DDBMs. Hirt and Kühl (2018) describe Model-as-a-Service and Prediction-as-a-Service as two other types of offerings. These offerings can be differentiated by the type of exchange of value objects (Leski *et al.*, 2021; see also section 5.4.4.3). A value object, as described in the e-3 value ontology, *"is of value for one or more actors. Actors may value an object differently and subjectively, according to their own valuation preferences"* (Gordijn and Akkermans, 2003, p. 120). Concerning DDBMs, such a value object can be *data* (e.g., Dehnert *et al.*, 2021), *models* (e.g., Hirt and Kühl, 2018) or *predictions* or insights in general (e.g., Schüritz *et al.*, 2019b).

By data, we understand a tradeable collection of *"codified observation[s] fixed in a tangible medium"* (Thomas *et al.*, 2023, p. 256). Shared data can be in the form of specific data points, whole data sets (or data streams) or aggregated data (e.g., via descriptive statistics). By *model*, we understand a program or function that can identify patterns or provide predictions based on previously unseen input data. A model is a result of applying a machine learning algorithm to a set of (training) data. A model consists of its code and configuration. Hirt and Kühl (2018) differentiate between base models specific to one particular problem and transfer models that can be applied or transferred to a set of similar problems. The type of *prediction* encompasses identifying patterns, predicting events or attributes, or recommending actions based on incoming data applied to a learning model (Hirt and Kühl, 2018). Predictions also represent target-specific insights that are shared to solve a specific (decision) problem of the customer and create customer benefit and, in return, generate revenue.

As Figure 6.4 illustrates, data-, model, and prediction-sharing business models can be understood as three subtypes of DDBMs. Differentiating DDBMs based on exchanged value objects is still under-represented in the DDBM literature, but a reasonable differentiation when it comes to knowledge risks: We assume that sharing different types of value objects leads to different types of risks.

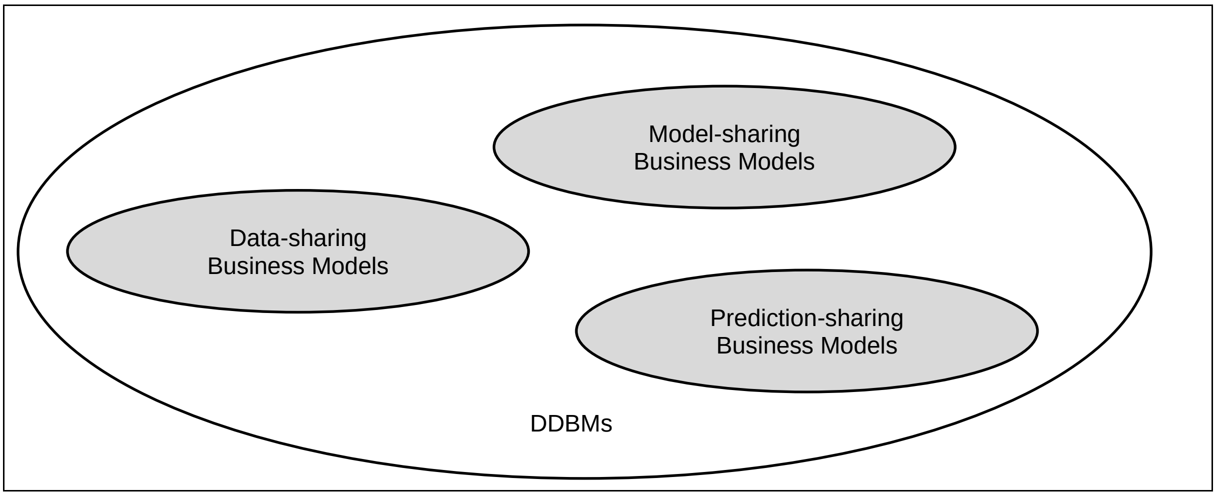


Figure 6.4 Subtypes of DDBMs based on exchanged value objects.

Examples of DDBMs that provide *data* as an exchanged value object are API-based data-sharing business models in logistics (e.g., Möller *et al.*, 2020b). In such data-sharing business models (Schweihoff *et al.*, 2023) or "data-as-a-service" business models (Chen *et al.*, 2011), the business model owner grants other parties access to his own data set in exchange for compensation (Schweihoff *et al.*, 2023; Vesselkov *et al.*, 2019). One major obstacle to data sharing in organisations is the concern about exposing sensitive data and giving competitors a competitive advantage (Gelhaar and Otto, 2020; Schweihoff *et al.*, 2023). Thus, security aspects, such as usage restrictions or cryptography, must be implemented in such business models (Schweihoff *et al.*, 2023).

Examples of DDBMs that provide *models* as an exchanged value object are Language-Model-as-a-Service (Sun *et al.*, 2022). In such a model-as-a-service business model, the user provides or uploads data to the service provider who builds (trains) a model based on this training data and his own human and/or machine intelligence (Hirt and Kühl, 2018).

Examples of DDBMs that provide *predictions* as an exchanged value object are prediction APIs (Santhosh *et al.*, 2019). In a "prediction-as-a-service" or more general "analytics-as-a-service" business model, the provider applies a (machine learning) model to the input data provided by the customer to generate a prediction of events, recommendations or to identify patterns and finally to support decisions or automate actions for the customer (Hirt and Kühl, 2018; Schüritz *et al.*, 2019b). We subsume these different terms under the term prediction for the context of this chapter.

6.3.2.2 Knowledge Risks Emerging from Data Sharing

Large-scale data sharing can cause leakage of competitive knowledge and intellectual property (Zeiringer and Thalmann, 2020; Zeng *et al.*, 2012). This risk is called knowledge risk and comprises potential knowledge attrition, loss, leakage or spill-over of knowledge that could adversely affect the organization's strategic advantage (Durst and Zieba, 2017; Perrott, 2007).

Competitive knowledge of a firm can be discovered from shared data sets using advanced analytics methods (Ilvonen *et al.*, 2018). Further, it is difficult for firms to evaluate which knowledge could be discovered by external actors from shared data (Zeiringer and Thalmann, 2020). Known approaches for external acquisition of competitive knowledge that endanger a firm's intellectual property are information leakage in supply chains (Zhang *et al.*, 2012), industrial/data espionage (Thiel and Thiel, 2015), or data breaches (Khan *et al.*, 2021). An adversarial actor could also obtain valuable knowledge by reverse-engineering the firmware of a physical product to reconstruct an embedded algorithm (Thiel and Thiel, 2015). For instance, it is technically possible to reverse-engineer black-box neural networks (e.g., Oh *et al.*, 2019) or to steal machine learning models via API access (e.g., Tramèr *et al.*, 2016).

The described attacks can lead to unintended leakage or spill-over of knowledge, denoted as knowledge risk (Ilvonen *et al.*, 2018; Zeiringer and Thalmann, 2020). A knowledge risk is the *"measure of the probability and severity of adverse effects of any activities engaging or related somehow to knowledge that can affect the functioning of an organisation on any level"* (Durst and Zieba, 2018, p. 2). Knowledge risks can be analysed by the factors that cause them, and the preventive measures organisations can take (Durst and Zieba, 2017). Managing knowledge risks in terms of knowledge protection is one core strategy of knowledge management (Loebbecke *et al.*, 2016). It is crucial for organisations as knowledge is essential for competitive advantage (Jennex and Zyngier, 2007). Therefore, knowledge protection prevents unwanted knowledge leakage to non-authorized people and organisations (Manhart and Thalmann, 2015). Existing knowledge protection literature focuses on formal and explicit knowledge. It does not consider tacit knowledge in organisations (Manhart and Thalmann, 2015) and the knowledge that can be discovered from data streams (Ilvonen *et al.*, 2018). While explicit knowledge (e.g., materialised in data-related value objects) could quickly leave a company, tacit knowledge is more difficult to transfer (Durst and Zieba, 2017; Mohamed *et al.*, 2007).

Our conclusion from this chapter's literature is that DDBMs can be differentiated based on the offering or, in particular, exchanged values. Based on the literature, we have stated that offerings in DDBM can be distinguished by three types of value objects: data, models and predictions. Further, knowledge protection literature recognises data sharing as a knowledge risk in general and that extracting knowledge from shared value objects is possible via data science. We already have the first evidence from previous research that exchanging data-related value objects can lead to knowledge risks from the previous chapter. Nevertheless, the relationship between knowledge risks related to and exchanged data-related value objects in DDBMs has not been studied, and this connection has not been made by previous literature.

6.3.3 Detailed Research Approach

The study presented in this chapter study aims to explore knowledge risks specific to DDBMs due to the specific nature of value objects. Given the novelty of the problem and lack of understanding of how and if knowledge risks occur in DDBMs, we applied an exploratory, qualitative research design that is appropriate for investigating why a certain phenomenon occurs (Yin, 2009). The research design is qualitative, as we analysed interview data (see data collection section below), and exploratory, as we used a bottom-up data analysis method as informed inductive coding (see data analysis section below).

6.3.3.1 Data Collection: Sampling and Interviews

Due to the tacit and sensitive nature of the topic for organisations, we decided on expert interviews in three rounds as our primary data source (see Table 6.7), as interviews allow comprehensive discussions (Yin, 2009). As interview partners, we selected 28 experts, 18 from industry (I1- I18) and 10 from research institutions (R1-R10) (see Tables in Appendix L to Appendix N).

We followed a purposive sampling strategy (Etikan, 2016) and, in particular, an expert sampling strategy that is useful “when investigating new areas of research” and in particular when “there is currently a lack of observational evidence” (Etikan, 2016, p. 3). As it was challenging to identify suitable cases (i.e., organisations) where knowledge risks have or could occur, as such information is not publicly available, we also selected consultants and researchers as informants that reported such cases. Academic experts reported on their experience and cases of knowledge risks in DDBMs based on their collaboration with industry (e.g., as part of research or consulting projects). We selected experts based on their knowledge and experience in developing DDBMs or supporting organisations in that process. For academic experts, we considered their recent publications on DDBM or knowledge risks, as an additional selection criterion. The selection of experts in the initial interview round was broader: we also selected experts in business model innovation and knowledge risks in general to explore the topic. We searched for experts in our immediate network and through an extended network on LinkedIn platform (2nd order contacts).

We conducted the interviews as face-to-face meetings or via digital communication software and audio-recorded them. Appendix A provides a detailed description of the interviewed experts.

The scope of the **first interview round** was very broad, serving as a starting point to explore knowledge risks in DDBMs. After initial data analysis, we found that differentiating and analysing knowledge risks in DDBMs based on exchanged value objects is interesting and reasonable. Therefore, we conducted seven additional and more focused interviews with additional experts. In this **second interview round**, we presented and discussed the three data-related value objects (data, model, and predictions) and asked about cases and their relation to knowledge risks. In the first round, not all value objects were covered in each interview as the insights emerged over time. Further, we investigate motivations and practices in the design phase of a DDBM in detail, as we could now ask more focused questions in the second round of interviews.

At the beginning of our semi-structured **interview guideline**, we presented working definitions of central concepts and an abstract problem definition, illustrated with a case example. The interview was divided into two parts: The first two-thirds of the interview focused on exploring the problem of knowledge risks in DDBM. The last one-third (only in interview round 1) focused on discussing requirements for ICT tools identifying and describing knowledge risks in DDBMs (see previous Chapter 6.2 and Fruhwirth *et al.*, 2021b). We asked the interview partners for real examples from their context to concretise and ground the discussion as much as possible within their experience. The guideline was tested with a PhD student from the same subject (with practical experience) and methodological knowledge (training) regarding the guideline's comprehensibility, question flow and structure (for the guideline, see Appendix O). We adjusted our interview guideline for the **second set of interviews** through detailed questions (e.g., regarding protection measures) and a short presentation of our interim results. We presented each type of value object shortly and asked the experts how they perceived the knowledge risk related to each value object (for the guideline, see Appendix P).

To validate our results, we conducted a **third interview round** with five additional industry experts in data analytics. The interviews lasted between 40 and 59 minutes. We again presented our problem definition, the concepts from the data analysis step after the two previous rounds and the five types of risks identified. Further, we provided one slide per type of risk with a short description and one example from the initial expert interviews. The three guiding questions for the evaluation interviews were: 1) Do you perceive these risks as relevant for your business? 2) Are there any other types of risks missing in that context? 3) Is the description of each risk reasonable for you? (for the guideline, see Appendix Q).

	Interview Round 1	**Interview Round 2**	**Interview Round 3**
Interview participants	16 Interviews 7 Researchers (R1-R7), 9 Industry Experts (I1-I9) active in data-driven services, business model innovation and knowledge risks	7 Interviews 3 Researchers (R8-R10), 4 Industry Experts I10-I13 active in data-driven services	5 Interviews 5 Industry Experts (I14 - I18) active in data-driven service
Duration	35 - 75 minutes	38 - 59 minutes	40-59 minutes
Goal, main questions and content	Focus on knowledge risks in DDBMs in general.	Focus on knowledge risks from sharing data-related value objects (data, models and predictions)	Evaluation of results Presentation of 5 types of knowledge risks
Main outcomes	Knowledge risks differ if data, models or predictions are shared	Identified five types of risks based on the three types of value objects	Subtypes of risks for each type of shared value objects & contextual factors.

Table 6.7 Overview of our data collection process.

6.3.3.2 Data Analysis

Interviews were fully transcribed and cleaned. Quotes used in this publication from interviews conducted in German were translated into English (marked with a "*") and reviewed by a second researcher. We analysed this data following a qualitative content analysis approach via informed inductive coding (Mayring, 2015) using MAXQDA V.11.

For analysing the **first round** of interviews, the dimensions of analysis were themes that corresponded to the leading interview questions and developed a provisional coding scheme to structure the data. The major themes from the interview guideline have been "causes for knowledge risks", "consequences of knowledge risks", and examples. For the theme of the causes, we generated "influencing factors" and "mechanism" as our major categories. We distinguished between "type of knowledge risk" and "second-order consequence" for the consequence theme. We have informed our inductive categories based on the literature presented in the background section, as Mayring, 2015 suggested.

The intermediate category system was iteratively discussed among three researchers to focus the exploratory research until we arrived at three different types of data-related value objects (data, models, and predictions) that were suitable to analyse and distinguish knowledge risks in DDBMs, as they imply different types of knowledge risks. The value object types are based on the literature, e.g., Gordijn and Akkermans (2001) for the basic concept of value object; and, e.g. Hirt and Kühl (2018) for specific value object types data, models and predictions.

For analysing the data from the **second round** of interviews, we tightened the codes and category scheme and dropped all unrelated to knowledge risks associated with exchanged value objects (e.g., dropping codes like knowledge risks arise from leaving data scientists). If we identified new themes, we created new codes and matched them to the existing category scheme. We extended our categorisation scheme to describe the relation between value objects and knowledge risks. We constructed further categories to analyse and describe the risks, such as "protection measures", "knowledge retrieval mechanism", "type of knowledge", the "reason for sharing/exchanging", and "influencing factors" with different subcategories and codes informed by the literature. Appendix S shows exemplary text segments and corresponding codes mapped via the type of value object to the "Knowledge Protection Measure" category. In the last iteration of data analysis after the second interview round, we derived for each type of value object one or two types of risks (see results section).

Evaluation Interviews: For analysing the *third round of interviews*, we focused on identifying subtypes of risks to have a more differentiated view of the risks. Therefore, we also re-coded the data from the first two rounds of interviews. Further, we aimed to identify contextual factors that influence the risks. Therefore, we simplified our category system to types of knowledge risks (integrating "reason for sharing/exchanging" and "knowledge retrieval mechanism" from round 2), contextual factors (integrating "influencing factors" and "type of knowledge" from round 2) and “knowledge protection measures”. We found that the risk is higher when competitive knowledge is involved and that balancing expected benefits and risks was perceived as important. Further, we found from our additional interviewees that trusted relations and contractual regulations are two important protection measures.

6.3.4 Results

Different types of value objects lead to different types of risks: the risk of leaking competitive knowledge from shared data; the risk of leaking competitive knowledge by using a data service; the risk of leaking competitive knowledge from shared model; the risk of inference on the original training data from a shared model and the risk of reconstructing a model from shared predictions. For each type of value object, we present different types of risks, contextual factors influencing the risk and knowledge protection measures. Table 6.8 gives an overview of our results by stating the type of value object, then the (sub-) type of risk, contextual factors and knowledge protection measures. Subsequently, sections 6.3.4.1, 6.3.4.2 and 6.3.4.3 describe the risks associated with the value objects data, models, and predictions, respectively.

Value Object	Risks (and sub-risks)	Contextual Factors	Knowledge Protection Measures
Sharing Data	The risk of leaking competitive knowledge from shared data. The risk may arise - when sharing data sets in open data initiatives, - when sharing data with partners for joined data service development, or - when offering data-as-a-service, the customer could resell the data to third parties.	The risk of knowledge leakage depends on the context, i.e., the value of the knowledge, that could be discovered from shared data. The risk was perceived as critical, if shared data relates to competitive knowledge. Example: Competitive knowledge about production processes or product configurations or their development could be discovered from shared data.	Classify data sources Involve a data platform Use secure technologies (e.g., encryption) Share only synthetic data Use data anonymization Build trusted relationships Set up appropriate contracts (e.g., NDAs) Share models instead of data Do no not share data as an over-cautious measure Run the service on-premise or apply federated learning mechanisms
	The risk of exposing competitive knowledge by using a data (prediction) service		
Sharing Model	The risk of leaking competitive knowledge from the shared model. The risk may arise - If the user is able to reconstruct the parameters or configuration from a shared black-box model. - If the provider needs to explain how the model comes to certain decisions or predictions - If the model is leaked to a third party, e.g., while collaborating with a startup to build the model	The risk of knowledge leakage depends on the context, i.e., if competitive knowledge can be derived from a shared model. - Knowledge of the model generation process and domain knowledge that is materialized in the model - Example: In consulting and engineering, preserved domain knowledge from experts is leaked when white-box models are shared. - The knowledge risk depends on if the model can be transferred to other application scenarios, or if it is very specific.	Implement legal protection mechanism (e.g., regulate IP regarding model creation in contracts) Define and identify what information should be revealed by the model Take technical measures (e.g., share only black-box models or use synthetic data for training a model) Offer the model as a service via a platform or an API (i.e., only sharing predictions)
	The risk of inference on the original training data from a shared model		
Sharing Prediction	The risk of reconstructing a model from shared predictions. Nevertheless, it is not so easy to draw clear conclusions - the inference is subject to probabilities.	The risk of knowledge leakage depends on the context, i.e., - if prior information on the model is available, - the variance of input data, and if the required expertise is available and the required effort is in relation to the expected gain.	Control the access to the service (limit the number of requests per time unit or limit the allowed value range) Build the business model arround dynamic data as a key ressource Implement a pay-per-use revenue model

Table 6.8: Overview of three types of data-related value objects and their relation to knowledge risks.

6.3.4.1 Sharing Data

The Risk of Leaking Competitive Knowledge from Shared Data

Organisations share data in a DDBM in return for economic or other non-financial benefits. Our interviewees are aware that knowledge can be discovered from data sets if domain knowledge, complementary data sets, or the necessary data analytics capabilities are available. The knowledge is represented implicitly in the data, and with data analytics methods, this knowledge can be discovered from the data, as one expert explained:

> *"With the help of methods, you try to make the implicit information in this data explicit. For me, the data are the shell of the information. If you share it with someone who knows how it works, then he can generate an incredible amount of insights from it, which definitely have a business-critical factor."* (I8*, CEO Data Science Company A)

The interviewee mentioned "an incredible amount of insights", which shows that he is aware of the risks but that it is very difficult to say which knowledge can be discovered exactly. This means that the data provider cannot specify the risk explicitly. Rather the risk is vague, and everyone has to be prepared for the unknown, as another expert mentioned:

> *"Indeed, it seems to me that the risk is a very high one. Because it's so undefined because you're extracting something from this data that wasn't expected."* (I5*, Director Digital Business)

This vagueness is a big challenge and makes the systematic assessment of knowledge risks in shared data sets challenging, especially if the business model owner is not aware of this implicit knowledge. We found that sharing data can lead to different knowledge risks depending on the business model.

Sharing data sets in open data initiatives could lead to a spill-over and thus imply knowledge risks: One motive to share data in the reported cases was to foster innovation and to create promising future business opportunities. The most extreme case for this direction was sharing data sets in open data initiatives so that others can build new services and the provider benefits from indirect revenues or reputation. However, this means that competitors could also access that data and could lead to an unintended spill-over of knowledge and thus imply knowledge risks, as one interviewee mentioned:

> *"All my competitors can also access this open data. And then, of course, I don't want them to gain too many insights into my operations so that they can discover my competitive advantage and re-engineer and exploit it. As an open data provider, I try to find this balance between knowledge protection and knowledge sharing."* (R8*, Researcher Data-Driven Service)

The interviewee mentioned a very important aspect: the balance between knowledge sharing and protection. Thus, while sharing data to foster innovation, organisations contrast the potential benefits with the potential negative impact of losing competitive knowledge. This is also the case if organisations share knowledge in a defined group, e.g., among project partners, to jointly develop a DDBM. Such stakeholders could also be in a competitive relationship.

Risk when exposing knowledge for joined data service development: When developing a new service or platform, the organisation must share data with its partners and thus implicitly also competitive knowledge. Thus, there is the risk of leaking competitive knowledge when jointly developing a DDBM and therefore sharing data (e.g., for training a machine learning model). One expert mentioned here a potential case from the automotive domain:

> *"If manufacturers A, B and C [...] are now jointly considering to build a data platform in order to generate telematics services that work everywhere, then this is fundamentally a knowledge risk."* (I8*, CEO Data Science Company A)

The interviewee finally points to the knowledge risk resulting from sharing data sets.

Risk of reselling data by the customer to third parties when offering data-as-a-service: One interviewee also mentioned the risk of reselling data by their customers to third parties when offering data-as-a-service. At the same time, he mentioned that they handle this via contracts:

> *"That is, of course, standard in our contracts, for the data they have only a pure right of use but no right of exploitation. The right of use, the separation is difficult again, because if I sell the data to some consultant, he interprets the data for himself in some way, he has used it, and with the knowledge generated he now advises someone else."* (I18*, Managing Director Data Service Company)

However, the expert also acknowledges the challenge of enforcing such contracts.

The Risk of Exposing Competitive Knowledge by Using a Data Service:

One particular type of risk in data sharing evolves when an organisation or their employees use another organisation's data or prediction service. In this case, the service user often has to share his data with the service provider and, by that, risk that competitive knowledge might spill over. This risk will become even more important with using AI services and data science pipelines in the cloud. One expert mentioned the case where knowledge might be leaked through an AI service:

> *"If you have employees who use ChatGPT, you also have the risk that information leakage happens - that information from your company goes somewhere else without anyone wanting it to. If you write a technical problem as a prompt, then OpenAI will also get your company secrets."* (I15, Freelance Consultant Data Protection & AI)

Contextual Factors

The severity of the risk emerging from sharing data depends on the context, particularly the *value of the knowledge*, i.e., if it is competitive knowledge that might be leaked. **Competitive knowledge about production processes or product configurations or their development** could be discovered from shared product-related data with the help of data science methods. Such knowledge is especially critical in complex engineering products, such as vehicles, that require special engineering knowledge and huge development efforts. Shared data sets often allow the retrieval of such knowledge for unintended reasons in addition to the used purpose it was collected and shared for. One interviewee mentioned an incident where a car manufacturer shared data with a production equipment provider for predictive maintenance and where the provider could discover competitive knowledge on the production process from the data:

> *“who could use this data to determine precisely when the customer was retooling his production line, how many units of a particular vehicle type were produced. Because he could derive exactly this data through various analyses.”* (I6*, Senior Manager Data Strategy Consulting).

The interview partner described a concrete incident from his practice and linked it to the challenge of complex analytics. Complex analytics comprise multiple data analysis methods applied to the shared data set and combining it with other (publicly available) data. One experienced manager further mentioned one imaginable example from the automotive domain where a car manufacturer would share data of his vehicles on a platform:

> *“You can’t upload all the data from the CAN bus, from the ECU. Otherwise, someone with malicious intent could extract a lot of information from it about the development of the vehicles, about the performance of the vehicles, about the quality. All of this could be extracted from such data”* (I8*, CEO Data Science Company A)

The interviewee is aware of the potential knowledge leakage and takes this into account while sharing. The consequence he described, in this case, is “you cannot share everything”. You rather have to select and share based on the expectation that others can retrieve. In our interviews, we found that a differentiated consideration of knowledge risks is necessary, as one manager from the semiconductor industry pointed out:

> *“On the other hand, when I talk about data that directly relates to the product, with which it is possible to draw conclusions about the architecture and technological specifics. Here, of course, the situation is different and the sensitivity of the information is higher.”* (I17*, Manager Data Analytics, Semiconductor Company)

On the other hand, the manager also mentioned that sharing operational data from their production machines for maintenance or optimisation was perceived as less critical, as no conclusions on competitive knowledge are possible.

The risk of knowledge leakage through data sharing depends on the context. If data is shared that relates to competitive knowledge, i.e., about their products or core processes, that allow an external party to make conclusions on the architecture or technology used, then it is perceived as critical. If the data relates to a more common context, such as the maintenance of machines, sharing data was perceived as less critical. Thus, what is competitive knowledge is very specific to the company and depends on its business model.

