Capturing Value from Data: Exploring Factors Influencing Revenue Model Design for Data-Driven Services

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Abstract. In recent years organizations have started utilizing big data and advanced analytics not just to support decision-making to raise process efficiencies, but also to engage in new data-driven services. These data-driven services complement the current product and service portfolio and create additional value for customers. In order to capture the value created, organizations need to design sustainable revenue models consisting of a revenue (how) and pricing (how much) mechanism. In order to develop a deeper understanding of one part of the decision-making process on revenue models, we apply a qualitative study and analyze the results through the lens of rational choice theory. Based on the interviews, we derived four factors – service characteristics, provider interests, customer interests, and market factors - influencing the design. By this, we contribute to the general understanding of the design of revenue models and enable further investigation into this field of research.

Keywords: Big Data, Business Model, Revenue Model, Revenue Mechanism

1 Introduction

Every organization is concerned by the dawning era of big data analytics [1]. They are pushed to make use of data analytics to stay innovative and ahead of competitors [2]. Organizations mostly leverage data analytics to support their decision-making and improve process efficiencies, e.g. by continuously monitoring market trends to better allocate their sales force across different business units. However, in order to stay competitive in an ever servitizing economy, companies may use data analytics to create new products and services [3]. This can be achieved by either wrapping the product or service with data analytics [4] or by introducing entirely new data-driven business models [5]. Rolls-Royce, for example, has gone down the path of reinventing its service portfolio by enriching the use of a physical product – jet engines - with data analytics. By providing detailed product usage data (e.g. fuel consumption, temperatures, altitude), its customers can drive efficiencies in product usage [6].

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Data-driven services are characterized by relying on data as their key resource and analytics to provide value to the customer. To take advantage of the value creation opportunities of these data-driven services, companies must design a suitable revenue model as part of their overarching business model [7–9] (cf. Figure 1). A process that is found to be a major challenge for organizations that approach datatization [10]. The question of how to design revenue models has already been challenging in the context of servitization and has not yet been answered conclusively [11]. Initial studies shed light on the availability and usage of revenue models for data-driven services in general [e.g. 11, 12]. Companies still need to decide which model is appropriate for their particular data-driven service. We want to investigate this decision-making process to approach this rather underappreciated field in research. In this explorative study we first investigate the decision-making process to build a better understanding of the factors influencing the choice of a revenue model. By that we aim to contribute to the general understanding of revenue models in the context of data-driven services. In particular, we contribute factors that represent an influence on the decision-making process for revenue mechanisms and we demonstrate that rational choice theory can be leveraged to explain our observations.

We initially focus on the analysis of data-driven services due to the current interest and demand in the market. In contrast to other services (e.g. air travel, maintenance services), data-driven services are characterized by being scalable through IT infrastructure and the fact that data, as a key resource, can be reused simultaneously at no additional cost [14]. Our research is guided by the overarching research question:

"What are the factors influencing the decision-making process for a revenue mechanism for data-driven services in a B2B environment?"

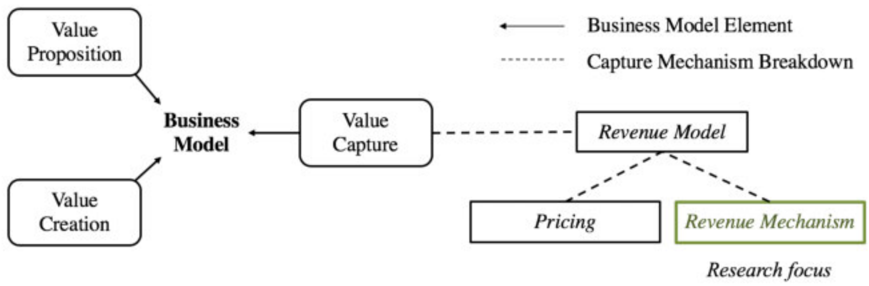

Figure 1. Research focus

We conducted interviews with 14 experts that were involved in the design of revenue models for data-driven services. By applying a qualitative content analysis and looking at the results through the lens of rational choice theory, we derived and analyzed four factors influencing the decision-making of the revenue mechanism for a data-driven service.

The remainder of the paper is structured as follows: section 2 introduces data-driven offerings and elaborates on the current state of research on revenue models. Section 3 illustrates how we collected data and the means of analyzing it. The results of our interview study are being presented in section 4. The paper closes with a brief summary, discussion, study limitations and managerial implications in section 5.

