Understanding the Role of Data for Innovating Business Models: A System Dynamics Perspective

Matthias Förster[1], Bastian Bansemir[2], Angela Roth[1]

[1] Friedrich-Alexander University Erlangen-Nürnberg, Chair of Information Systems - Innovation & Value Creation, Nürnberg, Germany
{matthias.f.foerster,angela.roth}@fau.de
[2] BMW Group, Business Model Development, München, Germany
{bastian.bansemir}@bmw.de

Abstract. Data have become a key ingredient for ICT-enabled business models. Nevertheless, there is great uncertainty among scholars and practitioners alike about how to leverage data as an essential innovation resource. This raises the question of how to design data roles to innovate business models. To answer this question and to facilitate a deeper, cause-effect-relation understanding of the interdependencies between data roles and business models, system dynamics was chosen as the approach of analysis. Within a multiple case study of five business model cases with multiple embedded units per case, the study shows that there are four recurring basic data role patterns e.g. 'incremental improvement' or 'initial data boost' and two data role characteristic patterns, describing how data roles unfold within business models e.g. 'change in self-reinforcement' pattern. Overall, the patterns help to visualize and articulate data usage in business models and therefore contribute to the ongoing endeavor of innovating business models.

Keywords: Business Model Innovation, Big Data, System Dynamics, Data Role Patterns

1 Introduction

In the course of increasing digitalization, information and communication technology (ICT) has become both an enabler and constraint for new business models (BMs) [1]. ICT-enabled and dynamic business processes require a constant adapting and reshaping of BMs to cope with the continuously changing business environment across all industries [2, 3]. As a key ingredient or even ignitor for ICT-enabled innovating of BMs, 'digital data' have increasingly gained importance [4, 5]. This paper aims at facilitating a deeper understanding of how data innovate BMs, and shows the impacts of data on BMs. For this purpose, the paper examines the design of data roles, which are resulting from the usage of data to achieve an overarching business goal, e.g. efficiency gains through process transparency using IT systems, in order to innovate BMs. The term 'data roles' describes on a cause-effect-relation basis the task and underlying concrete impact of data on the elements of a business model (BM). Going one step further, the study enriches information systems (IS) research, with outlining

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the reciprocal relationship between IT-capabilities, the choice of data roles, and the interlink to BM configurations. Thus, the paper positions itself at the vertex of IS and business model innovation (BMI) research, because so far literature largely and particularly discusses how to make data consistent with business strategy [6], reflects the opportunities of leveraging data to innovate existing BMs, outlines how to build completely new BMs [7] or internet-based BMs [8], and addresses constructing and implementing data related adaptions and amplifications to existing BMs [4, 9, 10]. However, in order to be able to build completely new 'data-based' BMs [11], an awareness on how to design data roles to innovate BMs with consideration of data impacts on the BM is required. The failure of building these completely new BMs may be ascribed to a lack of knowledge regarding BMs and the concatenating management of digital data as an essential resource to innovate BMs. This is not a surprise due to the specific and partly fuzzy characteristics of data which make data as a resource difficult to manage [12, 13]. Because of these complex data characteristics, it is not sufficient to give way to simplifications and generalizations [14, 15] at the endeavor to understand the role of data to innovate BMs. Moreover, to grasp non-linear, cause-effect-relations between data roles and BMs, a novel data-focused perspective on BMs is required. To meet these requirements and to provide managers and scholars an advanced understanding of the dynamic data roles behind the static BM story, illustrated as target images in a BM (data) canvas [16–18], a dynamic and conceptual representation method is premised. System dynamics - a computer-aided approach to enhance analysis and decision making for complex systems [19] - turns out to be a suitable approach for this, due to it's potential of simplified and consistent representations of BMs, including quantified considerations of feedback loops and delays between the individual BM elements [20]. In case of our study, the interrelations and feedbacks between data roles and BMs are focused. With use of the system dynamics approach the study seeks to answer the following research question: ***How could data roles be designed to innovate business models?***

2 Theoretical Background

2.1 Innovating Business Models

According to Shafer et al. (2005) [21] the study's central subject of matter – BMs – are defined as 'the firm's logic of creating value'. Although many authors conceptualized a holistic view on the logic of a firm's value creation by outlining consolidated components of a BM, a common understanding is not overarchingly achieved [22]. Examining the most cited publications on this topic one may conclude that there is common understanding among the following three components within the BM definition [11]: value proposition, value creation and value capturing [10, 23–28]. Gassmann et al. (2014) [17] breaks these three components down to four fundamental BM questions: "Who is my target customer?", "What is offered to the target customer?", "How to build and distribute the value proposition?" and "Why is the BM financially viable; what value is generated?" As the hackathon artefacts A1 and A4 of the empirical field (see figure 1) are based on the BM definition of Gassmann et al.