One interviewee, therefore, pointed to the direction that **internal balancing** *is necessary*, i.e., at what stage the retrieval of knowledge is not acceptable for the company any more. They need to take measures:

> *"The internal discussions have to be held about when we have reached a level where drawing conclusions about the data or, for example, the vehicle's configuration, the production, the development is no longer acceptable for us, and we therefore have to do something else."* (I14*, Consultant Data-Driven Services)

Knowledge Protection Measures

As we have seen above, knowledge risks in DDBMs are very contextual, i.e., if the shared data relates to competitive knowledge. One protection measure that our interviewees mentioned was to **classify the data sources** and to decide if this data can be shared or not, as one manager from the semiconductor industry mentioned:

> *"And you have to have business processes in place. That's what we have at our company in place, where you evaluate the data according to categories, from public to strictly confidential, for example."* (I17*, Manager Data Science, Semiconductor Company)

Another mechanism to tackle knowledge risks and enable data sharing is to **involve a data platform**. It mediates the data exchange between actors with technical measures implemented in the platform while preserving the provider's knowledge. The automotive manager further mentioned here:

> *"That's why there are all these data-sharing platform initiatives, [enabling] data exchange under the premise of knowledge preservation. So, I can retain my knowledge but still share data. However this may work, it's a task that probably needs to be solved so that it really takes off."* (I4*, Manager Automotive Company B)

The interviewee highlighted that knowledge protection concerns seem to be one of the main motivations for the rise of data platforms. However, he also acknowledges that protection concerns must be addressed properly before implementing a DDBM. There are also technical measures regarding **secure technologies**, like encrypting or decentralising data when performing data analytics and thus applying methods such as multi-party computation or homomorphic encryption. Another approach mentioned was to **share only synthetic data**, i.e., data generated by generative AI with similar properties necessary for sharing.

Our interviewees frequently also mentioned using **contracts** such as NDAs (Non-Disclosure Agreements) to tackle this risk. Nevertheless, they cannot prevent knowledge leakage when the contract is breached. Further, our interviewees mentioned *trusted relationships* frequently as a measure to mitigate knowledge risks. One practical approach mentioned was to begin sharing smaller and less critical data sets and to intensify the relationship over time.

Firms and customers might be *over-cautious* and over-protective and, therefore, **unwilling to share** their data for fear of knowledge risks. This would imply that the DDBM is not implemented. This is especially the case as there is currently much awareness of data-related risks. Our interviewees reported the fear that others could benefit more from sharing and, therefore, as a consequence, decided not to share the data. This is perceived as a barrier for DDBMs, as one data science manager in the automotive industry mentioned:

> *"Because all the companies in the [supply] chain are so afraid of losing know-how, they don't share the data. [...] This leads to the fact that it is sometimes difficult in the data environment for me to do business"* (I4*, Manager Automotive Company B).

Not realising a DDBM is the most extreme knowledge protection measure which is chosen if the perceived (vague) risks outweigh the perceived benefits of the DDBM. Therefore, our interviewees suggested balancing the expected benefits and possible risks:

> *"And then there is also the question of the benefit: How much information can I gain when I give out data for further processing, versus the risk, what am I giving away?"* (I18*, Managing Director Data Service Company)

Thus, the risk can be reduced by **running a data service or prediction model on-premise,** i.e., locally at the customer's premise, so that the data does not have to be shared. Another approach would be to use *federated learning architectures*, where the data stays local and only (transfer) models are shared or the weights of a neural network

Another knowledge protection measure is **sharing models instead of data**. Models are exchanged to protect the underlying data and allow a bidirectional flow of information without exposing competitive knowledge, as one data science professor explained:

> *"To build a model in order not to share the data. The model is already a risk mitigation method. With the goal, though, that you then have a flow of information in both directions."* (R2*, Professor for Data Science)

The important aspect mentioned here is that exchanging models is a risk mitigation strategy, which is part of DDBMs.

6.3.4.2 Sharing Models

The Risk of Leaking Competitive Knowledge from Shared Model

Competitive knowledge might be leaked by sharing models, as knowledge from experts (e.g., engineers) is introduced to the model in the process of creating or training (e.g., engineering knowledge about the ageing behaviour of a certain technical component). Models could also reveal information they have learned but not intended to be shared. If the model is shared *white-box-like* (i.e., sharing the code with parameters and configuration), competitive knowledge is likely shared, leading to a knowledge risk. For instance, models are delivered as part of a consulting or engineering project to support the customer in developing a DDBM, as one interviewee reported:

> *"We are a service provider for model development and algorithms, and we sell those directly to our customers, then we always sell a bunch of knowledge too."* (I4*, Manager Automotive Company B)

The interviewee highlights that, with the model, a huge amount of knowledge is transferred to the customer. Thus, our interviewees acknowledge that competitive knowledge could spill over to other actors if models are shared. The interviewed manager is already aware of this problem and mentioned later that there are hardly any organisational guidelines to ensure that shared models are not misused regarding knowledge leakage.

Reconstruct the parameters or configuration from a black-box model: Even if models are shared as black boxes, i.e., the configuration and parameters of the model are hidden, there is also the risk that knowledge can be retrieved through re-engineering of the model through specific data science methods from a theoretical point. Overall this risk was perceived as low compared to white-box models. One data analytics consultant reported here on one case:

> *"In general, you can re-engineer nearly every model if you know the input and the output. Then there are also algorithmic methods to decompose analytics models. There are methods from explainable AI to understand them. […] We see this more, and more frequently, our customers try to better understand how our models work."* (I6*, Senior Manager Data Strategy Consulting)

This example shows that business customers are already trying to understand and re-engineer models and that providers are aware of this fact. However, similar to other security mechanisms, it is a question of effort.

Needing to explain how the model comes to certain decisions or predictions: The requirement of fair, accountable, and transparent AI (FAT AI) creates a demand to explain how models come to a certain decision or recommendation. One professor in Business Analytics sees this as a challenging trend from the perspective of knowledge protection and reported on one case from an industry project:

> *"And there is a pressure here from the customer to the provider. Because you have to explain how a chatbot comes up with that conclusion. So, in that way, you are kind of exposing the algorithm behind this. [...] the openness of the algorithm means that you also expose knowledge."* (R3, Professor for Business Analytics)

This example shows that providers could be forced to expose their underlying models and algorithms, and thereof knowledge could be retrieved from the exposed model. Thus, FAT AI-compliant models or explainable AI approaches could reduce the protective effect of models in DDBM.

Leaking the model to a third party, e.g., when collaborating with a startup to build the model: A knowledge risk from sharing models could also arise when a model is jointly developed with a partner (e.g., an AI start-up) and the model is leaked there to a third party. One manager for instance, mentioned one potential scenario:

> *“Let's say I have a transformer model that knows exactly how I make a chip at our company. If I lose something like that out of my hands, for example, by cooperating with a startup or a partner company, whether it's small or large. Then I lose all know-how at the push of a button.”* (I17*, Manager Data Science, Semiconductor Company)

The Risk of Inference of the Underlying Training Data

Further, data science methods, such as model inversion attacks, allow someone to *infer the original data* used to train the model. Competitive knowledge might spill over when the model user can reconstruct the original training data from a shared model, in particular, to infer the structure of the data (e.g., particular data fields) or the structure in the data (e.g., properties of the sample and the bias in the data). According to data science literature, the so-called model inference is technically possible in particular cases (e.g., Fredrikson *et al.*, 2015Fredrikson et al., 2015). Our experts mentioned that this can happen if a model is in the status of overfitting. This is in particular important for generative models, where not the original training data is generated, but only similar data. One of our interviewees mentioned here one hypothetical example where this model inference could happen:

> *"[...] Then there is the risk that you are revealing information about your own data with the models. [...] Let's assume we take two insurance companies. They want to improve fraud detection. They exchange meta-information or train models together to do that. From that, you can get the structure of the data used for training. And that underlying structure can already give one insurance company, which of course is a competitor, a lot of information about the other."* (I9, CEO/Co-Founder Data Science Company B)

Contextual Factors

The risk of knowledge leakage from sharing models depends on the context, i.e., if competitive knowledge can be derived from a shared model. Especially in consulting and engineering, preserved domain knowledge from experts is leaked when white-box models are shared, as one interviewee reported:

> *“If I take these models and give them away, then I’ve taken the knowledge that I’ve discovered from people, from their actions, from their labelling, from their input, preserved it in the model, and sold it to the outside world. That’s a tremendous risk.”* (I4*, Manager Automotive Company B)

This case shows that expert knowledge from employees is materialised into models. As part of an engineering business, models are shared with their customers. Moreover, through sharing the model, materialised knowledge of their experts could spill over to their customers.

One expert from the semiconductor industry (I17) also mentioned a future example in terms of generative AI and transformer models that could explain how to build a technical system (e.g., a microchip). This could be a huge risk if such a model was trained with company-specific data and leaked (e.g., through a collaboration with a start-up).

The risk depends on how easily the model can be applied and **transferred to other application scenarios**, as one manager mentioned:

> *"If it [the model] is very specific to a problem, I'm not afraid. [...] If the model is very generic and easily transferable to different types of problems, to a different data set, to a different context, [...], then we have to be careful."* (P4*, Manager Automotive Company B)

The interviewer mentions, "I am not afraid" and "we have to be careful". Both phrases clearly indicate that this is a well-evaluated decision. Beyond abstract transferability, another organisation also needs the **capability** and knowledge to apply the model. Further, the availability of appropriate data sets where the model can be applied influences the risk, as one consultant mentioned:

> *"Without the raw data, the algorithm is less useful for me. [...] has the other party also the same raw data or other data with similar formats? If yes, then that is a big risk. [...] And the highest risks are in cases in which when the algorithm is leaked, and the raw data is available or reproducible."* (I6*, Senior Manager Data Strategy Consulting)

The interviewee points to the strategy of keeping the training data in the back and just sharing the model. This is especially important, as many successful DDBMs rely on unique dynamic data sets generated through using the service (e.g., location data of traffic participants to predict traffic jams). Thus, the model only has value if it is used in combination with this **available data**. Another influencing factor is the **volatility** of the model: The risk increases if the model is valid for a longer period. Whereas the risk is lower if a dynamic model is constantly adjusted and updated.

Models implicitly contain the knowledge represented by the data used to train the model. Building a model also comprises knowledge of how to create value-added information from raw data, as one consulting manager explained:

> *"[You need] a combination of knowledge of the data scientist who just looks at the raw data, at the graph, very simply speaking, and the engineer who knows exactly how the machine works, who knows exactly what it means when there's a pressure drop in the hydraulic arm of the welding robot."* (I6*, Senior Manager Data Strategy Consulting)

This statement shows that, on the one hand, domain-related knowledge, e.g., from engineering, is needed to train a model. On the other hand, knowledge from the data science discipline is also needed. Domain (expert) knowledge about a real-world phenomenon can add value to the model, such as specific casualties or relationships that cannot be discovered from data itself but needs additional contextual knowledge on the domain. Data science knowledge involves the labelling, preparing, and aggregating of the data and subsequent analytics and algorithmics and their combination.

Knowledge Protection Measures

Our interviewees mentioned that traditional **legal protection mechanisms** for IPR (e.g., patents) do not work for models. As the knowledge is only implicitly contained in the model, a lawsuit to convict the guilty seems very challenging. Therefore, the owner of the know-how and IP should be defined in contracts, e.g., the IP regarding the model creation remains at the provider.

Further, our interviewees mentioned **defining and identifying what information should be revealed by the model** and which not to build the model accordingly and ensure that the model is only used as intended. Models should be designed so that they only disclose the intended minimum amount of information (e.g., only the transfer function without revealing the influencing parameters (e.g., I17). This, again, requires alignment and balance between sharing and protecting knowledge.

The risk also depends on the balance between generated returns and the estimated risk. For instance, one expert mentioned that the monetary value of selling a model would be significantly higher than only sharing predictions, in particular, if the code of the model can be accessed. Thus, the risk can also be mitigated by adjusting the business model, or more precisely, the pricing model.

Thus, protecting knowledge in DDBMs is currently mainly performed via **technical measures**. One simple knowledge protection mechanism is to share only *black-box models*:

> *"For example, if I share the source code, where I can see every parameter of the [decision] tree, then it's clear that I'm selling critical knowledge. But in contrast, if I make predictions black box-like, then I would find it difficult to reconstruct the parameters."* (I2*, Data Scientist Automotive Company C)

Our interviewees suggest applying data science methods to prevent model inversion attacks, such as randomisation in training, differential privacy, or other anonymization methods. For example, our interviewees mentioned using different loss functions or synthetic data for model training.

Another protection mechanism is to keep the model within the organisation's knowledge boundary and **offer the model as a service via a platform or an API** (application programming interface). However, the user of the model has to share his data now with the service provider, which could create a knowledge risk for the user. The provider shares only the results.

6.3.4.3 Sharing Predictions

The Risk of Reconstructing a Model from Shared Predictions

Competitive knowledge might spill-over when plenty of predictions are shared, and the receiver is able to reconstruct the model or parts of the model based on these predictions. According to computer science literature, reconstructing models based on predictions is technically possible in particular cases (e.g., Tramèr *et al.*, 2016). However, such attacks can be mitigated easily by restricting the number of predictions or the value range. Thus, this risk was perceived as low.

One way to discover knowledge is to reconstruct the underlying model by provoking lots of predictions. Moreover, the model allows inferences about the materialised knowledge. One academic expert in knowledge protection pointed to the problem:

> *“If you sell many outcomes, yeah, then it would be even then possible to re-engineer the algorithm itself. If you are looking at what kind of results are created by what kind of data.”* (R5, Senior Researcher Knowledge Management)

However, the interviewee refers to “what kind of data”, and another interviewee, a data scientist, specify this in more detail:

> *“If you take a look at the predictions now, you’ll probably see a few features and check for which group it’s working better or worse. You’ll be able to reconstruct something there.”* (I2*, Data Scientist Automotive Company C)

As he says, “to reconstruct something there”, he acknowledges the big challenge of discovering competitive knowledge out of a prediction-based value proposition. However, our interviewees perceived the risk of knowledge leakage through sharing predictions as low, as, for instance, one interviewee said:

> *“For example, the customer only gets the results back. In that case, I think the risk is very low that any knowledge will drain from the provider because the customer doesn’t have access to that knowledge.”* (R8*, Researcher Data-Driven Services)

This statement shows that the knowledge is hidden and that the customer has no direct access to the model and the materialised knowledge in the model. On the other hand, one mentioned example of knowledge that could be reconstructed is the bias that the model has learned. Further, our experts (e.g., I17) noted that it is not so easy to derive clear conclusions - the inference is subject to probabilities

Contextual Factors

Reconstructing the model from predictions is possible from a theoretical point of view. However, in reality, this is not trivial and requires some **prior information on the model available**. How easy it is to reconstruct the model also depends on its complexity and the input data variability, as one expert in the field of DDBMs explained:

> *"The heart of a good model is the variance of the input factors. And if I just offer an API, where I only provide a result to certain input values, but the input data that have led to that model has more variety than I'm allowing through the API, I can actually [prevent that well]."* (I5*, Director Digital Business)

As this quote shows, re-engineering a model based on lots of "results" that we call predictions **depends on the variance of the input data** if it covers the whole input space. The knowledge is hidden and is materialised in the prediction model itself. The single prediction thus offers only a small and scattered glimpse of the model. Many predictions need to be collected or even provoked in a systematic attack to re-engineer knowledge:

> *"If you send enough different queries, you can already [reconstruct] what knowledge is materialised in the model. Depending on the complexity of the problem, this might be a task at the moment, which do not allow model re-engineering due to the complexity."* (I1*, Data Analytics Consultant)

This quote shows that reconstructing knowledge is possible but *requires significant effort and expertise*. If insights about the model are successfully collected, knowledge could be discovered. Further, one must balance the effort if it is worth it for the attacker.

Knowledge Protection Measures

When predictions are shared through access to a prediction model, one simple protection measure is to **control the access** in terms of the number of allowed requests, the minimum time span between two requests, and the range of input values. Limiting the number of requests prevents brute force attacks for reconstruction and also denial of service attacks.

Potential attacks could be recognised through atypical requests, e.g., uniformly distributed across the input space, as training and re-engineering a model requires a broad range of input data. Our interviewed expert continued:

> *"First of all, when someone penetrates me and asks me questions over the entire vector space, then I notice that this is atypical. That would be a uniform distribution in the query, which is totally atypical for such a thing, there you rather have a normal distribution in the queries."* (I5*, Director Digital Business)

One protection measure is to build a prediction service that relies on **dynamic data,** such as real-time vehicle location data, generated through service usage and not shared with other actors. Even if the prediction model could be reconstructed based on many predictions, the knowledge cannot be applied as one malicious actor cannot access the necessary data. Another protection measure lies in the design of the business model: in prediction-as-a-service business models*,* **pay-per-use revenue models** are often used, which means that requesting lots of predictions gets expensive, and by that, even if something could be reconstructed from the model, it was compensated monetarily.

6.3.5 Discussion

6.3.5.1 Discussion of Problem and Risk Relevance

In our interviews, we found that knowledge risks are a relevant topic in data-driven business models. For the three types of value objects data, model and prediction, we identified five types of risks that arise when they are exchanged in a DDBM: The risk of leaking competitive knowledge from shared data, the risk of exposing competitive knowledge by using a data service; the risk of leaking competitive knowledge from a shared model; the risk of inference of the underlying training data; and the risk of reconstructing a model from shared predictions.

The validation interviews confirmed the five types of risks, i.e., no additional types were suggested or emerged, and the description of the existing ones were sufficient. The risk of exposing competitive knowledge by using a data service was perceived as the most relevant risk in the validation interviews, as one expert brought it to the point: *"I think that is the biggest but also very hard to grasp threat or fear that the management in the industry has now"* (Industry Expert 14). One problem is that the risk is very difficult to grasp. Therefore, there is sometimes a lot of fear, and as a consequence, companies are very cautious, and DDBMs may not be realised.

Knowledge risks in DDBMs depend on contextual factors of the DDBM itself. The risk depends on the area of the company from which data-related value objects are shared: For instance, if data is shared to optimise an ancillary process (e.g., maintenance of production machines), the risk is perceived as less critical. Whereas, if data from their core process allows inference on their core processes, e.g., the design and configuration of products, the knowledge risk was perceived as critical. Thus, it always needs to be assessed if the (potential) leaked knowledge is competitive and business-critical. Our data also suggest that knowledge risks are particularly relevant in knowledge-intensive businesses that want to innovate towards DDBMs in addition to their existing business model. In such business models, domain expert knowledge (e.g., engineering) is materialised in models that are shared with customers and partners as part of a DDBM. Thus, competitive knowledge might be put at risk. Further, in business models with complex systems and high competition (e.g., the automotive or semiconductor industry), organisations are very restrictive about data sharing, as corporate secrets might be shared with the data.

Knowledge risks in DDBM differ from knowledge risks associated with traditional business models. As more areas of an organisation are digitised, there is a risk that more competitive knowledge is materialised in (AI) models. These, however, are easy to transfer, compared to traditional business models, where engineers from the competition need to be headhunted, or a product needs to be reverse engineered. In DDBMs, leaking a model could be sufficient for knowledge leakage. With the spread of generative AI and transformer models, we assume this aspect will become even more important in the upcoming years (cp. Tredinnick and Laybats, 2023). Thus, the question of how to protect knowledge and IP in DDBMs will become more important.

6.3.5.2 Discussion of Protection Measures - How to deal with the risk?

We found that knowledge risk in DDBMs can be mitigated by technology (which might be fast changing), by business model design options, and by ensuring transparency, building trust and contractual regulations. As a synthesis of these three areas of action, one major strategic implication of our work is that knowledge risk mitigation in DDBMs needs a differentiated and balanced assessment if the perceived risk has a negative economic impact or if it is acceptable compared to the expected return.

Technology to mitigate knowledge risks

A knowledge risk can often be reduced upfront by technology. Computer science literature discusses several technical attacks to retrieve something from data and models (see, e.g., Kaissis *et al.*, 2020). Such attacks encompass training data leakage, model stealing, reverse engineering or membership inference (Hanzlik *et al.*, 2021). Preventing such attacks or exacerbating the knowledge discovery process can be done by technical measures that relate to contemporary computer science research (see, e.g., Kaissis *et al.*, 2020). Privacy-preserving technologies tailored to the context of big data analytics ensure the confidentiality of the data (e.g., Yakoubov *et al.*, 2014). Examples of such privacy-preserving technologies are multi-party computation (e.g., Archer *et al.*, 2018), data anonymization (Zeiringer *et al.*, 2024), homomorphic encryption (e.g., Alabdulatif *et al.*, 2020), watermarking (e.g., Regazzoni *et al.*, 2021) or meta- and transfer machine learning (e.g., Hirt and Kühl, 2018), which were also mentioned by our experts as technical protection measures. Such technology, like multi-party computation, have already been found as protection measures to mitigate knowledge risks in data-centric collaborations (Zeiringer, 2021).

Summing up, the level of knowledge protection from a technology perspective highly depends on data science innovations and thus is a moving target. Thus, it is important to continuously monitor advances in computer science, both in terms of potential attacks and retrieval mechanisms and technical protection measures. This means technical expertise is needed in the strategic discussions for designing DDBMs.

Measures in business model design to mitigate knowledge risks

Proper design of a DDBM, particularly a proper choice of value object itself, is also a knowledge protection measure. A model can be shared when sharing data is considered too risky (i.e., competitive knowledge could be discovered from the data). Sharing models instead of data as a protection measure has been shown in the case of an R&D collaboration in the semiconductor industry (Kaiser *et al.*, 2021). Also, instead of providing data to use a (prediction) service, federated machine learning can be applied (Hirt and Kühl, 2018). In federated machine learning, the model is distributed to where the data is instead of gathering the data where the model is (Kaissis *et al.*, 2020). When sharing a model is considered as too risky (i.e., competitive knowledge could be discovered from the model), predictions can be shared. Instead of giving out the prediction model, it can be accessed via an API enabling pay-per-use business models (Hanzlik *et al.*, 2021). Also, detailed adjustments of the offering, such as limiting the number of access queries or the allowed data range of input values, could reduce the risk.

Nevertheless, there is a trade-off between sharing model (where the service provider risks a knowledge leakage) and sharing data (where the service user risks a knowledge leakage). Running a machine learning model on a client's computing systems can raise the fear of leaking details of the model, giving away the service provider's competitive knowledge (or IP) (Hanzlik *et al.*, 2021). A protection against direct model access is an offline deployment of machine learning as a service (i.e., client site execution where model and computation remain secret) (Hanzlik *et al.*, 2021).

Summing up, we assume from our explorative study that addressing knowledge risk concerns already during the design phase of a DDBM via suitable business model design (and in particular, a proper choice of the value object as part of the value proposition) is a key success factor for DDBM. This also depends on available technology and thus goes in line with the technical developments in the field.

Transparency, trust and contracts to mitigate knowledge risks

Beyond addressing knowledge risk by technology and adjustments in the business model design, we found transparency, establishing trustful relationships and proper contracts as a third opportunity to mitigate knowledge risks in DDBMs. We assume that doing business with data in a B2B context will be only sustainable and profitable in the long term when data transparency and trust is part of the value proposition. Trustful relationships through openness and security standards have also been noted as one measure to address knowledge risks in data-centric collaborations (Zeiringer, 2021). Further, it is important to have proper contract regulations regarding the allowed usage of shared data-related value objects and instruments/sanctions for breaches. Nevertheless, these aspects have not been the focus of this study but have been mentioned frequently by the interviewees, e.g., that they have contractual regulations, such as NDAs, in place.

Strategic implication: Multi-perspective assessment and balancing of knowledge risks

To manage knowledge risks in DDBMs, it is important to assess the risk differentiated and balance sharing and protecting knowledge in a DDBM, as we perceived that there is partly very much fear, insecurity or overcautiousness regarding sharing data-related value objects. Knowledge protection literature suggests assessment and preventive measures (i.e., a clear risk assessment) and awareness for managing knowledge risks in data sharing via digital supply chains (Zeiringer and Thalmann, 2022). Also, our interviewees suggested a differentiated view on the risks: When is competitive knowledge shared, or can be discovered from a shared data-related value object? Is it company-critical knowledge? Is there an imminent business risk if something goes wrong? Second, there is also the question of to whom the knowledge goes. Is it a competitor, where it leads to a competition problem or to other stakeholders, where it is less problematic? Third, also the effort and outcome of attacks need to be evaluated. What is the effort to reconstruct something compared to the expected gain? Can reliable statements be discovered or only probabilities? Further, it must be evaluated up to which point it is acceptable that conclusions on the competitive knowledge can be drawn and at what point the risk is so high that measures must be taken. Thus, it is important to balance knowledge sharing and protection (Manhart and Thalmann, 2015) and balancing estimated returns and acceptable risks in a DDBM (Casadesus-Masanell and Ricart, 2010).

This balancing and differentiated view are, in particular, important, as some of our interview partners mentioned that ideas for DDBMs are often not realised because actors are afraid of sharing data and thus implicitly risk unwanted knowledge spill-overs. Data exchange represents an obstacle due to confidentiality and privacy concerns (Miorandi *et al.*, 2012). Thus, knowledge risks can be a barrier to innovation and influence the adoption of DDBMs. Considering them already during business model design and understanding the choice of value objects as a possible knowledge protection measure can help overcome this barrier.

Embedding the Discussion into Current Literature Streams

Our findings also relate to current literature streams in the context of data-driven business models: data privacy and security in DDBMs, enhancing inter-organisational data sharing via data intermediates and trust-enhancing technologies, or the advancement of data-driven business models towards AI-based business models.

