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FOCUS THEME

Enabling individualized recommendations and dynamic pricing of value-added services through willingness-to-pay data

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Abstract When managing their growing service portfolio, many manufacturers in B2B markets face two significant problems: They fail to communicate the value of their service offerings and they lack the capability to generate profits with value-added services. To tackle these two issues, we have built and evaluated a collaborative filtering recommender system which (a) makes individualized recommendations of potentially interesting value-added services when customers express interest in a particular physical product and also (b) leverages estimations of a customer's willingness to pay to allow for a dynamic pricing of those services and the incorporation of profitability considerations into the recommendation process. The recommender system is based on an adapted conjoint analysis method combined with a stepwise componential segmentation algorithm to collect individualized preference and willingness-to-pay data. Compared to other state-of-the-art approaches, our system requires significantly less customer input before making a recommendation, does not suffer from the usual sparseness of data and cold-start problems of collaborative filtering systems, and, as is shown in an empirical evaluation with a sample of 428 customers in the machine tool market, does not diminish the predictive accuracy of the recommendations offered.

Keywords Collaborative filtering · Dynamic pricing · Willingness-to-pay · Service science · Design science

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Motivation and research problem

During the last decades, in most developed countries we have been witnessing a transition from a primarily goods-based to an increasingly service-based economy (OECD 2005). For example, in the U.S. services account for over 80% of current gross domestic product and total employment. One explanation for the growing importance of services is the observation that the sole production of physical goods is increasingly becoming a commodity which can be almost equally provided by a constantly growing number of companies around the world (Rai and Sambamurthy 2006). At the same time, services represent a means of offering more differentiated value propositions that are thought to lead to higher margins as well as superior levels of customer satisfaction and loyalty (Howells 2003). Following this major economic development, many manufacturing companies, which traditionally have been used to competing on the quality or price of physical objects, are starting to bundle their core products with related value-added services. Examples can be found in the automotive (such as automobile plus insurance, maintenance, trade-in, etc.) or telecommunication (such as mobile phone plus calling plan, internet access, location-based services, etc.) industry, but also in B2B markets like the mechanical engineering industry (such as machine tool plus integration, start-up, training, operating personnel, etc.).

However, especially manufacturers in B2B markets are struggling to advance their service business (Oliva and Kallenberg 2003). Our experience has shown that, striving to expand their portfolio with value-added service, they often encounter, amongst others, two significant problems: First (P1), in technology-centered markets manufacturers often have difficulty in efficiently communicating and promoting intangible services to their customers (Homburg et al. 2004). Second (P2), manufacturers often fail to realize a profitable price premium for bundling value-added services with their products, as—especially for capital-intensive industrial goods—customers often take such add-ons for granted (Gebauer et al. 2005).

In this context, the aim of our research is to explore the extent to which recommender systems, as known from popular B2C e-commerce platforms such as Amazon, iTunes or Netflix, can help overcome the issues described. Although recommender systems have long been a research topic in e-commerce, surprisingly little work investigates their application for industrial, high-involvement products or complex services in B2B markets (Choi et al. 2006). Furthermore, though from a provider's perspective recommender systems act as valuable marketing tools with numerous benefits (Schafer et al. 2001), previous research has paid little attention to incorporating advanced pricing mechanisms and profitability considerations into the design of such systems. In this paper we report on the design of a recommender system that

(a) makes individualized recommendations of value-added services when customers express interest in a certain physical product (addressing P1), and at the same time
(b) leverages estimations of a customer's willingness to pay to enable a dynamic pricing of those services and the incorporation of profitability considerations into the recommendation process (addressing P2).

Following the methodology of design science (March and Smith 1995; Hevner et al. 2004), we evaluated the feasibility and utility of the proposed artifact by implementing a proof-of-concept software prototype and conducting an empirical study with 428 customers of the German mechanical engineering industry. With the data collected we carried out a series of experiments to evaluate the effectiveness of the developed artifact.

The remainder of this paper is structured as follows: In "Theoretical background" we provide an overview of recommender systems and outline some dynamic pricing strategies based on willingness-to-pay data. In "Design of the ServPay Recommender" we present the design of the proposed system, namely the ServPay Recommender. In "Empirical evaluation of the ServPay Recommender", based on data from an empirical study in the machine tool market, we train the developed prototype and evaluate its effectiveness for recommending value-added services based on willingness-to-pay data. In "Considering profitability when making recommendations" we demonstrate how the ServPay Recommender enables dynamic pricing strategies for value-added services. Finally, in "Conclusions, limitations, and outlook", we discuss the results and limitations of our work and offer an outlook for further research.

Theoretical background

A recommender system is a software application that suggests items of interest such as products or services to users based on preferences they have expressed, either explicitly or implicitly (Manouselis and Costopoulou 2007). Preferences denote the relative advantage of one option over another. A preference corresponds to the perceived value-in-use (Alderson 1957) of a product or service and can be represented as partworths, importance weights or ideal points (Green and Srinivasan 1990).

Recommender systems can be systematized in two dimensions:

According to the basis on which recommendations are made, recommender systems can be classified into the following categories (Balabanovic and Shoham 1997): content-based methods, collaborative filtering methods, and hybrid methods. Systems applying content-based methods recommend items that are similar to items a user preferred in the past. In contrast, systems applying collaborative filtering methods recommend items that other users with similar preferences ("peers") liked in the past. Hybrid methods combine aspects from content-based methods with collaborative filtering.

According to the technique used to compute recommendations, recommender systems can be classified into memory-based and model-based approaches (Adomavicius and Tuzhilin 2005). Memory-based techniques apply heuristics to continuously analyze live data about users and items, such as transactions, shopping carts, or click streams. Model-based techniques, in contrast, calculate recommendations using an ex-ante learned mathematical preference model built from some underlying data set or expert knowledge.

This classification raises the following question: Which type of recommender system is appropriate for our context? Content-based approaches stem from the information retrieval discipline. Usually, they calculate the similarity between two items using text analysis techniques (such as term frequency—inverse document frequency or the vector space model). Hence, these systems heavily rely on the availability of quality textual descriptions of items, e.g. in the form of standardized sets of keywords or attributes. As our scenario is characterized by highly heterogeneous and intangible value-added services, ranging from hotline services to eco-friendly disassembly, the availability of suitable textual item descriptions is problematic. In such situations, where the feasibility of describing an item in text form is limited (e.g. for experience goods like movies, music, or personalized services), researchers (such as Shardanand and Maes 1995; Adomavicius and Tuzhilin 2005) advise designers to apply collaborative filtering methods. Following this advice, we further have to decide whether to use memory-based or model-based collaborative filtering. Memory-based techniques work directly on the transactional data available in an e-commerce system. The advantage of this approach is that recommendations are always up to date and the system learns with each new transaction made. However, the usual heuristics require a substantial amount of data to work on until reliable recommendations can be made. In the literature, these issues are referred to as sparsity or cold-start problems and represent a major drawback considering our situation of high-involvement B2B products and related services that customers usually buy with a rather low purchasing frequency.

