OPTIMIZING SERVICE VALUE CREATION WITH SMART, CONNECTED PRODUCTS

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ABSTRACT

Purpose: This paper describes a novel quantitative model for the design of the service interactions in the life cycle of customers using smart connected products – typically in industrial environments, i.e., in Industry 4.0 context – with the goal of optimizing mutual service value creation for both the customer and the provider.

Design/Methodology/approach: The presented novel methodology is based on a quantitative system modelling of the mutual value creation both for the customer and the provider as a function of the provider's effort to leverage the data of smart connected products, by focusing on the customer's perceived value, on the one hand, and the provider's value, on the other hand. The impact on value creation is modelled independently for the customer and the provider, respectively, within their specific value framework. For optimizing value creation, a multi-objective optimization approach is applied.

Findings: The quantitative model considering the provider's and customer's benefits and efforts reflects that utilizing data resources of smart connected products impacts the mutual value creation in different ways: first, it impacts the customer's value in context. Second, it impacts the value created for the provider by influencing the customer relationship with effects on, e.g., customer lifetime value, acquisition, retention, or new service development, and by influencing the costs for service provisioning. The model captures both sides of the value creation as a result of the design choices. Based on this, approaches from multi-objective optimization are used for optimizing the value created both for the customer and the provider, leading to a subset of Pareto-optimal designs. The application of the quantitative model to typical actor to actor interactions shows that they are mostly not Pareto-optimal and thus have improvement potential for increasing total value creation.

Research limitations/implications: This conceptual model can (and should) be further validated and refined in practical business contexts. Possible extensions are discussed such as, e.g., a market model which relates the created customer value to market demand.

Practical implications: The model presented in this paper provides a new framework which can be used by firms for designing optimized services and optimize their offering and adoption by customers across the customer relationship lifecycle.

Originality/value: The innovation of this paper is the new approach quantitatively linking customer and product life cycle design choices to value creation.

Paper type: Conceptual paper.

Key words: smart services, smart connected products, customer relationship lifecycle, interaction modelling, value creation

1. INTRODUCTION

1.1 The Shift to Services Value Creation

In this paper, we address the question of how to design mutual service value creation within the actor to actor interaction in socio-technical systems, consisting of human actors and smart, connected products. We propose a novel quantitative approach for modeling the relation between the effort for data-driven value creation at the various phases of the customer relationship lifecycle, and its effect on the mutual value creation. Combining this model with approaches from multi-objective optimization, optimum levels of data-driven value creation from both the customer and the provider perspective can be determined. Thus, the proposed model allows the identification of service designs which are optimized in terms of their value creation and value capture.

The concepts introduced with the S-D Logic provide a theoretical framework for the design of value creation in service ecosystems - networks of actors that generate value for each other by service interactions (Vargo et al., 2008; Vargo & Lusch, 2004). Values arise in the interaction between human individuals or – the longer the more - between human individuals and machines in the form of digital actors (Maglio & Lim, 2018) (Fig. 1). With the advent of digital technology, service systems have evolved towards hybrid socio-technical systems. There is the new premise that thanks to data science, digital actors will increasingly act autonomously and become user-individualized (Mele et al., 2018; Sampson & Chase, 2020), e.g. develop adaptively in value creation, respond to their (human) counterparts and allow them more degrees of freedom in their decisions (Maglio & Lim, 2018). In this perspective, data-driven value creation based on digital actors can be related to customization, taking into account that data is used for the service value proposition that specifically targets at the customer's job to be done and pains in a given context and phase of the relationship lifecycle. Creating service value based on data from digital products leads to the concept of smart, connected products (Porter & Heppelmann, 2014).

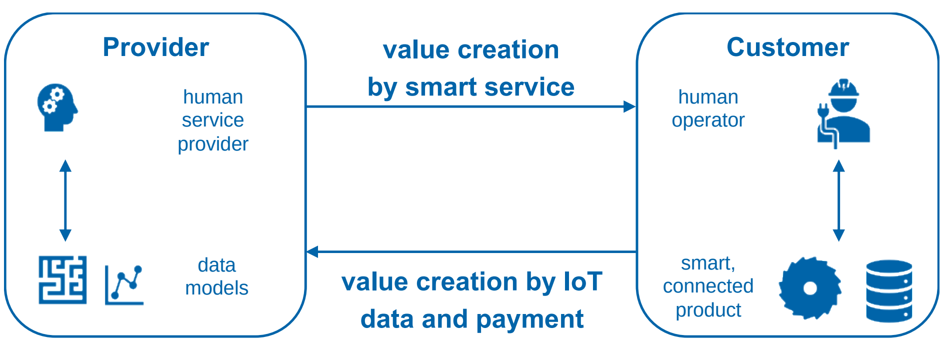

Fig. 1: Service value creation with smart, connected products.