With our study we connect to current literature on privacy and security in DDBMs. Privacy can be a threat or an opportunity (competitive advantage) in a DDBM. Therefore, privacy and data-driven business must go hand in hand (Schäfer *et al.*, 2023a). Cybersecurity and privacy have been found as important capabilities for a DDBM to ensure confidentiality (Stahl *et al.*, 2023). Ensuring data security via secure processes, legal frameworks and usage policies has been also found as a design principle for DDBMs (Azkan *et al.*, 2022). Thus, security is an important factor in implementing DDBMs (Rashed *et al.*, 2022). Security can be implemented via technological measures (e.g., encryption) and organisational measures (e.g., contractual agreements) to increase trust and transparency in data sharing (Azkan *et al.*, 2022; Stahl *et al.*, 2023). Overall, the strategic integration of IT security is seen as a key challenge in digitalization projects (Guggenmos *et al.*, 2022) and DDBMs in particular. And therefore, risk management activities need to be aligned with the process of developing DDBMs (Schäfer *et al.*, 2023a). In previous studies, the fear or risk of leaking sensitive information and competitive knowledge has been listed as one of many barriers in data sharing and DDBMs (e.g., Azkan *et al.*, 2022; Fassnacht *et al.*, 2023). In this study, we provided an in-depth study of this specific risk. Further, with our work, we extend existing literature on privacy and security in DDBMs, that often has a focus on personal data, with the additional perspective of knowledge risks, particularly that competitive knowledge can be leaked when exchanging data-related value objects in a DDBM. Further, we identified particular measures to manage knowledge risks as part of security in DDBMs.

Our results also connect to the current discussion in the literature on secure data exchange across the value chain with the help of data intermediaries (e.g., Stachon *et al.*, 2023), such as data spaces (e.g., Gieß *et al.*, 2023), and trust-enhancing technologies (Schäfer *et al.*, 2023b), such as Multi-Party Computation (e.g., Agahari *et al.*, 2022). These solutions address the risk that companies could lose competitive advantage when they participate in data sharing (e.g. Agahari *et al.*, 2022) or the fear that shared data could be misused against them (e.g., Opriel *et al.*, 2021). Data spaces also aim to solve the issue of data sovereignty when sharing data (e.g. Gieß *et al.*, 2023). In this chapter, we point to specific protection measures via data intermediates (like Data Marketplaces) and secure technologies (like Multi-Party Computation) and provide an application scenario in the context of DDBMs to prevent knowledge risks.

Our results also connect to the current debate in the literature on the advancement of DDBMs towards business models built around machine learning and AI (e.g., Vetter *et al.*, 2022; Weber *et al.*, 2022), where the issues of organisational data sharing will become even more important (Kanbach *et al.*, 2023). (Generative) AI is data-driven and requires large amounts of data and, therefore, will affect organisational data sharing (Strobel *et al.*, 2024). In such business models, data is used to train AI models instead of generating insights; these AI models are then embedded in services and products (Weber *et al.*, 2022). AI-based business models induce, in particular, the automation of knowledge work through AI (Coombs *et al.*, 2020). AI can complement or substitute humans at work (Murray *et al.*, 2021). This delegation of tasks is related to agentic Information Systems (Baird and Maruping, 2021). Such AI systems generate models that “provide descriptions and explanations for organizational knowing processes”, contain prediction and decision functions and can perform real actions in the environment (Shollo *et al.*, 2022, p. 9). Thus, competitive knowledge can be materialized in AI models. When these models are used in a service or is part of an offering, competitive knowledge could be leaked – a risk that we denoted as knowledge risks in this study. In our results we have already pointed in that direction. Thus, we contribute the perspective of knowledge risks to the topical literature on understanding and realizing AI-based business models.

6.3.6 Conclusion

In this chapter we explored different types of risks in DDBMs along three basic types of value objects: data, models and predictions as an additional theoretical investigation out of design cycle four. The knowledge risk depends on the individual context and requires balancing between sharing and protecting knowledge and balancing acceptable risk and expected returns in a DDBM. Further, the risk can be mitigated by technical protection measures, by adjusting the business model design and by transparency, trust and contracts. Therefore, strategic decisions on designing and implementing DDBMs require an interdisciplinary approach from a business, legal and technology perspective.

With this chapter, we contribute to the knowledge base that knowledge leakage is a relevant risk factor in DDBMs. With this insight, we address the gap outlined in Chapter 4.1 to address specific risks in data-driven business models. Knowledge risks in DDBMs differ from knowledge risks associated with traditional business models, as competitive knowledge is materialized in data or (AI) models, which makes knowledge more explicit to transfer. Thus, with our findings, we contribute a new risk that could occur in a DDBM and by that extending the existing debate on data privacy and security in DDBMs (e.g., Azkan *et al.*, 2022; Schäfer *et al.*, 2023a). We add the perspective of competitive knowledge that needs to be protected.

- Thus, with that insight we contribute to the understanding of data-driven business models: Exchanging data, models and predictions in a data-driven business model induce the risk of leaking critical knowledge (see *Contribution 6*, Chapter 7.2).

Further, we contribute to the knowledge base that knowledge risks should be considered already in the design phase of a DDBM, and their management requires an interdisciplinary approach via a differentiated and balanced assessment. Also, the level of knowledge protection from a technology perspective highly depends on computer science innovations and thus is a moving target.

- Thus, with that insight we contribute to the design of data-driven business models: Designing and implementing data-driven business models require a multi-disciplinary approach (see *Contribution 7*, Chapter 7.2).

Nevertheless, our research is not without limitations. Due to the novelty of this topic, the availability of research data was limited, as both cases where a knowledge risk in a DDBM was identified and experts that encountered such a risk in that context are challenging to identify. Collecting data from real-world cases via company representatives was difficult, as such information is usually not publicly available and shared. Further, regarding the data collection process, we relied on expert opinions and their perception of knowledge risks in DDBMs. Sometimes the interviewees mentioned no real-world cases but described knowledge risks that they assumed to be relevant.

In this exploratory research, we did not focus on quantifying the risks, i.e., estimating the probability and economic impact, as these depend highly on the individual context. Further research could develop and evaluate a set of criteria to assess and quantify the risk of knowledge leakage through shared value objects. Related research has already been conducted in the area of open data sharing (e.g., Enders *et al.*, 2020). Based on this, a structured framework could be developed for managing (i.e., quantifying and evaluating) knowledge risks in DDBMs, thereby extending existing work on identifying knowledge risks (e.g., Fruhwirth *et al.*, 2021b).

- This connects to one general outlook perspective of this thesis: studying quantitative methods for evaluating data-driven business models (*Outlook 1*, Chapter 7.5).

Further, we state that knowledge risk in data-driven business models will become even more relevant with the extensive usage of machine learning and AI in DDBMs, particularly in knowledge work and knowledge-intensive businesses as competitive knowledge can be materialized in (AI) models. In this chapter, we striped this topic at the edge. Through the intensive usage of AI tools in the cloud, like large langue model-based tools (e.g., *ChatGPT* or *deepl* for translators) by employees of an organisation, sensitive information and therefore competitive knowledge might be leaked. Such AI models might also expose information they have learned but were not intended to, e.g., in large language models. Furthermore, through the increasing importance of explainable and trustworthy AI, an organisation might have to open their models and expose competitive knowledge. Finally, with developments in generative AI, models will become more powerful, especially in engineering and knowledge-intensive companies. If AI can replace knowledge work, then leaking such a model would imply a huge risk.

➢ This connects to one general outlook perspective of this thesis: AI and ML-based business models (*Outlook 4*, Chapter 7.5).

Finally, based on our cases, we can see that the type of business model also influences the risk, e.g., sharing data in open data initiatives (with an open circle of stakeholders) implies a different risk than sharing data to develop a data-driven service with dedicated partners jointly. Therefore, we see one avenue for future research to investigate contextual factors of knowledge risks in DDBM in more detail. We assume that knowledge risks are, in particular, critical for knowledge-intensive businesses and business models with complex systems and high competition (e.g., the automotive or semiconductor industry). Such organisations are very restrictive with data sharing as corporate secrets might be shared with the data.

➢ This insight connects to the general setting of the case study, where the original problem emerged. Comp is a knowledge intensive business. When implementing data-driven services based on their expert knowledge, they risk leaking that knowledge via the exchange of data-related value objects.

Summing up, one approach to prevent knowledge risks is building partnerships with data marketplaces to exchange data and train models securely. In the following Chapter 6.4, we will investigate the types and properties of data marketplaces from a business model perspective.

6.4 Data Marketplaces as one Solution to Enable Data Sharing and to Prevent Knowledge Risks[47]

6.4.1 Introduction

As we have seen in the previous chapters, exchanging data across organisations in a data-driven business model can lead to unwanted knowledge spillovers. Organisations are often unwilling to share valuable data with other stakeholders due to potential risks or a lack of trust (Dahlberg and Nokkala, 2019). Collaborating with data marketplaces in a DDBM was identified in the previous chapter as one approach to mitigate those knowledge risks as they act as middle-man and enable secure and privacy-preserving data exchange. Due to the need for organisations to acquire external data, securely exchange data, and explore new revenue opportunities by reselling the data they collected internally, the number of data marketplaces has grown in recent years (Carnelley *et al.*, 2016; Muschalle *et al.*, 2012).

Further, data have special characteristics as compared to tangible goods. Data are easy to transport, share, or copy and can be equally used in any location or environment, giving them advantages over any other product (Liang *et al.*, 2018). Unlike tangible goods, no established rules and market mechanisms exist for pricing data assets (Fricker and Maksimov, 2017; Moody and Walsh, 1999) and match buyers to sellers (Agarwal *et al.*, 2019). In addition, it is often difficult for data buyers to evaluate data assets before purchasing and fully disclosing and accessing them; a conundrum is also known as *Arrow's Paradox* (Arrow, 1962; Stahl *et al.*, 2017).

Data marketplaces seem to be one approach to overcoming those challenges (Agarwal *et al.*, 2019; Özyılmaz *et al.*, 2018) and are one actor in data-driven business models. Nevertheless, data marketplaces need an appropriate business model to remain economically sustainable. Due to the special characteristics of data as economic goods, as compared to tangible goods, such as a lack of established rules and market mechanisms for pricing data goods, data marketplaces have distinct characteristics that differentiate them from other electronic marketplaces. In this chapter, we aim to identify characteristics of data marketplaces through the lens of business models by addressing the following question:

What are the characteristic elements of data marketplaces from a business model perspective?

To identify those characteristics, we developed a taxonomy. Taxonomies are used to classify objects of interest in the domain of interest and help understand the complexity of the domain and its concepts (Nickerson *et al.*, 2013). To develop the taxonomy, we used the structured and well-

[47] This chapter is based on Fruhwirth, M., Rachinger, M. and Prlja, E. (2020), "Discovering Business Models of Data Marketplaces". In Proceedings of the 53rd Hawaii International Conference on Systems Science 2020, Maui, pp. 5738-5747. The empirical part of this chapter has been conducted by Prlja Emina as part of her Master's thesis that the author of this PhD thesis co-supervised and laid the foundation of the mentioned paper.

tested method of Nickerson *et al.* (2013). We conducted a literature review to identify conceptual characteristics of data marketplaces and used a final set of 20 cases of data marketplaces to revise our taxonomy empirically. We identified 16 key dimensions that are used to distinguish and explain the characteristics of data marketplaces from a business model perspective. The developed taxonomy contributes to the existing body of knowledge by establishing a common understanding of data marketplaces from a business model perspective.

The rest of this chapter is organised as follows: Section 6.4.2 provides additional background on digital platforms and data marketplaces. Section 6.4.3 describes our detailed research methodology, the steps of taxonomy development, and how we collected and analysed our empirical data. Section 6.4.4 presents the individual elements of our taxonomy, a frequency analysis, four archetypes of data marketplaces, and four cases illustrating the found archetypes. We close the chapter by discussing the implications of our research, reflecting on its limitations and describing possible directions for further research (section 6.4.5).

6.4.2 Additional Background on Digital Platforms and Data Marketplaces

Digital platforms, often referred to as “electronic marketplaces” or “multilateral marketplaces”, are businesses that enable and support interactions between distinct but interdependent groups of users (customers and suppliers). These groups perform exchanges of goods by using pricing strategies (Gawer, 2014; Osterwalder and Pigneur, 2010). The platform acts as a facilitator of these interactions and as participants co-create value between each other. A product or service of a platform provides more value to its users as more users adopt it (Osterwalder and Pigneur, 2010; Shapiro and Varian, 2010). Such network effects create self-reinforcing mechanisms that lead to market leadership, a large customer base, an economy of scale, and boundaries for other players (Carnelley *et al.*, 2016; Eisenmann *et al.*, 2006). Market place participants do not necessarily represent two different groups of users but can take both the roles of buyer and seller (Täuscher and Laudien, 2018). When data are subsequently traded as economic goods in electronic marketplaces, data marketplaces emerge as a type of marketplace with distinct characteristics.

Data marketplaces are electronic platforms facilitating data exchange (Stahl *et al.*, 2014). According to Stahl *et al.* (2016), an electronic marketplace is a data marketplace if data trading is its main value proposition. A data marketplace ecosystem consists of *data providers*, *data buyers*, *third-party service providers* and a *marketplace owner* (Spiekermann, 2019). Data providers offer their data on a marketplace, allowing it to be queried by data buyers and expect to obtain revenue by selling data. Data buyers are interested in buying datasets they need and display a positive willingness to pay for data (Kushal *et al.*, 2012). Data buyers use purchased data to support decision-making processes (Deichmann *et al.*) or build new services and business models. Third-party service providers can provide applications or algorithms that add value to data assets. The data marketplace owner collects and hosts data from providers and sells data to buyers

(Spiekermann, 2019). Marketplace participants must be able to upload, browse, download, buy, and/or sell machine-readable data on a data marketplace.

Consequently, this excludes the services that only offer links to data locations without hosting the data. Moreover, data must be hosted by the providers who clarify the origin of the data. Carnelley *et al.* (2016.) emphasize additionally that data marketplaces have to be digital platforms and not only data repositories or cloud service providers. Encouraged by the definition of electronic marketplaces provided by Schmid and Lindemann (1998), which involves *buying* and *selling* activities, we excluded open data marketplaces in this research because they lacked a profit-oriented nature (Zuiderwijk *et al.*, 2014). Open data portals, government agencies, and non-government organizations that provide free of charge were also excluded from the scope of data marketplaces since they do not provide any market mechanism for buying and selling.

Although the body of literature on data marketplaces has grown in recent years, little research has been conducted on systematising and consolidating the characteristics of data marketplaces from the perspective of business models (Spiekermann, 2019).

6.4.3 Detailed Research Approach

We selected the taxonomy-building approach Nickerson *et al.* (2013) proposed to identify the characteristics of data marketplaces. Taxonomy building is commonly used to classify, clarify, understand and systematically analyse complex problems or domains. The approach of Nickerson *et al.* (2013) involves combining knowledge from the literature and analysing objects of interest from the real world. It is generally a well-accepted and frequently used method in the area of business models for information systems, such as car-sharing business models (Remane *et al.*, 2016), digital business models (Bock and Wiener, 2017) or FinTech business models (Eickhoff *et al.*, 2017). In the following section, we describe how we developed our taxonomy by following the seven-step process for taxonomy development proposed by Nickerson *et al.* (2013) (see Figure 6.5). As part of this process, we defined the meta-characteristic, which is a basis and limitation for discovering dimensions and characteristics. Furthermore, we defined the ending conditions of this process due to its iterative nature. Third, the process can continue along one of two paths: a conceptual-to-empirical approach, building the taxonomy from relevant literature, or an empirical-to-conceptual approach, building the taxonomy from investigating empirical cases. After each approach, we checked the ending conditions: If the ending conditions are not met, an additional empirical-to-conceptual or conceptual-to-empirical iteration follows.

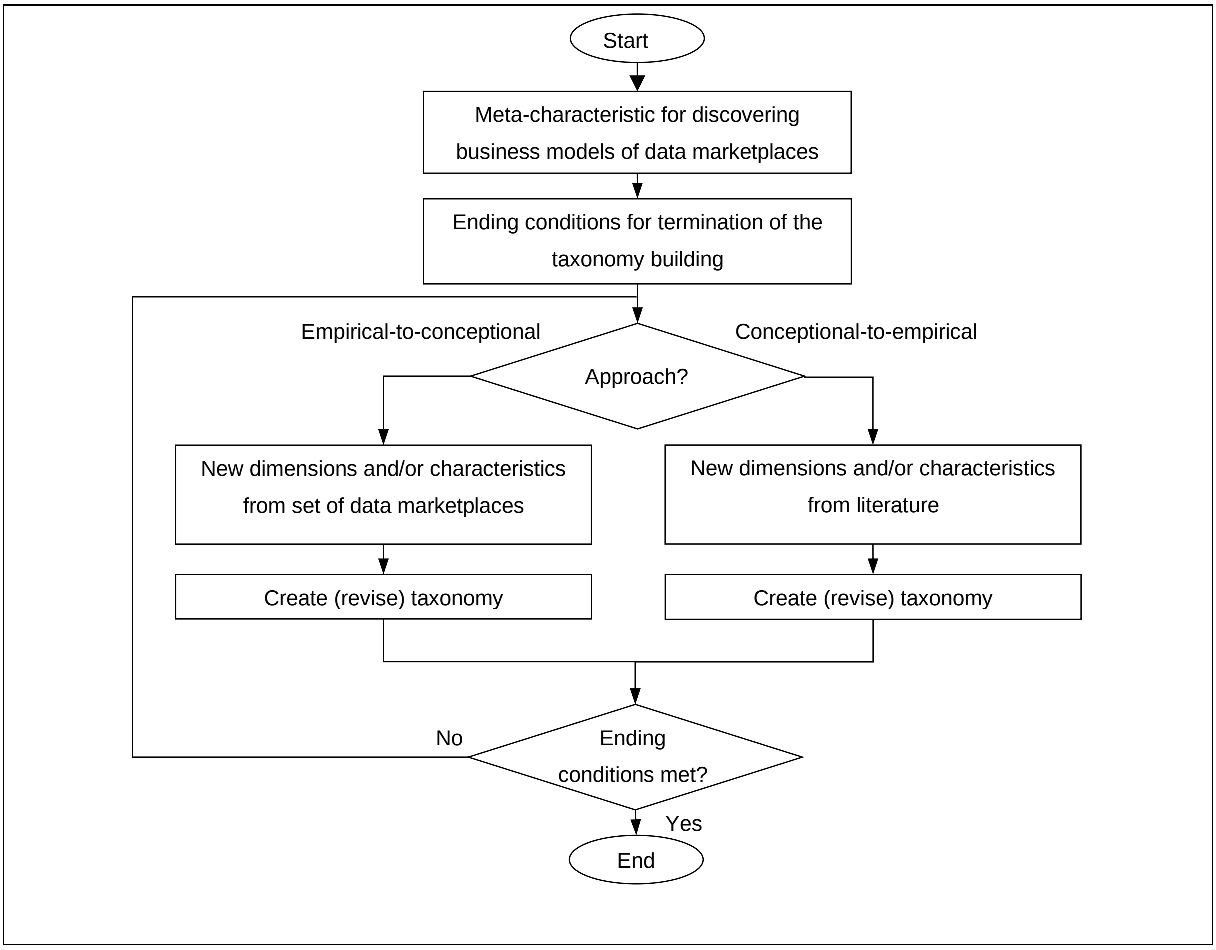


Figure 6.5: Applied research process following Nickerson *et al.* (2013).

Define meta-characteristic: As the goal of this chapter is to identify characteristics of data marketplaces from a business model perspective, we defined the basic elements of a business model (value proposition, value delivery, value creation and value capture (Remane *et al.*, 2017; Teece, 2010)) as the meta-characteristic.

Determine ending conditions: We followed the ending conditions suggested by Nickerson *et al.* (2013) regarding the objective and subjective ending conditions. The conditions and their fulfilment after each iteration are listed in Appendix V.

Selected approach: As part of our taxonomy development process, we conducted two conceptual-to-empirical iterations and five subsequent empirical-to-conceptual iterations. In the following section, we describe the activities in both approaches.

Conceptual to empirical (c2e): We applied a conceptual-to-empirical approach in the first two iterations. We integrated relevant characteristics from the existing literature on taxonomies of platform business models and marketplaces (Täuscher, 2016; Täuscher and Laudien, 2018) as well as from previous work on data marketplaces (Fricker and Maksimov, 2017; Koutroumpos *et al.*, 2017; Muschalle *et al.*, 2012; Stahl *et al.*, 2017; Stahl *et al.*, 2014).

Empirical to conceptual (e2c): In the next iterations, we classified the business models of existing data marketplaces from empirical data. To systematically identify the relevant objects for the inductive iterations, we adopted the rigorous procedure for literature reviews from Vom Brocke *et al.* (2009). We searched for data marketplaces using the Google search engine, using the browser in incognito mode to avoid carry-over effects from previous search queries. We applied the following keywords during our search: "data marketplace," "data market," "data trading platform," "data platform," "buying data", and "data brokers." Moreover, data marketplaces that had already been surveyed in the background literature were included in our database. This search process led us to identify a complete set of 58 data marketplaces. We drew on information from company websites, white papers and news articles mentioning a data marketplace. We excluded companies that provided insufficient information from the database. If possible, we also created an account for each data marketplace to observe its functionalities and offerings. We considered only data marketplaces with available information in English. To create a representative set of platforms, we filtered the initial set of objects in two iterations: Before the taxonomy development, objects were excluded if they did not fulfil our definition of a data marketplace (see background section 6.4.2). During the taxonomy development, an additional set of objects was excluded if no sufficient public information was available about the data marketplace[48] or if we encountered technical failures and location issues (e.g., unsupported area) while accessing data marketplaces. Further, we excluded data marketplaces that were still under construction or in the testing phase. The list of identified data marketplaces and the exclusion criteria can be found in **Appendix T**. After applying our inclusion and exclusion criteria, we arrived at a final set of 20 data marketplaces.

Checking ending conditions was done after every iteration until every condition was satisfied, which terminated the analysis. This process is shown in **Appendix V**.

Appendix V: Check of ending conditions after each iteration of the taxonomy building approach.

The last step in our research was identifying **archetypes** of data marketplaces by using the taxonomy's characteristics and following the guidelines of Yin (2009) and Doty and Glick (1994). This approach involved recognizing similarities and dissimilarities within the cases and, eventually, separating mutually similar groups between them. We grouped the analysed data marketplaces according to their characteristics.

6.4.4 Result: Taxonomy and Archetypes of Data Marketplaces

We established a taxonomy system to characterise data marketplaces using the lens of business models. As Table 6.9 shows, our taxonomy consisted of dimensions and characteristics. We structured the dimension along the basic elements of a business model (value proposition, value delivery, value creation and value capture (Remane *et al.*, 2017; Teece, 2010)). A detailed

[48] We did not contact marketplace operators by direct e-mail correspondence or phone calls to obtain further information.

description of the elements of the taxonomies and their origins can be found in Appendix W. Characteristics that did not occur in the final dataset of twenty data marketplaces were not included in the taxonomy. The excluded characteristics were “Government” as a data origin, “Web interface” as a data access type, “XML” and “RDF” as data output types, “Complete access” as pre-purchase test-option, the domains of “Scientific” and “Social media”, “C2C” and “C2B” marketplace types and the “Free” and “Two-part tariff” pricing model. In addition, if no information on a dimension was available, the “No info” characteristic was introduced. Further, we counted the characteristics frequencies in the final dataset of twenty marketplaces.

The value creation perspective of data marketplaces

The **platform infrastructure** dimension refers to the architecture of a data marketplace as a multi-sided platform. In a centralized data marketplace, data is offered via a centralized location, whereas in a decentralized data marketplace, data assets remain at the data provider, e.g. by using a blockchain (Koutroumpos *et al.*, 2017). The results indicate that approximately two-thirds of the investigated platforms operated in a centralized manner, while only one-third operated in a decentralized manner. The **data origin** dimension specifies where the offered data comes from (i.e., internet, self-generated, user-generated, community, government or authority) (Stahl *et al.*, 2017). Self-generated data from private sources represented the most prominent source of data.

The **review system** dimension describes if data assets are evaluated by users or the marketplace (Täuscher, 2016; Täuscher and Laudien, 2018). Interestingly, eighteen of the twenty data marketplaces either did not have a review system or offered no information on a review system.

The value proposition of data marketplaces

The **privacy** dimension indicates if data marketplaces offer privacy-preserving mechanisms as part of their value proposition to increase the data providers’ willingness to share their data while preserving the privacy and confidentiality of the data. Half of the investigated data marketplaces offered to protect privacy guarantees through encryption or anonymization of data assets. Although half of the data marketplaces did not provide any information about privacy, we maintained this dimension due to its relevance and the problem of knowledge risks described in the previous chapters. Fourteen of the twenty data marketplaces guarantee the quality of data assets as part of the value proposition, which is indicated in the **data quality guarantee** dimension. The **time relevancy** dimension describes whether the marketplace offers static or dynamic (i.e., regularly updated) data sets (Stahl *et al.*, 2017). Seventeen of the investigated twenty data marketplaces also offered regularly updated datasets combined with static or regularly updated ones. The **pre-purchase testability** dimension refers to *Arrow’s* Paradox if data assets can be accessed before purchase to evaluate the value of the data (Stahl *et al.*, 2017). Thus, data offered on marketplaces should come with corresponding metadata describing their amounts, origins, characteristics and other information that the buyer should know before purchasing (Spiekermann *et al.*, 2018). Only seven of the twenty data marketplaces offered restricted access to data assets before purchase, whereas the majority did not offer pre-purchase testability of their data sources.