(2014), the BM understanding of this study is oriented on the conceptualization of the BM components: How (value creation), what (value proposition), value (value capturing) and who (key customer). Since the emergence of the internet economy the topic of innovating BMs has gained much popularity [29], and BMI can be seen as a subordinate BM research stream. With the opportunities of the internet and the accompanying ICT, firms obtained a broad armamentarium to completely change the rules of competitive environment [30] by approaching the customers with entirely new, data-based BMs [31]. However, innovating BMs remains an ambiguous concept. Thus, different research streams consider BMI either as a process (e.g., search, experiment, transformation), while another stream see BMI as a output. [32]. As our research is based on a hackathon where 171 students innovated BMs by initiating and ideating new BMs based on the firm profiles, capabilities and existing BMs, we understand BMI as a process. This is in line with the research question *"How could data roles be designed to innovate business models?"*, which also provides support for the ideation process of innovating BMs. Furthermore, system dynamics as a dynamic BM experimentation, modelling and simulation approach also understands innovating BMs as a process. In comparison, most conventional approaches fall short grasping the dynamics of BMs over time. They depict innovation as a static image or a 'snapshot' of a BM at a certain point in time, i.e. when it functions as wished. But a BM - especially a data-based BM [2] - is by no means a purely static concept. It must constantly be innovated and adapted to changing internal and external forces [25] in order to protect the recently implemented BM against imitations [10, 28], or react [32] to strategic discontinuities or global competition [33]. However, especially long-established firms, struggle with constantly innovating BMs due to the complexity of inherent IT-systems and -infrastructure or path dependency such as legacy systems and products [10]. Therefore, innovating BMs is often lengthy, risky or costly, or at worst, all three of the before mentioned challenges [34]. These challenges can be overcome and BMs can be made manageable by adopting an effectual attitude toward BM modelling and experimentation [35]. Chesbrough (2010) states: *"[Model] experiments will fail, but [if] they inform new approaches and understanding, this is to be expected - even encouraged"* (Chesbrough, 2010 p. 362). Also, Osterwalder et al. (2005) [36] claim that *"simulating and testing business models is a manager's dream"* (Osterwalder, 2005 p. 16). In other words, to overcome the above mentioned 'deadlock' for established companies and to keep pace with the dynamically changing ICT-enabled business environment, new data-related approaches for innovating BMs must be developed. BM simulation, more precisely the system dynamics approach, appears to be a suitable and necessary means to innovate BMs.

2.2 System Dynamics

System dynamics is a simulation and experimentation approach for enhancing analysis and decision-making on complex and dynamic systems [20]. System dynamics was initially developed by J. W. Forrester in 1968 [37] as a methodology developed from several scientific approaches including system theory, information science and cybernetics [38]. System dynamics is considering all elements of a system as actively influencing the behaviour of the system through interdependencies and mutual interactions of elements, so-called feedbacks. The cyclic consequences inside a system are represented by causal-loop diagrams (CLDs). A CLD shows a sequence of events (actions, information, objects, people) successively causing another event until the first mentioned event is caused again. These feedback loops can either be self-reinforcing and dominating the system over time due to exponential growth effects, or self-correcting and balancing a system due to corrective and attenuating effects [39]. The CLD visualization of several reinforcing or balancing, non-linear, multi loop conditions help people to remove cognitive barriers for understanding the complexity of a system. For managing highly interrelated, complex systems such as BMs, system dynamics uses computer-aided modelling and simulation tools like Powersim or Vensim. These computational simulation tools help managers to quantify flows (information, goods, people or financial means) inside BMs, and therefore, provide managers and scholars the opportunity to test and gauge their decisions and to learn about the consequences of their actions in complex corporate and industry contexts of their BMs [20, 37]. Understanding, testing and gauging BM decisions is especially important during the ideation phase of innovating BMs where managers generate new BM ideas by overcoming the current BM logic through reflecting novel, non-trivial changes in the way the BM elements are interrelated [32]. System dynamics has been applied to various BM domains like transportation [38], economic and ecological sustainability [40] or the revolutionary and evolutionary market strategies at the automotive security equipment sector [41].