2 Related Work

In this section, we give a brief introduction to data-driven offerings and revenue models. Furthermore, we show that there is a need to develop an understanding of the factors that influence the choice of a revenue model.

2.1 Data-Driven Offerings

With the ever-increasing amount of data being generated, many organizations have realized that there is value hidden within this data. Often, data is generated as a byproduct of other activities e.g. through the use of sensors that connect the digital and physical world [15, 16]. An increasing amount of enterprises are making use of that data by developing new data-driven services or shifting their entire business model to be more data-driven. For instance, machine manufacturers start collecting real-time product usage data in order to move from reactive to predictive maintenance activities to reduce the costs of downtime [17].

Exploring the field of big data and its applications, e.g. for developing data-driven offerings, is not new. For instance, Manyika et al. [16] provide a broad overview on how the use of big data and services impact innovation, competition, and productivity. Chen et al. [15] explore ways in which insights derived from the use of big data can have an impact on different domains while highlighting the importance of the evolution of business intelligence and analytics over the past decades. Hartmann et al. [5] develop a taxonomy of data-driven business models and argue that the effective use of big data, e.g. by offering purely data-driven services, could lead to a competitive advantage. In their recent work, Wixom and Ross [4] propose three ways for enterprises to monetize their data: internal improvements, wrapping, and selling. They argue that besides deriving internal efficiencies, organizations can engage in becoming an information business by using data analytics to offer stand-alone services (selling) or to enhance the value of an existing core product or service through analytics (wrapping).

As organizations start developing new data-driven offerings, the question on how to capture the value of such offerings emerges and organizations are still struggling with answering it [10]. Revenue models describe the mechanism to capture this value and function as a critical component of the overall business model of the organization [18].

2.2 Revenue Models for Data-Driven Offerings

Literature on revenue models offers a multitude of perspectives on what they are: “revenue streams” [19] “pricing mechanisms” [20] and “payment model” [21] are some of the most common ones. While some of them have a customer view (e.g. payment model), others focus on the way the service provider captures an offering’s value (e.g.

revenue streams). Eventually, the meaning of a revenue model boils down to being a mechanism to capture the value of a good or service [8]. The definition of a sustainable revenue model is crucial for the viability of a business. Therefore, scholars agree that the revenue model is a critical component of the overall business model [7, 18, 22, 23].

The revenue model describes an overall architecture, which essentially consists of two key elements: revenue mechanism and price setting [8]. While price setting deals with how much to charge for a service or product, the revenue mechanism targets the question how to charge. The process of pricing a new product or service usually follows one of three approaches: cost-based, competition-based or value-based pricing. Since pricing is a complex field of research by itself, our study focuses on the decision-making process of revenue mechanisms. A study conducted by Schüritz et al. [12] provides an initial overview of the revenue mechanisms most commonly used by organizations offering data-driven services: in the availability-based model, also called subscription model, customers pay a service fee for a particular time period in which the service is being made available – independent of how much the offering is essentially used during that period [24, 25]. In contrast, a usage-based revenue mechanism only allows the provider to earn revenue when the service is actually used by the customer. This requires the definition of a unit of measure for the service to be charged [26]. Another model is so-called performance-based; in this case, the compensation of the provider is dependent on outcome generated for the customer [27, 28]. Also, multi-sided revenue mechanisms exist; they involve two or more interdependent customer groups. Google Adverts is a popular example of this model since it acts as a 'hub' that connects an advertiser and an end customer indirectly.

Data-driven services may also be used as a free add-on to an existing product or service. In such cases, the organization has chosen an indirect payoff model since the service is paid for by the revenue stream generated through the core offering itself.

Previous studies, such as the one conducted by Schüritz et al. [12], have shown that organizations have deployed various revenue mechanisms. However, little is known about the decision-making process that lets an organization select a revenue mechanism and reject others. A recent study conducted by Sprenger et al. [13] sheds a light on this topic by exploring the evolutionary changes of revenue mechanisms for digital offerings to support managerial decisions. The scholars suggest that the choice of the most suitable revenue mechanism depends on (1) the type of digital offering, (2) the stage of evolution and (3) six additional constrains. However, most research conducted on the topic of revenue models for digital businesses focuses on pricing decisions [29] or explores the trade-off between free vs. paid approaches for digital content [30].