	Dimension	Characteristics					
Value Creation	Platform infrastructure	Centralized (13/20)	Decentralized (7/20)				
	Data origin	Internet (1/20)	Self-generated (10/20)	User (3/20)	Community (2/20)	Authority (4/20)	
	Review System	User reviews (2/20)	Reviews by marketplace (2/10)	None (9/20)	*No info (7/20)*		
Value Proposition	Privacy	Anonymized (6/20)	Encrypted (2/20)	Both (2/20)	*No info (10/20)*		
	Data quality guarantee	Yes (14/20)	No (6/20)				
	Time relevancy	Static (3/20)	Dynamic (11/20)	Both (6/20)			
	Pre-purchase testability	None (12/20)	Restricted access (7/20)	*No info (1/20)*			
Value Delivery	Data output type	CSV/XLS (6/20)	JSON (4/20)	Report (1/20)	Multiple options (4/20)	*No info (5/20)*	
	Type of access	API (7/20)	Down-load (4/20)	Specialized Software (3/20)	API/Down load (4/20)	*No info (2/20)*	
	Additional purchase support	With additional costs (8/20)	Included in price (3/20)	No (9/20)			
	Domain	All / Any (5/20)	Finance (2/20)	Geo (2/20)	Address (2/20)	Sensor (4/20)	Personal (5/20)
	Marketplace participants	B2B (9/20)	C2B (3/20)	Any (8/20)			
	Smart contract with blockchain	Yes (9/20)	No (11/20)				
Value Capture	Pricing model	Usage-based (7/20)	Package pricing (3/20)	Flat fee tariff (5/20)	Freemium (4/20)	*No info (1/20)*	
	Price discovery	Fixed prices (11/20)	Set by sellers (6/20)	Set by buyers (1/20)	Auction (1/20)	Negotiation (1/20)	
	Payment currency	Crypto (6/20)	Fiat (13/20)	Both (1/20)			

Table 6.9: Identified dimensions and characteristics of data marketplaces.

Value delivery perspective of data marketplaces

The **data output type** describes the technical format of the data asset (e.g., CSV/XLS, JSON or report) (Stahl *et al.*, 2014). The **type of access** dimension describes how data assets can be accessed (i.e., via API, download or specialized software). Fifteen of the twenty data marketplaces relied on APIs or downloads to offer access to data. The **additional purchase support** dimension indicates if additional services (e.g., for data analysis) are offered for free with an additional fee. More than half of the investigated data marketplaces offered additional purchase support, predominantly for an extra charge. The **domain** dimension specifies the information the data asset contains (e.g., financial or sensor data) (Fricker and Maksimov, 2017; Stahl *et al.*, 2014). We identified no specific focus regarding the domain of offered datasets. The **marketplace participant** dimension refers to the stakeholders that are matched via a data marketplace (Täuscher and Laudien, 2018). While almost half of the data marketplaces also took a B2B focus or no focus, three of the twenty data marketplaces used a C2B model. The **smart contract with blockchain** dimension describes if smart contracts are used as a privacy-preserving and safe payment method to enforce trust. Almost half of the investigated data marketplaces (nine out of twenty) offered smart contracts with a blockchain.

Value capture perspective of data marketplaces

The **pricing model** dimension indicates the strategy of a data marketplace for gaining profit (Muschalle *et al.*, 2012; Stahl *et al.*, 2014). The most prominent pricing models used were usage-based models (used by eight out of twenty data marketplaces), a flat fee tariff (used by five data marketplaces) and the freemium-model (used by four out of twenty data marketplaces). Furthermore, the **price discovery** dimension describes how the price of a data set is determined before the transaction (Täuscher, 2016; Täuscher and Laudien, 2018). Eleven out of twenty data marketplaces relied on fixed prices, while six data marketplaces relied on prices set by sellers. The **payment currency** dimension indicates in which form a data marketplace handles payments. Fiat money was the most prominent payment currency, while only six offered payments via cryptocurrency. Only one data marketplace offered both payments with cryptocurrency and fiat money.

Archetypes of Data Marketplaces

As described in the method section, we also explored patterns in the distinct characteristics of the investigated data marketplaces to identify archetypes of data marketplaces. We looked for meaningful similarities and dissimilarities within the cases by comparing the different dimensions of our taxonomy. The four archetypes differed in the dimension of platform infrastructure (centralised vs. decentralised). Centralized data marketplaces also differ in whether they provide encryption and smart contracts or not. Decentralized data marketplaces differed if they offered self- or user-generated data, obtained from the personal domain, operated in a C2B context and if data could be accessed via API/download or by use of specialized software. The final sample of twenty data marketplaces was assigned to one of four archetypes each. Table 6.10 provides an overview of the archetypes and lists the representative data marketplaces and their main characteristics.

Centralized data trading: With eleven out of twenty data marketplaces, the “standard centralized” archetype was the most common in the dataset. This type of data marketplace has similar characteristics to conventional online marketplaces: offering possibilities to trade data efficiently. Data marketplaces of this archetype do not rely on a specified data origin, data domain, data output type, or pricing model.

Centralized data trading with smart contract: Only one marketplace in the dataset fits this archetype. Although it had a centralized infrastructure, it encrypted the data stored in the marketplace and supported smart contracting with a blockchain. Due to its centralized characteristic, this specific archetype of data marketplace supports straightforward data trading while addressing security and legal issues that can occur in centralized data marketplaces.

Decentralized data trading: Five of eleven data marketplaces fit into this category. This archetype relies on the decentralised infrastructure typical for smart contracting. Marketplaces of this archetype guarantee data quality. They sell self-generated, dynamic data. None of the investigated data marketplaces provided additional services. Four out of five of the data marketplaces of the "decentralized data trading" archetype supported cryptocurrency solely, while one supported both crypto- and fiat currency.

	Centralized data trading	**Centralized data trading with smart contract**	**De-centralized data trading**	**Personal data trading**
Data marketplace example	Quandl	Dawex	IOTA	Datacoup
Value creation	Centralized	Centralized	De-centralized	De-centralized
Value proposition	Anonymized Dynamic datasets	Encrypted Static and dynamic datasets	Encrypted Dynamic datasets	Anonymized Dynamic datasets
Value delivery	API or download Restricted access to data samples B2B No smart contract	API or download Restricted access to data samples B2B Smart contract	API No test data samples B2B Smart contract	Specialized software to access No test data samples C2B Smart contract
Value capture	Freemium pricing Prices set by sellers Fiat currency	Usage-based pricing Prices set by sellers Fiat currency	Flat fee pricing Price set by sellers Cryptocurrency	Usage-based pricing Fixed prices Cryptocurrency

Table 6.10: Illustrative examples for the four archetypes of data marketplaces.

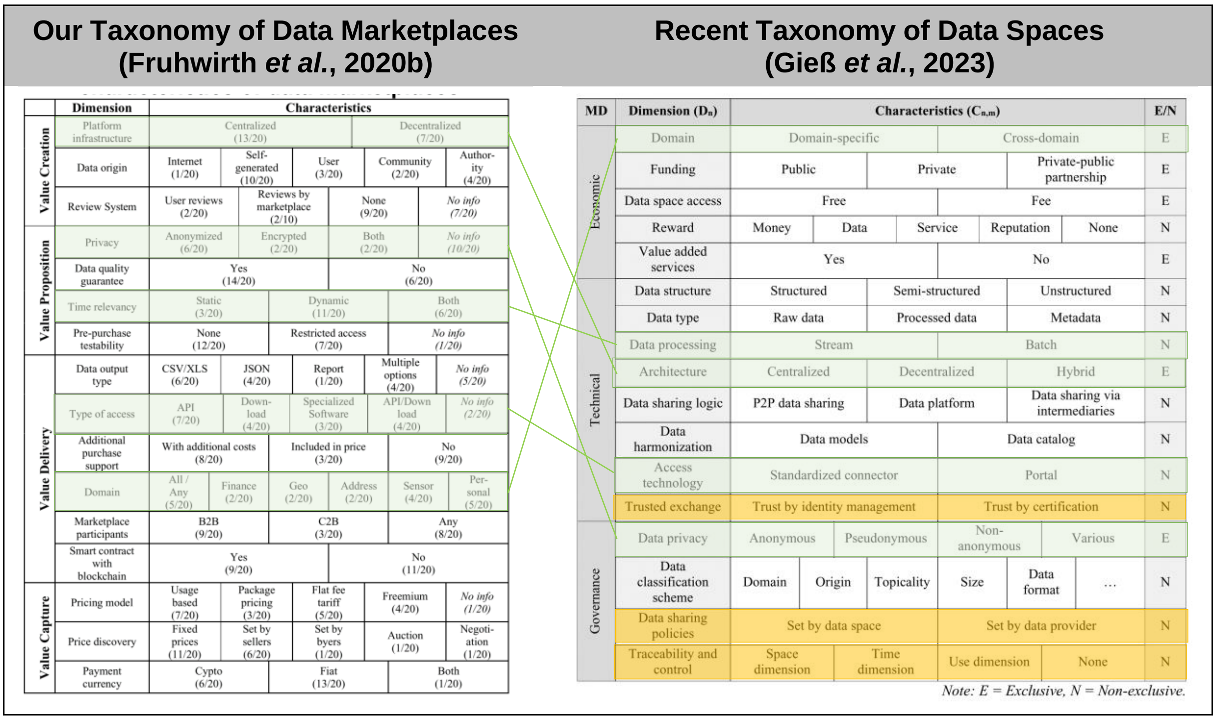
Personal data trading: Three out of twenty marketplaces explicitly allowed users of the data marketplace to expose data for trading. Therefore, this archetype has a consumer-to-business characteristic and trades user-generated personal data. Data trading is performed through the use of simple, specialized software.

6.4.5 Discussion and Conclusion

In this chapter, we used the lens of business models to propose a taxonomy for data marketplaces, one actor in a data-driven business model that enables secure data exchange and can prevent knowledge risks. The developed taxonomy consists of dimensions and characteristics derived from conceptual considerations (Fricker and Maksimov, 2017; Koutroumpos *et al.*, 2017; Muschalle *et al.*, 2012; Stahl *et al.*, 2017; Stahl *et al.*, 2014; Täuscher, 2016; Täuscher and Laudien, 2018) with the addition of new categories, identified by using empirical material from a sample of twenty data marketplaces. Appendix W outlines all conceptual and empirical dimensions and characteristics used for taxonomy building and their origins. Only conceptual characteristics in the empirical material were subsequently considered to build the taxonomy. The taxonomy was structured following the basic business model elements (Remane *et al.*, 2017, remane; Teece, 2010), as illustrated in Table 6.9.

Looking at Table 6.10, the main criterion that separated data marketplaces was whether data marketplaces stored their data in a centralized or decentralized manner (e.g., using a blockchain). In that regard, anonymity and data encryption are major aspects differentiating data marketplaces. Despite their differences, all four archetypes had a focus on privacy measures in their value proposition. Thus, our findings highlight the need in the industry for secure data exchange while preserving competitive knowledge. Data marketplaces are both an enabler for new data-driven business models and a protection measure against knowledge risks. They are important actors in the value network of a data-driven business model (see also Chapters 5.4 and 6.2).

Comparing our results with previous investigations on the topic (Spiekermann, 2019) indicates that data marketplaces are still evolving, and a dominant business model of data marketplaces is yet to emerge. With the rapid advancement of the field in the area of data-driven business, the concept of “data spaces” recently emerged. One position paper showed defined a data space as *“a decentralized infrastructure for trustworthy data sharing and exchange in data ecosystems based on commonly agreed principles”* (Nagel and Lycklama, 2021). A data space provides a framework to support data sharing within a data ecosystem (Curry *et al.*, 2022). According to Nagel and Lycklama (2021), a data platform and a data marketplace are two central building blocks of a data space. Thus, we see that these concepts are closely interconnected with each other.



Our Taxonomy of Data Marketplaces (Fruhwirth *et al.*, 2020b)

	Dimension	Characteristics					
Value Creation	Platform infrastructure	Centralized (13/20)	Decentralized (7/20)				
	Data origin	Internet (1/20)	Self-generated (10/20)	User (3/20)	Community (2/20)	Authority (4/20)	
	Review System	User reviews (2/20)	Reviews by marketplace (2/10)	None (9/20)	*No info (7/20)*		
Value Proposition	Privacy	Anonymized (6/20)	Encrypted (2/20)	Both (2/20)	*No info (10/20)*		
	Data quality guarantee	Yes (14/20)	No (6/20)				
	Time relevancy	Static (3/20)	Dynamic (11/20)	Both (6/20)			
	Pre-purchase testability	None (12/20)	Restricted access (7/20)	*No info (1/20)*			
Value Delivery	Data output type	CSV/XLS (6/20)	JSON (4/20)	Report (1/20)	Multiple options (4/20)	*No info (5/20)*	
	Type of access	API (7/20)	Download (4/20)	Specialized Software (3/20)	API/Down load (4/20)	*No info (2/20)*	
	Additional purchase support	With additional costs (8/20)	Included in price (3/20)	No (9/20)			
	Domain	All / Any (5/20)	Finance (2/20)	Geo (2/20)	Address (2/20)	Sensor (4/20)	Personal (5/20)
	Marketplace participants	B2B (9/20)	C2B (3/20)	Any (8/20)			
	Smart contract with blockchain	Yes (9/20)	No (11/20)				
Value Capture	Pricing model	Usage based (7/20)	Package pricing (3/20)	Flat fee tariff (5/20)	Freemium (4/20)	*No info (1/20)*	
	Price discovery	Fixed prices (11/20)	Set by sellers (6/20)	Set by byers (1/20)	Auction (1/20)	Negotiation (1/20)	
	Payment currency	Cypto (6/20)	Fiat (13/20)	Both (1/20)			

Recent Taxonomy of Data Spaces (Gieß *et al.*, 2023)

MD	Dimension (D_n)	Characteristics ($C_{n,m}$)						E/N
Economic	Domain	Domain-specific	Cross-domain					E
	Funding	Public	Private	Private-public partnership				E
	Data space access	Free	Fee					E
	Reward	Money	Data	Service	Reputation	None		N
	Value added services	Yes	No					E
Technical	Data structure	Structured	Semi-structured	Unstructured				N
	Data type	Raw data	Processed data	Metadata				N
	Data processing	Stream	Batch					N
	Architecture	Centralized	Decentralized	Hybrid				E
	Data sharing logic	P2P data sharing	Data platform	Data sharing via intermediaries				N
	Data harmonization	Data models	Data catalog					N
	Access technology	Standardized connector	Portal					N
	Trusted exchange	Trust by identity management	Trust by certification					N
Governance	Data privacy	Anonymous	Pseudonymous	Non-anonymous	Various			E
	Data classification scheme	Domain	Origin	Topicality	Size	Data format	…	N
	Data sharing policies	Set by data space	Set by data provider					N
	Traceability and control	Space dimension	Time dimension	Use dimension	None			N

Note: E = Exclusive, N = Non-exclusive.

Figure 6.6: Comparing our taxonomy of data marketplaces (Fruhwirth *et al.*, 2020b) with a recent taxonomy of data spaces (Gieß *et al.*, 2023) (green = overlap, yellow = new characteristic regarding trust, security and privacy in inter-organisational data sharing.

Recently information systems research has started investigating a taxonomy for data spaces (e.g., Gieß *et al.*, 2023) that show great overlap (see Figure 6.6), e.g., with regard to technical aspects (like architecture, data types), domain or privacy. New elements are for instance, (i) how trust is enabled (by identity management or certification), (ii) who sets the data sharing policy, (iii) mechanism regarding traceability and control. These new characteristics highlight the need for trust, privacy and security in inter-organisational data sharing.

Our taxonomy and archetypes provide an overview of the current business models of data marketplaces and subsequently extend the findings of Spiekermann (2019). Our results also allow researchers and practitioners to easily anchor and communicate the dimensions and characteristics of data marketplaces. In addition, the established taxonomy can be used by practitioners as a basis to design business models for data marketplaces in the future. If required, the taxonomy can easily be extended following the process proposed by Nickerson *et al.* (2013) to include additional elements. This is important since investigations on business models used in data marketplaces represent a rather new and rapidly evolving research area, where new characteristics or dimensions of data marketplaces' business models are likely to emerge. Further, this deeper understanding of data marketplaces supports designing DDBMs that engage a data marketplace as a key partner to exchange data and thus prevent potential knowledge risks securely.

- With these insights, this chapter contributions to the general understanding of data-driven business models (see section 7.2.3), in particular by studying patterns, characteristics and dimension of data marketplaces' business models – one type of DDBMs (with regard to data platform) and one actor in a DDBM that aims to prevent knowledge risks.

Nevertheless, the research presented in this chapter is not without limitations. First with regard to evaluation, we have not evaluated the taxonomy beyond the method provided by Nickerson *et al.* (2013). Due to the increased popularity building taxonomies among Information Systems researchers, also advancements in the method of taxonomy development and evaluation could be observed during writing of this thesis (visible, for example, in the following papers: Szopinski *et al.*, 2019, Szopinski *et al.*, 2020). Furthermore, the presented taxonomy is a snapshot as of 2020. Due to rapid advancements, the taxonomy needs to be updated continuously, as new characteristics and dimensions could be identified. This is in particular important due to the emerging field of data spaces (Gieß *et al.*, 2023). Further, detailed limitations regarding the taxonomy building method can be looked up in the corresponding paper (Fruhwirth *et al.*, 2020b).

- These outlined limitations relate to two overall limitations of this thesis: First, with regard to the evaluation of the artefacts presented in this thesis (see *Limitation 2* in Chapter 7.4) and second, with regard to the fast development and advancement the DDBM field and also the corresponding standard of research methods in the information systems community which is in particular important for the earlier studies in this thesis that got published around 2020 (see *Limitation 3* in Chapter 7.4).

Concluding this chapter, data marketplaces are both an enabler for data-driven business models and a protection measure against knowledge risks.

6.5 Conclusion on Supporting Evaluation and Decision-Making

Summary: Chapter 6 focused on evaluation and decision-making in DDBMs. First, we presented an overview of the decision criteria for a stage-gate process. One important decision criterion is the risks associated with new DDBMs. One particular risk is the leakage of competitive knowledge through exchanging data-related value objects. Therefore, we developed a visual tool in Chapter 6.2 to identify knowledge risks in a DDBM design. In Chapter 6.3, we investigated risks and protection measures related to exchanging those value objects. Finally, in Chapter 6.4, we investigated Data Marketplaces as one measure to mitigate knowledge risks and enable data exchange across organisations.

Learnings from Chapter 6.1: We developed a set of evaluation and decision criteria, assigned them to the phases of a business model innovation process and operationalized them by a questionnaire and a visual tool including Likert-scales. These outcomes contribute to the business model innovation process of Chapter 4.2 by supporting and informing the gate decisions. Further, this set of criteria enables managers to assess the maturity of a business model initiative. We learned that each phase of the process focuses on a different criteria category; thus, specific aspects are more important at specific stages. Further, we learned that the information for each criterion gets more detailed and precise over time. Third, the category of risks is a complementary dimension to all other categories, as uncertainties in the other categories (e.g., financials or customer demand) can represent potential risks for the business model.

Learnings from Chapter 6.2: We identified that knowledge risks are a relevant decision parameter in the design process of DDBMs. Knowledge risks in data-driven business models occur when valuable knowledge of a company is materialised in data-related value objects and used as the basis of an offering. By exchanging such objects, critical knowledge may leak the organization’s boundaries and risk the company's competitive advantage. Further, we crafted design requirements for decision support and instantiated and evaluated a visual tool that supports identifying and discussing knowledge risks in DDBMs. Our evaluation found that the representation was easy to understand and was perceived as useful for discussing knowledge risks in a given DDBM. It was perceived as helpful as it visualises the different flows of knowledge, money, and data between actors in the network. Thus, it enables DDBM designers to identify unwanted outflows of knowledge and balance them with the exchanged benefits.

Learnings from Chapter 6.3: We learned that exchanging data, models and predictions in DDBMs can lead to knowledge risks. These knowledge risks depend on the individual context and require balancing between sharing and protecting knowledge and balancing acceptable risk and expected returns in a DDBM. Further, the risks can be mitigated by technical protection measures, by adjusting the business model design and by transparency, trust and contracts. Therefore, strategic decisions on designing and implementing DDBMs require an interdisciplinary approach from a business, legal and technology perspective. In particular, we suggest involving data analytics and artificial intelligence experts in those top-level decisions is important.

Learnings from Chapter 6.4: In this chapter, we have investigated data marketplaces from a business model perspective by building a taxonomy and identifying four archetypes. We found that privacy aspects (e.g., anonymization or encryption) are important to the value proposition. This underlines our proposition that data marketplaces are important in enabling data-driven business models and preventing knowledge risks.

Overall contribution: In Chapter 6, we showed that risks are an important evaluation and decision criterion and that data-driven business models bring new types of risks. Visualizing a business model from a network perspective can help identify potential unwanted knowledge flows and potential knowledge risks already in the design phase of a DDBM. Differentiating these flows by the type of value object (data, models and prediction) is one approach to assess the risk differentially. Identifying and managing such specific risks requires an interdisciplinary approach from a business, legal and technology perspective.

Outlook: In Chapter 6, we have investigated knowledge risks, only one specific type of risk and decision criteria in DDBMs. Due to the specific characteristics of data as a key resource in business models, other important criteria and risks exist that should be investigated. Furthermore, this chapter only focuses on qualitative methods and tools to support evaluation and decision-making. Further research should also focus on quantitative methods.

Part III
Contributions

Chapter 7

Discussion and Conclusion

“A good discussion increases the dimensions of everyone who takes part.”

Randolph Bourne[49]

7.1 Summary of Research Questions

Data-driven business models (DDBMs) are one opportunity for business growth and competitive advantage. However, this business model transformation is challenging, particularly for offline-established organisations. In general, tools and methods support practitioners in developing new business models. As we have seen, there is little literature available supporting data-driven business model innovation. Existing research focuses on understanding the phenomenon and nature of data-driven business models (e.g., through developing taxonomies) by studying the business model of start-ups. Further, business model tools are mostly designed on a conceptual basis and evaluated with experts or students. However, they need to be adapted for, introduced to, and evaluated in real-world organisations. Finally, little design knowledge is available on designing such tools and methods. Therefore, we formulated this thesis's research goal: *How can we design tools, methods, and concepts to support data-driven business model innovation in offline-established organisations?*

By studying the literature on DDBMs and business model innovation and our experience in the case study, we identified three research gaps that led to our research questions. Firstly, data-driven business model innovation is a long and challenging process. However, the existing literature is fragmented, and it is unclear to what extent existing business model processes and tools can be adapted. A comprehensive toolbox and process design are missing for DDBMs (RQ1). Second, DDBMs differ from traditional business models and are new to many firms. Thus, they need support in the early idea generation phase to find potential DDBM ideas that fit their specific environment. The literature currently does not provide sufficient support for that problem (RQ2). Third, DDBMs can lead to new risks, as data is a new key resource. Business developers must identify and manage such risks while designing a business model. Existing literature has not studied specific risks in DDBMs and cannot provide sufficient tool support for evaluation and decision-making in DDBMs (RQ3). To explore if we reached our research goal, we will first discuss the results of each research question separately and then come to an overall conclusion.

[49] https://www.inspiringquotes.us/author/5392-randolph-bourne, accessed on 09.05.2022, 07:37.

Summary of research question one: What process design would systematically allow offline-established companies to develop data-driven business models?

To answer this research question, we first conducted a structured literature review on tools and methods supporting data-driven business model innovation. We analysed the supporting artefacts based on the business model elements included, the type of contribution (e.g., a visual tool) and the type of thinking. The results show that there is little specific information available for DDBMs. In particular, we identified three research gaps and avenues for further research: First, existing tools are disconnected, and there is no overarching process design. This gap is also the focus of research question one. Second, little is available for evaluating and managing risks in data-driven business models. This gap is addressed in research question three, and we discuss its results below. Third, there is little IT support available, which we have not addressed in our research chapters, but we will discuss it in the outlook section of this thesis. Further, we provided the first toolbox for DDBMs, structuring existing tools by the phases of a business model innovation process.

In the second research chapter, we have developed a business model innovation process based on the case study and the practical work with *Comp*. We have derived design requirements and design features for such a process. We instantiated one process design in the context of *Comp* that was discussed with the management and introduced into the organisation. To generalise our findings, we also crafted three design principles for a business model innovation process: consider convergent and divergent thinking, structure the process along with decision criteria and formalise tacit knowledge of the organisation in a business model innovation process. However, we have not evaluated how well such a process design supports the development of DDBMs, which delimits the validity of our results.

Business model innovation can be decomposed into *activities* structured by process *phase*s. *Tools* and methods support these activities, e.g., collecting or documenting information in a canvas or guide the operationalisation of specific activities, e.g., identifying risks in a business model. When designing a business model innovation process, one should identify necessary activities based on literature and current practice at the organisation and map them to existing available tools. Unaddressed problems are opportunities to design support.

In both studies of Chapter 4, we found a distinction between *generic and context-specific* tools and methods. Besides generic tools, such as the Business Model Canvas, tools for specific types of business models, such as DDBMs, are available. They complement generic representations of a business model with specific aspects of the respective type of business model (e.g., with data as a key resource or analytics as key activities). Further, tools and methods are available for designing, evaluating, or implementing specific business model elements (e.g., revenue models). Therefore, we also considered research from similar fields, such as “data-driven innovation” or “data-driven services”, covering only parts of a business model. We derived generic design principles for all types of business model innovations from the process perspective. In the process instantiation, we also adopted details to cover the specifics of DDBMs through checklists or specific tools like the Data Product Canvas.

In both studies, we assigned activities and tools to the concepts of *convergent and divergent thinking*. Every phase in business model innovation has a divergent and a convergent part. Considerations are made for several design options of a DDBM or its individual building blocks in each phase. Tools and methods support these activities following a divergent logic. At the end of each phase, a decision is made for one option of multiple DDBM designs or their elements and/or to continue with this option. Throughout a business model innovation, selection decisions are made on a more granular and specific level (e.g., selecting one type of revenue model at a later stage). These activities are supported by tools or methods following a convergent logic. The next two research chapters investigated supporting tools, methods, and concepts for idea generation (RQ2) and evaluation (RQ3) related to divergent and convergent thinking.

Summary of research question two: How can we support idea generation and design during a data-driven business model innovation?