The interaction among humans and technical agents is conceptually discussed in the literature about socio-technical systems (e.g., (Jones et al., 2018; Lu et al., 2020; Schroeder et al., 2020)). Those human and technical actors interplay in ecosystems and create value (Windsor, 2017) in the sphere of the service interaction (Schüritz et al., 2019). The concept of this paper is based on the approach of (Meierhofer & Heitz, 2021), which investigates the optimization of value creation and value capture along the customer journey.

1.2 Value Creation in Service Interactions along the relationship lifecycle

For the providers, the service business has considerable value potential by creating additional revenue, increasing customer loyalty and making customer acquisition more effective. They extend their product business by selling services with higher margins (Ebeling et al., 2014). Value for the customers is created in the form of higher performance, lower operational risks, and reduced fixed costs (Kowalkowski & Ulaga, 2017).

In principle, this cycle of success has been described in the service profit chain. It describes how satisfied employees and excellent service quality create value for both customers and providers. Satisfied and loyal employees lead to better service quality, to more satisfied and then loyal customers and this in effect to a more successful company (Heskett et al., 1994). A variety of positive effects along the chain have been empirically well proven since it's description. Apart from the importance of employee satisfaction these are especially the characteristics of customer relations and external service quality. Individualized services can contribute strongly to the level of service quality and value perceived by customers. An important effect on the value from customer relationship for companies derives from lower cost of service for loyal customers and higher income from cross- and up-selling. This is mainly based on a better knowledge of customers and in the context of this research based on more and better data about the customer (Hogreve et al., 2017).

(Reinartz et al., 2004) describe the management of customer relationship as management processes along the lifecycle of customer relationships. In their model they name three main CRM-processes relationship initiation at the beginning of the customer relationship, maintenance and termination of customer relationships. In their model the maintenance phase has two main goals expanding customer relationships, meaning socializing new customer and to intensify relationships both in terms of loyalty and in terms of expanding the value in terms of cross- and upselling as the first phase. The second part of maintaining relationships is stabilizing them in terms of not losing the customers again. As the greatest potential of creating value from smart connected product data lies in the maintenance phase but the two subphases of very different goals and potential, we will stick with a four phase model of customer relationships here and distinguish "expand" and "stabilize" (Fig. 2).

In the initiation phase of customer relationships customers have not yet bought smart connected products and there is no data available from them to generate value from. During the expansion phase the available data enables the generation of value through additional and more individualized smart services. In the stabilization phase this customer value has the potential to constitute a hurdle to switch providers because it will have to be generated all new in a new customer relationship. In the terminate and win-back phase there is potential value for providers from the data as well as it helps to decide which customer relationships to terminate and which customers to try to win back.

Models for quantifying and measuring the service value in the process or customer relationship lifecycle are described in, e.g., (Lemon & Verhoef, 2016; Mourtzis et al., 2018). (Roels, 2014) provides a modelling approach for value creation in a service encounter as a function of the joint effort between the customer and the provider with (Karmarkar & Roels, 2015) introducing the expectation gap between the obtained and expected customer benefit to the models. (Levin et al., 2000) models the discrete phases of a customer dialogue as a vector whose elements stand for costs for different dialog dimensions in the phases of the dialogue.

Value creation for the provider is realized during the interaction with the customers along the customer relationship lifecycle. Thus, when analyzing the effect of improvements in service provisioning by leveraging data resources, it is important to consider the long-term effects, e.g. increased loyalty and reduced churn probabilities, as these directly impact the value creation for the provider. Quantitative models have been proposed in literature linking acquisition efforts, provision costs and service revenues on one hand, and churn probabilities on the other hand, with customer lifetime value (e.g., (Gupta et al., 2006; Heitz et al., 2011, 2014; Malthouse & Blattberg, 2005; Rust et al., 2004)). However, the effect of design choices on the lifetime value has not yet been analyzed and implemented in these models.