While the work conducted by Schüritz et al. [12] and Sprenger et al. [13] sheds some light on revenue mechanisms for data-driven services in general, no conclusive work has been done to understand the decision-making process on revenue mechanisms.

Picking a revenue mechanism is a decision made on an organizational level. Nevertheless, it always comes down to an individual or group of individuals deciding. The process of determining which options are available, then choosing the most preferred one is widely discussed in rational choice theory. Individuals aim to maximize their utility (u), which can be understood as the organization's objective such as profit or revenue maximization. Since employees are incentivized to contribute to the firm's objective, e.g. through bonus payments, they adopt this view in the decision-making process. Choosing among alternatives A = {a1, a2,…,aj} is further guided by personal preferences and constrains, which may help us in understanding how decisions are made [31].

3 Research Design

To get a better understanding of the factors that influence the choice of a particular revenue mechanism for data-driven services, we follow a rigorous qualitative research process that is based on a set of interviews. Despite the fact that this study leverages procedures strongly associated with the grounded theory methodology (GTM) (e.g. open and axial coding), it omits elements such as memoing and theoretical sampling [32]. Therefore, we consider our approach for data collection and analysis a qualitative content analysis based on Krippendorff [33] and Bengtsson [34].

3.1 Data Sources

In order to understand how providers of data-driven services have designed their revenue model, we needed to collect data that gives us precise information on all the influencing factors, which were considered during the decision-making process.

In a first step, we collected data of publicly available cases from service providers that offer data-driven services in a B2B context (e.g. through websites, customer references, and news articles). Our working assumption is that the results of this study may differ when looking at B2B vs. B2B services. For this reason and limitations in resources available, we initially focus on one type only. The identified use cases served as a pre-study to inform next steps of our research. In particular, we were able to define more specific criteria for the sampling of interviewees and for the development of tailored questionnaires. Since the data collected through the case analysis did not provide enough detail to derive reasons why particular revenue models have been chosen, we decided to collect data by conducting a series of interviews with representatives of service providers that offer data-driven services and that were involved in the decision-making process.

Our prior collection of service providers of data-driven services served as sample frame for our interview study. All of these companies have already implemented data-driven services and have gone through the decision-making process of selecting a revenue mechanism. For the sampling of the interviewees, we followed a criterion-i purposeful sampling approach [35]. The criteria were defined that only representatives, who were directly involved in the decision-making process are subject of interest for interviews. We therefore focused on approaching the product managers and heads of service for the particular data-driven service via LinkedIn. The expected small number of respondents were either themselves available for an interview or forwarded our request to a colleague with better insight in the design of the revenue model. This approach has yielded a total of 14 interviews, which have been conducted in the time frame between August 2016 and June 2017. The interviewees hold various positions within their organizations such as product manager, head of service and head of innovation. The focused data-driven services are offered by global leaders in the fields of manufacturing, IT services, logistics and telecommunications. An overview of the interviewed organizations partners is given in Table 1.

Table 1. Overview of interviewed companies

Company	*Revenue (2017 in bn €)*	*Employees*	*Countries active*	*Number of interviews*
Manufacturing I	3,8	11.000	50	1
Manufacturing II	84,3	370.000	>150	1
Manufacturing III	0,8	3.500	40	1
Manufacturing IV	78,1	400.000	60	1
Manufacturing V	4,2	19.000	60	1
Manufacturing VI	3,6	13.500	70	1
Manufacturing VII	43,0	160.000	79	1
Manufacturing VIII	8,7	61.000	>100	1
Teleco	52,0	130.000	24	2
IT Services	1,0	7.000	7	2
Logistics[1]	164,3	290.000	>150	2

In order to create an open discussion situation in which the interviewee is willing to discuss the topic, a semi-structured interview approach is chosen. The questions asked during the interviews covered four themes: motivation to introduce a data-driven service, service type offered, revenue mechanism selection, and pricing strategy. While all of the sections contributed to the results of the study, the focus lay on the third one: revenue mechanism. Interviewees were asked why they selected a particular model and why others were rejected. The interviews took place in two phases: the first set of eight interviews were used to explore the inquiry and inform phase two, allowing for a set of more in-depth questions. In the subsequent set of interviews, the same questions as in phase one were asked and, additionally, some assumptions derived from the initial interviews were explored. Most of the interviews have been conducted over the phone with few exceptions where in-person meetings were made possible. Interviews have been transcribed except for one case in which the interviewee preferred the researcher to take notes.