To answer this research question, we first have developed a matrix that helps to categorise existing data-driven innovation ideas and guides the direction of idea generation workshops. Next, we have crafted the Data Product Canvas, a visual collaborative tool to structure idea generation workshops and document ideas for DDBMs. The canvas focuses on the value proposition of a DDBM, as the value creation logic is different from traditional business models. We further investigated the data-based value creation logic by developing an ontology in more detail. Finally, we developed a framework of involved actors and exchanged values in a DDBM to bring the key partner perspective into idea generation.

We have evaluated and applied the tools in several workshops within *Comp* and other organisations. The tools were perceived as useful and sufficient to generate ideas for a data-driven business. Due to their usefulness, adapted versions have been offered on the *Business Makeover* platform[50], demonstrating practitioners' interest. Nevertheless, we have not evaluated a method of use, i.e., how to use these tools in combination as part of this thesis. This would be one next step based on the results of this thesis (see Section 7.5.3 on page 226).

As mentioned before, we have developed idea-generation tools specific to DDBMs. Practitioners need to understand the specific characteristics of new business models, such as DDBMs (e.g., patterns, the data-based value creation logic, types of value propositions, data sources or analytics key activities). DDBM-specific tools can help practitioners be aware of these characteristics in the idea generation and design phase. The most important aspect is that the offerings of DDBMs

[50] https://businessmakeover.eu/tools/safe-deed-data-driven-business-canvas accessed on 10.05.2022, 15:21.

support customers in their decision-making problems. Further, possible characteristics of one DDBM element can also support the idea generation process, e.g., by providing cards as an add-on to a canvas (see Breitfuß *et al.*, 2023 and outlook of Section 5.2) or listing essential roles to identify key partners (see Leski *et al.*, 2021 and Chapter 5.4). However, for experienced users, generic tools, such as the Business Model Canvas, would also be sufficient to generate good DDBM designs.

Visual tools described in Chapter 5 fulfil three functions: First, they help analyse, classify, or visualise the current situation in a company or business model (e.g., existing ideas). Second, they help to guide practitioners in generating new ideas. Third, they also help evaluate ideas using the value creation logic or a list of characteristics for one DDBM element. For further research, one may develop reflective questions for each tool to implement the first evaluation as part of the method of use:

- “Have we considered all elements?”
- “Has the business model design internal consistency?”
- “Are there other possibilities for improving the business model design?”

These considerations on evaluating a DDBM design lead us to the discussion of research question three.

Summary of research question three: How can we support evaluation, decision-making and risk management during a data-driven business model innovation?

Our literature review in Chapter 4.1 and Fruhwirth *et al.* (2020c) revealed that little research has been conducted on evaluation and risk management in DDBMs. In this review, we proposed a promising avenue for further research: Designing decision support for evaluating DDBMs and investigating criteria and risks specific to DDBMs. We have done this in Chapter 6 to address research question three of this thesis: First, we identified evaluation criteria for DDBMs and instantiated them in a visual tool. In the rest of Chapter 6, we investigated one risk factor specific to DDBMs in depth. In a case study with *Comp*, we identified knowledge risks as a new type of risk in DDBMs. Data-based value objects are exchanged in DDBMs, which can lead to unintentional exposure of critical information or knowledge. We designed and evaluated a tool to identify such risks in a network-based representation of DDBMs. Further, we investigated the nature of knowledge risk in an expert interview study. As a protection measure, we discovered types of data marketplace business models. To our knowledge, this thesis is the first piece of research investigating evaluation and risk management specific to DDBMs.

We gave only a short overview of evaluation criteria for DDBMs in this thesis and performed only a “light” evaluation within *Comp*. Thus, in this direction, there is enough space for further research. However, we also conducted extensive research with external experts and data regarding knowledge risk, leading to reliable results. The evaluation of the tool's effectiveness is merely missing as a methodological limitation (see also Chapter 7.4, page 214). One important aspect that remains unanswered in Chapter 6 is how to quantify the risks and evaluate DDBMs quantitatively. We will write more about this topic in the outlook of this thesis (see section 7.5.1 on page 223).

Specific types of business models (e.g., DDBMs, car-sharing business models, or blockchain business models) can involve new types of risks due to new technologies or a new value-creation logic. However, this opens opportunities for researchers in business model risk management. Therefore, we propose a four-step approach for researchers dealing with new business model risks based on our experience and results in Chapter 6:

1. Identify a new risk for one type of business model (e.g., DDBMs) in case studies or collaboration with companies. It is also possible to identify such risks theoretically (e.g., through reasoning about the impact of new technology), and then one should ensure its practical relevance.
2. Understand the nature of the risk and provide a (theoretical) framework as a basis for discussion and common language (e.g., investigating types of data-based value objects and their implications on knowledge risks with expert interviews).
3. Design and evaluate a tool to identify the risk in a business model design (in addition to a generic “checklist” with all types of risks) (e.g., by using a network-based representation to identify critical flows of data-based value objects that could lead to knowledge risks).
4. Identify and take appropriate measures in the business model design (e.g., using data marketplaces to enable data exchange without exposing critical information or knowledge).

In this thesis, we have shown how to design tools, concepts, and processes to support the development of DDBMs. In detail, we investigated supporting idea generation and identifying knowledge risks. We provide design knowledge that other researchers and practitioners can reuse.

7.2 Overall Reflection and Contribution

The contributions of this thesis can be summarised in three directions: contributions regarding the design of business model innovation processes (section 7.2.1), contributions regarding the design of supporting tools and methods (section 7.2.2) and contributions regarding the understanding and design of data-driven business models (section 7.2.2). Table 7.1 summarises the contributions of this thesis.

Directions	Contributions
Contributions Regarding Process Design	• Contribution 1: Three design principles for a business model innovation process: ○ Structure the process along investment decision points ○ Support convergent and divergent thinking within each phase ○ Enable organisational learning • Contribution 2: Tools and methods bring the specific aspects of DDBMs into the process
Contributions Regarding Tool Design	• Contribution 3: DDBM-specific tools are adapted versions of generic Business Modell Innovation tools that incorporate the specific knowledge and properties of DDBMs • Contribution 4: The underlying theoretical concept must be understood when designing tools.
Contributions Regarding Understanding and Designing DDBMs	• Contribution 5: Data-driven business models generate customer value by using a data product to support a customer's decision problem. This value-creation logic has to be kept in mind when designing new DDBMs. • Contribution 6: Exchanging data, models and predictions in a DDBM can induce the risk of leaking critical knowledge. This risk needs to be considered already during the design of DDBMs. • Contribution 7: Designing and Implementing DDBMs requires a multi-disciplinary approach

Table 7.1: Overview of contributions of this thesis.

7.2.1 Contributions Regarding Process Design[51]

In this thesis, we make two contributions regarding the design of a business model innovation process. In general, designing a business model innovation process can be viewed from two perspectives: what the users expect from a process (design requirements) and how to design such a process (design principles). This thesis contributes three salient design principles that are not specific to DDBMs and can be transferred to other types of business models in a similar organisational context (*Contribution 1*). The second contribution is the understanding that activities and tools bring in the specifics of DDBMs to a business model innovation process (*Contribution 2*).

[51] This section is based on Chapter 4.2, which included a reflection and discussion of the design process and the corresponding publication - Fruhwirth, M., and Pammer-Schindler, V. (2023): “Towards Principles for a data-driven business model innovation process – a design science case study” in Proceedings of the 36th Bled eConference – Digital Economy and Society: The Balancing Act for Digital Innovation in Times of Instability, A. Pucihar, M. K. Borštnar, R. Bons, G. Ongena, M. Heikkilä, D. Vidmar (eds.). June 25 – 28, 2023, Bled, Slovenia, pp. 545-560. **Awarded with the outstanding paper award**

Contribution 1: Three design principles for a business model innovation process

Design Principle 1: Structure the process along investment decision points: Based on the insights generated in this thesis, we suggest that a process should be structured along with management (investment) decision points and criteria that inform these decisions. This principle follows a structured innovation approach (Wirtz et al., 2016) and reflects offline-established organisations' management steering and hierarchical control structure (Rummel et al. 2022). Our findings align with Lange *et al.* (2021), who found that incumbent organisations use Stage-gates for a stop-or-go decision during DDBM innovation. Also, Geissdoerfer (2019) found evidence that “milestones” and “gates” are used to structure sustainable business model innovation in practice. Nevertheless, the literature has neglected to define specific decision points apart from Tesch *et al.* (2017), who empirically investigated decision points and criteria in business model innovation. In this thesis, we have also investigated evaluation and decision criteria for DDBMs in general and knowledge risks as one specific risk in detail.

Design principle 2: Support convergent and divergent thinking within each phase: Based on the insights generated in this thesis, we suggest that a process design should support cyclic convergent and divergent thinking within each phase. This principle reflects the iterative and agile nature of digital innovations in general (Ghezzi and Cavallo, 2020; Rummel *et al.*, 2022) and DDBM innovation in particular. In Chapter 4.1, we have already structured existing tools and methods to support convergent and divergent thinking. Further, this principle aligns with research on DDBM innovation processes, as Hunke *et al.* (2017) already visualise convergent and divergent thinking parts in their process structure. In general, cyclic divergent and convergent thinking relate to topical approaches such as Design Thinking and Lean Start-Up for business model innovation (Brown, 2008; Ries, 2011; Rummel *et al.*, 2022).

Nevertheless, there is a tension between these two design principles, i.e., the required iterative and flexible character (within each phase) with alternating divergent and convergent activities and the strict stage-gate logic (at the gates between the phases) to release further resources or terminate a DDBM innovation. Other literature has addressed this issue, e.g., Cooper and Sommer (2016) found that IT and manufacturing firms combined agile development methodologies and Stage-Gate approaches for software or physical product development. Rummel *et al.* (2022) found that manufacturing firms with a B2B business model use hybrid agile and Stage-Gate models for their business model innovation process in digital transformation. Also, a recent study on the organisational implementation of AI (Hopf *et al.*, 2023) found this tension between an agile and structured management approach.

Design principle 3: Enable organisational learning: Based on the insights generated in this thesis, we suggest that a process design should enable organisational learning, as our third design principle states. This principle reflects what we observed in our case study with Comp: DDBM innovations often happen bottom-up in the departments with customer interactions, as domain experts are often close to the (decision) problem that can be addressed with a data analytics solution. Therefore, they generate learnings and insights about DDBM innovation that need to be transferred to the organizational system. These domain experts also need the skills and tools for business model innovation to develop new DDBMs successfully. Thus, by incorporating best practices and learnings, a business model innovation process can be the vehicle for knowledge transfer from individuals to the organization and vice-versa (Sosna et al. 2010). Offline established organizations require such tools and methods (as studied in this thesis) to transfer knowledge on DDBMs to specialized departments within the organization. According to Berends *et al.* (2016), business model innovation emerges through a combination of different learning mechanisms, in particular, cognitive search via business model design (e.g., Osterwalder and Pigneur, 2010) and experimental processes via effectuation (e.g., Sosna *et al.*, 2010). Our principle also relates to recent research (Wu and Wang, 2023), which focused on knowledge management and organisational agility in data-driven business models during the digital transformation of healthcare organisations (Wu and Wang, 2023).

Contribution 2: Tools and methods bring the specific aspects of DDBMs into the process

These design principles of our *Contribution 1* are not specific to DDBMs. They can be transferred to processes for other types of business models in similar contextual settings. On a more specific level, regarding the configuration of its features - the activities and tools – the process presented in this thesis is very specific for DDBMs, as the tools and activities bring in necessary knowledge for DDBMs. Thus, the second contribution of this thesis is that tools and methods bring the specific aspects of DDBM into the process. Previous work (e.g., Hunke *et al.*, 2017; Rashed and Drews, 2021) already showed that the activity level shapes the specific characteristics of DDBMs in a process. Thus, tools and methods support the activities within each phase and bring in the knowledge and specifics for a business model, such as DDBMs. Organisations and individuals can learn about the characteristics of this new type of business model by suggesting DDBM-specific activities, tools, and methods. Recent literature has investigated DDBM-specific activities during business model innovation (Lange and Drews, 2020; Rashed and Drews, 2021). Also, in this thesis, we have analysed the literature on and designed several tools specific to data-driven business models.

7.2.2 Contributions Regarding Tool Design

Overall, we have seen that tools also need a method of use to instruct practitioners how to use them. Further, the tools must be embedded into the superior process and activities. DDBM-specific tools can be understood as adapted versions of generic business model innovation tools that incorporate the specific knowledge and properties of DDBMs (*Contribution 3*). The underlying theoretical concept must be understood when designing specific business model tools (*Contribution 4*).

Contribution 3: DDBM-specific tools are adapted versions of generic Business Modell Innovation tools that incorporate the specific knowledge and properties of DDBMs

DDBM-specific tools are special manifestations of general tools tailored to DDBM that bring in the specific knowledge and properties of DDBMs. The Data Product Canvas (Chapter 5.2) is a specialized representation of a component-based canvas (Osterwalder and Pigneur, 2010; Osterwalder *et al.*, 2014). Further, our framework of actors and exchanged values (see Chapters 5.4 and 6.2) can be viewed as a specialized adaption of network-based representations of business models (Brillinger, 2018; Gordijn and Akkermans, 2001) with DDBM-specific actors (e.g., data marketplaces) and DDBM-specific exchanged values (e.g. data, models and predictions). In particular, we contributed in Chapter 6.2 the requirements to represent the flow of data and knowledge as value objects and to represent the knowledge boundary to identify knowledge risks. These specialized representations allow the analysis of specific properties of DDBMs, such as knowledge risks (see Chapter 6.2). In other cases, such as the SWOT analysis (see Figure 4.9), the tool and its method of use remain the same, but additional guiding questions specific to DDBMs are provided based on the learnings from the case study. This contribution also aligns with Zolnowski (2015), who adapted a generic business representation to a more specific problem context: supporting the design of Service Business Models.

Contribution 4: The underlying theoretical concept must be understood when designing tools.

Each tool depicts a theoretical concept or knowledge of DDBMs that needs to be understood during tool design. This knowledge can be retrieved from the knowledge base (i.e., prior studies in the literature) or the application context (i.e., as an empirical study) as part of the design science research project. In Chapter 5.3, we have developed an ontology of the data-based value creation logic based on the literature. This ontology can inform the tool design of an adapted version of the Data Product Canvas. In Chapter 6.3, we empirically studied knowledge risks in DDBMs via 28 expert interviews. Those insights inform a visual tool to identify knowledge risks in DDBM by providing types of risks, contextual factors and protection measures that support managing knowledge risks.

Other studies have implicitly followed this approach of using a theoretical concept as a basis for tool design: Kiefer *et al.* (2020) used the taxonomy of Hunke *et al.* (2019) as a theoretical basis for their Analytics-Based Service Canvas. Further, the Ontology of Osterwalder (2004) formed the theoretical basis for the Business Model Canvas (Osterwalder and Pigneur, 2010). Avdiji *et al.* (2020) formalized this approach in their design theory for visual inquiry tools as their first design principle: *“The first step toward the development of the tool is the creation of a conceptual model that frames and articulates a management concept of interest.”* (Avdiji *et al.*, 2020, p. 21). Others followed his recommendation in the context of DDBM and created an ontology as part of their design process (e.g., Kayser *et al.* 2019; Kronsbein and Mueller, 2019).

7.2.3 Contributions Regarding Understanding and Designing DDBMs

As part of this thesis, we have also investigated several theoretical phenomena and characteristics of data-driven business models as part of supporting tools, methods and concepts. We have learned that DDBMs generate customer value using a data product to support a customer's decision problem (*Contribution 5*). Further, when exchanging data, models and predictions in a DDBM, there is the risk of leaking competitive knowledge, which needs to be considered during the design of a DDBM (*Contribution 6*). Finally, we have learned that designing and implementing DDBMs requires a multi-disciplinary approach (*Contribution 7*).

Contribution 5: Data-driven business models generate customer value by using a data product to support a customer's decision problem. This value-creation logic has to be kept in mind when designing new DDBMs.

In this thesis, we showed that data-driven business models have a special customer value creation logic: Via data analytics, insights are generated from data that are packed in a data product that the customer can use to support his decision problem. By using the data product, the customer generates value-in-use, whereas the provider can only propose a value. In return, the provider earns some monetary or non-monetary benefits. Hunke *et al.* (2021a) have also studied how customer value is generated in analytics-based services: by making data usable, delivering data-based insights, providing recommendations, or enabling novel ways of business. Lim *et al.* (2018) also investigated data-based value creation in information-intensive services. They also state that value is generated in information use. Our contribution is also in line with Rashed *et al.* (2022), who stated that *"the generated value must be kept in focus throughout the DDBM innovation initiative".* Generating customer value from data can either follow a data- or business-first approach (Stahl *et al.*, 2023).

This understanding of DDBM and its value creation logic emerged over time through this research, particularly during the interaction with the companies and continuously reflecting the literature. We formalized this understanding of the data-based value creation logic in the ontology of chapter 5.3. This insight also connects to Contribution 4, as this (theoretical) understanding of the data-based value creation logic formed the basis for the design of the Data Product Canvas, presented in Chapter 5.2.

Contribution 6: Exchanging data, models and predictions in a DDBM can induce the risk of leaking critical knowledge. This risk needs to be considered already during the design of DDBMs.

In this thesis, we found that data-driven business models lead to new types of risks and studied one specific risk in detail: the leakage of knowledge through the exchange of data, models and predictions (see Chapters 6.2 and 6.3). Our contribution is that the risk of knowledge leakage by exchanging data-related value objects is a relevant risk factor in DDBMs and can be a barrier to the adoption of DDBMs. Knowledge risks in DDBMs differ from those associated with traditional business models, as competitive knowledge is materialized in data or (AI) models, making knowledge more explicit to transfer. We found that the risk depends on the exchanged value object and contextual factors and proposed several strategies to address the risk. Our contribution is the insight that considering knowledge risks already in the business model design and understanding the choice of value objects as a possible knowledge protection measure can help to address this risk. Further, a balanced view between sharing and protecting knowledge is necessary.

With this contribution, we address the gap outlined in Chapter 4.1 to address specific risks in data-driven business models, and overall, with that, we contribute risk to the theoretical understanding of data-driven business models. Knowledge risks have been studied in adjacent fields such as data-centric collaborations (Zeiringer and Thalmann, 2022) or digital transformation (Ilvonen *et al.*, 2018). Such risks must be considered already during the design of a business model (Brillinger *et al.*, 2020). Thus, with our findings, we contribute a new risk that could occur in a DDBM and extend the existing debate on data privacy and security in DDBMs (e.g., Azkan *et al.*, 2022; Schäfer *et al.*, 2023a). We add the perspective of competitive knowledge that needs to be protected to this debate. Thus, it is important to be aware of the protection that multi-disciplinary teams can achieve.

As we have already stated in Chapter 6.3, this contribution also relates to current literature streams in the context of data-driven business models: (i) data privacy and security in DDBMs (e.g., Schäfer *et al.*, 2023a), (ii) enhancing inter-organisational data sharing via data intermediates and trust-enhancing technologies (e.g., Agahari *et al.*, 2022; Stachon *et al.*, 2023), and (iii) the advancement of data-driven business models towards AI-based business models (e.g., Kanbach *et al.*, 2023).

Contribution 7: Designing and Implementing DDBMs requires a multi-disciplinary approach

Based on the findings of this thesis, we propose that designing and implementing a DDBM requires a multi-disciplinary approach and data science skills at the top management level. In Chapter 5.2, we found that generating ideas for DDBMs and data products requires experts from both the business and data domains. For designing a data product, i.e., a compelling value proposition for a DDBM, the needs of the customers (business view) and what is technically possible (data view) are necessary. To address this potential gap we have designed the Data Product Canvas

(Fruhwirth *et al.*, 2020a) and later the Data Service Cards (Breitfuß *et al.*, 2023) as interventions to bridge these domains.

Further, in Chapter 6.3, we proposed that managing knowledge risks in DDBM requires a multi-disciplinary approach from a legal, business, organisational and technological perspective, which means that technology and strategic business decisions must go hand in hand. We found that assessing the risk differentiated and balancing sharing and protecting knowledge in a DDBM is important, as there is sometimes fear, insecurity or overcautiousness regarding sharing data-related value objects. This fear can be overcome via an interdisciplinary approach.

Our contribution aligns with Rashed *et al.* (2022), who state that *"DDBM innovation initiatives must be conducted by interdisciplinary and rather stable teams with end-to-end responsibility"*. Also, Stahl *et al.* (2023) state that innovating DDBMs requires multiple capabilities that need to be developed. Similarly, Hopf *et al.* (2023) recently found that successfully implementing DDBMs and AI requires top management with basic AI and ML skills and senior data science who are deeply involved in developing new business models.

7.3 Reflection on Methodology

In this thesis, we followed Design Science Research (Hevner *et al.*, 2004) as the overall research paradigm of this thesis. DSR aims to develop new and innovative solutions (i.e., artefacts) for a certain class of problems, i.e., in our case, how to support designing and evaluating data-driven business models in offline-established organisations. In the following, we will reflect on the research approach of this thesis using the seven criteria that Hevner *et al.* (2004) recommended for Design Science Research.[52]

Guideline 2 - Problem Relevance: Design Science Research aims to develop solutions, i.e. artefacts for relevant and important business problems (Hevner *et al.*, 2004). Generating new business (models) with data has been stated as a relevant business problem both in research (e.g., Günther *et al.*, 2017) and practice (e.g., Seiberth and Gründinger, 2018). An early interview study (Fruhwirth *et al.*, 2018; not included in this thesis core) and our case study confirmed the challenge of developing data-driven business models in offline-established organisations and that supporting tools, methods and processes are needed. Exploring the literature at an early stage of this PhD thesis (see the structured literature review presented in Chapter 4.1 and Fruhwirth *et al.*, 2020c) and our interactions with an offline-established organisation (*Comp*) in the case study enabled us to formulate research questions addressing both gaps in the literature and problems of practical relevance. The practical relevance has further been confirmed in the interactions with other organisations, whether in interviews or workshops.

Guideline 6 - Design as a Search Process: Hevner *et al.* (2004) argue that design is a search process to discover an effective solution for a problem out of a set of possible solutions. Therefore, one might decompose a problem into simpler sub-problems. Progress in this problem-solving activity is made iteratively as the scope of the design problem is expanded. The research presented in this PhD thesis can also be seen as a search process structured along the design cycles presented in Section 3.2.3 and Figure 3.2. We iteratively identified problems of practical relevance, designed and evaluated artefacts and applied them to the application context (*Comp*). This was especially possible because we combined Design Science Research with a case study approach. At distinct points, we investigated a certain aspect or problem in-depth outside the DSR cycles and the case study, such as developing a taxonomy of data marketplaces. For designing specific artefacts, we also followed well-established research methods (as Figure 7.1 illustrates), e.g., by following the phases of Peffers *et al.* (2007) to design and evaluate the Data Product Canvas as part of Design Cycle 2 (see Chapter 5.2).

One good example of this iterative search process was the perspective of knowledge risks. We instantiated a DDBM with a network-based representation in the context of *Comp* and identified that knowledge risks can be a potential risk in DDBMs (see Chapter 6.2). To further understand the

[52] We used here the numbering of the guidelines as proposed in Hevner *et al.* (2004).

problem, we conducted an explorative interview study and identified types of risks, influencing factors and protection measures (see Chapter 6.2). Finally, we investigated data marketplaces, one potential protection measure in depth (see Chapter 6.3).

Thus, summing up, our research approach can be viewed from two angles: We followed the iterative design cycles proposed by Hevner (2007) in the case study context from one angle. From the other angle, we followed well-established research methods for sub-problems and aspects in this thesis.

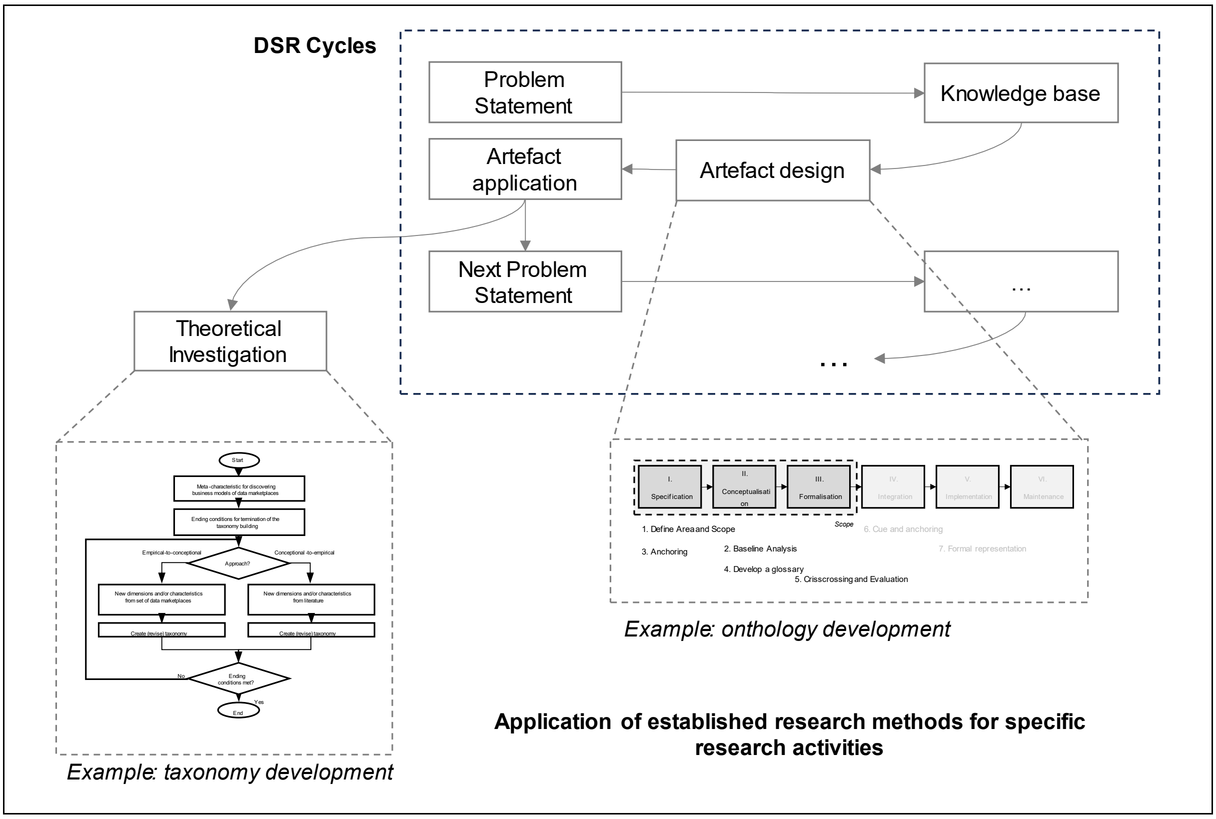


Figure 7.1: Visualisation of the sequential design cycles and application of established research methods for theoretical investigations outside the cycles (left) and for the artefact design within one cycle (right).