Thus, despite many publications in this field, there is a lack of quantitative models for value in service interactions along the customer relationship lifecycle. In particular, it is not clear how the increased customized value creation potential in hybrid ecosystems as postulated by (Maglio & Lim, 2018; Mele et al., 2018; Sampson & Chase, 2020) quantitatively impacts the value created. On the one hand, we would expect that investing in value creation based on data generally increases the service value created for the customer, even if sharing data with the provider may represent a cost factor for the customer. But it also creates additional cost for the provider for processing that data, in particular for developing and operating the data infrastructure and the data models, thus reducing the value created for the provider. The efforts to utilize the data for value creation can be made at different phases of the customer relationship lifecycle, and the value effects might depend strongly on the phase. Hence, it is not clear, at which phase which level of effort for data-driven value creation should be chosen.

Addressing this gap, the research question of this paper is: How does leveraging data from smart, connected products along the customer relationship lifecycle quantitatively impact mutual value creation and how can this value be optimized? For answering this question, we suggest a novel approach by quantitatively modelling mutual service value creation along the customer relationship lifecycle, explicitly taking into account the value of data. In Section 2, the model is described. In Section 3, we apply it to an exemplary case study and show how it can be used to optimize mutual value creation.

2. MODEL FOR MUTUAL VALUE MUTUAL CREATION

Our modelling approach describes the relation between the intensity of data utilization for customized value creation on the one hand, and its impact on the customer and the provider value on the other hand. The model is based on the customer relationship lifecycle described in section 1.2, as value creation is specifically realized in these phases (Fig. 2). As said, we model that utilizing data for value creation manifests itself by providing a higher level of service value customized for the beneficiary in its context and more value for the provider.

From the perspective of the beneficiary, perception of value creation is governed by the customer's expectation for service value that is individualized to its needs and its context, e.g., the condition and criticality of a specific machine representing the smart, connected product. This expectation is modelled by the vector variable $\vec{C} = (C(1), C(2), \dots C(n))$ with n denoting the number of the lifecycle phases (n=4). If the expectation is not sufficiently met, the customer has to exert an effort (vector variable $\overrightarrow{Ce}$ in the model). For the provider, the customized value creation leads to a corresponding effort, expressed by the vector variable $\vec{P}$ (Section 2.1).

2.1 Model for the Customer and Provider Effort along the Customer Relationship lifecycle

The lower part of Fig. 2 visualizes the value creation in the customer relationship lifecycle by showing the individual customer expectations and the efforts by the providers per phase of the relationship lifecycle. In each phase, the customer has a given degree of expected customized service value, with a completely nonspecific, standard service as reference case, e.g., a maintenance service that does not consider the specific data of a machine and its context. This is modelled by the variable $C(i)$ ($1 \le i \le n$, $n=4$) in the example, with $C(i)$ being normalized to the interval [0…1], which makes up the vector $\vec{C}$ of length n. $C(i)=0$ means no customer expectation for customized value, $C(i)=1$ maximum expectation.

The customer's expectations are mirrored by the provider's effort to meet them– indicated by the variable $P(i)$ with $1 \le i \le n$, with $P(i)$ being normalized to the interval [0…1], or the vector $\vec{P}$, respectively. Here, $P(i)=0$ means the provider invests no effort for customized value, $P(i)=1$ maximum effort.