3.2 Data Analysis

The 14 interviews are analyzed using qualitative content analysis. In this particular case, two coding cycles are conducted: to account for the explorative nature of topic, we pick an open coding approach for the first iteration, followed by axial coding [36]. The software MAXQDA is used to support this work.

[1] Figures refer to the parent company of the organization interviewed

In the first iteration, we start with no pre-defined list of codes. The transcribed interviews are labelled according to our research objective, identifying all factors that are influencing the choice of the revenue mechanism. Initially, 32 different codes are identified by the researchers. In a subsequent step, codes are grouped into categories and subcategories by two researchers in a workshop. The outcome of the coding of the first eight interviews serves as an input for the next interview set.

For the second iteration, we choose an axial coding approach. This step ensures that the codes identified in the first iteration are reassembled and that categories and subcategories relate to each other accordingly [37]. Glaser [38] stresses the importance of this step since it requires sharpening the code for achieving its best fit. The final number of interviews we conducted was driven by our sampling criteria and by the availability of the interviewees during that time. Furthermore, we did see a saturation in the data in the final interviews.

Finally, to verify the results, we ask two independent researchers to code all interviews again based on the coding structure derived from the second coding cycle. To ensure objectivity and validity of the results, we calculate the intercoder reliability as an indicator of measurement consistency. An 85% mapping of the coded segments ensures a high confidence level in the results. Discrepancies between the researchers are discussed until an agreement is reached.

4 Influencing Factors

Designing a revenue model is a critical part of releasing new offerings to market as it describes the process of capturing the value of the offering. In some cases, the revenue model may even decide if the offering becomes a success [7]. Therefore, the decision for a particular revenue model is of high importance. Based on our interviews, we understand that there are two key decisions the provider has to make: how (revenue mechanism) and how much (price) to charge the customer. Unlike for the design of a product or service, we could not see formal processes or methods in the organization to decide on a revenue model, but we identified a series of factors that influence the decision-making process. When looking at an organization as a decision-making unit, the factors can be regarded through the lens of the rational choice theory (RCT) as preferences and constrains that inform the decision-making process. RCT postulates that the agent (an individual or organization) aims to maximizing the outcome of a rational decision while having the choice among multiple alternatives. The maximization of the net benefit, or utility, is driven by the benefit and costs as well as the level of risk that arises [31]. While the service provider eventually is the one to make the decision on the shaping of the revenue mechanism, decision-making on the customer side (i.e. purchase vs. non-purchase of a service) also needs to be taken into account. This means that both, the provider and the customer, intend to maximize their utility. In the following, we draw parallels between the decision factors identified and notions of RCT.

We have identified four groups of factors: service characteristics, provider interests, customer interests, and market factors. The revenue mechanism is chosen for a specific data-driven service, which is driven by certain characteristics. We can see that these specific characteristics itself have an influence on the choice of the revenue mechanism. Further, both provider and customer have individual interests and preferences regarding the revenue mechanisms that influence the choice. Finally, provider and customer interact in the context of an industry or market, which may have an influence on the selection of the revenue mechanism as well.

4.1 Service Characteristics

Data-driven services are such that rely on data as their key resource and analytics to provide value to customers. The offered services, however, may substantially differ from each other: for instance, there are heavy equipment manufacturers that start providing monthly usage reports to the operator of the machines for predictive maintenance purposes or a mobile phone network operator that provides targeted advertising services based on customer movement data. The nature of these offerings in itself can differ substantially and have an influence on the selection of the revenue mechanism. We identified two characteristics that play a role in the decision-making process: the usage pattern and the level of integration with a core product or service.

The usage pattern describes the frequency the customer actually uses the offering, which is often defined by the service itself. For instance, an alarm service of machinery that has to continuously monitor and process data in order to detect abnormalities. Hence, the data-driven service is provided continuously and adds value not just at a certain point in time. The choice of the revenue mechanism should therefore reflect that value for the customer is created on a continuous basis. The product manager in manufacturing company IV emphasizes this point using a different example: "(…) for a dashboard service, a pay-per-use model does not make sense since looking at the dashboard once represents a use. But this is not how a dashboard works. Dashboards show changes over time and need to analyze data continuously." In scenarios where the value of a service is usually derived from using it occasionally, e.g. generating a quarterly report on energy consumption from a utility provider, other revenue mechanisms may be more appropriate to use (e.g. usage-based).