3 Research Design

3.1 Case Study Design

To explore how data roles could be designed to innovate BMs an exploratory multiple case study was carried out. The case study method aims at retrospectively comprehend complex issues of a contemporary phenomenon within a real-life setting. Furthermore, the case study method is useful when literature and theoretical knowledge do not fully delineate the issue of research with appropriate certainty and clearness [42]. We see these aspects of a multiple case study as given in our study, since the case units of the case study were carried out in the context of an industry-initiated and -derived student hackathon with real-life oriented design decisions in the hackathon process to increase the significance for industry. Additionally, the process was accompanied and supervised by a total of three industry partners. The empirical field of the multiple case study was a hackathon, a collaborative event where 33 student teams ideated BMs for the mobility sector. These 33 teams were split to five different cases, which represented the five essential actors in the mobility sector. Each actor had different pre-settings through company history, firm resources and capabilities, existing BMs and financial KPIs. These actors were: an automotive OEM, mobility fleet operator, digital mobility aggregator, public transportation company and a new automotive rebel OEM. These five mobility actors were represented multiple times as embedded units per case.

3.2 Hackathon Design

Hackathon Approach

A hackathon is a marathon coding event in which a group of predominately computer programmers or IT-designers are intensively involved in developing a software prototype for a specific application, or applying a technology prototype for a specific purpose over a short period of time [43–45]. In this study, software developments or technology applications (the pure coding) were in the background. The objective of the hackathon was to let student teams compete against each other in a partially defined competitive environment with the task to come up with innovative data-based BMs Hence, to quickly and interactively generate and test BMs for real-life problems in a simulation environment [44, 45] - in our case the manifestation of future mobility.

A hackathon can be carried out with different target groups according to the statement of problem and the desired prototype output [46]. For this hackathon, student teams represent a scientifically significant and suitable hackathon execution group for two main reasons: Firstly, they are unbiased and open minded regarding new, disruptive ideas because of no long-term organizational affiliation. Therefore, more distinguishable results can be expected than with a purely industry hackathon. Secondly, to meet the needs of future customers by means of new innovative BMs, it is essential to include today's students in the innovation process of these BMs.

Future Mobility Hackathon

The Future Mobility Hackathon was a collaborative project between two university institutions of Switzerland and a German car manufacturer to foster creativity and a spirit of innovation among students while leveraging the power of system dynamics, and to support the practice partner to gain an advanced understand of future mobility needs. A total of 171 participants from both university institutions worked in teams to ideate, model and analyse innovative but also viable BMs for the mobility sector. The hackathon was conducted on a total of four dates during October and November of the year 2017. Throughout the hackathon the teams developed a series of six BM artefacts to go from an innovative idea and target image of the BM, based on the BM definition concept of Gassmann et al. (2014) [17] (BM magic triangle) to graphical illustrations and evaluation models for the dynamics of the BM (CLDs). The hackathon concept was fitted by industry-derived design decisions like different pre-settings of the hackathon players e.g. firm history, resources and capabilities, and university program-related design decisions like the release of the hackathon competition evaluation criteria at the beginning of the event to ensure the industry significance and to support the students in two ways: reducing the complexity of innovating BMs, and increase the students' identity with the object of study and therefore their creativity in the innovation process.

3.3 Data Selection and Collection

As stated above, five different hackathon BM cases, each with multiple embedded units (in total 33 teams) were examined in the multiple case study according to the case study method of Yin (2012) [42], which can be divided into 3 main phases: 1) define and design, 2) prepare, collect and analyse, and 3) analyse and conclude. In the first phase the data selection was carried out. Impartially of the team performance in the hackathon, the authors selected all generated artefacts (6 artefacts per team; 33 teams in total) throughout the hackathon process. The data collection (case study method phase 2) took place based on several data sources (see figure 1): sketched and computer-aided artefacts (A1-A6) ranging from a rough description of the target image of the BM by means of the BM magic triangle [17], over differently sophisticated CLDs of the BMs (which show the dynamics of the teams' ideated BMs) to the BM pitch presentations in the final competition round. The artefacts (A1-A6) were collected through submissions at the end of each hackathon competition phase. During the hackathon phases where the teams actively ideated, conceptualized and adjusted their artefacts, qualitative team observations were carried out by 6 hackathon supervisors. The focus of these team observations was on the team debates regarding data inside the artefacts and on the team's notion about how data roles could be designed to innovate BMs. These qualitative team observations were an important part of the data collection to give the authors a deeper understanding of data roles in BMs and to find out if there were conflicting views on the usage and role of data. Figure 1 explains for each phase of the hackathon the outcomes of the hackathon, which way they were collected (submission, team observations, or semi-structured interviews) and their input for the case study.