Model-based techniques that learn a preference model from an external data source, e.g. a customer survey, may represent a viable way of overcoming this problem. Here, we refer to Ansari et al. (2000), who suggest that preference models stemming from the marketing discipline, especially conjoint analysis, offer particularly good alternatives. Conjoint analysis is not only a popular method of building preference models but is also frequently used to estimate a customer's willingness to pay for a certain product or service. This feature makes conjoint analysis particularly suitable for our setting. Because conjoint analysis in its original form requires considerable user input, it is usually impractical for use as the core of a recommender system (Ansari et al. 2000). Hence, we decided to adapt an approach proposed by De Bruyn et al. (2008). To build a conjoint-based recommender system requiring minimal user input, they have tested methods of reducing the efforts of traditional conjoint analysis to a limited set of questions that are easy to answer and do not require extensive expertise. The predictive accuracy of their resulting collaborative filtering system is equal to the accuracy of a full-scale conjoint analysis but requires asking only a handful of easy-to-answer questions for making recommendations.

Virtually all of the currently applied recommender systems are built upon the concept of preference. Measuring a customer's willingness to pay presupposes assessing the customer's preferences, but it can also provide the opportunity to elicit additional information such as the maximum price that is acceptable for a physical good or service from the customer's point of view (Nagle and Holden 2002). Furthermore, in contrast to preferences, willingness to pay distinguishes favorable buying options from non-favorable options, for which a customer might have a positive preference—but no appropriate willingness to pay. Hence, using the concept of willingness to pay instead of preference makes the decision task more realistic and hence might increase the predictive accuracy of a recommender system.

Additionally, using willingness-to-pay data enables opportunities for implementing dynamic pricing strategies. Dynamic pricing allows companies to adjust the prices of identical goods or services to correspond to a customer's willingness to pay and is frequently used for online selling in B2C and B2B markets (Elmaghraby and Keskinocak 2003).

On the one hand, dynamic pricing mechanisms can be based on interactive price discovery processes with individual customers, such as through auctions, negotiations, or reverse pricing (*interactive pricing*).

On the other hand, dynamic prices can be based on expected short-term consumer behavior as a take-it-or-leave-it price, subject to factors such as time of sale, expected demand or resource availability (*dynamic price posting*) (Elmaghraby and Keskinocak 2003; Kauffman and Wang 2001; Schwind 2007). In dynamic price posting, goods and services are often priced for maximum resource utilization by exploiting assumed but not statistically surveyed differences in customers' willingness to pay (Desiraju and Shugan 1999). A typical example is yield management, which is frequently applied to profitably fill capacities for perishable services such as airline travel or hotel rooms (Schwind 2007). In dynamic price discrimination, another example of dynamic price posting, a customer's willingness to pay is estimated by means of statistical methods. This approach can be implemented in e-commerce applications and is expected to yield superior returns for a seller (Schwind 2007; Bichler et al. 2002), assuming that an adequate estimation of willingness to pay is possible.

Our approach—building a recommender system for value-added services in the B2B sector based on willingness-to-pay data—focuses on dynamic price discrimination, provided that a customer is willing to accept the configured offer. In addition, our approach can be used to inform a negotiation process as in interactive pricing. In the latter scenario, the recommendation would act as a starting point to make customers aware of value-added services and determine their willingness to pay before starting detailed negotiations.

Design of the ServPay Recommender

Conjoint analysis has gained widespread attention and increasing acceptance as a preference and willingness-to-pay measurement tool in marketing theory and practice (Gustafsson et al. 2007). It can be particularly valuable to assess a customer's willingness to pay for bundled goods or services (Bouwman et al. 2007). A conjoint analysis typically comprises three consecutive steps: First, a collection of distinguishing attributes (such as brand, performance, color, price) of an item under study (such as a laptop computer) is identified. Based on permutations of these attributes, a set of conjoint cards is created, each representing a fictional item. Second, the conjoint cards are presented to a potential customer. The customer is asked to evaluate the cards with respect to the perceived utility of the items described on the cards. Third, estimation procedures are applied to the evaluations of the conjoint cards to derive the customer's utility function (i.e. preferences) regarding the selected item attributes.

As already mentioned, classic conjoint analysis is rarely used in recommender systems due to the substantial customer input needed (i.e. ordering conjoint cards with regard to their perceived utility). Existing conjoint-based recommender systems either focus on very homogeneous items which can be described by a few common and standardized attributes (for instance, Schneider (2005) applies conjoint analysis to generate recommendations for investment funds described by two attributes only) or require customers to answer a large number of questions (see Scholz (2008) for a discussion of different profile designs for conjoint analysis in the context of recommender systems). Nevertheless, conjoint analysis offers a promising way to model customer preferences and willingness to pay at the same time. In their work, De Bruyn et al. (2008) explore possibilities of minimizing customer input by applying different algorithms—cluster classification, Bayesian treed regression, and stepwise componential segmentation—to the data of an ex-ante conducted conjoint analysis. In their analysis, stepwise componential segmentation dominated the other two algorithms. This is why they propose an approach comprising the following three steps:

1. *Data Collection*: Perform a conjoint analysis eliciting customer preferences combined with a survey on demographics and intended product use with a sufficient and balanced sample of the customer base.
2. *Model Development*: From these data, build a preference model representing the statistical relationships between customer characteristics, i.e. demographics and intended product usage, and customer preferences. Using a stepwise componential segmentation algorithm, cluster customers according to the similarity of their preferences and identify an optimal set of corresponding most informative customer characteristics that describe the clusters.
3. *Questionnaire-driven Recommendations*: When a potential customer browses the e-commerce website, ask the customer to answer questions about the most informative customer characteristics to predict his or her cluster membership. To make a recommendation, compute the customer's preferences according to the preference model developed in step 2.

We adapted this approach to fit the special characteristics of value-added services in B2B markets and allow for a measurement of a customer's willingness to pay. The resulting steps are shown in the procedure model in Fig. 1, which we will explain in detail in the consecutive sections.

Data collection

When deciding on a method to derive customers' preferences, one has to account for the specific context of the item under study. Industrial goods and services usually represent high-involvement purchases that are subject to a complex and individual decision-making process and are described by a large number of relevant attributes (Stremersch et al. 2001). Furthermore, the market for product-related services in the machine tools industry is characterized by extremely heterogeneous customer needs. Thus, a large number of heterogeneous services has to be considered.