Guideline 1 - Design as an Artifact: Hevner *et al.* (2004) stated in their guideline that DSR needs to produce a viable artefact. Within this thesis, we have produced not only a single but multiple artefacts that support organisations in developing data-driven business models. Our considerations for artefacts started with visual tools that support idea-generation activities. Later, we also investigated specific concepts, like knowledge risks. Finally, we aimed to reflect and synthesize all artefacts and acquired design knowledge into design principles, requirements and features of a business model innovation process. One could argue that the design principles represent a "meta-artefact".

In contrast, the developed tools and concepts that are connected to certain design features and phases of the process can be depicted as "sub-artefacts". Other PhD theses in the context of digital business models have also followed this multiple artefact strategy. For example, Terrenghi (2019) and Tesch (2019) empirically investigated aspects of a business model innovation process and designed tools and methods that support the development of business models for Cyber-Physical Systems and the Internet of Things.

Another research approach for a thesis would have been to focus on a single artefact. This approach would have allowed a more rigorous design and evaluation of the single artefact. Dedicated chapters and papers of such a thesis would have covered evaluation studies (e.g., workshops, experiments) and identified requirements via a structured literature review or an explorative interview study. Other PhD theses have followed such single artefact approaches in the context of business models. For instance, Osterwalder (2004) developed a business model ontology in his PhD thesis. Zolnowski (2015) developed in his PhD thesis an adapted version of the Business Model Canvas for Service Business Models, and Kühne (2021) designed s and evaluated in her PhD thesis the Data Insight Generator, a canvas to support the design of data-driven business models.

Deciding for a single artefact strategy would have also allowed us to follow, for instance, the DSR framework from Sonnenberg and Vom Brocke (2012), who suggested performing multiple evaluations in the course of a DSR project, starting with evaluating the problem until evaluating the artefact in a real-world context.

Nevertheless, to reach the research goal of this thesis, it was necessary to investigate multiple artefacts, which is also reflected in the three research questions. In our DSR cycles, we were able to identify multiple problems (e.g., how to support idea generation, how to identify and manage risks) and to provide several artefacts, such as instantiations (e.g., the Data Product Canvas as a visual collaborative tool), constructs (e.g., a taxonomy of business models for data marketplaces), and conceptual models (e.g., the data-based value creation logic).

Guideline 5 - Research Rigor: Hevner *et al.* (2004) further stated that DSR must rely on applying rigorous methods. In this thesis, we used well-established methods for specific activities within the DSR cycles, such as Nickerson *et al.* (2013) for developing a taxonomy, Webster and Watson (2002) and Vom Brocke *et al.* (2009) for conducting a structured literature review or Fernández-López *et al.* (1997) and Kishore *et al.* (2004) for crafting an ontology. Nevertheless, we must note that the same level of rigour could not be reached in all research sub-studies. This is because we also followed a multiple artefact approach (see our reflection on Guideline 1) and iteratively identified and explored problems of practical relevance (see our reflection on Guideline 6), and it was not possible to conduct all design sub-studies with the same rigorous approach in the scope of this thesis. We denote this as a limitation of this thesis (see Limitation 4 in section 7.4).

Guideline 3 - Design Evaluation: Hevner *et al.* (2004) also pointed out that a design artefact needs to be rigorously evaluated, e.g., its utility or efficacy, via evaluation methods. We have already reflected on evaluation methods in the methodology chapter (see section 3.1.4). We evaluate the artefacts presented in this thesis using different methods (e.g., workshops for the Data Product Canvas or expert interviews for our network-based representation) and in different depths (e.g., number of evaluation steps or participants). The evaluation happened within the case study and outside with experts and company representatives. Overall, our goal was to use and evaluate the artefacts in a naturalistic way, i.e., with target users from offline-established organisations that aim to develop data-driven business models. Nevertheless, we also see a major limitation of this thesis in the artefact evaluation, which we will reflect on in the limitations (see Limitation 2 in Chapter 7.4).

Guideline 4 - Research Contributions: Hevner *et al.* (2004) states that effective design science research needs to contribute in one or more of the following directions: (i) design artefact, (ii) extending existing foundations in the knowledge base, and/or (iii) methodology (e.g., new evaluation methods or metrics). We have already reflected on the contributions of this thesis in section 7.2 (Overall Reflection and Contribution). In our thesis, we provided multiple artefacts, whereas the design principles can be seen as some kind of "meta-artefact". We refer here to the reflection on guideline 1 above (Design as an Artefact). As stated in section 7.2, we also contribute to the understanding and design of data-driven business models. Thus, we provide valuable foundations for other tool designers and/or practitioners aiming to develop new DDBMs by contributing (i) design artefacts and (ii) extending existing foundations on data-driven business models.

Hevner *et al.* (2004) also highlighted the importance of instantiating design artefacts. In this thesis, we instantiated artefacts in a way that they can be used by practitioners directly. In particular, we refer here to the Data Product Canvas, where we provided a template that can be directly used in workshops and a method of use that explains how to use it.

Finally, Hevner *et al.* (2004) state that Design Science Research need to solve an important, previously unsolved business problem. As our reflection on Guideline 2 (Problem Relevance) stated, we could address a topical business problem in this thesis. Especially regarding knowledge risks in data-driven business models, we addressed a problem that has not been studied before and provided both an artefact (i.e., a network-based representation to identify knowledge risks) and a framework with protection measures to solve the problem.

Guideline 7 - Communication of Research: Hevner *et al.* (2004) suggest that DSR need to be effectively communicated. Overall, the activities, artefacts and outcomes of the DSR cycles have been published in two journal publications (one still under minor revision), six peer-reviewed conference contributions and one research-in-progress workshop paper that are publicly available. Target readers are practitioners and researchers from Information Systems and Business Modelling. Table 1.1 in the introduction shows the connection of the thesis chapters to the publications, and Table 3.1 links the chapters to the corresponding DSR cycles. Only the two introductory chapters 5.1 and 6.1, and the research chapter 5.3, have not been published.

7.4 Limitations[53]

This section will discuss the limitations of this thesis and its results and contributions. Typically, limitations result from the selected research approach and methods, the novelty of the topic, or the evaluation settings.

Limitation 1 – Single Case: One decision we have made in the research design of this thesis was to ground the empirical part in a three-year single case study with one organisation from the automotive industry (*Comp*). This had the advantage of having access to rich data from the organisation and having the opportunity to actively participate in data-driven business model innovations without any issues regarding confidentiality compared to acting with multiple companies. On the other hand, this approach delimitates making generalized statements based on our results, as substantial parts of this thesis originated from the case study. Nevertheless, we addressed this limitation by also approaching experts and organisations outside *Comp* for certain aspects: We evaluated some of our artefacts on a broader basis by also consulting external experts (e.g., for the network-based representation, see Chapter 6.2 and Fruhwirth *et al.*, 2021b) or conducting evaluation workshops with other offline-established organisations (e.g., for the Data Product Canvas, see Chapter 5.2 and Fruhwirth *et al.*, 2020a). Also, the external experts and practitioners confirmed the relevance of the problems addressed in this thesis and the usefulness of the designed tools, methods and processes.

This limitation particularly affects our results from Chapter 4.2 (design requirements and design features of a data-driven business model innovation process.). We addressed the single case study limitation in this study, as we aimed to generalise our results through reflection and abstraction to craft three design principles as the main contribution of this chapter. Further, we discussed these principles with respect to current literature and described how these appear in other similar processes.

Also, the evaluation or demonstration of the artefacts developed in the “smaller” research studies (Chapters 5.1, 5.4, and 6.1) has been conducted only within the case company. Nevertheless, these studies contributed little to the overall contributions of this thesis as they are more or less “introductory” studies and build the bridge between the research questions.

Limitation 2 – Evaluation: The second limitation lies in the evaluation of our artefacts, in particular regarding their effectiveness and the number of evaluation participants in some cases. Further, with the evaluation conducted, we cannot make a statement in this thesis about how well our artefacts support data-driven business model innovation compared to other interventions or the absence of any innovation. This limitation regarding evaluation is due to our multi-artefact strategy,

[53] Parts of this section are based on the respective research papers and the text on their limitations. We will indicate this in the corresponding paragraphs.

which we have already reflected in Section 7.3 above. We already considered conducting experiments as an evaluation method to compare the effects of our artefacts with other interventions (e.g., for the network-based representation from Chapter 6.2). We decided not to conduct such experiments for one reason: The target users of our artefacts are executives and business managers with many years of professional experience. This focus implies that the number of evaluation participants was sometimes very limited. However, for experiments, one would recruit students as evaluation participants for economic reasons and availability.

In our study presented in Chapter 4.2, we did not formally evaluate the process, although we discussed interim outcomes and the final process design with responsible managers of *Comp*. One fruitful evaluation for future research here would be to show how our process improves the performance and outcome of a DDBM innovation. 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). A challenge in comparative field studies will be to find suitable cases that can be followed throughout a longer period.[54]

Further, our evaluation of the Data Product Canvas (Chapter 5.2) via workshops is not comparative. We, therefore, cannot state whether or how much it better supports idea generation in data-driven business model innovation compared to other artefacts. However, our evaluation approach allowed us to recruit target users of our artefact as evaluation participants since they supported exactly the target group (company representative) in their ongoing tasks (identifying opportunities for data-driven (business model) innovations). In the workshops, the participants developed DDBM ideas for their respective companies and participated in the workshops because this was currently a task for them. Furthermore, a large part of the data collected in the workshops is based on observations of the involved researchers; hence, the results might show a bias towards the expectation of the researchers, who are also the designers of the artefact, that the intervention works.[55]

For the evaluation of our data-based ontology presented in Chapter 5.3, future research could look deeper into relevant evaluation criteria for ontologies and evaluate our ontology with expert interviews and a larger number of use cases. Also, the major limitation of Chapter 5.4 is the sparse evaluation, which is only conducted by three experts from one company (our case company). The framework should be applied to more cases from multiple industries to improve this framework and make our results more generalizable.

[54] This paragraph is based on Fruhwirth, M., and Pammer-Schindler, V. (2023): “Towards Principles for a data-driven business model innovation process – a design science case study” in Proceedings of the 36th Bled eConference – Digital Economy and Society: The Balancing Act for Digital Innovation in Times of Instability, A. Pucihar, M. K. Borštnar, R. Bons, G. Ongena, M. Heikkilä, D. Vidmar (eds.). June 25 – 28, 2023, Bled, Slovenia, pp. 545-560. **Awarded with the outstanding paper award**

[55] This paragraph is based on Fruhwirth, M., Breitfuß, G., and Pammer-Schindler, V. (2020): “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.

Overall, comparative evaluation methods, such as experiments, would require many participants; students are often recruited in practice. With the evaluation approaches in this thesis, we involved target users of our artefacts, i.e., experts and practitioners responsible for (data-driven) innovations.

Limitation 3 – Not all studies of this thesis have the same level of rigour in their research approach. One limitation is induced by the overall research design of this thesis. We have identified (research) problems through our design cycles and conducted sub-DSR projects or sub-research studies. Some research problems have been investigated in-depth with a rigorous methodological approach, whereas other studies have been conducted in a more lightweight way. In particular, this limitation concerns Chapters 5.1 and 6.1, denoted as "introductory studies" in this thesis that describe the broader context in idea generation and evaluation. Further, the study presented in Chapter 5.4 has also been conducted lightweight and builds the bridge between idea generation and risk chapters. We noted this limited rigorous approach as a limitation of the respective chapters.

We have considered this limitation in the formulation of the overall contributions of this thesis. The contributions of this thesis, presented in Chapter 7.2, are packed with insights from the more rigorous studies presented in Chapters 4.1, 4.2, 5.2, 5.3, 6.2 and 6.3.

Limitation 4 – A long period has passed since some studies have been conducted, combined with the fast development and advancement of the DDBM topic. One additional limitation of this thesis was that the research of some parts of this thesis was conducted four to five years ago. This is particularly challenging in rapidly changing technologies such as (big) data analytics and artificial intelligence. Starting our research on data-driven business models in 2019, little was available, particularly with regard to tool support, as the literature review from Chapter 4.1 revealed. Five years later, the field has moved on, and a lot more is available.

In particular, this limitation concerns the studies presented in 4.1 (structured literature review) and 6.4 (taxonomy of data marketplaces) that were completed in 2019. Nevertheless, with the two corresponding papers, we could contribute to the knowledge base early in the research field, which is also reflected in the number of citations (57 and 43 as of March 2024).

In 2024, much more is available in the knowledge base concerning process models and the understanding of data-driven business models. Figure 7.2 illustrates the number of publications containing the term "data-driven business model" retrieved from the major IS database AIS eLibrary[56]. We can see a strong increase since 2018, with a decline in 2020 that the COVID pandemic could have caused and a decline in 2023 that could be caused by the switch of research interest from data-driven business models to AI-based business models.

[56] https://aisel.aisnet.org/

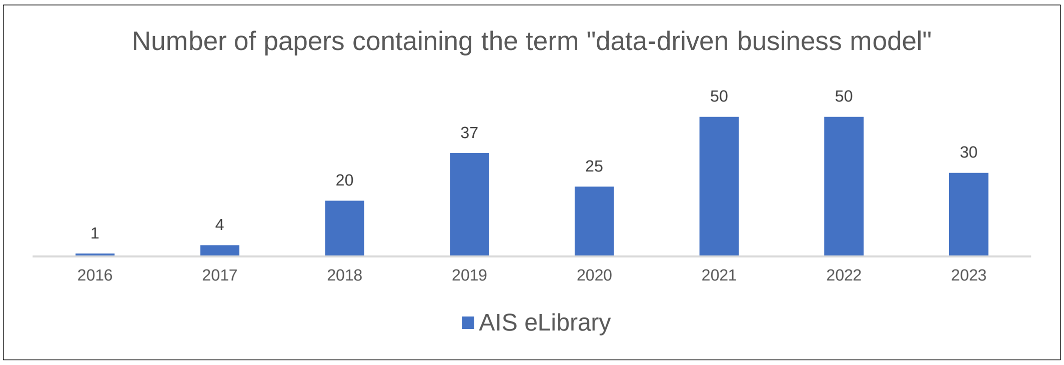


Figure 7.2: Number of publications containing “data-driven business model” retrieved from AIS eLibrary database (status February 2024).

Furthermore, as mentioned before, we recently observed a transition of the topics, e.g., from data-driven business models to AI-based business models or from data marketplaces to data spaces. We will reflect on that development in AI and the implication for future research in section 7.5.4 of this thesis.

Overall, we have addressed this limitation in the thesis by including recent papers in the respective chapter discussions to connect our findings with the advancements in the field and the current status of the knowledge base. This was particularly important for studies that had already been conducted a few years ago.

7.5 Outlook

During this PhD thesis, we identified four promising directions for further research that we only touched on in this thesis. First, there is a need for quantitative methods to evaluate (data-driven) business models. Second, other researchers should design IT-based tools to support data-driven business model innovation. Third, it is necessary to design interventions to introduce business model tools, methods, and processes to organisations. Finally, with the advancement in machine learning and artificial intelligence - AI that is now data-driven - we see further development from data-driven towards AI-based business models.

7.5.1 Using Quantitative Methods for Evaluating Business Models

In practice (as we have also experienced in our case study), business model designs are often evaluated qualitatively (e.g., through customer interviews or SWOT analysis). Also, the evaluation methods described in Chapter 6 have a qualitative character. Qualitative evaluation results are converted into a Likert scale using the decision support system described in Chapter 6.1 based on expert assessments. In some situations, management also wants to inform their investment decisions based on quantitative data, such as an estimated return on investment. It is also unclear what threshold must be reached for quantitative criteria for a go-decision (e.g., number of lead customers acquired or interviews conducted).

A structured literature review by Tesch and Brillinger (2017) differentiates between qualitative and quantitative evaluation methods. Examples of the latter are market simulations (Kauffman and Wang, 2008), technology forecasting (Bouwman and van Der Duin, 2007), customer surveys (Giessmann and Stanoevska, 2012) and financial spreadsheets (Gordijn and Akkermans, 2001). First, research endeavours started to develop data-driven methods for business model evaluation (e.g., Augenstein and Maedche, 2017). Nevertheless, they are not introduced to and used in practice.

One problem in practice is that there is little data available for quantitative calculations (e.g., estimating a market size) to estimate the potential of a business model design. In particular, financial numbers, such as return on investment, affordable losses, or cash flow statements, are interesting for practitioners. Estimating financial returns and revenues is even more difficult to estimate than costs and efforts. This means that quantitative evaluation results are subjected to assumptions and uncertainties and might not be reliable decision support. Therefore, we see the following promising research questions on quantitative evaluation approaches for further research:

- What is the current state of quantitative evaluation in practice, and what approaches are used?
- What are suitable quantitative criteria and corresponding quantitative tools and methods for the early stages of business model innovation where little information is available?
- How do we deal with uncertainties and incomplete data in quantitative methods?

- How do we use data analytics and data mining methods for automated evaluation approaches?

To address these questions, we see three promising research directions: First, other researchers could conduct interviews and surveys with business modellers and managers to explore the current practice with quantitative methods in the industry. Such studies could show opportunities for design researchers, i.e., for what evaluation questions quantitative tools and methods are missing. Second, other researchers could look into similar fields, such as business analysis and adopt tools and methods to deal with uncertainties and assumptions (e.g., probabilistic models or Monte Carlo Simulations). Third, other researchers could design evaluation approaches using data mining to perform certain evaluations automatically. Promising examples in the context of DDBMs would be an automatic evaluation of data sources against data quality or value. When using quantitative and data-driven methods, the next consequent and logical step would be to digitally implement tools, methods, and processes in IT systems.

7.5.2 Implementing IT-based Business Model Tools and Processes

Tools, methods and processes described in the research chapters of this thesis were implemented as templates or clickable presentations. We use them as printed versions (e.g., a canvas) or as part of *PowerPoint* presentations during meetings and workshops with *Comp*. Also, the process design and toolbox were implemented as a clickable *PowerPoint* presentation, with hyperlinks to tools and methods stored on an IT server. Further, we already discovered in our structured literature review (see Chapter 4.1 and Fruhwirth *et al.*, 2020c) that there is little IT support available to support data-driven business model innovation and proposed one promising direction for further research. We found here that digitally tracking results and changes and enabling consistency and transfer of information across tools could be valuable add-ons to existing tool support (see 4.1.6.3 and Fruhwirth *et al.*, 2020c).

Information systems support business model innovation (Hanelt *et al.*, 2015; Osterwalder and Pigneur, 2013; Veit *et al.*, 2014), particularly through software-based tools for Business Model Development (Szopinski *et al.*, 2019). One approach is digitally representing and changing business model designs using a modelling language (Fritscher and Pigneur, 2014a; John *et al.*, 2017). The basic idea is to replicate the sticky note experience from paper-based business modelling (e.g., with the Business Model Canvas) in a software tool (see Fritscher and Pigneur, 2014a, 2014b). One goal here is to support the idea-generation process through machine-generated ideas (John, 2016), implement pre-filled business models (Athanasopoulu *et al.*, 2018), or activate business model tools (Szopinski, 2019). Another goal is to enable collaboration for business model development in distributed teams (Ebel *et al.*, 2016). Research also has developed a decision support system for business model validation (Dellermann *et al.*, 2018), adopted data-driven methods (e.g., Augenstein and Maedche, 2017) or implemented reflection for sustainable business models (Schoormann *et al.*, 2018). Further, many business model development tools are available in practice (Szopinski *et al.*, 2019). Klein *et al.* (2022) recently investigated existing software tools that support business model innovation and found that early phases of business model innovation are well supported, but later phases are hardly represented. This analysis underpins the importance of future research investigating IT support over the whole business model innovation process.

Existing Information Systems research focuses on business model development (i.e., creativity support systems) and implementing one representation or method for business modelling. However, there is also the need for consistent process support (Terrenghi 2019) and the combination and connection of different tools and methods (Fruhwirth *et al.*, 2020c; Szopinski *et al.*, 2019). Practitioners and management should be supported across the business model innovation with a structured management process, and IT implementations must go beyond a digital visualisation of a Business Model Canvas (Terrenghi *et al.*, 2017). Little design-relevant knowledge of such systems is available in the literature. Therefore, we see the following promising research questions on IT support in data-driven business model innovation (which we will refer to as a business model management tool) for further research:

- How can a business model innovation process be implemented as a software-based management tool?
- What would be the (design) requirements of such a tool?
- What are such a tool's functions (design features), and how can they be implemented in practice?
- What are the design principles for business model management tools?

We have already started investigating these questions in our case study with *Comp*, e.g., in discussions and meetings with managers. Nevertheless, an in-depth scientific investigation and practical implementation were out of the scope of this PhD thesis and the case study project. We started considering potential functions listed in Table 7.2 of a business model management tool and made the first sketches of a user interface.

Function	**Description**
Collaboration	• Enable virtual collaboration within the business model innovation team (e.g., comments to documents or a chat function) • Enable selective access to documents also for people outside the business model innovation team. • Identify and invite experts/departments for specific tasks or questions during business model innovation (e.g., the legal department)
Documentation	• Uploading of documents and reports (e.g., a completed Business Model Canvas) • Structured documentation of additional materials during business modelling (e.g., industry reports, posts from competitors) • Tracking activities (e.g., conducted customer meetings or workshops)

Process Guidance	• Defining and describing stages and providing a checklist of activities necessary in each phase • Recommending tools for specific activities or questions
Reporting	• Enabling transparency on the progress of use cases to the senior management • Providing decision support and KPIs (e.g., number of customer interviews conducted) for each use case • Overview of the portfolio of innovation cases and their status
Toolbox	• Providing web-based digitised tools at one centralised point
Training and Learning	• Providing knowledge on business model innovation (e.g., videos, tutorials, explanation of tools and examples) • Enabling reflection and learning on successful and unsuccessful business model innovation initiatives

Table 7.2: Potential functions of a business model management tool.

We also discussed implementing a business model management tool based on existing project management solutions like *Jira*. Such a business model management tool would also act as a knowledge management system, as it formalises the tacit knowledge of business model innovation. Nevertheless, to be valuable in practice, such tools also must be introduced to and adopted in the organisation, leading to the third direction for further research.

7.5.3 Designing Interventions for Introducing Business Model Tools, Methods and Processes in Organisations

Tools, methods and processes developed and described in this thesis are introduced to *Comp* and deployed on a digital server as part of the research project. The literature generally focuses on evaluating tools and methods with students, experts or practitioners in artificial settings. Researchers facilitate its usage during evaluation workshops. Little has been written about introducing business model tools into practice and practitioners adopt them in organisations. Schwarz and Legner (2020) also highlight this gap and state that there is little empirical evidence about the role and usage of business model tools in innovation. Therefore, we developed one question for further research: How can we design interventions to successfully introduce business model tools, methods and processes into organisations that practitioners then adopt?

We have already started investigating this question in our case study with *Comp*. Nevertheless, an in-depth scientific investigation and practical realisation were out of the scope of this PhD thesis and the case study project. Therefore, we see four steps for other researchers to address this question:

First, one should develop a **method of use** for each business model tool that gives basic instructions and suggestions on how a tool can be used without the facilitation of a researcher (or external consultant). For instance, Osterwalder and Pigneur (2010) comprehensively explain the

Business Model Canvas and how to use it in practice. Further, we also developed a method of use for the Data Product Canvas (see Chapter 5.2 and Fruhwirth *et al.*, 2020a). We added this method of use to the instantiation of the business model innovation process (see Chapter 4.2). In general, few research articles also provide a method of use for their tool, which was also confirmed by our structured literature review (see Chapter 4.1 and Fruhwirth *et al.*, 2020c). Avdiji *et al.* (2020) found evidence for stabilising the direction of use of visual collaborative tools based on the designers' experience in many workshops. However, regarding design science research, there is – to the best of our knowledge – nothing available on how to design and evaluate a method of use for a business model tool.

Second, one should make their business model tool and the method of use available via a public (or company internal) **platform**. This could also include illustrative examples, cases, tutorials and videos on how to use the tool. Again, the best-practice example is the *Strategyzer* website[57], which provides many resources, including a fee-based training course for using the Business Model Canvas. For instance, in the context of this thesis, we have refined the Data Product Canvas and provided an adapted version, including a method of use via the *Business Makeover* platform[58]. Further, we have made a description and illustrative example of the Data Product Canvas available for *Comp* via their internal information systems.

