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To Sell or Not to Sell: Knowledge Risks in Data-Driven Business Models

Michael Fruhwirth

Viktoria Pammer-Schindler

Stefan Thalmann

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Research-in-Progress

Michael Fruhwirth
Know-Center GmbH
mfruhwirth@know-center.at

Viktoria Pammer-Schindler
Know-Center GmbH
vpammer@know-center.at

Stefan Thalmann
University of Graz
Stefan.thalmann@uni-graz.at

Abstract

Data plays a central role in many of today's business models. With the help of advanced analytics, knowledge about real-world phenomena can be discovered from data. This may lead to unintended knowledge spillover through a data-driven offering. To properly consider this risk in the design of data-driven business models, suitable decision support is needed. Prior research on approaches that support such decision-making is scarce. We frame designing business models as a set of decision problems with the lens of Behavioral Decision Theory and describe a Design Science Research project conducted in the context of an automotive company. We develop an artefact that supports identifying knowledge risks, concomitant with design decisions, during the design of data-driven business models and verify knowledge risks as a relevant problem. In further research, we explore the problem in-depth and further design and evaluate the artefact within the same company as well as in other companies.

Keywords

Behavioral decision theory, data-driven business model, design science research, knowledge risks.

Motivation

Many of today's successful businesses have data as a central resource in their business model (BM), as prominent examples of Facebook, Amazon or Google show. Now, data-driven business models (DDBMs) are in the focus of both practice and academia (Günther et al. 2017; Hartmann et al. 2016). Also born offline organizations investigate the business value of data and seek for new DDBM (Seiberth and Gründinger 2018). Through more and more comprehensive data sets combined with advanced analytics methods, knowledge on real world phenomena can be discovered and materialized in models or algorithms. Thus, not only data but also knowledge-related value objects can be part of an offering, like selling predictions or models (Hirt and Kühl 2018). However, exchanging data across organizations, can lead to unwanted knowledge spillovers (Ilvonen et al. 2018). This leads to risks for organizations in designing DDBMs. Following the call on more IS research on methods and tools for supporting BM innovation (Veit et al. 2014) and specifically the call for research on risk and risk management (Tesch and Brillinger 2017) as well as the call for more research about managing knowledge risks in strategic IS settings (Loebbecke et al. 2016), we aim to answer the following question: *How to identify knowledge risks while designing data-driven business models and provide decision support for considering knowledge risks in business model design decisions?* To answer this research question, we follow a Design Science Research (DSR) approach (Hevner et al. 2004) embedded in a research project with an automotive company.

Background

Data has been recognized as a source for improving and innovating BMs (Günther et al. 2017). We understand BMs here 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). A data-driven business model (DDBM) is a business model relying on data as a key resource (Hartmann et al. 2016), creating customer value with analytics capabilities (Wixom and Schüritz 2017), offering data, knowledge or decisions (Hartmann et al. 2016; Wixom and Schüritz 2017) to realize monetary value (Schüritz et al. 2017). Thus, data represents both a firms resource (Hartmann et al. 2016) and a flow across business actors in DDBM. Data flows are important when analyzing BMs in value networks (Solaimani et al. 2015), e.g. in the context of cyber physical systems (Terrenghi et al. 2018) or for identifying risk factors (Brillinger, 2018).

These data flows are the reason why knowledge risks are associated with DDBM: Value networks in DDBM imply inter-organizational sharing of data, and critical knowledge could be derived via data analytics from such data (Ilvonen et al. 2018), thereby leading to unwanted knowledge spillovers (Loebbecke et al. 2016). "Knowledge spillover takes place when valuable knowledge spills out of the organization to competitors who use this knowledge to gain competitive advantage" (Durst and Zieba 2017, p. 54). The knowledge-based value proposition that is at risk in DDBM is however typically not explicit, as the knowledge is only implicitly represented by the dataset or by the knowledge-based value proposition (e.g., observing a single recommended item in an electronic store doesn't leak the complete recommender algorithm, but observing many recommended items in an electronic store may do so). E.g. in particular, machine learning models can be retrieved by malicious competitors via API access (Tramèr et al. 2016). Such risks need to be considered while designing DDBM.