Based on expert interviews we identified 17 types of services (attributes) to be included in the study, each of which is described by 2 to 4 service levels (amounting to a total of 52 attribute levels, see Table 3). In order to assess such complex decision tasks hybrid conjoint analysis methods are commonly used. We therefore adopted the basic idea of hybrid methods (such as the ACA) by splitting the evaluation task into a compositional and a decompositional part. Within the decompositional part all attributes are presented simultaneously. Studies that include many attributes might overstrain the respondents with too much information, such that simple decision heuristics might be more suitable than trade-off decisions (for other actions taken to ensure trade-offs see Table 5). Hybrid methods avoid these problems by adapting the interview to the attributes relevant to a respondent (using a respondent's answers from the first compositional part of the interview).

Most preference elicitation techniques are based on a linear utility model, i.e. the total utility of an alternative is derived from the sum of the partworths that are caused by its respective attribute levels (Hair et al. 2010). The application of such a linear utility model is only viable if the following assumptions are satisfied:

1. Linear models are based on trade-off decisions, i.e. a good level of one attribute can compensate for a less preferred level of another attribute (Butler et al. 2001).
2. The preference for an attribute level should be independent from levels of other attributes. This concept is called additive independence. Preference independence is an important issue and must be considered when selecting attributes and levels to be assessed within a study. In this study, we used expert

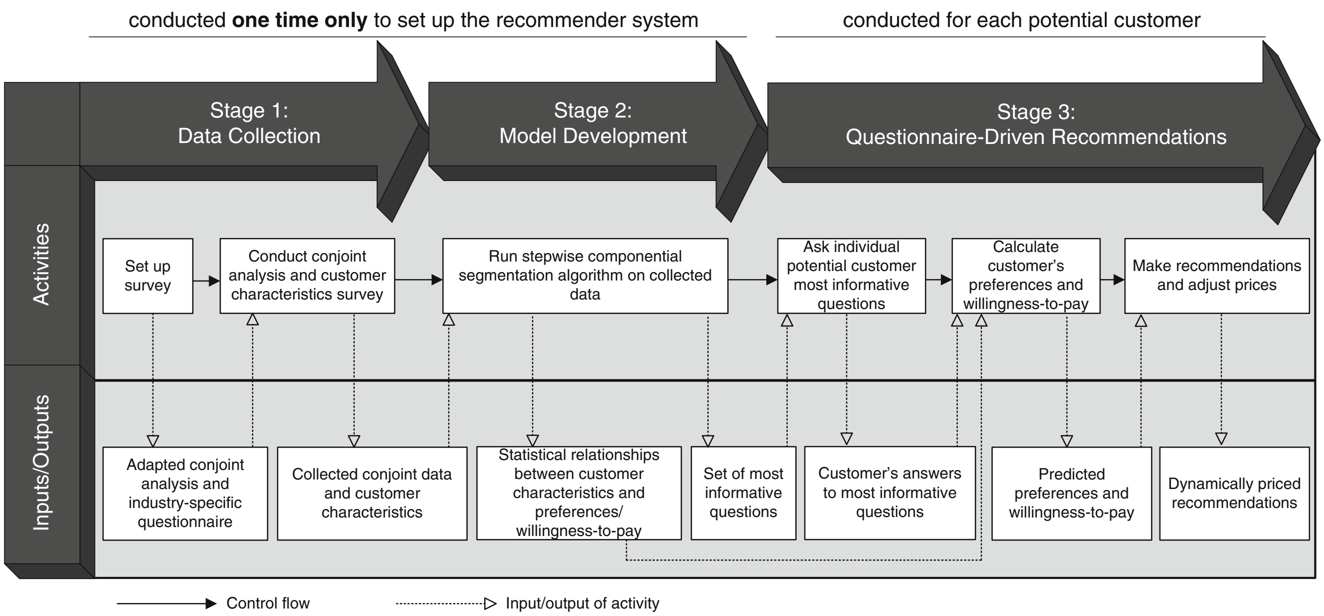

Fig. 1 Overall procedure of the proposed approach

interviews to identify interaction effects. We found no evidence for the presence of interaction effects within the selected set of attributes. We therefore apply an additive main-effects model, which is a common approach in preference measurement. In any case, additive models are usually robust and able to identify the preferred alternative, even if the independence assumption is not satisfied (for more detail see Butler et al. 2001).

Existing hybrid methods (e.g. ACA, HILCA) assess willingness to pay by using price as an attribute (multi-attribute alternatives with differing price levels are presented to the customers for evaluation). However, because our sample is characterized by highly heterogeneous services, predefining price levels might result in unacceptable attribute levels and foster the use of simple decision heuristics. Therefore, we have excluded the attribute price. Instead, the respondents are asked to reveal their willingness to pay directly on a dollar metric. This bears several advantages: No a-priori information about price acceptance ranges is needed, the scale is interpreted equally by all respondents, and the open-ended scale benefits the evaluation of heterogeneous items. To ensure consistent scaling across all respondents, the ratings are not conducted in absolute dollar terms but rather in percentages representing a price premium for the value-added service in relation to the price of the core product. Price premiums of 0% represent a no-buy option for that service.

In the following, we will explain the steps of the ServPay Conjoint Analysis (SPCA, see also Fig. 2 and Table 4):

1. *Selection of relevant services*: From the expert interviews, we know that not all services are relevant for all respondents. In order to avoid information overload we applied an approach based on Voeth et al. (2007). In the first step the respondents receive a comprehensive list of attributes (in our case 17 types of services related to a machine tool, such as a service hotline) described by different attribute levels (in our case 2 to 4 service levels, such as availability of 8 h, 12 h or 24 h a day). The respondents select those services that they deem relevant for purchase in addition to the core product (step 1 in Fig. 2). Only the services selected are further considered in the subsequent steps.
2. *Rating of relevant services:* The services selected as relevant are subjected to a compositional evaluation process (step 2 in Fig. 2). As stated above, in our SPCA we used a dollar metric for rating service levels (Pessemier et al. 1971).
3. *Rating of service bundles:* Finally, the most important services, with the highest deviation between the best and worst individual rating, serve to generate service bundles. These service bundles are created on an individual level using orthogonal designs based on Addelman plans (Addelman 1962). The resulting alternatives are presented to the respondent for evaluation on the dollar metric in a conjoint task (step 3 in Fig. 2). Each respondent is asked to evaluate a maximum of 16 service bundles.