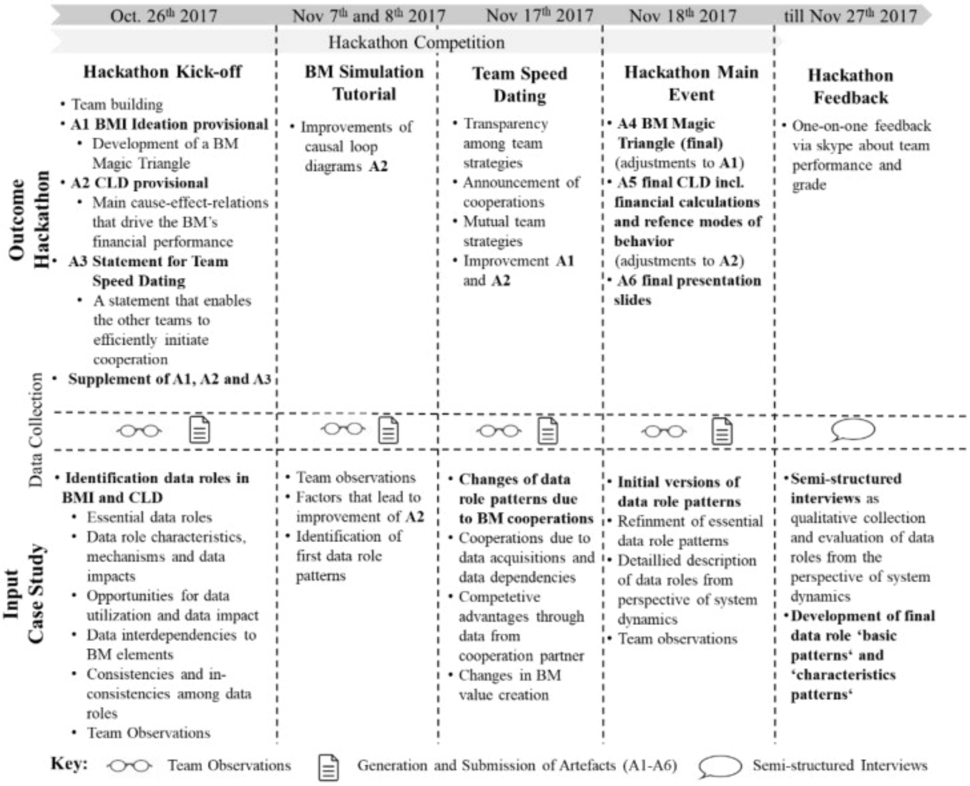


Figure 1. Data collection of the case study

Based on the findings from the analysis of the artefacts as well as the team observations, semi-structured interviews [47] were conducted with 24 of 33 hackathon teams in the aftermath of the hackathon. Since the interviews were not mandatory for the students, not all student teams agreed to be interviewed. The aim of the semi-structured interviews was firstly to uncover personal experiences, knowledge and attitudes of the hackathon participants regarding the design of data roles to innovate BMs. Secondly, the semi-structured interviews aimed at validating and enriching data from the preceding analyses of the hackathon artefacts and team observations to better explain data roles in BMs in order to obtain more objective findings as a valid foundation for further research. The 24 interviews were conducted based on a questionnaire, consisting of five open-ended questions. The questions were arranged in a way that at first the interviewees were free to state and explain the roles of data in their BM as they thought of them, how important they consider these data roles to innovate BMs, and on how they designed and realized them in their artefacts. These questions were followed by more specific questions in which the interviewees had to find and explain data roles, their characteristics and impacts on BM elements inside their CLD artefacts.