When designing BMs, decision-makers have to find a balance between acceptable risk and estimated return (Tesch and Brillinger 2017). Designing a BM therefore needs to be understood as a set of choices (Casadesus-Masanell and Ricart 2010). Tools that aim to support decision making therefore need to focus not only focus on the estimation of returns, but also on relevant risk factors of a BM (Brillinger 2018). Existing research already identified data as a risk factor in supply chain integration (Ilvonen et al. 2018) or BMs (Brillinger 2018) and data risk assessment as an activity in the BM innovation process (Hunke et al. 2017). One way in which tools can support decision-making in the face of risk factors is to clearly represent relevant information associated with the risk to decision makers (Tesch and Brillinger 2017).

Methods and tools have already emerged that support the innovation of BMs in a corporate context, e.g. serving as a structured representation and communication tool (Täuscher and Abdelkafi 2017), as decision support for evaluating BMs and inform decisions (Tesch and Brillinger 2017), or identifying BM risks (Brillinger 2018). Although, there are few novel tools and methods available which incorporate data a specific lens of analysis, that are not widely accepted, e.g. connecting data with the value proposition (Kühne and Böhmann 2019), representing data flows in cyber physical systems (Terrenghi et al. 2018) or supporting data-driven ideation workshops (Kronsbein and Mueller 2019). Fewer are available for the evaluation of and decision support for DDBM. As stated above, DDBM however incorporate an additional dimension of risks, specifically the risk of critical knowledge spillover through the data-driven offering. Thus, decision makers require decision support to inform their decision on sharing and protecting core knowledge. i.e. balancing acceptable risk and estimated return in a knowledge related value proposition. To the best of our knowledge no research exists that focuses on decision-making with respect to knowledge risk within the process of designing DDBM.

Research Approach – Design Science Research

We follow a DSR approach to answer our research question *how to represent knowledge risks of DDBM in the design process to provide suitable decision support*. DSR was chosen as answering the research question necessitates the development of a design artefact, namely the risk representation. The research presented in this paper is embedded in a three-year applied research project that aims to develop DDBM for an automotive company (*Comp*). To assure the collaborating organization a high level of anonymity, only minimal information about the cases are provided. *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. *Comp* wants to offer new products and services based on data analytics.

With respect to DSR, *Comp* constitutes the environment in which research problems are defined and shown to be relevant (Hevner et al. 2004). Our research approach 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 rigor, with Behavioral Decision Theory (Simon 1959) as guiding theory, and additional background from

IS research on DDBM innovation, and decision support artefacts. In the present paper we report four iterations. Of these, iterations one and two showcase the wider research project setting and the background work done and necessary to investigate the research question. Iterations three and four showcase the relevance of the research question, the developed design artefacts, and the relationship of designed artefacts both with guiding theory, and background literature. Table 1 illustrates our intermediate results structured along the three cycles of DSR (Hevner et al. 2004). The iterations are described in detail the next section below.