To combine the advantages of telephone interviews (e.g. fewer item omissions, better representativeness, higher response rates) with the advantages of web surveys (e.g. greater reliability; Roster et al. 2004, Fricker et al. 2005), we performed a telephone-aided web survey for the one-

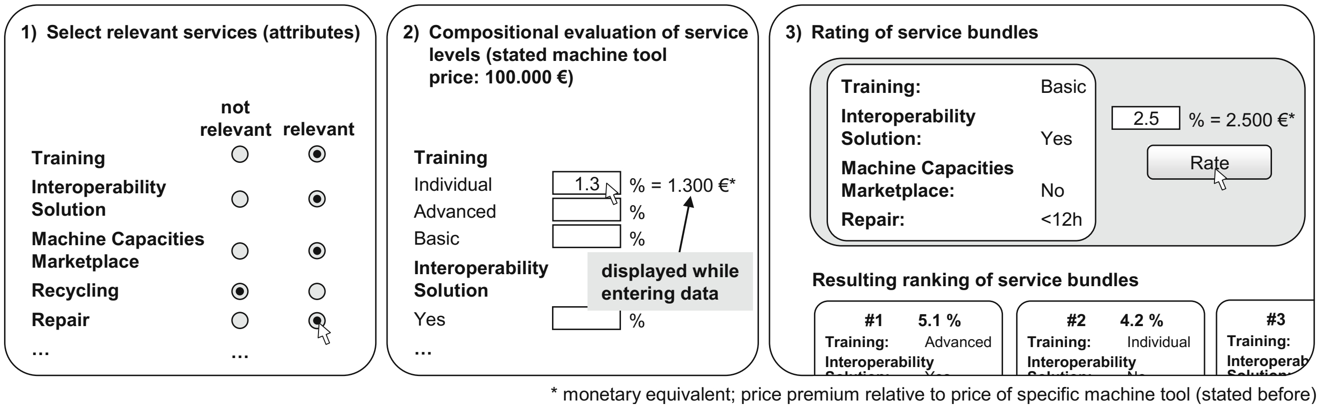

Fig. 2 ServPay Conjoint Analysis

time data collection required to train our recommender. We ensured that the respondents were sufficiently familiar with the evaluation task at hand by only interviewing decision makers who had bought a machine tool within the previous 3 years. The survey consisted of four parts. In the first part, participants were made familiar with the study background; specifically, we asked them to imagine again buying a specific machine tool and to describe it in terms of the machine technology, price, and preferred supplier. We thus ensured that the machine tool served as a reference point for the subsequent evaluation task. The second part of the study consisted of the SPCA approach as previously described. To simplify the conjoint task we ensured that each customer rating (expressed as a relative dollar metric in percentage) translated immediately into an absolute euro value (monetary equivalent; see Fig. 2), based on the price of the machine tool that the respondent had specified at the beginning of the survey. The third part of the survey was a holdout task in which respondents ranked four randomly selected service bundles containing service levels of the four most relevant services. The results of this holdout were used to assess the predictive accuracy of our recommender system later on. Finally, respondents filled in a questionnaire with 52 additional demographic questions and questions regarding the intended product usage derived from a widespread industrial buying behavior model (Johnston and Lewin 1996). Furthermore, the respondents were asked to state their function in the company and their role in the buying process to ensure that they qualified as decision makers. To avoid order effects and to reduce reliability concerns caused by respondent fatigue, the sequence of the presented services in the first and second step of the conjoint procedure, as well as the demographic and product usage questions, randomly rotated among respondents (Schuman and Presser 1996).

Initially, a total of 3,909 buying center members from the customer database of a German machine tool manufacturer were contacted. 428 representatives participated in the final survey (see Figs. 7 and 8). This is a response rate of approximately 11%, which is satisfactory when compared to other empirical studies in the German B2B sector (Homburg and Garbe 1999).

Model development

Several approaches have been proposed to overcome the extensive data requirements of classic conjoint analysis. For example, De Bruyn et al. (2008) enhance the componential segmentation algorithm proposed by Green (1977) and Green and DeSarbo (1979). The resulting stepwise componential segmentation incorporates customer characteristics into the preference model by expressing a customer's preference partworths as linear combinations of their customer characteristics. In our example, this means that it is assumed that preferences for certain value-added services (such as a service hotline with 24/7 availability, maintenance with response time < 12 h) as well as the customer's willingness to pay are expected to be a function of the customer's demographics (such as industry sector, company size, market position) and the customer's intended usage of the core product (such as mode of production, processed materials, precision of end product). Whereas classic conjoint methods compute those functions for each individual customer, stepwise componential segmentation approximates a customer's preference partworths as a linear combination of a vector of the customer's characteristics and a matrix of parameters to be estimated. These parameters embody and quantify the statistical relationships between customer characteristics (rows of the matrix) and customer preferences/willingness to pay for certain services (columns of the matrix, see Fig. 3). This matrix is not specific to a particular customer but is calculated for the entire population.

In order to identify the most informative customer characteristics, i.e. the most informative questions to be asked, a stepwise procedure is executed. The algorithm starts with a customer characteristics vector of size 1 and an averaged preference score for the whole customer population. Subsequently, the vector is extended by one element at a time. The selection of the optimal next element is performed by testing all possible customer characteristics one by one and eventually adding the one that leads to the highest incremental improvement. An optimal stopping rule for this algorithm would be to use an F-test to verify that the last k parameters added to the model are not different from zero (if this is true, the accuracy has not been improved). As De Bruyn et al. (2008) outline, the rejection of this null hypothesis is very unlikely and entails lengthy calculations without yielding major improvements of the predictions. Therefore, they propose setting an arbitrary stopping rule. Accordingly, our procedure stops as soon as the inclusion of additional customer characteristics does not improve the adjusted R^2 of the predicted preference/willingness-to-pay score and the self-reported preference/willingness-to-pay score (known from the previous data collection phase) by at least 0.05. The result is an 'optimal' set of questions on customer characteristics to predict a customer's preferences and willingness to pay.

$$\beta_i = (\psi \cdot D_i) : \forall i; \tag{1}$$

$$y_{ij} = \left(\beta_i \cdot X_{ij}\right) \rightarrow (2\mathrm{b})\widetilde{y}_{ij} = \left(\beta_i \cdot X_{ij}\right) \tag{2a}$$

$$SSE = \sum_{i=1}^{I} \sum_{j=1}^{J} \left(y_{ij} - \widetilde{y}_{ij}\right)^2 \tag{3}$$

with:

$1..i..I$	respondents
$1..j..J$	item profiles rated by respondents
$1..k..K$	preference partworths to be estimated, one per attribute level, including an intercept
$1..q..Q$	respondent descriptor variables
y_{ij}	self-reported preference/willingness-to-pay scores given by the i^{th} respondent to the j^{th} item profile
$\widetilde{y}_{ij}$	predicted preference/willingness-to-pay scores for the i^{th} respondent to the j^{th} item profile
β_i	vector of preference/willingness-to-pay partworths of the i^{th} respondent
X_{ij}	vector of attribute levels of the j^{th} profile rated by the i^{th} respondent (with K elements)
D_i	vector of descriptor variables for the i^{th} respondent (with Q elements)
Ψ	matrix of parameters to be estimated (with K rows and Q columns)

More formally (De Bruyn et al. 2008): Stepwise componential segmentation distinguishes two effects in the estimation of preferences/willingness to pay: a main attribute-level effect that reflects the average partworth (Moore 1980) caused by the attribute levels of an item pooled across all respondents (estimated using OLS regression), and additional interaction effects between attribute levels and descriptor variables. Equation 1 models both effects, such that the preference/willingness-to-pay partworths $ß_i$ are expressed as a linear combination of the descriptor variables D_i and a matrix Ψ, which expresses the statistical relationships between preference/willingness-to-pay partworths and descriptors. In contrast with traditional conjoint analysis, for which all $ß_i$ vectors are modeled individually, this approach estimates $ß_i$ at the population level with an optimization of matrix Ψ. The estimation of $ß_i$ is conducted in a way that the sum of squared errors (SSE), which is the sum of the squared differences (Eq. 3) between the self-reported (y_{ij}, Eq. 2a) and predicted ($\widetilde{y}_{ij}$, Eq. 2a) preference/willingness-to-pay scores, is minimized.