Further, the integration with the core offering influences the choice of the revenue mechanism; i.e. the extent to which the data-driven feature is integrated with a core product or service. Data-driven offerings may be provided as a stand-alone service such as a navigation app on the smartphone or integrated with a core product or service such as system status monitoring for an elevator. A high level of integration between the data-driven service and the core offering makes it often difficult to distinguish the value created through the data-driven service from the one created through the core product or service. In such cases, services are often not charged separately and more likely to be charged indirectly through the revenue stream of the core product or service. With a decrease in the level of integration between the core offering and the data-driven service, there is an increase in the likelihood that an additional and therefore separate revenue mechanism for the data-driven service is chosen by the provider.

4.2 Provider and Customer Interests

Undisputedly, the provider of a product or service has an interest in capturing the value created by their offerings - not just to cover the costs but to create a sustainable business model with attractive profits. On the other side, customers that benefit from the offering and see how value is created for them are willing to pay for it. Therefore, the interests and preferences of the provider and the customer have an influence on the selection of the revenue mechanism. There are four dimensions – economical, relationship, capability, and common practices – within this group of factors that influence the choice of the preferred revenue. Economic objectives describe how financial targets that the provider and the customer deem relevant to their business strategy can influence the selection of a revenue mechanism. The relationship perspective between the two parties focuses on the level of trust and therefore supports or inhibits the implementation of certain mechanisms. Based on technical and knowledge capabilities, particular revenue mechanisms are enabled or prevented. Further, common practices outline habits and preference of the provider and customer for a revenue mechanism design.

Economical. While overarching financial objectives of organizations include the maximization of profits or revenues, operational targets can influence the selection of the revenue mechanism for data-driven services. Depending on how the management team sets these targets, certain models are more advantageous to implement than others. A project manager from an IT service company stresses the challenge in this: "Yes, we have also thought about it [a usage fee model], but we noticed that [with this model] we would place ourselves in a less favorable position (…) because of the usage behavior (…)." Financial objectives among our company sample vary broadly - even within one industry. Some organizations have a strong focus on ensuring that they have a quick and reliable return on investment since the setup of data-driven services often requires substantial upfront investments. For example, a product manager in manufacturing company II notes: "(…) I have to think from the perspective of a supplier. I must get a return on my investment. And for that reason, it is not important for me, if he [the customer] looks at the dashboard one time or one hundred times." Consequently, the provider choses a mechanism where it can achieve a short-term return on investment. Furthermore, the ability of organizations to plan future cash flows with certainty is significant; organizations therefore oftentimes prefer mechanisms that have a fixed payment schedule (i.e. subscription model): "(…) a recurring payment is always attractive, simply because we have more predictable revenues, this holds true for the customer as well as for you, you have a continuous revenue stream, too. This way, both sides, provider and also user can plan the whole thing in a better way." (Business Development Manager – Telco Industry). Providers need to ensure that running costs (e.g. server infrastructure) are covered; this is especially relevant for data-driven services that require to be available around the clock. Examples include the availability of a dashboard or an alert service. Subscription models are an example of a revenue mechanism that allows the provider to cover these running costs with a high level of certainty while e.g. usage-based models could lead to a gap in the revenue stream since they are less predictable.

Customers prone to risk avoidance may have an increased need for spending money in a very conscious way; i.e. customers only want to pay for the service when it is needed. A usage-based model is an example of a mechanism that supports this objective. Consequently, we can infer that the level of risk averseness of the provider and the customer alike define a personal preference in the decision process and therefore impact the order of preferred choices.

Relationship. The way the provider and customer regard and behave towards each other defines their business relationship. It is in the interest of the provider to build a long-lasting relationship in order to maximize the customer's lifetime value. The level of trust between the business partners is one factor that influences the strength of the relationship. Building trust into the provider to deliver the service in quality comes over time and sometimes requires the provider to give away a service for free at first before being able to charge for it. A product manager in manufacturing company I notes: "(…) we have done it in a way where, after installing the heavy equipment machinery, we offered it [the service] for free for two years and then started charging for it". The quality of the relationship, hence, enables or inhibits the use of certain revenue mechanisms. For example, a performance-based revenue mechanism can only be applied if there is a high level of trust: "(…) as long as I cannot prevent, on a technical level, that nobody can manipulate [results], in their favor, then such models [performance-based] are only possible with mutual trust" (Product Manager – Manufacturing Company VI).