Iterations, Evidence	Relevance Cycle	Rigor Cycle	Design Cycle
Iteration 1: Scoping and Ideation **Goal**: Identify requirements for tools and methodologies that support the design process **Evidence**: 17 interviews with managers (duration between 30 and 70 min), one workshop (4h, 4 participants), one-day ideation workshop with 10 participants	**Problem Statement**: Need suitable tools and best practices for guiding the development process of DDBM. **Application of artefact**: Matrix structures existing use cases of *Comp*.	**Knowledge Base**: Literature on data monetization patterns and the business model innovation process.	**Artefact**: Matrix for structuring existing use cases in relationship to different ways of generating value with data (data monetization patterns) and different levels of maturity (phases in business model innovation process).
Iteration 2: Decision Making **Goal**: Identify decision criteria specific for DDBM **Evidence**: Idea selection and aggregation (4 meetings with 1 company representative), Decision making workshop (60 min, 4 participants)	**Problem Statement**: Find a suitable representation of and decision criteria for DDBM use cases to inform decision-making within the design process of a DDBM. **Application of artefact**: structuring 23 DDBM ideas of *Comp*.	**Knowledge Base**: Literature on realizing customer value with data analytics. **Guiding Theory**: We are analyzing our decision problem with the lens of Behavioral Decision Theory (Simon 1959).	**Artefact**: Data Product Canvas as representation of DDBM use cases. **Design Requirement**: Representation needs to focus on the main elements of a DDBM, in particular data sources, analytics activities, data-driven value proposition and customer needs.
Iteration 3: Refining Decision **Goal**: Suitable representation for business interactions in DDBM serving as decision criteria. **Evidence**: One workshop (2h, 4 participants).	**Problem Statement**: For every interaction with an actor, the exchanged data, services, money need to be transparent to decide on benefits and risks. **Application of artefact**: Representing one DDBM with various with data, money and value flows.	**Knowledge Base**: Literature on value network and flow-based representation of BMs. **Guiding Theory**: Along with Behavioral Decision Theory we identified further decision inputs: actors, the exchanges between actors and the balance of value of exchanges.	**Artefact**: representing a DDBM as an actor network, extended with visualizing data flows **Design Requirement**: The artefact should incorporate a transaction-based representation of BMs and data as an additional value flow to inform decision.
Iteration 4: Focus knowledge risks **Goal**: Suitable representation to support identification of knowledge risk and balance risks and benefits in a DDBM design process. **Evidence**: planned (see outlook)	**Problem Statement:** Need to decide on what knowledge to share (monetize) and what knowledge to protect in a DDBM. **Application of artefact**: Representing one DDBM with additional knowledge flows and knowledge boundary.	**Knowledge Base**: Literature on knowledge risks and knowledge boundary. **Guiding Theory**: Behavioral Decision Theory: knowledge flows as an additional decision input for data completeness and flow-based representation with knowledge boundaries as supporting cognitive processes to identify knowledge risks.	**Artefact**: Extended flow-based representation of actor interactions with knowledge boundary and differentiated flow (data vs. knowledge). **Design Requirement**: Differentiate between data and knowledge-related flows and representing the knowledge boundary.

Table 1. Overview of the conduced DSR project

Results

Iteration 1: Scope and Ideation

During scoping and ideation for DDBM at *Comp*, decision makers were faced with the challenge to find methods and tools supporting the DDBM process. To identify requirements for supporting the DDBM design phase, and to explore *Comp's* existing DDBM ideas, we conducted 17 interviews with managers from different business units. We identified as one concrete requirement of *Comp* to categorize DDBM ideas. In addition to the interviews, we conducted a literature review to find suitable approaches meeting the requirements of *Comp*. In particular, we identified five patterns of data monetization (Breitfuß et al. 2019), and six phases of the DDBM innovation process (Hunke et al., 2017). Based on the literature review, we noticed the scarce related work on the topic.

We created a matrix that maps ideas for DDBM to these categories. This matrix (the design artefact of iteration 1) was discussed in a half-day workshop with four managers of *Comp* who are specifically responsible for data-driven innovations. We again 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) as well as other organizations (4). Based on interviews and workshops, we identified as requirement the need for a structured representation of DDBM that is able to structure discussions and ideation by focusing on data analytics-related value propositions and to identify relevant decision criteria for evaluating ideas.

Iteration 2: Framing the Problem Statement as a Decision Problem

Building on iteration 1, the goal of iteration 2 is 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 Behavioral Decision Theory (Simon 1959) as a guiding theory. Behavioral 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 a decision support (Osterwalder and Pigneur 2010; Tesch and Brillinger 2017) via structuring the required decision inputs, ensuring data completeness in line with Behavioral Decision Theory. Based on this background from Behavioral 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 a component-based representation of DDBM as design artefact. We defined as main elements the following, in line with prior published research where available: data as a key resource (Hartmann et al., 2016), analytics key activities (Wixom and Schüritz 2017), data-driven value proposition (Hartmann et al. 2016) and customer problems and needs (Osterwalder and Pigneur 2010).

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 further elaborate and explore two of the 23 DDBM ideas. One of these was prioritized and was 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 artifact; and it was expected that this would be necessary to inform further decision-making.

Iteration 3: Refining the Decision Problem

Based on the insight of iteration 2, for every business interaction with an actor, the exchanged data, services and money need to be transparent. This is necessary to be able to decide on benefits and risks in the design process; and on the overall feasibility of an DDBM idea. This can be understood as visualizing the roles, deliverables and transactions of a value network (Alee, 2008).