Questionnaire-driven recommendations

The most informative customer characteristics derived from the stepwise componential segmentation algorithm form a set of questions that is a key part of the user interface of our recommender system. Once the recommender system is integrated into an e-commerce platform, each potential customer can fill in the questionnaire while searching for information about an industrial product. After evaluating the answers to these questions the recommender system immediately estimates the customer's preferences/willingness to pay for each service using the ex-ante assembled matrix Ψ.

Figure 4 illustrates the estimated preference/willingness-to-pay scores of a potential customer who has answered the three most informative questions (see Fig. 4) as follows: 'agree' (which equals a score of 6 on a 7-point Likert scale, see Fig. 3), 'not confident' (score=2), and 'aerospace'. On the basis of these answers for each service the system computes the preferences and willingness to pay as the sum of the base value and the values of the three descriptors (if applicable).

The system identifies the most preferred service level for each service and ranks them in descending order. Moreover, as a dollar metric has been used in the conjoint analysis, the predicted scores at the same time represent the customer's estimated willingness to pay for each service. Hence, services with a willingness to pay ≤ 0 are filtered out. In the example presented, the willingness to pay for the interoperability solution would be an additional 1.94% of the machine tool price, the willingness to pay for advanced training would be an additional 1.06%, and the willingness to pay for a machine capacities marketplace would be an additional 0.78% of the machine tool price. A complete

	Training Individual	Advanced	Basic	…	Interoperability Solution	…	Machine Capacities Marketplace
Base	1.79	1.90	0.91	…	4.56	…	2.38
Descriptor 1 (1)	-1.21	-1.33	-1.06	…	-3.79	…	-1.07
Descriptor 2 (2)	-0.04	-0.18	0.17	…	0.38	…	-0.74
Descriptor 3 (3)	-0.80	-0.66	-0.31	…	-3.00	…	-0.86

(1) For answers between 1 (strongly disagree) and 4 (indifferent) to the statement: "The acquisition of this machine tool would be a rather new type of purchase for us."
(2) For answers between 1 (not at all confident) and 3 (only slightly confident) to the question: "How confident are you of the machine tool's ability to perform as expected?"
(3) For answer "Aerospace" to the question: "Which industry does your company belong to?"

Fig. 3 Elements of matrix Ψ representing the statistical relationships between customer characteristics (descriptors) and preferences/willingness to pay for value-added services

service bundle consisting of an interoperability solution (+1.94%), advanced training (+1.06%) and a machine capacities marketplace (+0.78%) would correspond to a total price premium of 3.78%. This information may be used to instantly adjust the displayed price information (dynamic price discrimination, see "Theoretical background") or—more appropriate in our context—to convey this data to a sales representative so that he or she can leverage subsequent price negotiations (interactive pricing, see "Theoretical background"). Figure 5 shows the graphical user interface of the ServPay Recommender.

Empirical evaluation of the ServPay Recommender

To evaluate the effectiveness of the ServPay Recommender we conducted ten cross-validations and randomly split our survey data into 10 training sets (90% of participants) and 10 testing sets (10% of participants; each respondent is part of only one testing set). On the basis of the collected preference/willingness-to-pay data and customer characteristics, we performed a stepwise componential segmentation for each training set and identified the most effective customer characteristics. From the estimated training set matrix we predicted the preferences/willingness to pay of each respondent in the corresponding testing set (out-of-sample test), using that respondent's answers to the selected questions. Finally, the value-added services that led to the highest estimated overall scores were recommended.

To confirm the effectiveness of our out-of-sample recommendations, we referred to the results of the holdout task (see "Data collection") and calculated the first choice hit rate, a common goodness-of-fit index for rank-order data that indicates the ability to predict the participant's most preferred alternative (Grover and Vriens 2006). The first choice hit rate specifies the percentage of times the applied method correctly predicts each individual's preferred alternative for the four possible choices in the holdout set. Hence, it assumes a deterministic choice rule, i.e. that each user of the recommender system chooses the service bundle with the highest overall utility. This makes the first choice hit rate suitable for situations in which consumers normally choose only one option to buy (Green et al. 1993). This is a realistic assumption for heterogeneous markets involving sporadic, non-routine, low frequency purchases (Green and Krieger 1988) such as high-involvement B2B products and supplementary services. As the benchmark for comparison, we considered the in-sample predictive accuracy of the individual-level estimations, i.e. the predictions of a full-scale conjoint analysis without stepwise componential segmentation.

Table 1 shows the predictive accuracy of the ServPay Recommender in comparison to the full-scale conjoint analysis, averaged across all 10 cross-validations. By applying the defined stopping rule and asking additional questions until the increase of adjusted R^2 drops below 0.05, a total of three most informative questions emerged. Including these questions improves the adjusted R^2 from 0.0670 in the initial step to 0.5598 after the third question. The full conjoint analysis requires 70 questions to achieve a first choice hit rate of 59.77%. In contrast, the ServPay Recommender with the stepwise componential segmenta-

Fig. 4 Estimated preference/willingness-to-pay scores of a potential customer (example)

	Training Individual	Advanced	Basic	…	Interoperability Solution	…	Machine Capacities Marketplace
Base	1.79	1.90	0.91	…	4.56	…	2.38
Descriptor 1	n.A.	n.A.	n.A.	…	n.A.	…	n.A.
Descriptor 2	-0.04	-0.18	0.17	…	0.38	…	-0.74
Descriptor 3	-0.80	-0.66	-0.31	…	-3.00	…	-0.86
Sum	**0.95**	**1.06 (No. 2)**	**0.77**	…	**1.94 (No. 1)**	…	**0.78 (No. 3)**