3.4 Data Analysis

We started our analysis for *the design of data roles to innovate BMs* with reflecting the BM magic triangle artefacts A1 and A4 in order to understand the BM target images and why data were used within BMs to get a first sentiment on data roles (see figure 2 step 1). To enhance the quality of this step of analysis and to check if there were conflicting views on the usage and role of data within the team, or if we might have misunderstood the artefacts, we cross-checked them with the qualitative team observations. In case that the teams have expanded their BMs by collaborating with other teams, we also analysed the artefacts A3, because collaborations may have an impact on the use of data. In step 2 we analysed the CLD artefacts A2 and A5 to understand the BM dynamics, reasons for data usage and positions of data as well as their impacts on the BMs. Moreover, we analysed the dynamics and consequences of data impacts (data loops) on BMs. In step 3 we extracted the identified data loops and cross-checked their validity, objectivity and reliability with the data loops inside and outside the cases. Again, we cross-checked the data loops with qualitative team observations and afterwards we validated and enriched our findings with data from semi-structured interviews. Based on step 1-3 we developed the six abstracted and generalized data role patterns that describe how data roles could be designed to innovate BMs (step 4). Figure 2 shows the 4-step analysis that identified the data role patterns.
Using the example of the illustrated ‘the more the more’ data role pattern at figure 2, we will briefly explain how to read our findings (data role patterns). The circle, called ‘loop’, represents the core mechanism of a BM. The general rule of system dynamics states that any intervention of an event triggers effects that eventually refer back and cause the same event again. This coherent relation is illustrated through circles (loops) based on several individual ‘events’. The data-affected loops can be self-reinforcing, represented by a plus with a circular arrow around it or balancing, represented by a minus with a circular arrow around it. For matters of reading comprehension, the

authors recommend reading the abstracted and generalized data role patterns, in the direction of the data impact (data impact direction is highlighted by bold arrows). In case of the above stated loop this means: The more useable data (e.g. infrastructure, vehicle, road environment) is generated through a higher utilization rate of shared autonomous driving cars, the more [higher] data quality can be ensured. More [higher] quality improves the relative level of competition and thereby attracts more customers, which lead to a higher use of the service, and thus to a higher data generation, with which the quality of the shared autonomous driving service can be improved again. The loop is self-reinforcing.