Analyzing the partner network in a BM is an important step for improving the decision base (Brillinger 2018), especially for *Comp* as the selected BM use case contains the usage of external data sources and provision of corresponding value in exchange. 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 Behavioral Decision Theory, we identified as further decision inputs actors, the exchanges between actors and the balance of value of exchanges (Brillinger 2018). Based on this background, and the relevance identified within *Comp* to represent business interactions and network, 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 design artifact within iteration 3, a representation of DDBMs as value network including actors, value exchanges and customer needs as the main elements. 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. Exchanges are triggered by customer needs.

We instantiated this representation with the selected DDBM use case within *Comp*. The DDBM was discussed and refined in two two-hours 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 aging models of physical components based on data from different data sources. Based on this model, *Comp* is able to sell predictions for residual life time and value, as well as usage recommendations. Already 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 BM 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-spillovers.

Iteration 4: Focus on core knowledge asset and knowledge risks

Based on the workshop's insight from iteration 3 that knowledge is the critical asset of a DDBM, we frame a more detailed decision problem: Find a trade-off between benefits of monetizing knowledge (i.e., knowledge as part of the value proposition (Hartmann et al. 2016)) and the risk of losing this knowledge. To take this decision seriously, decision makers needs transparency about the knowledge contained in the exchanged data sets or digital value objects. This is as well 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 on 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 lead to a risk/benefit decision between sharing or protecting knowledge-related assets. With the lens of Behavioral Decision Theory, this 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 and 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. The DDBM of *Comp* (from iteration 3) was represented as an instantiation of the refined artefact. To ensure anonymity Figure 1 shows a fictitious DDBM as an illustrative example. BM owner is exchanging data against money with Data Provider to build a data-driven model of a real-world phenomenon based on his own expert knowledge. Thus, BM owner is materializing his core knowledge in a digital value object. All other services (i.e., making predictions or recommendations from customer data based on the model) the BM owner is offering are relying on that core knowledge. BM owner is offering two data services to customers from the same (A) and different (B) industry respectively. In the former case, BM owner wants to protect his core knowledge embedded in the value proposition to assure competitive advantage and to prevent unintended knowledge-spillover; and in the latter sharing the knowledge with other industries is seen as less critical.