Third, one should also develop a **training course** about new business models, such as DDBMs, and how to use business model tools, methods and processes. In the context of this thesis, we have developed a lecture, “Foundations on data-driven business models”, as a 2-hour digital life training via *Webex* for the employees of *Comp* with more than 60 participants. The lecture was divided into four parts: (1) Motivation: Why it is important to consider DDBMs in traditional and offline established organisations. (2) Explaining the basic characteristics of a DDBM and its value creation logic (see Chapter 5.3) by developing a data-driven innovation for a fictitious company in the context of bakeries and weather data. (3) Give an overview of existing DDBMs at *Comp* by reusing the previous concept. (4) Q&A session, where the employees can ask questions about their business area's specific problems and opportunities. We note here that it is important to ground all the content in the organisation's context (e.g., by giving examples of types of data sources available in their organisation).

Finally, after one has developed a method of use, provided it via a platform, and trained employees on the new tool, method or process, observing how a tool is used and adopted in practice is worthwhil**e**. Data could be collected via interviews or interpretative case studies. For instance, Fritscher and Pigneur (2014a) investigated the key features of a digital implementation of the Business Model Canvas target users adopted by analysing the software tool's usage data. Business model tools could be used by employees of an executive department responsible for business model innovation or by innovation managers within the business units. These insights

[57] https://www.strategyzer.com/canvas/business-model-canvas accessed on 16.05.2022, 11:05.
[58] https://businessmakeover.eu/tools/safe-deed-data-driven-business-canvas accessed on 16.05.2022, 11:10.

from studying the usage and adoption of business model tools in organisations should be reflected in an adapted design of such tools.

7.5.4 AI and ML-Based Business Models

Now, five years after the start of this thesis, we can observe a debate in the literature on the advancement of DDBMs towards business models built around machine learning and AI (e.g., Vetter *et al.*, 2022; Weber *et al.*, 2022). This discussion is fuelled by the recent advancements in Generative AI (Feuerriegel *et al.*, 2024; Haefner and Gassmann, 2023; Kanbach *et al.*, 2023). AI is data-driven and requires large amounts of data, affecting organisational data sharing (Strobel *et al.*, 2024). In such business models, data is used to train AI models instead of generating insights; these AI models are then embedded in services and products (Weber *et al.*, 2022). AI-based services can complement or substitute humans at work (Murray *et al.*, 2021) and induce the automation of knowledge work through AI (Coombs *et al.*, 2020). This task delegation relates to agentic Information Systems (Baird and Maruping, 2021). Nevertheless, implementing AI in organisations leads to new challenges; for instance, AI projects are often managed like traditional IT projects (Hopf *et al.*, 2023). The research community has just started to study AI-based business models (Weber *et al.*, 2022).

From a business model perspective, AI-based business models can be seen as advancing data-driven business models since modern AI is mainly data-driven. Weber *et al.* (2022) argue that there are certain overlaps with data-driven business models. Still, they go beyond them in certain aspects, such as new value propositions or AI technology being at the centre of the business model. Thus, the general question emerges with regard to supporting business model innovation: What are the differences, critical elements and “specialities” of AI-based business models compared to other data-driven business models? This question frames three directions for future research in the context of this thesis.

Direction 1: What is the underlying customer value creation logic of AI-based business models? We have addressed this question as an avenue for future research in Chapters 5.2 and 5.3. Weber *et al.* (2022), for instance, mention several core AI values, such as “cognitive insights”, “monitoring and anomaly detection”, or “process and task support”. Shollo *et al.* (2022) dug deeper into that topic and identified three different value-creation mechanisms of machine learning: knowledge creation, task augmentation and autonomous agents. From a tool perspective, one promising direction for future research would be to extend the data-based value creation logic to an AI-based value creation logic and, in a second step, design or adopt tools, such as a canvas or set of cards that support organisations in developing AI-based services.

Direction 2: What are new and specific risks in AI-based business models? We pointed to that question in Chapter 6.3 when studying knowledge risks in data-driven business models. We have seen that competitive knowledge can be materialized in AI models. When these models are used in a service or are part of an offering, competitive knowledge could be leaked – a risk that we denoted as knowledge risks in this thesis. We mentioned several potential risks concerning AI-based business models. First, through the intensive usage of AI tools in the cloud, like large langue model-based tools (e.g., *ChatGPT* or *deepl* for translators) by employees of an organisation, sensitive information and, therefore, competitive knowledge might be leaked. Such AI models might also expose information they have learned but were not intended to, e.g., in large language models. Second, through the increasing importance of explainable and trustworthy AI, an organisation might have to open their models and expose competitive knowledge. Third, with rapid developments in generative AI, models will become more powerful, especially in engineering and knowledge-intensive companies. If AI can replace knowledge work, then leaking such a model would imply a huge risk. Beyond this knowledge risk, future research should also identify and investigate other risks implied by AI-based business models and potential measures. Weber *et al.* (2022) mentioned, for instance, ethical constraints.

Direction 3: What additional knowledge must be incorporated into a business model innovation process to capture the specifics of AI-based business models? This question connects to Chapter 4 of this thesis. For instance, Åström *et al.* (2022) developed a three-phase process framework for AI-based business model innovation. Their framework identifies prerequisites for AI-based value creation to reach a validated AI opportunity, focusing on matching value capture mechanisms and developing a commercially ready AI business model offer. Sjödin *et al.* (2021) further add that AI-based business model innovation requires developing and scaling AI capabilities via business model innovation principles. For instance, the authors highlight agile customer co-creation as one of the business model innovation principles. Thus, the question for future research is what additional activities need to be incorporated into a business model innovation process and what additional tools and methods are needed to bring in the specific knowledge of AI-based business models and support the corresponding activities.

Part IV
Appendix

Chapter 8 References

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Chapter 9 Appendix

9.1 Appendix to Chapter 4.1

Appendix A: Overview of analysed publications along the concepts of three concepts "type of contribution", "type of thinking supported" and "element of business model".

Publication		Type of contribution						Type of thinking		Business model element		
	VHB-JOURQUAL3	Taxonomy	Pattern / type	Visual tool	Method	IT-tool	Process	Divergent	Convergent	Value creation	Value proposition	Value capturing
Agrawal *et al.* (2018a)	C			●				●		●	○	
Benta *et al.* (2017)	n/a			●			○	●		○	○	○
Bock and Wiener (2017)	A	●						●		●	●	●
Brillinger (2018)	B			○	●				●	○	●	●
Brownlow *et al.* (2015)	n/a	○			●			●		●	●	●
Enders *et al.* (2019)	C	●							●			●
Engelbrecht *et al.* (2016)	B	●						●		○		○
Exner *et al.* (2017)	n/a	●		●	○			●		●	●	●
Förster *et al.* (2019)	C		●	○					●	●		
Hartmann *et al.* (2016)	C	●	●					●		●	○	●
Hunke *et al.* (2017)	n/a						●					
Hunke and Wambsganß (2017)	n/a			●				●		●		
Hunke *et al.* (2019)	B	●						●		●	○	
Hunke and Schüritz (2019)	D			●				●		●	○	
Kammler *et al.* (2019)	B			○	●			●		●		
Kayser *et al.* (2018)	n/a				○		○					
Kronsbein and Mueller (2019)	C			●	○			●		●	○	
Kühne and Böhmann (2018)	D			○						●	●	●
Kühne and Böhmann (2019)	B			●				●	○	●	●	
Mathis and Köbler (2016)	n/a			●	○			●		●		
Nagle and Sammon (2017)	B			●	●			●		●		
Rizk *et al.* (2018)	C	●						●		●	●	
Schmidt *et al.* (2018)	C		●					●		●	○	●
Schüritz and Satzger (2016)	n/a		●							●	●	●
Schüritz *et al.* (2017a)	B				○		●			●		
Schüritz *et al.* (2017b)	C		●					●				●

Spiekermann *et al.* (2018)	D					●				●		
Sprenger and Mettler (2016)	B		●					●		●	●	●
Terrenghi *et al.* (2018)	B			●		○		●		●	●	●
Wixom and Markus (2015)	n/a				○				●	●		
Wixom and Schüritz (2018)	n/a				○				●			●
Zolnowski *et al.* (2016)	B		●					●		●	●	●
Zolnowski *et al.* (2017)	D				●				●			●

9.2 Appendix to Chapter 4.2

Appendix B: Historical overview of collected data and outcomes in the case study

Collected data from the case organization	Outcomes for the Data-Driven Business Model Innovation Process
04/2018 - 08/2018 17 Interviews with managers about the role of data in their business (as-is analysis)	Overview of existing data sources and adaptation of existing tool: *Data Map* (e.g., Mathis and Köbler, 2016) Structuring existing DDBM use cases at *Comp*. Developed a new tool: Matrix (see Chapter 5.1) Identified organization-specific requirements and challenges regarding data sources
10/2018 One-day idea generation workshop with 12 managers	Generated 96 ideas for potential data-driven business models Developed the *Data Product Canvas* for structuring idea generation workshops (see Chapter 5.2)
11/2018 Evaluation and prioritization of ideas	Developed the first set of evaluation criteria for selecting data-driven business model ideas Application of criteria to 23 data-driven business model ideas by two researchers and one manager of *Comp*
01/2019 - 12/2019 Designing business model opportunities in the field of electrification (3 workshops and several meetings with responsible managers)	Identified and analysed stakeholders and their benefits and data sources for one new business field Refined a network-based representation of data-driven business models (see Chapter 6.2)
2019 Designing revenue models for one DDBM case at *Comp*	Designed a decision support tool for designing revenue models for a data-driven business model (unpublished, not included in this thesis)
2020 - 03/2021 Testing business model ideas, e.g., with customer interviews	Applying the tool in one DDBM case at *Comp* together with the responsible manager Adopted the testing business model cycles of BMI Lab (BMI Lab) and Bland *et al.* (2020) for the context of *Comp*

	Applied the method in two DDBM cases and prepared and conducted customer interviews as an exemplary evaluation method
2020 11 Interviews with managers on their experience and practice with business model innovation by a master student	Identified requirements for a data-driven business model innovation process Created an overview of already used tools and best-practices in business model innovation at *Comp*
2020 - 03/2021 Participation in meetings and workshops of a cross-functional digitalization initiative	Identified requirements for a data-driven business model innovation process Discussed interim design features of the data-driven business model innovation process and collected feedback
2019 - 04/2021 Designing and applying evaluation and decision criteria for data-driven business models	Set of evaluation and decision criteria for different stages of a business model innovation process (see Chapter 6.1) Operationalisation of criteria through scales and a visualization (unpublished) Applied the artefact in three DDBM cases at *Comp* with responsible managers
02/2018 - 01/2021 discussions, meetings and workshops with three decision makers responsible for DDBM innovation in different business units at *Comp*	Collecting requirements for a data-driven business model innovation process Presenting interim results as well as design features for a data-driven business model innovation process and collecting feedback

Appendix C: Overview of participants in interview round 1 of our case study.

ID	Position	Business Unit	Date
1	Business Manager Analytics Software	C	16.04.2018
2	Product Manager Data Service	A	25.04.2018
3	Team Lead Engineering	A	26.04.2018
4	Department Manager	A	26.04.2018
5	Business Development Manager	B	27.04.2018
6	Program Manager	B	03.05.2018
7	Application Manager	B	03.05.2018
8	Product Manager Software Tool	A	08.05.2018
9	Department Manager Software Tool	C	14.05.2018
10	Product Manager Software Tool	B	16.05.2018
11	Business Manager Service	B	16.05.2018
12	Business Development Manager	C	24.05.2018
13	Team Lead Engineering	A	09.07.2018
14	Technology Strategist	B	12.07.2018
15	Project Manager Research	B	18.07.2018
16	Product Manager Hardware Tool	B	02.08.2018
17	Product Manager	D	02.08.2018

Appendix D: Interview guideline of interview round 1

Part 1: available data sources

- What data does your product, service or department currently generate or collect? Who owns this data?
- How is this data currently used?
    - Not used
    - To support processes and decisions
    - To improve the current product or service
    - Part of the service
    - Other
- What other data could you collect through the usage of your products or services?
- To what extent do you use data from other department or external data, for example from customers or also data providers for the product or service?
- What external data (sources) would be potentially interesting?
    - What data can your users provide?
    - What data can your partners provide?
    - What open data is accessible?
    - Which data can be acquired?

Part 2: Customer and data value

- What is the added value of this data? What information or answers can be / are derived from these data?
- What added value could be derived from the data, for example, if they were combined with other data sources?
- For which customer group is this added value relevant?
- Which (decision) problem can be solved for the customer? / What benefit is currently created with this data? For which customer group?
- Which data does the customer?
- Which processes can be accelerated or facilitated with the data?
- Which customer problems could be solved with additional data?

Part 3: Data monetisation

- How do you currently monetize this data?
    - Not yet
    - Selling the data to other companies
    - Providing analytics on this data to other companies
    - Other

- What ideas do you have for generating additional business from this data? What could be the business model?
- What should happen that you to use or even monetize this data in the future? / What conditions should be in place?
- What could be possible hurdles?
  - Legal situation
  - Technical challenges
  - Reputation
  - Customer (e.g., necessary change in the way of working, ...)
  - Trust, confidentiality

Appendix E: List of interview partners in case study interview round 2[59]

No.	Position	Duration
1	Team Leader	48 min
2	Department Manager	63 min
3	Product Manager Software	50 min
4	Business Area Manager	48 min
5	Program Manager	45 min
6	Project Manager	43 min
7	Solution Manager	68 min
8	Development Manager	51 min
9	Product Manager	54 min
10	Product Manager	61 min
11	Director	47 min

[59] These interviews were conducted by Maximilian Ferstl in the course of his Master’s Thesis, I co-supervised. I have used the results for the development of design knowledge presented in Chapter 4.2.

Appendix F: Interview guideline of interview round 2[60]

Guiding Questions

- How is business model innovation being done at Comp?
- What best practices and lessons learned in the field of BMI do you know?
- What requirements do employees place on processes to make them as user friendly and as much likely to be used as possible?

Demographic Data

- In which department do you work?
- What is your current role and your main responsibilities?

Business Modelling

- What is a business model? How do you bound this term?
- What is business model innovation in your understanding?
- Are you dealing with business model innovation in your job?
- How much time do you invest on that topic?
- Do you know any guidelines for business model analysis and development at Comp?
- Which challenges do you currently see in business model innovation?
- Do you know the following tools/methods? Have you worked with them? What are your experiences? Do you emphasize its usage?
    - Business Model Canvas
    - Value Proposition Canvas
    - Business Model Patterns
    - Scenario Technique
    - Data Map
    - Data Product Cavnas
    - Data Service Cards
    - User Stories
    - Customer Persona
    - SWOT Analysis
    - PESTEL Analysis
    - Porters 5 Forces
    - Stakeholder Analysis
    - Return on Investment calculations
    - Business Roadmap
    - Customer Surveys

[60] This interview guideline was developed by Maximilian Ferstl in the course of his Master's Thesis, I co-supervised. I have used the results for the development of design knowledge presented in Chapter 4.2.

   - Business Model Risk Matrix
   - Digital Value Creation Framework

Business model development in practice

- Was there a structured business model innovation approach in one of your latest projects?
- What was the approach and who was responsible for it?
- Which business modelling tools/methods were used in that project?
- When and how did you apply those tools?
- Did the use of those tools give you insights you would otherwise not have come across?
- Was the customer involved in the development of new business models? If yes, at what time and how did you discuss new business models with the customer?
- Do you think a defined business model development process at Comp could add value or help avoid failures in projects? Would you follow such a process?
- Are you used to follow processes in other areas of your work? In which contexts do you follow processes, and do you see a benefit in that?
- How could an ideal tool guide you through the business modelling process?
- Do you know any tool that could be suitable for that purpose?
- Do you want to share any additional best practices or lessons learned from business model development?

Appendix G: Overview of Phases and Gates of the implemented process.

Phase / Gate	Definition and Goal
Phase 0 Initiation and Ideation	Goal: Generate ideas for new data-driven business models. Describe the business model idea by focusing on the addressed customer problems and needs and vision for the solution. Show the potential and relevance for investing time and resources to further elaborate the idea
Gate 0	Commitment to provide business resources for further analytically elaborating the business model idea
Phase 1 Analytical Feasibility	Goal: Evaluate the business model idea analytically prior to technical developments. Analytically evaluate the business model. The focus here is on testing market-related assumptions (e.g., needs, competition, or customers) in the business model. Prepare the decision to invest in prototyping.
Gate 1	Decision to test business model sketch with a prototype
Phase 2 Prototyping and Validation	Goal: Evaluate your business model through prototypes and customer interactions. Testing the business model through successful prototypes and customer interactions. The focus here is on testing technical and financial assumptions in your business model. Prepare the decision to implement and rollout the business model at least in a sub-market.
Gate 2	Decision to implement business model in a (sub-) market
Phase 3 Implementation and execution	Goal: Implement and roll out the business model Implement and roll-out the business model in at least a sub-market and scale the business model. Monitor the execution of the business model and ensure its sustainability. If necessary, adapt the business model and react to the changing environment.

9.3 Appendix to Chapter 5.4

Appendix H: Identified publication from the database search and selection process

- (Allee, 2008)
- (Braganza, 2004)
- (Briscoe and Wilde, 2006)
- (Brownlow *et al.*, 2015)
- (Chan and Hsu, 2012)
- (Chang and West, 2006)
- (Chowdhury and Akesson, 2011)
- (Cova and Salle, 2008)
- (Curry, 2016)
- (Enders *et al.*, 2019)
- (Engelbrecht *et al.*, 2016)
- (Goes and Park, 1997)
- (Grotherr *et al.*, 2018)
- (Härting *et al.*, 2018)
- (Immonen *et al.*, 2014)
- (Kaiser *et al.*, 2019)
- (Kindström *et al.*, 2015)
- (Krumeich *et al.*, 2012)
- (Li and Fan, 2011)
- (Liu *et al.*, 2010)
- (Papert and Pflaum, 2017)
- (Peters *et al.*, 2016)
- (Schmidt *et al.*, 2018)
- (Schüritz *et al.*, 2019b)
- (Schymanietz and Jonas, 2020)
- (Sklyar *et al.*, 2019)
- (Täuscher and Laudien, 2017)
- (Terrenghi *et al.*, 2018)
- (Turetken *et al.*, 2019)
- (Vargo and Lusch, 2011)
- (Zolnowski *et al.*, 2016)

Appendix I: Initial framework from the literature review before evaluation

Actors	**Attributes**	Integration to BM
		Scope
	Roles	Resource Integrator
		Service Provider
		Physical Product Provider
		Data Collector
		Data Supplier
		Technology Provider
		Customer
		Financier
		Research Organization
		Standardization Bodies & Regulators
Exchanged entities		Money flow
		Intangible non-financial flow
		Tangible non-financial flow

9.4 Appendix to Chapter 6.1

Appendix J: Assignment of evaluation criteria to gates of the business model innovation process

	Gate 0	Gate 1	Gate 2
Customer demand	Meaningful customer problem	Unique value proposition Lead customers Ease of value communication	Successful prototyping and customer interactions Willingness to pay Customer adoption
Market and competition	Alignment with market and industry trends	Competitive intensity Market size and growth rate Time-to-market vs. window of opportunity	Imitation and protection
Organisation and strategy	Strategic fit Strategic importance	Possession of core competencies Team and industry experience Synergies	Influences on processes and required changes Commitment of stakeholders
Data and technology	Availability of data sources	Technological complexity Technological effort (software development, analytics, data storage, …) Technical gap	Results from technical proof of concept and data analytics
Financial rationale	Scalability	Affordable loss Rough cost and benefit estimation	Viable business case calculation (ROI, financial plan, …)
Risks	-	Level of uncertainty / risk per category	Results from a detailed business model risk evaluation

9.5 Appendix to Chapter 6.2

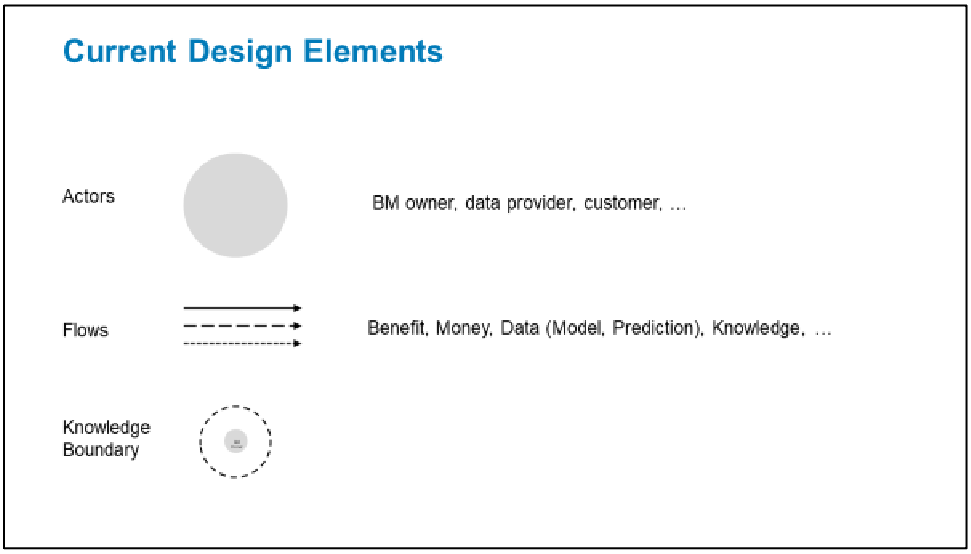
Appendix K: Evaluation Script

<u>Description and discussion of the artefact:</u>

We have designed an artefact as part of a design-oriented research study to support the business model innovation process to visualise knowledge risks:

- *What specific support is needed for knowledge risk identification or decision support? In which phases? What information is needed?*
- *Which requirements would such an artefact have to fulfil?*

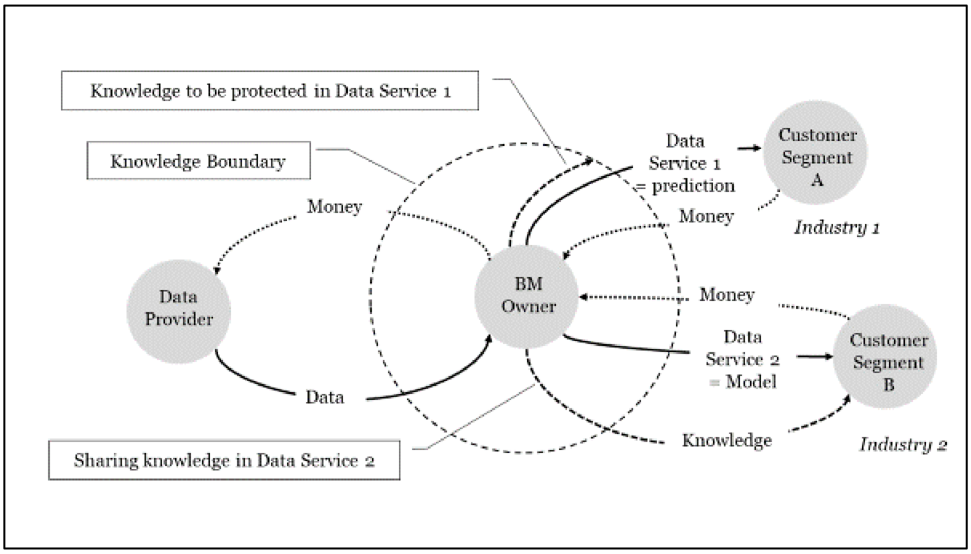
Our tool is a flow-oriented representation of business networks with the elements of stakeholders (such as customers or data providers) and the exchanged value flows (money, data, knowledge, service/goods). Furthermore, the Knowledge Boundary is shown using a circle around the company.



- *Can you spontaneously illustrate here with this artefact a business model example from your practice or from your experience / that from the previous question?*

If not, I have brought you an illustrative example:

Business Model Example: the BM Owner trades data for money with a data provider to create a data-driven model of a real physical phenomenon based on his own expert knowledge (for example, the ageing behaviour of a technical component or weather-dependent consumption behaviour for meat). Thus, the "BM Owner" materializes his core knowledge in a digital value object. Other services (e.g., predictions or recommendations from customer data based on the model) offered by the BM Owner rely on this core knowledge. The BM owner offers two data services to customers from the same (Customer Segment A) and different industries (Customer Segment B). In the former case, the BM owner wants to protect its core knowledge embedded in the value proposition to secure a competitive advantage. In the second case, sharing or passing on knowledge with customers from another industry is seen as less critical.



- *Is this representation or its elements suitable for representing data-driven business models or identifying knowledge risks?*
- *Can you think of any elements that are missing in this representation? (Completeness) Or is it possible to omit any of the elements shown? (Simplicity)*

Intention to use:

- *Could you imagine using this artefact yourself - if so, in what context?*
- *What is still missing for the artefact to be useful?*
- *For which circumstances could the artefact fit?*
- *What does the artefact need to consider/have to be usable in practice?*

Open question:

- *Where else could the artefact be used?*
- *How could the artefact be extended?*
- *What other artefacts (tools, methods) or approaches do you know, or can you imagine, that help identify knowledge risks in DDBM, thereby supporting a company's design and decision process?*

9.6 Appendix to Chapter 6.3

Appendix L:List of interviewed experts in interview round 1.

ID		Position	Area	Industry	min[61]	Lang.[62]
R1	PhD	Professor	Digital Platforms	Research	36	EN
R2	PhD	Assistant Professor	Business Model Innovation	Research	61	DE
R3	PhD	Professor	Business Analytics	Research	35	EN
R4	PhD	Assistant Professor	Data Science	Research	56	DE
R5	PhD	Senior Researcher	Knowledge Management	Research	67	EN
R6	PhD	Professor	Business and Knowledge Management	Research	60	DE
R7	PhD	Professor	Knowledge Management and IT	Research	59	EN
I1	MS	Consultant	Data Analytics	Consulting	39	DE
I2	MS	Data Scientist	Data Analytics	Automotive	52	DE
I3	MS	General Manager	Cyber Risk Management	Information Technology	63	DE
I4	PhD	Manager	Data Analytics	Automotive	62	DE
I5	PhD	Director, CIO	DDBM	Information Technology	76	DE
I6	MS	Senior Manager	DDBM	Consulting	67	DE
I7	PhD	Senior Manager	Digital Business Models	Automotive	48	DE
I8	MS	CEO/Co-Founder	DDBM	Information Technology	70	DE
I9	PhD	CEO/Co-Founder	DDBM	Information Technology	45	DE

[61] Duration of the interview in minutes
[62] Language of the interview

Appendix M: List of interviewed experts in interview round 2.