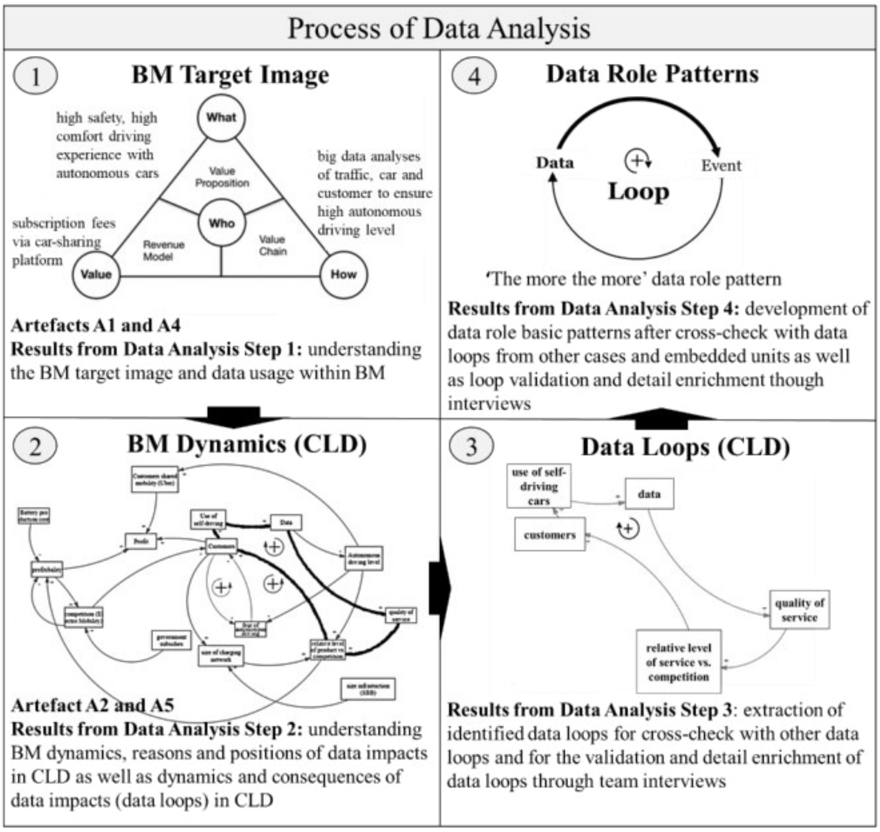


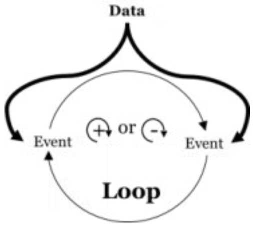
Figure 2. Process of data analysis

4 Findings

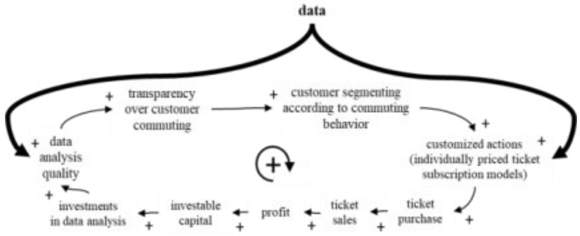
This chapter outlines the six key findings of the multiple case study. According to the research question "*How could data roles be designed to innovate business models?*" the authors identified the following recurring six data role patterns. These are: **'incremental improvement'** (**KF1**), **'initial data boost'** (**KF2**), **'business enabling'** (**KF3**) and **'the more the more'** (**KF4**). As all five cases of the case study with their multiple embedded units compose of these four data role patterns, they are called 'data role basic patterns'. Moreover, the study identified certain, complex characteristics of these patterns, describing the combination of the four 'data role basic patterns' (**'mix and match'** (**KFa**), and the dynamics and thus implicit change in the mode of action of the patterns (**'change in self-reinforcement'** (**KFb**). These patterns are called 'data role characteristic' patterns. The following tables (table 1 & 2) represent the key findings of the study with brief descriptions of their data role mechanisms, revised snippets of the original CLDs and the corresponding abstracted and generalized graphical data role patterns.

Table 1: Data role basic patterns

Key Finding 1: 'Incremental improvement' data role pattern



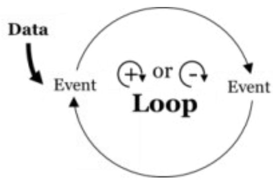
KF1 (#21)



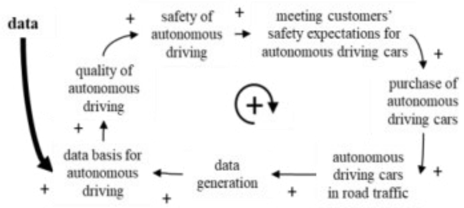
Description: Data are used to incrementally enhance the way a BM creates, captures or proposes value through data impact on one or more events of an existing BM loop. Data only induce incremental business improvements like enhanced transparency for customized actions. However, the traditional BM is only partially innovated.

Example: *Individually priced tickets: If a customer uses an app or the computer to book the daily subway ride from home to work, the transportation company knows through data analysis that the customer commutes daily, and thus can offer the customer an individually priced subscription. The BM is just incrementally improved and not fundamentally reinvented.*

Key Finding 2: 'Initial data boost' data role pattern



KF2 (#14)



Description: Through an initial, intense data-boost the events of the core mechanisms of a BM will be enriched with the necessary critical amount of data. Once the critical data amount is reached the functioning of the essential loops is initiated and the BM starts operating.

Example: *Safety of autonomous driving cars: If customers are willing to use autonomous cars in case that they are safer than non-autonomous cars, an initial high data volume (data boost) is necessary to ensure customers' minimum safety expectations of the service. Once the certain safety expectations have been met, the safety of the service doesn't need further significant increases.*

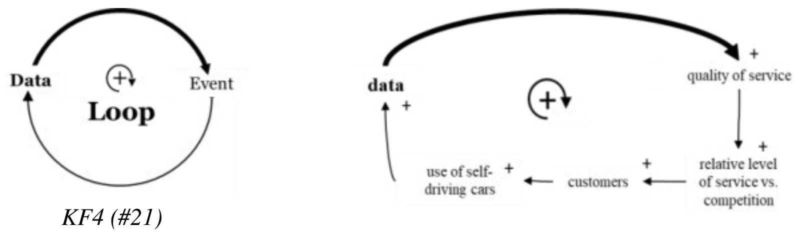
Key Finding 3: ‘Business enabling’ data role pattern

KF3 (#21)

Description: Data enact as business enabling because the BM is only made possible by the utilization of data, e.g. through data insights. Compared to the ‘initial data boost’ data role pattern, at this data role pattern, the core mechanisms of the BM have a constant, equally intense impact and dependency on data.