The examples show that the state of the relationship between the partners has an impact on the choice of the revenue mechanism and therefore acts as a constraint in the process. Providers can treat customers fairly and build a trusted relationship to ensure ongoing revenue streams or follow a strategy to extract the maximum amount of revenue and profit from the client while accepting that it may not return for re-purchase.

Capabilities. The complexity of a revenue mechanism and its initial definition, implementation and monitoring can vary broadly. Simple mechanisms, such as a subscription, are often better received and understood by the customer compared to more complex constructs (e.g. performance-based). Furthermore, a lack of availability of knowledge and tools to implement the more complex models further limits the selection of revenue mechanisms available. Therefore, the existing capabilities on provider as well as customer side enable, limit or restrict the implementation of revenue mechanisms. The head of technology of an IT services company describes these limiting constraints in the choice process: "We didn't have an advanced or automated billing system to do usage-based or performance-based billing, so we just charged customers based on a simple monthly subscription in the contract agreement – which was simple for everyone to understand, and also simple to implement."

Data-driven services offered by the provider support one or multiple business processes on the client side. In order to setup more complex revenue mechanisms (e.g. performance-based), the client has to have a good understanding of how the service interacts with its processes and impacts business outcomes. If this is not given, more simple revenue mechanisms should be applied (e.g. subscription model).

Common Practice. We identified three levels where habits and common practices influence the choice of the revenue mechanism: individual, organizational and industry. On an individual level, we can observe that personal preferences of the person in charge of making strategic revenue model decisions plays a role. The person may transfer personal experience into the business environment and require a service to be offered in conjunction with a particular revenue mechanism.

Within an organization, there is a tendency to apply the same revenue mechanism for new data-driven services as has been done for existing ones. On the one hand, capabilities and processes for the implementation of existing revenue mechanisms are likely to be already in place and, therefore, a smooth implementation can be ensured. The introduction of a new model, on the other hand, oftentimes requires the definition and implementation of new processes, which may create additional risk of failure both for the provider and the customer. Hence, similar to the economical perspective, the level of risk avoidance and therefore a personal preference is a driving factor for the choice of a revenue mechanism.

On an industry level, customers expect the availability of certain mechanisms as a consequence of being common practices. For example, customers may expect a service to be offered for free when an expensive piece of heavy equipment machinery is purchased. An interviewee from manufacturing company III explains: "(…) it's sometimes difficult to point out to the customer that he should pay so much for this [the service], because says, 'if I buy such an expensive machine from you, then it [the service] should be included'" (Head of Innovation/Strategy - Manufacturing). This describes a scenario where the service is bundled with a core product – described as "wrapping" by Wixom & Ross [4].

The shift of common practices and therefore the preference of customers within an industry can also require the provider to introduce new and unproven revenue mechanisms. For example, the customers' intent to shift the risk of service fulfilment and success towards the provider. An example of a revenue mechanism that helps achieve this objective is the performance-based one since the provider only gets paid in case of proven success. Failure of a provider to offer a revenue mechanism that enables the shift of risk towards the provider side may inhibit the sale of the service.

Despite the fact that the provider is the one to make the final decision on the revenue mechanism design, customer preferences need to be considered by the provider. Failure to do so may result in customers choosing the offering of a competitor or not making a purchase decision at all, which, in turn, impacts the net benefit of the provider.

4.3 Market Factors

While provider and customer are most directly involved in the value creation and value capture of the data-driven service, they do not interact in a vacuum. There can be additional players involved that have an influence on the selection of the revenue mechanism. The behavior of competitors can urge the provider to offer one revenue mechanism over another. Further, the collaboration with partners in an ecosystem may require the provider to align its revenue model design with that of other players.

Therefore, market factors are to be considered a constraint in the decision of the agent and, according to RCT, limit the number of choices available to maximize utility.