ID		Position	Area	Industry	Min	Lang.
R8	MS	Researcher & Consultant	Data-Driven Services	Research	50	DE
R9	PhD	Research Group Leader	Data Analytics	Research	53	DE
R10	PhD	Senior Lecturer and Senior Researcher	Data-Driven Services	Research	38	DE
I10	MS	Senior Manager	Data-Driven Transformation	Consulting	55	DE
I11	PhD	Head of Data Science	Data Privacy Technology	Information Technology	45	DE
I12	MS	CEO	Data-Driven Service	Information Technology	48	DE
I13	MS	Interim manager	Business Model Innovation	Consulting	59	DE

Appendix N: List of interviewed experts in interview round 3.

ID		Position	Area	Industry	Min	Lang.
I14	PhD	Consultant	Data-Driven Services	Information Technology	59	DE
I15	MS	Freelance consultant	Data Protection, Artificial Intelligence	Consulting	43	DE
I16	MS	Founder and Managing Director	Data Consulting	Consulting	50	DE
I17	Dr	Manager	Data Analytics and Digitalisation	Semiconductor	42	DE
I18	MS	Managing Director	Data-Driven Service Provider	Mobility	40	DE

Appendix O: Interview guideline of interview round 1

1. Could you please briefly describe your professional background and your current position in your business or organization?

2. How many years of professional experience do you have in this position or in this field?

3. To what extent are you dealing with (a) business models, (b) data analytics, (c) knowledge risks?

Thank you very much for these answers. Let us now move on to the topic at hand. In the following I have brought definitions of the most important terms to have a common understanding.

- *Business Model: "A business model describes the rationale of how an organization creates, delivers, and captures value." (Osterwalder and Pigneur, 2010)*
- *Data-Driven Business Model: "A data-driven business model is a business blueprint that describes how data are used as primary business resource to deliver value to customers and to convert this value into revenue and/or profit by means of direct or indirect monetization." (Seibert and Gründinger, 2018)*

- *Knowledge Risks: "Knowledge risk is a measure of the probability and severity of adverse effects of any activities engaging or related somehow to knowledge that can affect the functioning of an organization on any level." (Durst and Zieba, 2018)*
- *Business Model Risks: Business model risks are "all risks within the business model which can endanger the profitability and sustainability of the business model or even company goals and value". (Brillinger et al., 2017; Brillinger, 2018).*

In the context of a case study with a large industrial company, we have identified knowledge risks as a new challenge in data-driven business models in the B2B sector:

A company generates knowledge about real phenomena (physical, sociological, economic) by analyzing data from different sources (e.g., from some customers and research projects), which is materialized in the form of models or algorithms (e.g., data-driven model about the aging behavior of a device). The company now wants to develop new services / value propositions based on this knowledge. The knowledge is therefore a core element of a possible business model and thus also represents a competitive advantage. Therefore, the company wants to protect the knowledge and not monetize it directly, but only by means of predictions etc. In contrast to physical core resources (employees, machines, plants), algorithms or models can be transferred relatively quickly between organizations. In addition, it is technically possible to lose knowledge, for example that a customer/competitor can restore the configuration of a neural network via API access or that the knowledge is sold in the value proposition.

Example: A technical company U analyses data from different customers and projects and gains knowledge about a real phenomenon (aging behavior of a component). This knowledge is materialized in the form of a data-driven model. This ageing behavior is of high relevance for customers of U. U is therefore considering developing new data-driven business models with the model as a core element. An obvious solution would therefore be to sell the model directly.

4. Do you see this as a relevant problem? And do you know any similar examples?

5. How do you assess each of these consequences of knowledge risks as a possible/relevant problem in (or in the design of) data-driven business models? Is there an example known of each of these?

6. What other causes of risk could you imagine in this context in data-driven business models? Through conscious or unconscious decisions / actions of the company?

7. What consequences do you see based on these risks?

We have also identified the following consequences in knowledge risks from the literature:

- *Knowledge loss is a situation in which an organization loses some or all of its critical knowledge, for example, due to the departure or poaching of an employee, or technical failures (e.g., computer failure). (i.e., the knowledge is simply gone)*
- *Knowledge leakage is a situation where confidential organizational knowledge such as strategies, policies, product knowledge and confidential customer information falls into the hands of unauthorized persons. (i.e., the knowledge is now in the hands of an unauthorized person)*
- *Knowledge spillover is a situation where valuable knowledge migrates from the company to competitors who use this knowledge to gain competitive advantage (i.e., the knowledge migrates to a competitor; it can be used to damage the company)*

8. How do you assess each of these consequences of knowledge risks as a possible/relevant problem in (or in the design of) data-driven business models? For each, do you know any examples?

9. What other consequences could arise from such knowledge risks for the business model / for the company?

10. What examples from the practice of companies do you know where the topic of knowledge risks in data-driven business models is, was or could be relevant? What were the reasons for this? What were the consequences? (if not already mentioned)

Appendix P: Interview guideline of interview round 2

1. Please describe briefly in a few sentences your professional background and your current position in your company or organization!

2. How many years of professional experience do you have in this position or field?

3. Could you please describe in a few words what *[insert organization here]* does or what your business model is?

I would like to interview experts in the 3 topic areas of 1) Business Models and Service Design; 2) Data Science and Analytics; and 3) Knowledge Management and Security.

4. Could you please briefly assign yourself to one or more of the three areas where you are/were currently working and/or have experience?

[Introduction of same definitions and problem sketch as in the first interview guideline]

If possible, please answer the following questions from your own company's perspective. If this is not possible, I would also be pleased if you could give a general assessment

5. How do you perceive the problem of knowledge risks, as just described, as a relevant problem in your business model? / How do you perceive this problem in general in the design of data-driven business models?

6. What practical examples do you know where the problem of knowledge risks in data-driven business models is, was or could be relevant? What were the causes? What were the consequences?

7. What are potential mechanisms to reconstruct or access knowledge as a malicious actor?

8. What would be potential consequences of such knowledge risks for your/an organization?

9. What factors influence the risk of knowledge leakage through the exchange of data, models or predictions?

10. To what extent are such knowledge risks currently considered in the design of data-driven services or business models? Have you made any trade-offs between sharing and protecting knowledge?

11. What information do you need or have you used to assess such risks?

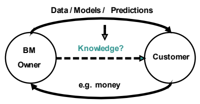
12. What protection measures have you implemented to avoid or prevent such knowledge risks?

In the first interview round of our study, we have identified three types of data-related value objects: data, models and predictions.

13. How do you perceive the knowledge risk for each of these three value objects? Does this differentiation make sense to you? Do you have any examples?

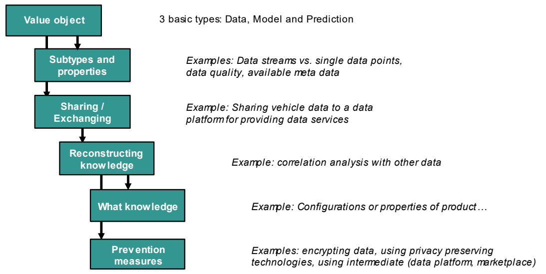
Appendix Q: Interview guideline of interview round 3

Knowledge Risks in Data-Driven Business Models



- Data-driven business models imply the inter-organizational exchange of data or similar value objects.
- Data science methods enable organizations to discover patterns and eventually knowledge from data.
- Thus, organizations might risk the exposure of competitive knowledge through sharing data-related value objects.

How we analysed the risks from our interview data



We identified 5 Types of Knowledge Risks

- Reconstructing Knowledge from Shared Data Sets
- Reconstructing Knowledge via Sharing Models
- Reconstructing Training Data From Shared Model
- Reconstructing a Model based on Shared Predictions
- Customer is sharing data to use a prediction service and knowledge can be retrieved

Type 1: Reconstructing Knowledge from Shared Data Sets

Working Definition: A knowledge risk in DDBMs occurs, when **data is shared** as part of a data product/service and the receiver can **discover competitive information/knowledge** from the shared datasets via applying data science methods, especially, when combining them with other (external) data sources.

Example: Sharing vehicle data to a data platform as part of a data service could lead to the leakage of sensitive product configurations of the vehicle.

"You can't upload all the data from the CAN bus, from the ECU. Otherwise, someone with malicious intent could extract a lot of information from it about the development of the vehicles, about the ***performance*** *of the vehicles, about the* ***quality****. All of this could be extracted from such data" (Industry Expert 8)*

Indeed, it seems to me that the risk is a very high one. Because it's so undefined, because ***you're extracting something from this data that wasn't expected****" (Industry Expert 5)*

Type 2: Reconstructing Knowledge via Sharing Models

Working Definition: A knowledge risk in a DDBM occurs when a **model is shared** and the receiver is able to **extract competitive knowledge** or sensitive information. The model can materialize domain knowledge from experts (e.g., engineers) that is introduced during the process of creating or training.

Example: Selling a prediction model as part of a service could lead to the leakage of engineering knowledge about the ageing behavior of a certain technical component.

"We are a service provider for model development and algorithms, and we sell those directly to our customers, ***then we always sell a bunch of knowledge too****" (I4)*

"If I take these models and give them away, then I've taken the ***knowledge*** *that I've discovered from people, from their actions, from their labeling, from their input,* ***preserved it in the model****, and sold it to the outside world.* ***That's a tremendous risk****." (I4)*

Type 3: Reconstruct the Training Data From Shared Model

Working Definition: A knowledge risk in a DDBM occurs when a **model is shared** and the recipient can **reconstruct the original training data** from a shared model. Thus training data is implicitly shared and competitive knowledge can be discovered from the training data (leading to Knowledge Risk Type 1).

Example: Insurance companies jointly training a model for fraud detection. Structure of training data reveals information.

"[...] Then ***there is the risk that you are revealing information about your own data with the models*** *[...] Let's assume we take two insurance companies. They want to improve fraud detection. They exchange metainformation or train models together to do that. From that, you can get the structure of the data used for training. And that* ***underlying structure*** *can already give one insurance company, which of course is a competitor,* ***a lot of information about the other****."* (Industry Expert 9)

Type 4: Reconstructing a Model from Predictions

Working Definition: A knowledge risk in a DDBM occurs when **plenty of predictions are shared** and the receiver is able to **reconstruct the model** based on these predictions. When the model could be reconstructed this leads to knowledge risk type 2 (discovering knowledge from a model) or knowledge risk type 3 (discovering training data from a model).

Example:

"If you take a look at the predictions now, you'll probably see a few features and check for which group it's working better or worse. You'll be able to reconstruct something there." (I2)

"The heart of a good model is the variance of the input factors. And if I just offer an API, where I only provide a result to certain input values, but the input data that have led to that model has more variety than I'm allowing through the API, I can actually [prevent that well]." (I5)

Type 5: Sharing data to use a prediction service

Working Definition: A knowledge risk in a DDBM occurs when the customer has to **share his data** with the provider in order to use a prediction service. And the provider could discover competitive knowledge from the shared data with the help of data science methods (see knowledge type 1).

Example: Customer shares data from the machines of a car manufacturing line with a service provider to use an optimization service. This data reveals sensitive information:

"who could use this data to determine precisely ***when*** *the customer was* ***retooling his production line****,* ***how many units of a particular vehicle type were produced****. Because he could derive exactly this information through various analyses"* (Industry Expert 6)

"Because all the companies in the [supply] chain ***are so afraid of losing knowhow, they don't share the data*** *[...] This leads to the fact that it is sometimes difficult in the data environment for me to do business"* (Industry Expert 4)

Questions for Validation of our Results

- *Do you perceive these risks as relevant for your business?*
- *Are there any other types of risks missing in that context?*
- *Is the description of each risk reasonable for you?*

Appendix R: Coding scheme with main categories.

Category	Description
Motives for sharing	This category describes motives why a type of value object is shared with other stakeholders,
Type of knowledge	This category describes different types of knowledge that can be discovered from data-related value objects.
Knowledge retrieval mechanism	This category describes mechanisms of how the knowledge can be discovered from the data-related value object by another party leading to a knowledge leakage.
Influencing factors	This category describes the circumstances that make knowledge retrieval and, thus a knowledge leakage possible. These factors influence the probability of the risk.
Knowledge protection measures	This category describes measures of how such knowledge leakage could be prevented by technical or business model design measures.

Appendix S: Snapshot of the coding scheme and exemplary text segments.

Text segment	Code	Type of value object	Category
"Ich mach das Ganze dann als Software-as-a-Service. Das wäre so die beste Mitigation." (P10)	Offer Model-as-a-Service as a protection measure	Model	Knowledge protection measure
"Wenn man das Modell nur als API zur Verfügung stellt, dann kann jemand zwar Anfragen stellen, da kann jemand das Modell aber noch nicht rekonstruieren." (P9)			
"... dass man verschlüsselte Daten für so eine Dienstleistung verwendet." (P1)	Using encrypted data	Data	
"Daten sollten auf jeden Fall verschlüsselt übertragen werden." (P11)			

9.7 Appendix to Chapter 6.4[63]

Appendix T: List of Exclusion Criteria and Excluded Data Marketplaces

Reason to exclude	Platform	Weblink
Not enough information available: direct contact with the data marketplace required	Acxiom	https://www.acxiom.com/what-we-do/data/
	BDEX	https://www.bdex.com/
	Data republic	https://www.datarepublic.com/
	Dex	https://www.dex.sg/
	Openprise	https://www.openprisetech.com/data-marketplace/
	Salesforce Datastudio	https://www.salesforce.com/products/marketing-cloud/data-sharing/
	Thinknum	https://www.thinknum.com/
Not enough information available: unable to create an account on the platform	Otonomo	https://otonomo.io/
	owerIQ	https://www.owneriq.com/Second-Party-Data-Education
	Quadrant	https://www.quadrant.io
	Synchronicity	https://synchronicity-iot.eu/
The platform is still under construction or in a testing phase.	netObjex	https://www.netobjex.com/data-marketplace/
	Bonseyes	https://www.bonseyes.com
	Datum	https://datum.org/
	Enigma	https://enigma.co/marketplace/
	Data Market Austria	https://datamarket.at/
The platform does not fit the definition of data marketplaces: it is only a data-related services	Bloomberg	https://www.bloomberg.com/professional/product/bloomberg-polarlake/
	Cognite	https://www.cognite.com/
	FactSet	https://www.factset.com/services/data-delivery
	Factual	https://www.factual.com/
	Kochava	https://www.kochava.com/kochava-collective/
	Radius	https://radius.com/
	Reply	https://reply.io/data-marketplace
	Sobloo	https://sobloo.eu/data
	Veracity	https://www.veracity.com/
	Cybernetica	https://cyber.ee/products/secure-data-exchange/
The platform does not fit the definition of data marketplaces: it provides only links to data	dmi	https://dmi.io/
The platform does not fit the definition of data marketplaces: A one-sided market	Knoema	https://knoema.com/
	Mmojo	https://mmojo.com/data-marketplace/
	Qlik	https://www.qlik.com/us/products/qlik-data-market
The platform does not fit the definition of data marketplaces: it provides only open/free data	Amazon AWS	https://aws.amazon.com/opendata/
	ArcGIS Hub	https://hub.arcgis.com/pages/open-data
	Figshare	https://figshare.com/

[63] The tables in this appendix have been taken from the Master Thesis of Prlja, Emina (2019): Discovering Business Models of Data Marketplaces where the empirical part of this chapter has been conducted. The author of this PhD thesis served as a co-supervisor.

	Google public data	https://www.google.com/publicdata/directory
	Mobility Data Marketplace	https://www.mdm-portal.de/en/
	OpenData – Socrata	https://opendata.socrata.com/
	OpenDataSoft	https://www.opendatasoft.com/
	OSDC	https://www.opensciencedatacloud.org/

Appendix U: List of analysed data marketplaces

		Value Creation										
		Platform infrastructure		Data origin					Review system			
		Centralized	Decentralized	Internet	Self-generated	User	Community	Authority	User reviews	Review by marketplace	None	No info
1	Advaneo	x			x				x			
2	Big	x			x							x
3	Caruso	x			x							x
4	Datahub	x					x					x
5	Marketscan	x					x				x	
6	OnAudience.com	x		x								x
7	oneTRANSPORT	x			x							x
8	Pitney bowes	x						x			x	
9	Quandl	x						x			x	
10	Red Lion Data	x						x			x	
11	Xignite	x						x				x
1	Dawex	x			x							x
1	Databroker dao		x		x				x			
2	Datapace		x		x					x		
3	IOTA		x		x						x	
4	Streamr		x		x						x	
5	Fysical		x		x						x	
1	Datacoup	x				x					x	
2	Opiria PData		x			x					x	
3	Wibson		x			x				x		

		Value Proposition																						
		Privacy				Data quality guarantee		Time relevancy			Type of access					Data output type					Pre-purchase testability		
		Anonymized	Encrypted	Both	No info	Yes	No info	Static	Dynamic	Both	API	Download	Specialized software	API/Download	No info	CSV/XLS	JSON	Report	Multiple options	No info	None	Restricted access	No info
1	Advaneo				x		x	x				x							x		x		
2	Big	x					x			x					x					x		x	
3	Caruso				x		x			x	x									x			x
4	Datahub				x		x		x					x					x		x		
5	Marketscan				x	x		x				x				x						x	
6	OnAudience.com	x				x				x					x					x	x		
7	oneTRANSPORT				x		x			x	x						x				x		
8	Pitney bowes				x	x			x					x					x			x	
9	Quandl	x				x			x					x		x						x	
10	Red Lion Data				x	x			x			x				x					x		
11	Xignite				x	x				x	x								x			x	
1	Dawex		x			x				x				x		x						x	
1	Databroker dao				x	x			x		x						x					x	
2	Datapace			x		x			x		x						x				x		
3	IOTA		x			x			x		x						x				x		
4	Streamr				x	x			x			x				x					x		
5	Fysical	x				x			x		x					x					x		
1	Datacoup	x					x		x				x							x	x		
2	Opiria PData			x		x		x					x					x			x		
3	Wibson	x				x			x				x							x	x		

		Value Delivery													
		Additional purchase support			Domain						Marketplace participants			Smart contract with blockchain	
		With additional costs	Included in price	No	All/Any	Finance/Economy	Geo	Address	Sensor	Personal	B2B	C2B	Any	Yes	No
1	Advaneo			x	x								x		x
2	Big		x							x			x		x
3	Caruso			x					x		x				x
4	Datahub	x			x								x		x
5	Marketscan	x						x			x				x
6	OnAudience.com	x								x	x				x
7	oneTRANSPORT		x						x				x		x
8	Pitney bowes	x					x						x		x
9	Quandl	x				x					x				x
10	Red Lion Data	x						x			x				x
11	Xignite	x				x					x				x
1	Dawex	x			x						x			x	
1	Databroker dao			x					x		x			x	
2	Datapace			x	x								x	x	
3	IOTA			x					x		x			x	
4	Streamr			x	x								x	x	
5	Fysical			x			x						x	x	
1	Datacoup			x						x		x			x
2	Opiria PData		x							x		x		x	
3	Wibson			x						x		x		x	

		Value Capture												
		Pricing model					Price discovery					Payment currency		
		Usage-based	Package pricing	The flat fee tariff	Freemium	No info	Fixed prices	Set by sellers	Set by buyers	Auction	Negotiation	Crypto	Fiat	Both
1	Advaneo	x					x						x	
2	Big					x				x			x	
3	Caruso			x				x					x	
4	Datahub				x		x						x	
5	Marketscan			x			x						x	
6	OnAudience.com		x				x						x	
7	oneTRANSPORT				x			x					x	
8	Pitney bowes			x			x						x	
9	Quandl				x			x					x	
10	Red Lion Data		x				x						x	
11	Xignite	x					x						x	
1	Dawex	x						x					x	
1	Databroker dao	x					x					x		
2	Datapace		x				x					x		
3	IOTA			x				x				x		
4	Streamr				x			x						x
5	Fysical			x							x	x		
1	Datacoup	x					x						x	
2	Opiria PData	x					x					x		
3	Wibson	x							x			x		

Appendix V: Check of ending conditions after each iteration of the taxonomy building approach.

	Ending condition	Iteration						
		1	**2**	**3**	**4**	**5**	**6**	**7**
		(c2e)		**(e2c)**				
Objective	All objects from the sample were examined					x	x	x
	No object was merged or split in the last iteration	x	x	x	x	x	x	x
	Every characteristic of every dimension describes at least one object							x
	No new dimensions or characteristics were added in the last iteration						x	x
	No dimensions or characteristics were merged or split in the last iteration		x					x
	Every dimension is unique	x	x	x	x	x	x	x
	Every characteristic is unique within its dimension	x	x			x	x	x
	Each cell is unique and is not repeated	x	x	x	x	x	x	x
Subjective	Concise – taxonomy is meaningful but not overwhelming							x
	Robust – dimensions and characteristics differentiate sufficiently					x	x	x
	Comprehensive – all dimensions of interest identified and possible to reuse					x	x	x
	Extendible – easy to add new dimensions/characteristics	x	x	x	x	x	x	x
	Explanatory – dimensions/characteristics can describe an object from the domain		x	x	x	x	x	x

Appendix W: Description of dimensions and characteristics of data marketplace business models

Dimension	Origin	Characteristic	Description of characteristic
Platform Infrastructure	Conceptual (Koutroumpos *et al.*, 2017)	Centralized	Data are stored and accessed from predefined storage spaces
		Decentralized	Data are stored decentralized (e.g., using blockchain)
Data origin	Conceptual (Stahl *et al.*, 2017)	Internet	Data are gathered from online sources (manually or automatically)
		Self-generated	Data are gathered from private sources
		User-generated	Data are collected from user inputs (e.g., in exchange for using a service)
		Community	Data are collected from marketplaces and crowdsourcing services
		Authority	Data are collected by institutions with a high level of proficiency
Review system	Conceptual (Täuscher, 2016; Täuscher and Laudien, 2018)	Reviews by users	Reviews directly between buyers and sellers
		Reviews by marketplace	Data marketplace provides reviews
		None	Data marketplace does not provide reviews
Privacy	Empirical	Anonymized	Data marketplace stores anonymized data
		Encrypted	Data marketplace stores encrypted data
		Both	Data marketplace stores anonymized and encrypted data
Data quality guarantee	Empirical	Yes	Data marketplace guarantees quality of purchased data
		No	
Time relevancy	Conceptual (Stahl *et al.*, 2017)	Static	Offered data does not change after its creation
		Dynamic	Regular updates to dataset needed to keep data valid
	Empirical	Both static and dynamic	Offer both static and dynamic datasets
Pre-purchase testability	Conceptual (Stahl *et al.*, 2017)	Complete access	Customers have complete access before paying for data
		Restricted access	Customers can access only part of the data before prior purchase

		None	Customers can not access data before paying for them
Data output type	Conceptual (Stahl *et al.*, 2017)	JSON	Format for semi-structured data
		CSV/XLS	Tabular data
		Report	Visualized data formats (e.g., PDF, DOC, JPEG)
	Empirical	Multiple options	Data marketplace offers multiple options for data output types
Type of access	Conceptual (Stahl *et al.*, 2017)	API	Use of a predefined protocol interface to access data
		Download	Data are accessed through downloadable file
		Specialized Software	Data marketplace requires designated software to handle data
	Empirical	API and Download	Data can be accessed via API as well as via download
Additional purchase support	Empirical	With additional costs	Data marketplace charges for additional services
		Included in price	Data marketplace offers additional services for free
		No	Data marketplace does not provide additional services
Domain	Conceptual (Fricker and Maksimov, 2017; Stahl *et al.*, 2017)	All/Any	Data marketplace not restricted to a certain domain
		Finance/Economy	Economics related data (e.g., stock market data or pricing data)
		Geo	Geographical positions expressed in coordinates
		Address	Lists of customer information (e.g., mail and E-mail addresses)
		Sensor	Data generated by or used for sensors (e.g., IoT data)
	Empirical	Personal	Data related to private information about individuals
Marketplace participants	Conceptual (Täuscher and Laudien, 2018)	B2B	Data marketplace operates exclusively in B2B
	Empirical	C2B	Data marketplace operates exclusively in C2B

		Any	Data marketplace not restricted in terms of buyers and sellers
Smart contract with blockchain	Empirical	Yes	Data marketplace offers an option for smart contracting
		No	Data marketplace does not offer an option for smart contracting
Pricing model	Conceptual (Muschalle *et al.*, 2012; Stahl *et al.*, 2014)	Free	Selected datasets are offered for free
		Usage based	Customers pay proportionally for units (e.g., API-calls or time)
		Package pricing	A selected amount of data is offered for a fixed price
		Flat free tariff	Full access to the data marketplace is offered for a recurring fee
		Two-part tariff	Combines a flat fee tariff with additional usage-based pricing
		Freemium	Basic features offered for free, additional features are unlocked for a fee
Price discovery	Conceptual (Täuscher, 2016; Täuscher and Laudien, 2018)	Fixed prices	Data marketplace offers fixed prices
		Set by sellers	Prices are set by sellers
		Set by buyers	Prices are set by buyers
		Auction	Buyers are bidding against each other
		Negotiation	Buyer and seller agree on an acceptable price for both parties
Payment currency	Empirical	Crypto-currency	Data marketplace handles payment via crypto-currency
		Fiat-currency	Data marketplace handles payment via fiat currency
		Both	Data marketplace handles payment both with fiat currency and crypto-currency