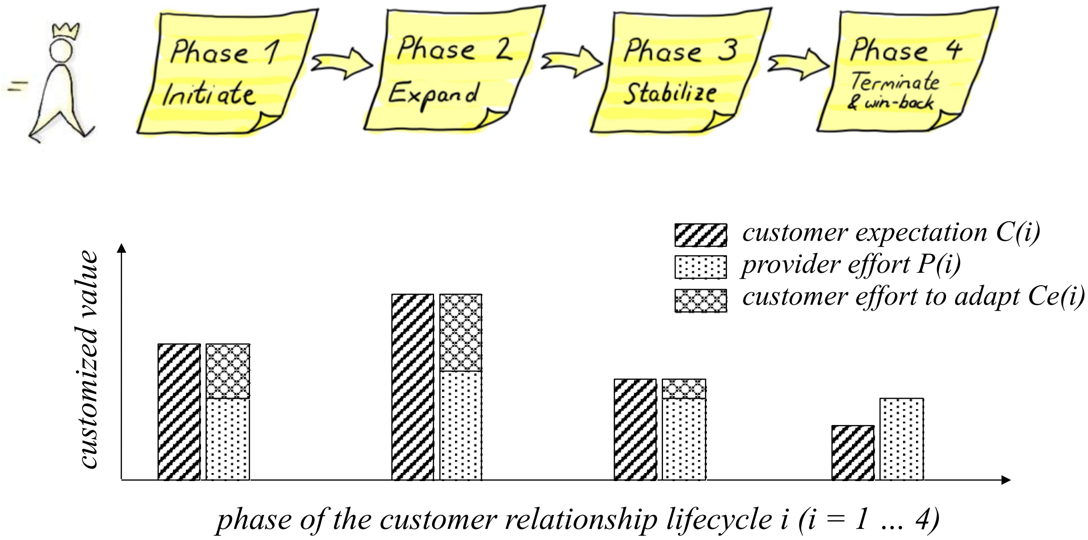

Fig. 2: Value creation along the customer relationship lifecycle.

If the customer has higher expectations in phase *i* than the provider is able to meet (*C(i) > P(i)*), the customer need is not sufficiently covered by the provider. This expectation gap, which is also reported in the literature in the context of service quality gap models (e.g., (Karmarkar & Roels, 2015; Parasuraman et al., 1988)), results in an additional effort of the customer when using the smart, connected product. We denote this non-fulfilment gap by the effort *Ce(i)* (with the corresponding vector $\overrightarrow{Ce}$). If the customer expectation is lower than the provider effort, there is no additional customer investment, but the provider wastes its effort. Therefore,

$$Ce(i) = \begin{cases} C(i) - P(i), & C(i) > P(i) \\ 0, & else \end{cases} \tag{1}$$

2.2 Quantitative Model for the Mutual Value Creation

According to (Golnam et al., 2012), the value created for the beneficiary actor (i.e., the customer) is given by its benefits after discounting off its service costs. We assume that value is created throughout the customer relationship lifecycle, and we model the cumulative value created for the customer, *Vc*, by a walk through the phases as

$$Vc = Vc_{base} - Pr - C_{effort\_customer} \tag{2}$$

with Vc_{base} denoting the value created for the customer by the service itself without any data-driven customization efforts along the customer relationship lifecycle. *Pr* denotes the price paid and $C_{effort\_customer}$ the total cost of the customer effort for compensating the expectation gap. $C_{effort\_customer}$ is a function of the total customer effort over all phases of the customer relationship lifecycle, $\overrightarrow{Ce}$ (elements as in Eq. (1)), i.e.:

$$C_{effort\_customer} = f_{customer\_cost}(\overrightarrow{Ce}) \tag{3}$$

The function $f_{customer\_cost}(\cdot)$ accounts for different weights of the customer effort in different phases of the customer relationship lifecycle and for possible non-linear effects. For example, the customer may assign little cost to investing a small effort but then get overly exhausted if the value provided gets too far apart of the expectation.

The value created for the provider can be formulated in a similar way. Similar to (Lieberman & Balasubramanian, 2007) and Eq. (2), we model the cumulative value created for a firm from a customer's walk through the relationship lifecycle as the net profit, i.e., the revenue after deducting the service delivery cost. Thus, *Vp* – the value created for the provider – is described as

$$Vp = Pr - C_{effort\_provider} + C_{benefit\_provider} + Vp_{base} \qquad (4)$$

where again *Pr* stands for the price paid by the customer. Vp_{base} accounts for potential additional elements of value capture such as, e.g., value in the form of customer co-creation (Saarijärvi et al., 2013). The total costs for providing the data-driven, customized service is described by $C_{effort\_provider}$. Analogous to Eq. (3), $C_{effort\_provider}$ is a function of the total provider effort for this over all phases of the customer relationship lifecycle, $\vec{P}$, i.e.:

$$C_{effort\_provider} = f_{provider\_cost}(\vec{P}) \qquad (5)$$

$C_{benefit\_provider}$ expresses the the value created for the provider by positively influencing the customer relationship with effects on, e.g., customer lifetime value, acquisition, retention, or new service development. $C_{benefit\_provider}$ is a function of the total provider effort over all phases of the customer relationship lifecycle, $\vec{P}$, i.e.:

$$C_{benefit\_provider} = f_{provider\_benefit}(\vec{P}) \qquad (6)$$

Again, the transformation functions $f_{provider\_cost}(\cdot)$ and $f_{provider\_benefit}(\cdot)$ of Eq. (5) and (6) reflect that fact that the costs and benefit may be phase-dependent and may depend non-linearly on the effort. E.g., customizing the phase "Expand" (e.g., tuning the smart, connected product to the context of the customer) may be expensive because there is not yet sufficient customer and product data available, whereas there are more efficient ways to customize the phase "stabilize".