Example: *<u>Pay how you use insurance rates</u>: Instead of annual vehicle insurance rates, customers pay proportionally based on their driving behaviour. Traffic rule violations are displayed directly in the vehicle to educate the driver. Unsustainable and vehicle-damaging driving is penalized by higher rates; correct driving is rewarded with lower unsurance rate. The accident risks for the insurance companies decline. Thus, they can offer cheaper rates. Cheaper rates increase the customes’ willingness to share driving behaviour data. The loop is self-reinforcing.*

Key Finding 4: ‘The more the more’ data role pattern



KF4 (#21)

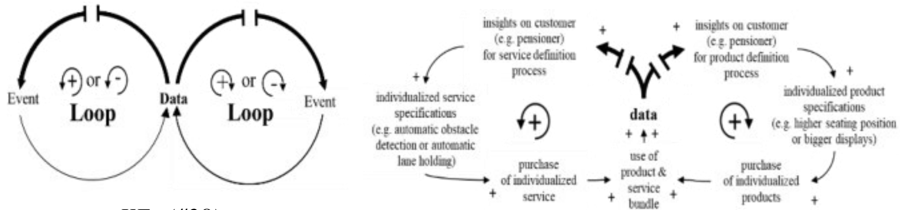
Description: BMs can have a ‘the more the more’ data role pattern e.g. regarding the quality of the offered service (value proposition) if 1) the quality of the service is directly improved by the quality of the database, and 2) the quality of database is improved by the amount of available data. ‘The more the more’ data role patterns are self-reinforcing.

Example: *<u>Service quality of autonomous driving</u>: The more an autonomous driving service is used, the more data are generated. With more data the algorithms for autonomous driving are getting better, and thus the quality of the service is getting better. The better the quality of the service, the higher the relative level of competition. Therefore, more customers use the service, and subsequently the loop reinforces again.*

As stated above, the study also identified two patterns which describe the characteristics of the four ‘data role basic patterns’. These so-called ‘data role characteristic patterns’ (see table 2) are **‘mix and match’** (**KFa**), and ‘**change in self-reinforcement’** (**KFb**).

Table 2. Data role characteristic patterns

Key Finding 5: 'Mix and Match' data role characteristic pattern

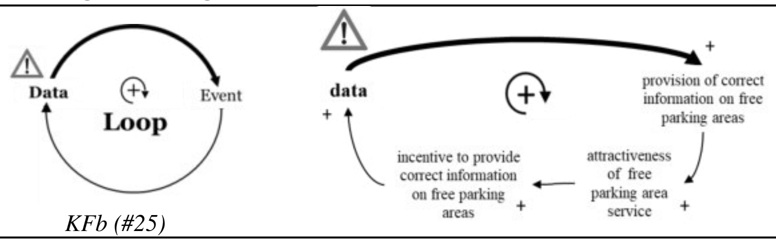


KFa (#28)

Description: On prominent characteristic of the four basic data role patterns is that they can be combined with each other in any form and number. In the exemplary graphical illustration two 'business enabling' data role patterns are arranged around data as the central point of both loops. Because of the centricity of data (two loops), data have an enormous impact on two complementary core mechanisms within BMs through simultaneous direct effects, and thus significantly determine the dynamics of a BM.

Example: *Individual cars with individual mobility services: Based on customer insights (e.g. customer is a pensioner) the firm can individually design cars according to customer preferences e.g. higher seating position and larger displays. Also based on customer data, the firm can offer complementary mobility services for the individually designed cars like lane holding assistants. Thus, the firm uses data to enable two different but complementary BMs, building an individual mobility environment for the customer.*

Key Finding 6: 'Change in self-reinforcement' data role characteristic pattern



KFb (#25)

Description: The pattern describes a possible dynamic behavior of a self-reinforcing data role over time. With changing data attributes as volume or quality, the role of data can change abruptly in the way it is operating in reinforcing loops. Therefore, a business-fostering, self-reinforcing loop changes to a business-destructing, self-reinforcing loop. Consequently, data become an exponentially growing threat to the BM. This pattern is an enormous uncertainty factor for BMs, because once an input flow (e.g. data volume) changes, the exponentially increasing consequences are hard to handle.