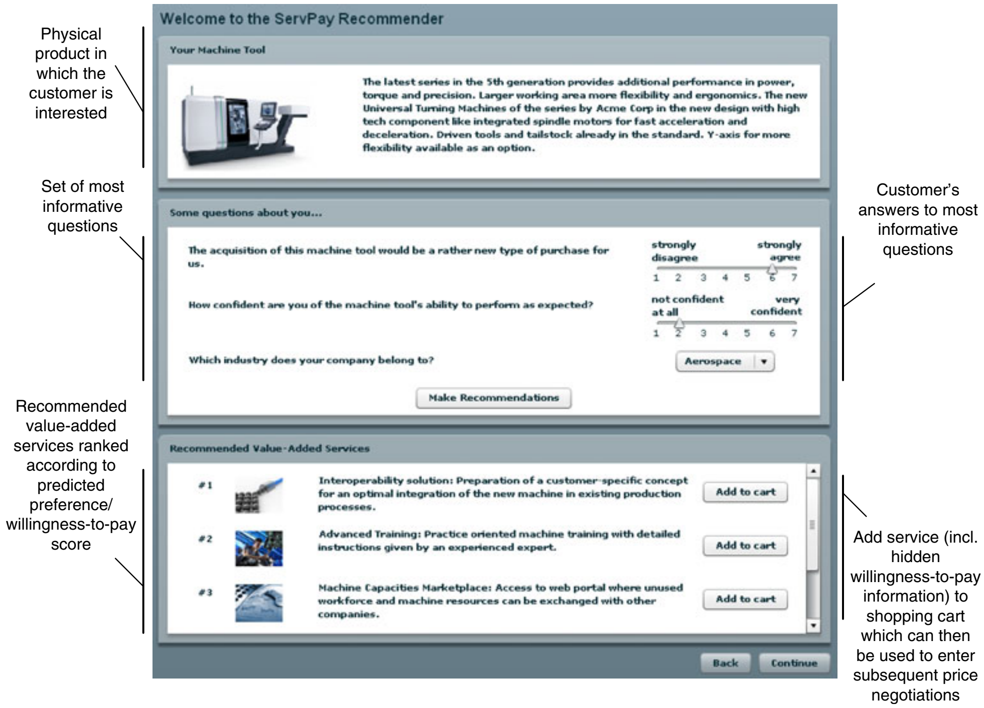

Fig. 5 Graphical user interface of the ServPay Recommender

tion algorithm reaches a first choice hit rate of 55.63% after asking only three questions. Although the predictive accuracy of the ServPay Recommender does not outperform full-scale conjoint analysis, we can infer from the results that the stepwise componential segmentation algorithm offers the same predictive accuracy (predictive accuracy not statistically different for $p<0.01$) as a full conjoint analysis with significantly less effort for the customer (3 instead of 70 questions needed).

The first choice hit rate evaluates the ability of a system to recommend the most promising alternative to the user. Even if a recommender system is able to identify the top alternative with regard to a user's preferences, it might fail to correctly predict the underlying absolute preference scores (Herlocker et al. 2004). For this reason, most recommender systems in commercial settings only display ranked lists and hide absolute preference scores. In our setting, however, the predicted willingness-to-pay scores are used to enable a dynamic pricing of the recommended services. Hence, the predictive accuracy regarding the absolute willingness-to-pay scores is of great importance. To evaluate the ability of the ServPay Recommender to predict willingness-to-pay scores we calculated two metrics, namely the Mean Absolute Error (MAE) and the Normalized Mean Absolute Error (NMAE). MAE measures the average absolute deviation between the predicted and the actual value of a variable. NMAE is the mean absolute error normalized with respect to the range of variable values. The latter metric is intuitive to interpret, even without a benchmark for comparison, as it measures deviation in percentages of the predicted values. Table 2 shows both metrics for the ServPay Recommender. Unfortunately, as our holdout task comprises only data about rankings of services and not about willingness-to-pay scores, it cannot be used as an out-of-sample evaluation data set. Hence, the presented metrics measure the predictive accuracy of the ServPay Recommender using the full-scale conjoint analysis as a reference method. The MAE amounts to an average absolute deviation of 11.39 points, which corresponds to a NMAE of 8.91%. This means that—compared to a full-scale conjoint analysis—we have a forecast error of about 9%. Taking this error into account, the actual willingness-to-pay score of the exemplary service bundle presented in "Questionnaire-driven recommendations" will probably lie in a corridor between 3.47% (3.78/1.0891) and 4.12% (3.78*1.0891). We believe that this loss in accuracy is tolerable considering the substantial reduction in effort.

Considering profitability when making recommendations

In the aforementioned experiments the available value-added services were ranked according to their computed preference/willingness-to-pay scores. This customer-focused perspective follows the logic applied in most recommender systems: "[...] most recommendations are

Table 1 Accuracy and effort of the ServPay Recommender and a full-scale conjoint analysis

	Full-scale conjoint analysis	ServPay Recommender with stepwise componential segmentation
First choice hit rate (accuracy)	59.77%	55.63%
Number of questions (effort)	70	3
Average incremental gain in accuracy per question	0.50%	10.21%

traditionally made merely based on purchasing possibility and customers' preferences" (Chen et al. 2008). However, from a provider perspective this strategy may not be optimal: "[...] preferences should not be the only concerns to enterprises. Profit margin is another crucial factor for sellers" (Chen et al. 2008). This inherent trade-off between customer and provider interests when making recommendations and pricing information available (Gorman et al. 2009) is underlined by a recent definition by Martin (2009): "A Recommender selects the product that if acquired by the buyer maximizes value of both buyer and seller at a given point in time".

As we based the ServPay Recommender on willingness-to-pay data rather than on preference data, some additional opportunities for balancing the two perspectives exist. Figure 6 presents different options addressing this trade-off, ranging from a primarily customer-focused perspective (option 1) to increasingly provider-focused perspectives (option 5).

Options 1 and 2 are solely based on willingness-to-pay data and represent the system design that has been presented and evaluated in this paper. In option 1 no price discrimination is applied and all customers pay the same list price for the recommended services. One can say that this configuration—interpreting willingness-to-pay information as customer preferences only and not capitalizing on the opportunity of dynamic pricing—represents the most customer-oriented option. Option 2, in contrast, (automatically) adjusts prices according to the willingness to pay of the individual customer. As mentioned earlier, depending on the market characteristics this can mean actually altering the price tag of a service on a webpage (dynamic price discrimination) or using the respective information in subsequent price negotiations (interactive pricing). In addition to willingness-to-pay data, options 3–5 also consider cost data, which have to be collected beforehand (such as by means of an activity-based costing approach). In option 3 services are still ranked by the customer's willingness to pay. However, services that have a negative contribution margin from a provider's perspective (defined here as willingness to pay minus direct costs) are filtered out. Option 4 goes one step further and ranks services by a combined willingness-to-pay and contribution margin score. An 'optimal' solution would be to rank the services in a way that, when moving from the best to the second best alternative, the decrease in willingness to pay is as low as possible and, at the same time, the increase in the contribution margin is as high as possible. An alternative straightforward heuristic would be to calculate the weighted sum of the willingness-to-pay and contribution margin values. Yet another—more probabilistic—approach is to calculate a kind of profit expectation value by multiplying the normalized willingness-to-pay value with the respective contribution margin (for a formal definition see Chen et al. (2008)). Finally, option 5 ranks services merely by their contribution margin and only indirectly, through the definition of the contribution margin formula, considers willingness-to-pay data, and hence customer preferences. This might push profit margins for the provider, but will probably harm the predictive accuracy of the recommender system, as the list of recommended services might not be in line with the customer's preference structure anymore.