3. MODEL APPLICATION

The model introduced in section 2 is now applied to investigate the value creation and capture for a specific customer-provider scenario. This scenario is exemplary, for the sole purpose of illustrating the application of the model. Our interest is focused on the question whether there is an optimum intensity of data-driven service customization in terms of mutual value creation, i.e., (*Vp*) and (*Vc*).

The example shows a provider who initially assumes that customized service value efforts have the biggest effect on mutual value creation if they are moderatly invested in the "Expand" phase and in the phase "Terminate & win-back" of the customer relationship lifecycle (operating point C in the example shown in Fig. 4). Thus, customization is used for increasing the customer lifetime value by creating customer loyalty during the extended "Expand" phase and for keeping back customers wanting to churn. However, as we will show, the application of the model suggests that focusing the customization effort on other phases of the customer relationship lifecycle can create considerably higher customer value at the same provider value (operating point A), or considerably higher provider value for the same customer value (operating point B).

3.1 Customer Model

For applying the model for the customer value *Vc* according to Eq. (1), (2), and (3), we assume a customer relationship lifecycle with four phases (*n*=4) and a customer with the following expectation for customization: $\vec{C} = [0.75, 1, 0.5, 0.2]$, with the values indicating the customer expectation for customization on a range [0…1]. This means that the customer expects quite high personalization in the phase "Initiate", maximum personalization in the phase "Expand", medium in the phase "Stabilize", and very little in the phase "Terminate & win-back". We chose these values for reflecting a use case of a production machine, e.g., a professional printer used in a small advertising company:

- For getting attracted by this service offer, a relatively highly personalized approach in the "Initiate" phase is necessary, since many alternative printer providers are available on the market.
- Furthermore, since the printer should easy to set up and configure based on the individual production requirements specified by the customer (e.g., paper format and quality, colour style etc.), the "Expand" phase needs substantial investment. Hence, customers have a very high expectation for customized value creation in this phase.
- During the "Stabilize" phase, the customer gets acquainted with the printer and therefore is able to adapt to its capabilities. Hence, we assume a medium expectation for personalization here, except for a highly personalized maintenance service in case of break downs. Of course, the provider has a strong interest in upselling and retention in this phase.
- When leaving the service at the end of the relationship lifecycle (phase "Terminate & win-back"), the customer does not care about a personalized handling and therefore, has low expectation, while the provider can get high value from using customer and product data in this phase for intensifying its win-back activities.

For the sake of simplicity, we assume the customer cost function $f_{customer\_cost}(\overrightarrow{Ce})$ of Eq. (3) to be linear ($C_{effort\_customer} = \sum \alpha_i \, Ce(i)$) with $\alpha_i = 0.25$, for all i) and the values $Pr = 1$ and $Vc_{base} = 2$.

3.2 Provider Model

The provider value *Vp* is modelled according to Eq. (4), (5), and (6) setting $Vp_{base}=0.5$ for simplicity. For shedding light on the value creation process for the provider, we model the provider's cost $f_{provider\_cost}(\vec{P})$ and benefit and $f_{provider\_benefit}(\vec{P})$ depending on the intensity $\vec{P}$ of utilizing data for the different phases of the customer relationship lifecycle as shown in the example of Fig. 3. As a simplifying assumption, we assume a similar order of magnitude in costs and benefit for the different phases.

- We broadly assume that the provider's cost and benefit for offering customization monotonically increases with its customization effort, except for the costs in phase "Stabilize".
- The customization costs for the phase "Initiate" grow faster than linear and the benefit grows slowly, assuming that a moderate level of customization can be achieved at relatively low costs, e.g., using ad words for attracting the attention of the advertising company, whereas high personalization requires highly advanced measures as there is basically no data available from the smart, connected product in this phase.
- We assume that the costs for customizing the phase "Expand" grow fast already at low degrees of customization because at this early stage the customer and its context are largely unknown to the provider, but a saturation at higher personalization because of assumed economies of scale once the customization infrastructure is in place. However, the benefit for the provider grows slowly as it has already completed the customer contract and does not see much additional benefit from providing more service value in this phase.
- A special case is modelled for the "Stabilize" phase: customization in this phase may be realized by collecting data on the usage patterns of the customer and the smart, connected product and adapting the service accordingly, e.g., for condition monitoring, maintenance, or performance optimization. This requires investments in analytics and big data infrastructure. If this is implemented at a large

scale, it can be deployed and applied to the mass of customers and use cases, finally resulting in decreased costs per individual walk through the customer relationship lifecycle. As customized service value provided to the customer in this phase has a strong impact on the customer loyalty and lifetime value, we assume the benefit for the provider to grow rapidly with more effort to use data for customization.