Competitors. While it is often difficult to compare data-driven services between providers due to their unique and new character, bidding situations sometimes allow to observe what competitors offer. In addition, some revenue mechanisms may be more frequently used than others. An interviewee describes this as: "This is common in this industry" (Head of Innovation/Strategy – Manufacturing Company III). Being able to offer a revenue mechanism that is not common (e.g. performance-based) in a particular setting or industry may be recognized as a competitive advantage since special capabilities are often needed for the implementation.

Partners. Oftentimes, providers of data-driven services do not have the internal capabilities to develop and run a service on their own (e.g. hosting & connectivity services) and hence are required to collaborate with sub-providers. Therefore, the provider is urged to pick a revenue mechanism that ensures a continuous cash flow (e.g. subscription model) to cover ongoing obligations towards its own partners. The product manager of manufacturing company I describes this using an analogy: "(…) like the landlord of a building has to decide which costs to absorb and which to pass on to the tenants [to remain solvent]."

Many services nowadays are sold through 3rd party platforms (e.g. Apple Store, Google Play Store). These platforms may constrain the revenue mechanisms that are allowed to be used through contracts with the provider of the data-driven service. In addition, offering bundles offerings with a sales partner may further constrain the choices since the strategy needs to be aligned with other parties' expectations.

5 Conclusion

In summary, our research explored the factors that influence the selection of a revenue mechanism for data-driven B2B services. In order to do so, we conducted 14 expert interviews and analyzed them by applying open and axial coding. This led to the identification of four influencing factors: service characteristics, provider interests, customer interests, and market factors. Provider and customer interests as well as market factors are further broken down into subcategories to account for the specifics of each influencing criterion.

Each of these factors influence the provider when designing a revenue mechanism. The particular shaping of some factors even enable, hinder or promote certain revenue mechanisms (e.g. the lack of technical capabilities or knowledge to define a unit of measure inhibits the implementation of usage- or performance-based models). The choice of a revenue mechanism requires the provider to synthesize all available information and to decide on the best strategy for the situation at hand.

Our contribution with this paper is two-fold: on the one hand, we derive factors that influence the decision-making process for revenue mechanisms for data-driven services, and, on the other, we point out a set of initial schemes on the direction that each factor may influence a decision for or against a particular mechanism. With this, we contribute to the general understanding of revenue models and lay the foundation for more elaborate research in the field that could eventually help identifying the appropriate revenue model for a data-driven service.

5.1 Discussion

Looking at the influencing factors derived from the interviews through the lens of rational choice theory shows that a major part of the results (provider and customer interests, market factors) can be explained by either personal preference of the decision-making unit – informed by their attitude towards risk - or a constraint. However, not all results can be linked to RCT: service characteristics shape a category of their own and therefore stand out from the rest. These insights extend the knowledge in the field of revenue model research for data-driven services and contribute to developing a better understanding of decision-making for such services. It shows that the characteristics of the service being offered has a particular impact on the revenue mechanism. Thus, there is an opportunity to identifying the most appropriate revenue model for a particular service. Our study extends extant literature in the field of data-driven service research and provides the basis for more research in this space.

5.2 Managerial Implications

The implications of this study for practice are relevant in such that the design of the value capturing mechanism, which the revenue mechanism is a part of, has an influence on whether an offering becomes a success for the organization or not. Our results show that the selection of the revenue mechanism is a complex and critical endeavor due to the number and variety of factors that need to be considered. We have shown that some of the factors not only call for the use of a particular revenue mechanism, but that they can also preclude their use. Organizations should be aware that not only their own interests, but an entire ecosystem of influencing factors play a role when designing an overarching revenue model for data-driven services.

5.3 Limitations and Future Research

Despite applying a high level of rigor, our analysis is not without limitations. The services analyzed in the context of this study all apply to business-to-business transactions. We encourage to repeat this study taking also B2C services into account and to compare the results. Furthermore, our sample was limited to a total of four industries. Extending the study to additional industries would allow verifying the results in a broader context.

We encourage future research on the topic of revenue mechanisms for data-driven services. From our point of view, there are several areas that would benefit from further research. For once, our study focused on the identification of influencing factors for the selection of revenue mechanisms, however, future research could further explore the importance of each of these factors; i.e. to conduct a quantitative study on the subject.

A further avenue to explore is to develop an understanding if the factors identified also hold true in the context of B2C offerings since we focused B2B offerings in this study.

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