With respect to the strategies outlined, it has to be noted that the dynamic pricing of services might be perceived as "unfair" if customers feel that a supplier is taking advantage of their inexperience, their lack of price sensitivity, or the lack of alternatives in the market (Bergen et al. 2003; Thaler et al. 1986). However, we argue that in numerous B2C service scenarios, such as for transportation and tourism services, dynamic pricing is widely accepted by customers. We believe that also for complex B2B services dynamic pricing is feasible, especially as in industrial settings services usually have to be priced individually to account for varying customer inputs (Frei 2006). This limits the customer's ability to successfully compare prices and hence creates opportunities for dynamic pricing. In our opinion, to be successful in the long run, pricing strategies should be designed to account for the perspectives of both suppliers and customers. Accordingly, Varian (1996) argues that Pareto efficiency related to sales can be achieved if the marginal willingness to pay of customers is equal to the marginal cost of a provider. Only a recommender system

Table 2 Predictive accuracy of the ServPay Recommender using the full-scale conjoint analysis as a reference method

	ServPay Recommender with stepwise componential segmentation
Mean absolute error (MAE)	11.39
Normalized mean absolute error (NMAE)	8.91 %

Fig. 6 Alternative configurations for the consideration of profitability in recommender systems

	Ranking	Filtering	Pricing
1	willingness-to-pay	willingness-to-pay <= 0	fixed list prices
2	willingness-to-pay	willingness-to-pay <= 0	price = willingness-to-pay
3	willingness-to-pay	contribution margin < 0	price = willingness-to-pay
4	willingness-to-pay & contribution margin	contribution margin < 0	price = willingness-to-pay
5	contribution margin	contribution margin < 0	price = willingness-to-pay

Customer focus

Provider focus

that is acceptable for both partners (Rossignoli et al. 2009) will foster long-term relationships (Wang et al. 2006).

Conclusions, limitations, and outlook

Manufacturers in B2B markets bundling physical goods with related services frequently struggle to communicate and promote their value-added services efficiently and fail to realize profitable prices for these offerings. The aim of our research has been to build and evaluate an efficient approach to offering individualized recommendations of value-added services and at the same time obtaining willingness-to-pay data that can be leveraged for dynamic price discrimination and profit optimization.

Traditionally, memory-based recommender systems in B2B settings suffer from a lack of transactional data due to a low purchasing frequency. To avoid the resulting sparsity and cold-start problems, we have presented a model-based recommendation approach based on preference and willingness-to-pay data derived from a newly developed conjoint analysis, the ServPay Conjoint Analysis. By modeling the statistical relationships between the collected preference/willingness-to-pay data and additional customer characteristics in a stepwise componential segmentation approach, a preference matrix and a set of most informative customer characteristics have been derived. Embedded in the ServPay Recommender, these two constructs allow for providing individualized recommendations of potentially interesting services to customers by asking only a handful of questions. As we used a dollar metric in the ex-ante conducted conjoint study, the collected preferences at the same time represent the customer's willingness to pay for the value-added services offered. Hence, besides acting as a decision aid for customers our approach can be used by providers to implement dynamic pricing mechanisms and incorporate profitability aspects into the recommendation process. As we have shown by presenting evidence from a field experiment with n=428 machine tool customers, the developed ServPay Recommender does not fall behind a full-scale conjoint analysis in terms of predictive accuracy while requiring significantly less customer effort.

Dynamic pricing should be implemented according to the characteristics of the market environment. Elmaghraby and Keskinocak (2003) postulate three main characteristics of the market environment that influence dynamic pricing strategies. First, it is intuitive that pricing with a fixed amount of inventory at hand has to be carried out differently than with a replenishment of inventories. Second, pricing has to be carried out differently for a dependent vs. independent demand over time. With dependent demand, pricing has to cater for the fact that selling a good or service today will diminish demand in the future (such as for capital goods), whereas with independent demand, purchase decisions are not affected by prior purchases (such as for eatables or haircuts). Third, myopic vs. strategic customer purchasing behavior of customers affects pricing decisions. While myopic customers make a purchase as soon as a stated price drops below a certain threshold without considering future prices, a strategic customer takes predictions of future prices into account when making a purchase decision. Most related work on dynamic pricing is focused on so-called NR-I-M / NR-I-S scenarios (No Replenishment of inventories—Independent demand of the buying situations over time—Myopic or Strategic customer behavior) or R-I-M scenarios (Replenishable inventory—Independent demand of the buying situations over time—Myoptic customer behavior) (Elmaghraby and Keskinocak 2003). Our approach, in contrast, focuses on the dynamic pricing of complex services in industrial B2B settings. Due to the non-storability of services, the typically long time-span of service contracts for durable physical goods, as well as the dependence of buying decisions on customer knowledge and strategic customer buying behavior, our paper presents an approach to establish dynamic pricing in NR-D-S (No Replenishment of inventories—Dependent demand of the buying situations over time—Strategic customer behavior) scenarios. Therefore, our approach will likely be subject to some limitations when applied in other scenarios. For instance, we expect that extensions to include inventory considerations would be necessary to fit the requirements of an R-D-S (Replenishment of inventories—Dependent demand of the buying situations over time—Strategic customer behavior) scenario.

Additionally, our approach might benefit from complementary knowledge-based recommendation approaches such as the bundling of physical goods and value-added services based on predefined configuration rules (Becker et al. 2009) or the semantic modeling of relationships between services, such as substitution, cannibalization, etc. (Lee et al. 2007). Also, memory-based collaborative filtering mechanisms might be added to our system to keep recommendations up-to-date as customer preferences and willingness to pay will likely change over time. Case study or action research could be used to investigate the developed artifact in its natural setting and assess its utility for promoting and optimizing manufacturers' portfolios of value-added services. Further research may also apply the proposed approach to other domains to identify and compare preferences, willingness to pay, and most discriminating customer characteristics in various settings.