- For the "Terminate & win-back" phase, we assume linearly growing costs since customizing this phase largely means implementing individual disengagement measures and customer retention measures based on personal interactions, e.g., by contact centre staff. However, a high investment in this phase is rewarding for the provider as it is thus more likely to win back customers and hence increase customer lifetime value.

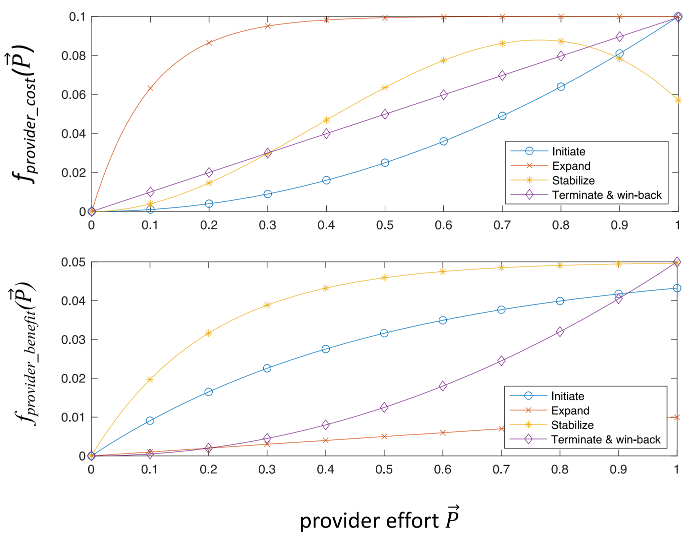

Fig. 3: Provider cost function and benefit function, $f_{provider\_cost}(\vec{P})$ and $f_{provider\_benefit}(\vec{P})$ (for the different phases of the customer relationship lifecycle).

3.3 Evaluation the Optimum Customization Degree

Given the customer and provider model of sections 3.1 and 3.2 above, the mutual value creation *Vc* and *Vp* is now computed for different constellations of the provider effort $\vec{P}$. For the scenario of applying the model, the customer is assumed to have the fixed profile of customization expectations described in section 3.1 (i.e., $\vec{C} = [0.75, 1, 0.5, 0.2]$). Against the background of this customer profile, the provider's effort $\vec{P}$ to adapt to these needs is modelled as described in section 3.2.

The standard procedure for evaluating the optimum provider effort $\vec{P}$ with respect to value creation would be to combine *Vp* and *Vc* into a common objective variable by a weighted sum and finding the effort $\vec{P}$ that maximizes this sum. However, in the case of the service ecosystem situation at hand here, *Vp* and *Vc* are not directly comparable because of the completely different value contexts of the customer and the provider which result in different, not comparable, valuation schemes (Leroi-Werelds, 2019).

An alternative approach for this situation is given by the concept of the multi-objective optimization (e.g., (Miettinen, 2008)). In this approach, all possible combinations of the independent variables (i.e., the provider effort $\vec{P}$) - impacting the two target variables *Vp* and *Vc* - are considered. The two target variables are represented in a scatter plot as shown in Fig. 5.

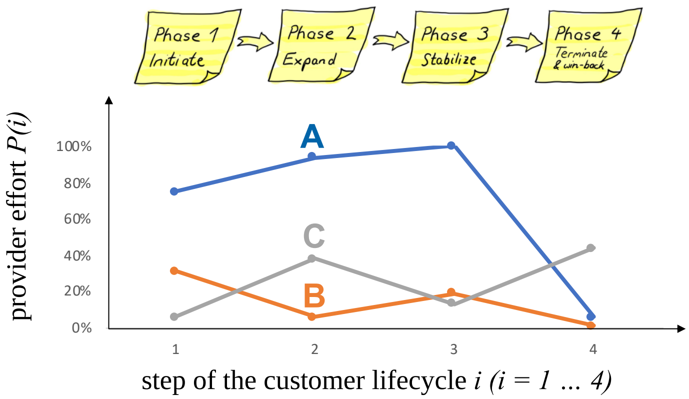

Fig. 4: Examples for the provider effort $\vec{P}$ during the phases of the customer relationship lifecycle.