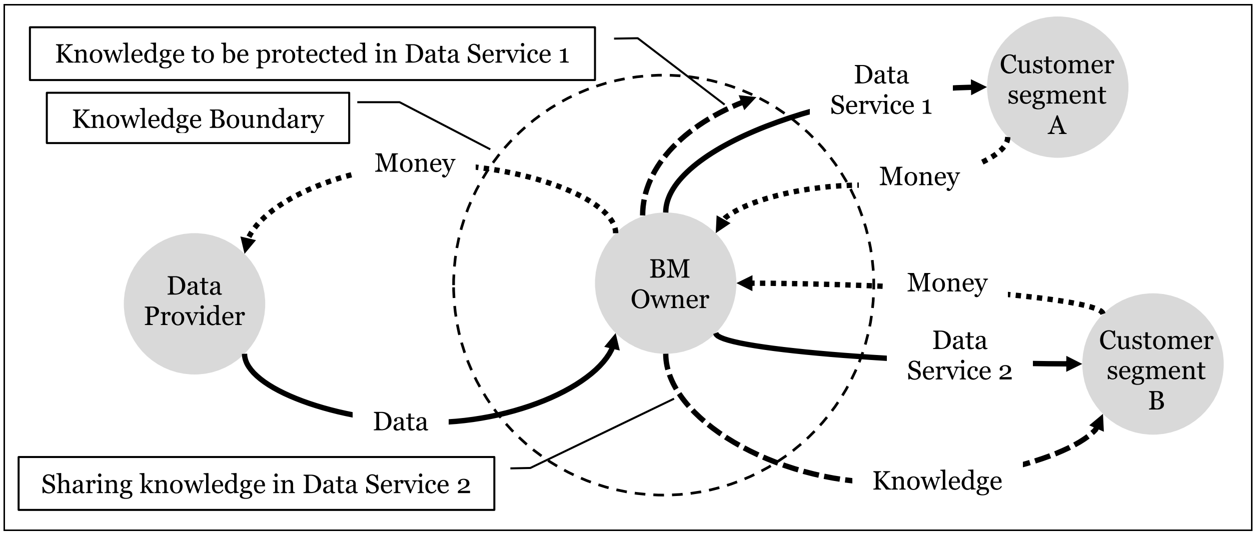

Figure 1. Concept of visualizing knowledge risks in a DDBM

Contributions

Our main contribution is twofold: First, we identified that knowledge risks are a relevant decision parameter in the design process of DDBM. Based on the Behavioral Decision Theory, we framed this insight as decision problem and collected first evidence for its relevance. We found this as an specific aspect of DDBM in contrast do non data-driven BM 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 knowledge intensive service business, as these have valuable core knowledge. In this regard, *Comp* serves as a typical case as it is offers services and products based on their expert know-how in automotive engineering.

Our second contribution are the design requirements for providing suitable 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 developed first prototypes considering our design requirements and we collected first evidence that those representations support the decision making during the DDBM design process. A baseline proposition for further research in the field therefore is: Considering knowledge risks in the design process of DDBM enhances the decision quality of the design process and thus the success of the DDBM.

Outlook: Problem Exploration and Artefact Evaluation

In order to complete our DSR project, we have to "observe and measure" (Peffers et al. 2007) how well our artefact enhances the decision quality in the design process of DDBMs. In order to do so, we follow a continuous evaluation approach, as suggested by Sonnenberg and Vom Brocke (2012). *First*, we want to further investigate the problem relevance of knowledge risks in DDBM. Therefore, we are currently conducting an interview study with approximately ten experts from the field of BMs, data analytics and risk management. The goal is here to further elaborate potential causes and consequences of knowledge risks in DDBM and corresponding measures for the BM. We will specifically also look for stories of failure of DDBM due to not considering knowledge risks in the design process. Further, we expect to craft additional design requirements from the interviews. *Second*, after refining our artefact, we plan to evaluate the structure of our artefact for simplicity and completeness as well as applicability again with expert interviews. *Third*, we want to evaluate that the final artefact enhances the decision quality in the design process of DDBM of *Comp* by taking knowledge risks into account. We plan to do this for a second DDBM use case within *Comp*. Further, based on the Behavioral Decision Theory we want to evaluate if and under which circumstances our artefact can enhance the decision quality in DDBM design process in other (than *Comp*) organizational contexts. For both, we plan to do participatory workshops with decision makers from *Comp* and other organizations We aim to measure perceived decision quality to evaluate efficacy of the artefact drawing on existing measuring instruments, e.g. (Tan et al. 1995).

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References

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

Brillinger, A.-S. 2018. "Mapping Business Model Risk Factors," *International Journal of Innovation Management* (22:05), 1840005.

Casadesus-Masanell, R., and Ricart, J. E. 2010. "From Strategy to Business Models and onto Tactics," *Long Range Planning* (43:2-3), pp. 195–215.

Durst, S., and Zieba, M. 2017. "Knowledge risks - towards a taxonomy," *International Journal of Business Environment* (9:1), pp. 51–63.

Gordijn, J., and Akkermans, H. 2001. "Designing and evaluating e-business models," *IEEE Intelligent Systems* (16:4), pp. 11–17.

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

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

Hevner, A., March, S., Park, J., and Ram, S. 2004. "Design Science in Information Systems Research," *Management Information Systems Quarterly* (28:1), pp. 75–105.

Hirt, R., and Kühl, N. 2018. "Cognition in the Era of Smart Service Systems: Inter-organizational Analytics through Meta and Transfer Learning," in *Proceedings of the 39th International Conference on Information Systems - Bridging the Internet of People, Data, and Things*, J. Pries-Heje, S. Ram and M. Rosemann (eds.), Francisco, CA, USA.

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

Ilvonen, I., Thalmann, S., Manhart, M., and Sillaber, C. 2018. "Reconciling digital transformation and knowledge protection: a research agenda," *Knowledge Management Research & Practice* (16:2), pp. 235–244.

Kronsbein, T., and Mueller, R. M. 2019. "Data Thinking: A Canvas for Data-Driven Ideation Workshops," in *Proceedings of the 52nd Hawaii International Conference on System Sciences*, T. Bui (ed.), Grand Wailea, Maui, Hawaii, USA, pp. 561–570.