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Appendix

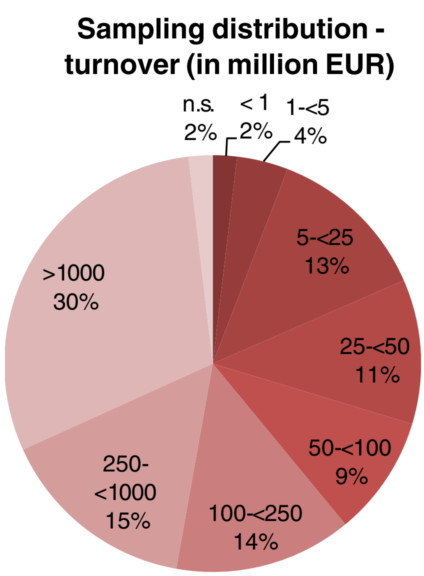


Fig. 7 Sampling distribution—turnover

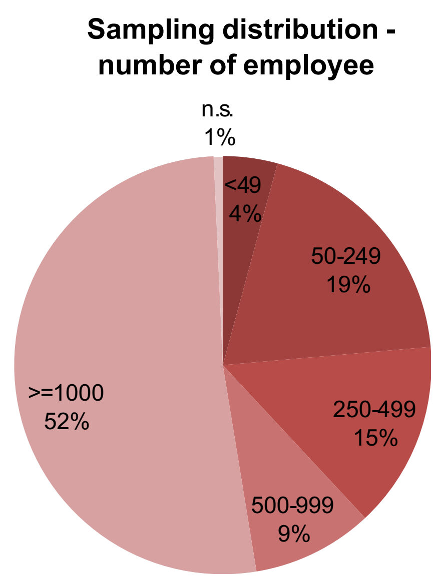


Fig. 8 Sampling distribution—number of employees

Table 3 Services and service levels assessed in the study

Service (attribute)	Service levels (attribute levels)			
	Best-practice level		Basic level	
status monitoring (SMS/Email/Online)	notification of status and errors		notification of errors	no
software training	individualized	advanced	basic	no
guarantee extension	12 months		6 months	no
3D CAD data of the machine	yes			no
feasibility studies	production of prototypes on test machines	simulation using virtual machines	expert assessment	no
machine capacities marketplace	yes			no
installation and startup	installation and 2-day on-site startup		installation and 1-day on-site startup	installation only
remote service	yes			no
price stability for spare parts	4 years	3 years	2 years	no
maintenance	< 12 hours	< 24 hours	< 48 hours	> 48 hours
service hotline	24/7 (7 days a week, 24 hours per day		weekdays 7:00–20:00, Saturday 7:00–12:00	weekdays 7:00–17:00 only
Guaranteed trade-in at actual value	trade-in, incl. disassembly and logistics		trade-in only	no
virtual machine	yes			no
interoperability solution	yes			no
software updates	subscription (automatic updates)		on request	no
training	individual	advanced	basic	no
availability of spare parts	consignment stock	< 24 hours	< 48 hours	> 48 hours

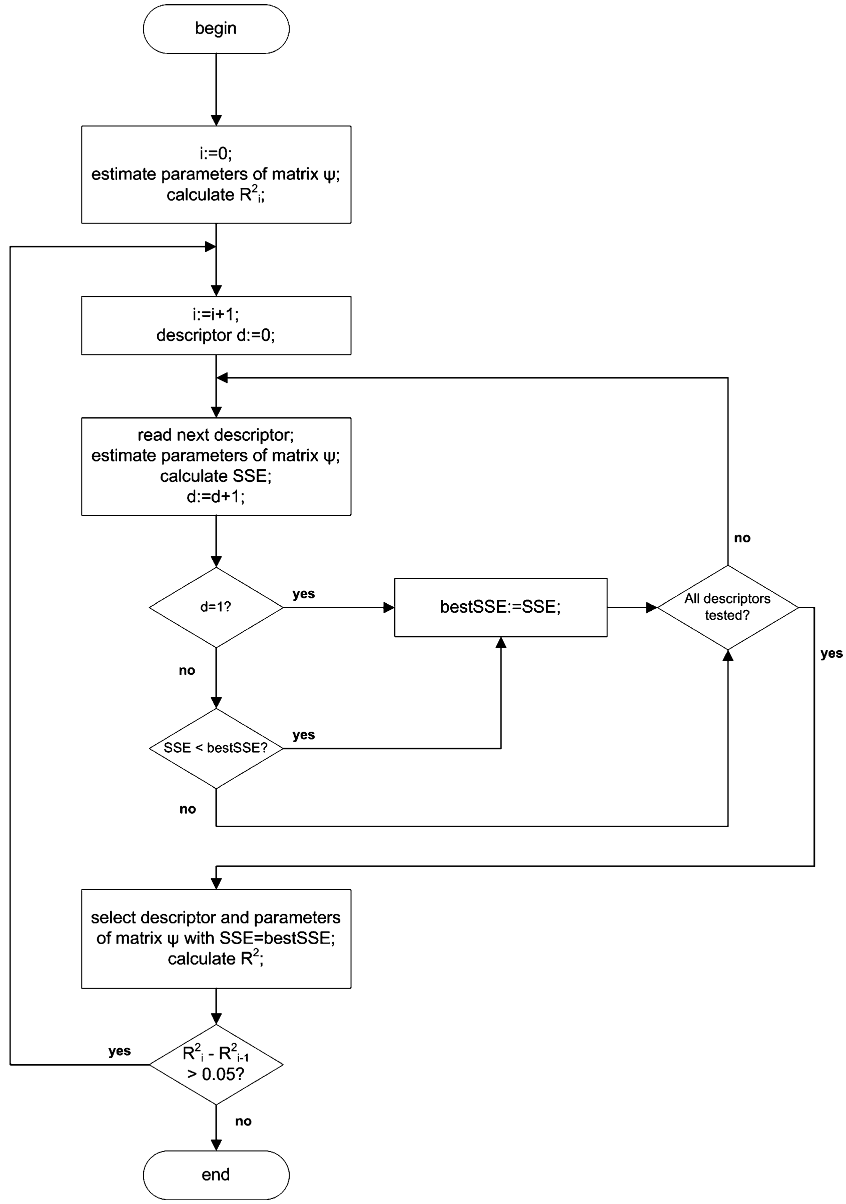
Table 4 Characteristics of the ServPay Conjoint Analysis

Type of conjoint analysis	Hybrid method based the following steps: 1. identification of relevant services 2. compositional part 3. decompositional part
Scale	Dollar metric
Utility model	Partworth model and linear utility function based on main effects
Experimental design	Individualized experimental design within the decompositional part based on Addelman plans
Estimation procedure	OLS regression

Table 5 Assumptions of the ServPay Conjoint Analysis

Assumption	Actions to ensure that the assumptions are fulfilled
Trade-off	- Definition of attributes and attribute levels based on expert interviews to ensure that heterogeneous customer needs can be covered - Stepwise approach to ensure that only relevant attributes are surveyed (1. selection of relevant attributes and 2. compositional part) - Dollar metric instead of assessing specific prices in order to avoid completely unacceptable price levels - Telephone-aided interviews to increase the motivation of the respondents during the evaluation task - Dollar metric was used to identify completely unacceptable service levels (respondents were able to enter a negative value if a level was unacceptable)
Linear utility model	- Expert interviews were used to identify possible interaction effects (no interaction effects were found)

Fig. 9 Stepwise componential segmentation algorithm



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