For the scenario shown in Fig. 4, the provider effort $\vec{P}$ was sampled in 16 equidistant steps for each phase of the customer relationship lifecycle. This results in the 16^4 possibilities of the provider effort vector – three of them exemplarily indicated by the trajectories A (investing a lot of effort for initiating, expanding, and stabilizing the customer relationship, i.e., "customer orientation"), B (investing just as much in the customer relationship to improve the provider value, i.e., "provider orientation"), or C (heuristically assuming that investing in expanding and win-back is optimal, i.e., "heuristic approach") (Fig. 4). These example trajectories correspond to the operating points later discussed in Table 1 and shown in Fig. 5. Each of the 16^4 trajectories and corresponding value constellation (*Vp*, *Vc*) represents a point in the scatter plot of Fig. 5, indicating the different possible service solutions. The upper right limit of the solution region defines the so-called Pareto front (see (Miettinen, 2008))

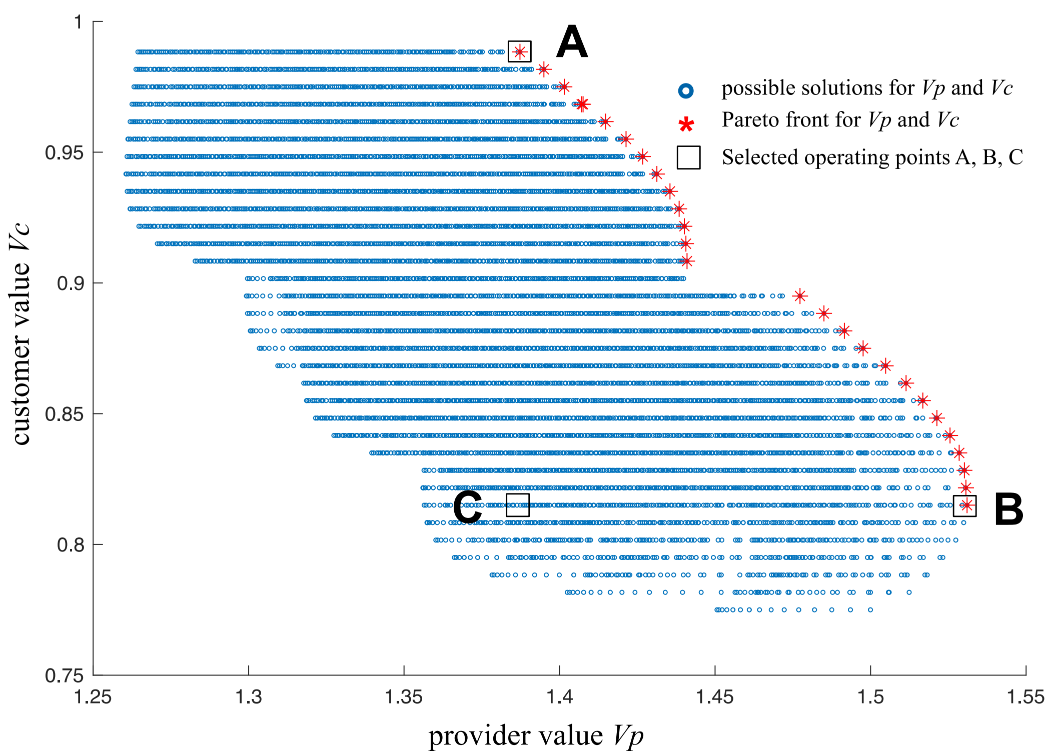

Fig. 5: Pareto front for *Vp* and *Vc* in the given example case.

As can be seen in Fig. 5, the vast majority of possible solutions (i.e., those below the Pareto front) are such that they can be improved both in provider value and in customer value, and thus do not represent useful solutions. What remains are the solutions on the Pareto front, where improving one value component (e.g., *Vp*) can only be achieved by worsening the other one (i.e., *Vc*). Hence, the Pareto front represents the optimal sub-set of possible configurations of data-driven value creation that the provider should select from. So, from a service design perspective, the possible solutions can be reduced to the solutions on the Pareto front. Within this sub-set, however, a trade-off between value capture and value creation for the customer has to be accepted.