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

Lee, J., Min, J., and Lee, H. 2015. "Setting a Knowledge Boundary for Enhancing Work Coordination and Team Performance: Knowledge Protection Regulation across Teams," in *Proceedings of the 36th*

International Conference on Information Systems - Exploring the Information Frontier, T. Carte, A. Heinzl and C. Urquhart (eds.), Fort Worth, Texas, USA.

Lifshitz-Assaf, H. 2017. “Dismantling Knowledge Boundaries at NASA: The Critical Role of Professional Identity in Open Innovation,” *Administrative science quarterly* (63:4), pp. 746–782.

Loebbecke, C., van Fenema, P. C., and Powell, P. 2016. “Managing inter-organizational knowledge sharing,” *The Journal of Strategic Information Systems* (25:1), pp. 4–14.

Manhart, M., Thalmann, S., and Maier, R. 2015. “The Ends of Knowledge Sharing in Networks: Using Information Technology to Start Knowledge Protection,” in *Proceedings of the 23rd European Conference on Information Systems*, J. Becker, J. Vom Brocke and M. de Marco (eds.), Münster, Germany.

Olander, H., Hurmelinna-Laukkanen, P., and Mähönen, J. 2009. “What's small size got to do with it? Protection of intellectual assets in SMEs,” *International Journal of Innovation Management* (13:3), pp. 349–370.

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

Peffers, K., Tuunanen, T., Rothenberger, M. A., and Chatterjee, S. 2007. “A Design Science Research Methodology for Information Systems Research,” *Journal of Management Information Systems* (24:3), pp. 45–77.

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

Seiberth, G., and Gründinger, W. 2018. “Data-driven business models in connected cars, mobility services and beyond,” *BVDW Research* 01/18.

Simon, H. A. 1959. “Theories of Decision-Making in Economics and Behavioral Science,” *The American Economic Review* (49:3), pp. 253–283.

Solaimani, S., Bouwman, H., and Itälä, T. 2015. “Networked enterprise business model alignment: A case study on smart living,” *Information Systems Frontiers* (17:4), pp. 871–887.

Sonnenberg, C., and Vom Brocke, J. 2012. “Evaluation in the Science of the Artificial: Reconsidering the Build-Evaluate Pattern in Design Science Research,” in *Design Science Research in Information Systems*: *Advances in Theory and Practice*, D. Hutchison, T. Kanade, J. Kittler, J. M. Kleinberg, F. Mattern, J. C. Mitchell, M. Naor, O. Nierstrasz, C. Pandu Rangan, B. Steffen, M. Sudan, D. Terzopoulos, D. Tygar, M. Y. Vardi, G. Weikum, K. Peffers, M. Rothenberger and B. Kuechler (eds.), Berlin, Heidelberg: Springer Berlin Heidelberg.

Tan, B. C.Y., Teo, H.-H., and Wei, K.-K. 1995. “Promoting consensus in small decision making groups,” *Information & Management* (28:4), pp. 251–259.

Täuscher, K., and Abdelkafi, N. 2017. “Visual tools for business model innovation: Recommendations from a cognitive perspective,” *Creativity and Innovation Management* (26:2), pp. 160–174.

Terrenghi, N., Schwarz, J., and Legner, C. 2018. “Towards Design Elements to Represent Business Models for Cyber Physical Systems,” in *Proceedings of the 26th European Conference on Information Systems: Beyond Digitization - Facets of Socio-Technical Change*, P. M. Bednar, U. Frank and K. Kautz (eds.), Portsmouth, UK.

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

Timmers, P. 1998. “Business Models for Electronic Markets,” *Electronic Markets* (8:2), pp. 3–8.

Tramèr, F., Zhang, F., Juels, A., Reiter, M. K., and Ristenpart, T. 2016. “Stealing Machine Learning Models via Prediction APIs,” *Proceedings of the 25th USENIX Security Symposium*, pp. 601–618.

Veit, D., Clemons, E., Benlian, A., Buxmann, P., Hess, T., Kundisch, D., Leimeister, J. M., and Loos, P. 2014. "Business Models: An Information Systems Research Agenda," *Business & Information Systems Engineering* (6:1), pp. 45–53.

Wixom, B. H., and Schüritz, R. 2017. "Creating Customer Value Using Analytics," *MIT CISR Research Briefing* Volume XVII, Number 11, November 2017.