Example: *App-based free parking area community service: A service where members tell each other about free parking areas in the city, is business-fostering, self-reinforcing until false data (e.g. by opportunism of residents in free parking streets) is distributed to the community network. False information leads to a lower attractiveness of the service, which reduces incentives for other users to make their known free parking areas available to the community. As a result, there is less correct information provided in the app and the attractiveness of the BM continues to decline exponentially (business-destructing loop).*

5 Discussion and Conclusion

The study aimed at facilitating a deeper understanding of how to leverage data as a new essential resource to innovate BMs. For this purpose, the paper examined - on the basis of an exploratory multiple case study [42] - the design of data roles to innovate BMs. Through the grounding on system dynamics [20] the identified data role patterns (KF1-KF4, KFa & KFb) provide an advanced understanding of the complex and dynamic data impacts and concrete interrelations with BMs. Moreover, the identified six data role patterns take the discussion of *"how to leverage data to innovate BMs"* one step further and provide generalized and consistent representations of how to design data roles for the viability of BMs. This distinguishes the study from previous contributions, which rather reflect the nature of data usage and the potential and importance of data for the core logic of a particular BM from a more static and conceptual level [7, 9, 48]. However, some may argue, that the patterns are relatively established knowledge, debating network effects, platform BM interdependencies or critical data masses for market strategies, but the authors are convinced that the paper is of novelty for the discussion of how to innovate BMs with data for three reasons: 1) visualization of data impacts, 2) possibility of data impact quantification, and 3) validation of known data roles in data-based BMs outside the realm of purely digital BMs. In detail:

Firstly, the data role patterns help to visualize complex, cause-effect-relations to contribute to an enhanced management articulation of data usage. Especially consequences of data usage to improve value creation, value capturing and value proposition via building a clear step by step chain of effects is of particular interest for scholars and managers alike. Therefore, the patterns help to overcome cognitive barriers at decision making both in highly volatile industries like emerging ‘blue oceans’ [49] and existing industries in transition such as mobility sector, health care, insurance, aviation or mechanical engineering. Secondly, applying system dynamics approach, managers, consultants and researchers are able to quantify data role impacts to test and gauge data usage to design the data roles best suited for the desired BM. Thirdly, the study explores that known cause-effect-relations of data roles from the realm of purely digital BMs, also apply at data-based BM in the industrial sector, where customer needs (e.g. mobility) are still realised by physical (non-digital) products like vehicles or trains. Hence, the findings contribute to an advanced understanding and management of designing data roles to innovate BMs impartially, be it a long-established industrial firm (e.g. an OEM, which integrate digital services in their current product offerings and IT-capabilities), a start-up /digital rebel (which builds BMs from scratch due to the utilization of data) or a highly digitalized incumbent firm (which expands its existing digital portfolio in new domains).

Also, the study has implications for scholars, because it provides a new, conceptual view (data role patterns) on a largely discussed issue [9-14] namely, how to leverage data to innovate BMs. Thus, the study builds i.a. on the research of Casadesus-Masanell and Ricart (2011) [50] on how to design a ‘winning BM’. Exposing causal insights on how to design data roles to innovate BMs, this study is giving a knowledge foundation on answering future research questions on how to design a winning ‘data-based’ BM. In accordance with the design decisions of the hackathon, the findings of this study are bounded. Therefore, further research projects should validate the identified patterns and search for additions and modifications under different settings of the empirical field. Due to the methodological approach of a multiple case study [42], qualitative data is collected and analysed. Future studies should carry out quantitative analyses to explore and quantify the intensity of data role impacts on BMs. Also, this study contributes to the ongoing research by setting out a first explanatory approach of how to design data-based BMs, considering data as a dynamic BM resource that is causally intertwined with the BM components value creation, value proposition and value capturing [11].

Analysing the data role patterns in light of resource-based view [51], i.e. understanding data as an existing or evolving resource, or a dynamic-capability [52] i.e. the management of data roles over time, may add considerable theoretical and conceptual insights, leading to fascinating and inspiring research questions and empirical approaches.

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