For the selected operating points A, B, and C in Fig. 5, Table 1 displays the values for the provider effort for customization *P(i)* and the resulting value captured by the provider (*Vp*) and created for the customer (*Vc*).

	Customization effort $\vec{P}$ of provider per relationship lifecycle phase (relative to max. effort) against the customer expectation $\vec{C} = [75\%, 100\%, 50\%, 20\%]$				**Mutual value creation**	
Operating point	**Initiate *P(1)***	**Expand *P(2)***	**Stabilize *P(3)***	***Terminate &win-back P(4)***	***Vp***	***Vc***
A: customer orientation	75%	94%	100%	6%	1.39	0.99
B: provider orientation	31%	6%	19%	1%	1.53	0.81
C: heuristic approach	6%	38%	13%	44%	1.39	0.81

Table 1: Customization effort and mutual value creation for selected operating points.

This makes evident that operating point C, which was assumed to be the initial choice of the provider, is far from being optimal. Changing the design to solution A allows the provider to create roughly 25% more customer value while keeping its own value constant. On the other hand, the provider could move to move to operating point B, which would allow to increase its own value by roughly 10% while keeping the value created for the customer constant. These are both remarkable improvements compared to the initial assumption of operating point A.

3.4 Discussion of the Model Application

The presented example shows that the vast majority of possible solutions are far from the optima on the Pareto front and can be improved at no extra cost simply by investing customization efforts in the right area. The fact that the Pareto Front consists of only a small number of solutions is found in most applications of multi-criteria optimization problems. Without a quantitative model of the resulting effect of value creation and value capture, it is not possible to determine whether or not a specific service design lies on the Pareto front.

Thus, the knowledge of the Pareto front and the service configurations associated with the solutions on the Pareto front enables a service provider to design the effort to use data for service customization and mutual value creation along the customer relationship lifecycle in a conscious way in order to realize an optimum constellation of customer and provider value. In particular, the service provider is prevented from sticking with a suboptimal constellation below the Pareto front, in which one of the values *Vp* or *Vc* can be improved without negatively impacting the other one (e.g., operating point C).

However, the service provider still has the open design question where on the Pareto front to select its operating point. It could, for instance, opt for a higher value creation for the customer while creating lower value for itself (point A in Fig. 5). This can be, for instance, a viable strategy in markets characterized by commoditization effects and fierce competition and thus a high negotiation power of the customer. On the other hand, a constellation as indicated by point B creates lower value for the customer but more of it for the provider. Depending on the competitive situation, this might be a better option than A.

Note that these considerations and improvements are only possible with a quantitative model that links the design variables (here the provider's effort for data-driven, customized value creation) with value creation and value capture. Since customer interaction, including human-machine interaction, is at the heart of every service, the customer relationship lifecycle is the natural object for establishing this link. With the presented model, we close a gap in the literature.

4. Open Questions and Research Outlook

Our approach establishes a valuable instrument for optimizing the design of new services, in particular the interaction design along the customer relationship lifecycle. It allows harvesting the economic potential of new data-based technologies for service customization. A validation of the practical applicability of our model will been done by field studies with firms offering services in hybrid ecosystems.

The proposed method of linking customization parameters with value outcomes is only a starting point. Further research should address the following open issues:

- Deriving and validating the customer cost function $f_{customer\_cost}(\overrightarrow{Ce})$ for prototypical service contexts like for different industry branches for smart, connected products.
- Develop instruments to derive the provider cost and benefit functions (graphs in Fig. 3) based on available information within the firm.
- Extending the approach for a population of many customers with different customization expectations.
- Apply the approach to different branches of manufacturing industries and firms in order to identify prototypical optimization potential by moving towards the Pareto front, starting from today's operating point.
- Extending the model with an additional market model, predicting the market demand as a function of the value creation for the customer. On a firm level, moving from A to B is expected to decrease the demand and reduce the total profit of the firm, which reduces the total value created for the firm.
- Use the model for determining the optimum price *Pr* of a service, offered in a specific market. This might be done by adding price sensitivity functions.
- The model described here is focused on a single walk through the customer relationship lifecycle. How can impacts on value beyond this be incorporated, e.g., additional future revenues due to good customer experience?

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