2010

Incorporating Willingness-to-Pay Data into Online Recommendations for Value-Added Services

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Journal:	*18th European Conference on Information Systems*
Manuscript ID:	ECIS2010-0064.R1
Submission Type:	Research Paper
Keyword:	Recommendation agent, E-business, Decision making/makers, Design/design science

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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 to their customers, and they lack the capabilities to generate profits with value-added services. To tackle these two issues, we design and evaluate 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) obtains estimations of a customer's willingness-to-pay to allow for a dynamic, value-based pricing of those services. The recommender system is based on an adapted conjoint analysis method combined with a stepwise componential segmentation algorithm to collect preference and willingness-to-pay data for value-added services. Compared to other conjoint-based recommendation approaches, our system requires significantly less customer input before making a recommendation and at the same time does not suffer from the usual cold-start problem of recommender systems. And, as is shown in an empirical evaluation with a representative sample of 428 customers in the machine tool market, our approach does not diminish the predictive accuracy of the recommendations offered.

Keywords: Model-Based Recommendations, Service Science, Design Science, E-Commerce (B2B).

1 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 US services account for some 80% of the current gross domestic product. One explanation for the growing importance of services is the observation, that the sole production of physical goods is more and more becoming a commodity which can be almost equally provided by a constantly growing number of companies around the world (Rai & Sambamurthy 2006). At the same time, services represent means to offer 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, traditionally used to compete on the quality and technological superiority of physical objects, start bundling their core products with related value-added services. Examples can be found in the automotive (e.g. automobile plus insurance, maintenance, trade-in etc.) or telecommunication (e.g. mobile phone plus calling plan, messaging and data services, media downloads, etc.) industry, but also in B2B markets like the mechanical engineering industry (e.g. machine tool plus integration, start-up, training, operating personnel, etc.).

However, especially manufacturers in B2B markets struggle to advance their service business (Oliva & Kallenberg 2003). Our experience has shown, that striving to expand their portfolio with value-added service they often experience, amongst others, two significant problems: First (RP1), in technology-centered markets manufacturers often have difficulties to efficiently communicate and promote intangible services to their customers (Homburg & Günther & Faßnacht 2004). Second (RP2), manufacturers often fail to realize a price premium for bundling value-added services with their products, as – especially for capital-intensive industrial goods – many customers expect to receive such add-ons free of charge (Gebauer & Fleisch & Friedli 2005).

In this context, the aim of our research is to explore in how far recommender systems as known from popular B2C e-commerce platforms such as Amazon or iTunes can help overcoming the described issues. 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 & Kang & Jeon 2006). Furthermore, though from a provider perspective recommender systems act as valuable marketing tools with numerous benefits (Schafer & Konstan & Riedl 2001), previous research pays little attention to incorporate advanced pricing mechanisms in the design of such systems. In this paper we report on the design of a recommender system that

(a) makes individualized recommendations of potentially interesting value-added services when customers express interest in a certain physical product (addressing RP1), and at the same time

(b) obtains estimations of a customer's willingness-to-pay to enable a dynamic, value-based pricing of those services (addressing RP2).

Following the methodology of design science (March & Smith 1995; Hevner & March & Park & Ram 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 one manufacturer and 428 of its customers in the German mechanical engineering industry. With the collected data we carried out a series of experiments to evaluate the effectiveness of the developed approach.

The remainder of this paper is structured as follows: In Section 2, we give an overview of the related work on recommender systems that fulfil our requirements and explain the design decisions we made. In Section 3 we present the design of our proposed recommender system, namely the ServPay Recommender. In Section 4, using data from the abovementioned empirical study we train the developed prototype and evaluate its effectiveness. In Section 5 we illustrate how the ServPay

Recommender can be integrated into a manufacturer's web presence. Finally, in Section 6, we discuss the results and limitations of our work and offer an outlook for further research.

2 RELATED WORK ON RECOMMENDER SYSTEMS

A recommender system is a software application that suggests items of interest such as products, services, or information to users based on preferences they have expressed, either explicitly or implicitly (Manouselis & Costopoulou 2007). Usually, recommender systems can be systematized in two dimensions. Regarding the basis on which recommendations are made, recommender systems can be classified into the following categories (Balabanovic & 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. Regarding the technique used to compute recommendations, recommender systems can be classified into memory-based and model-based approaches (Adomavicius & Tuzhilin 2005). Memory-based techniques apply heuristics to continuously analyze live data about users and items, e.g. 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 (e.g. tf-idf, VSM). 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 to describe an item in text form is limited (e.g. for experience goods like movies, music, or personalized services), many researchers (e.g. Shardanad & Maes 1995, Adomavicius & Tuzhilin 2005) advice 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 which each new transaction made. However, the usual heuristics require a substantial amount of data to work on until reliable recommendations can be made. In literature, this problem is referred to as the cold-start problem and represents 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 to overcome this problem. Here, we refer to Ansari, Essegaier and Kohli (2000), who suggest that preference models stemming from the marketing discipline, esp. conjoint analysis, offer particularly good alternatives. Conjoint analysis is not only a popular method to build preference models but is also frequently used to estimate a customer's willingness-to-pay for a certain product or service, which makes it especially suitable for our setting. Because conjoint analysis in its original form requires considerable user input, it is usually impractical as the core of a recommender system (Ansari et al. 2000). Hence, we decided to adapt an approach proposed by De Bruyn, Liechty, Huizingh and Lilien (2008). To build a conjoint-based recommender system requiring minimal user input, they test methods to reduce the efforts of traditional conjoint analysis to a limited set of questions that are easy to answer and do not require extensive expertise. Their resulting collaborative filtering system outperforms full-scale conjoint analysis in terms of predictive accuracy by asking users only a handful of easy-to-answer questions before making recommendations.

3 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 & Herrmann & Huber 2007). A conjoint analysis typically comprises three consecutive steps: First, a collection of distinguishing attributes (e.g. brand, performance, color, and price) of an item under study (e.g. a laptop) 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 order the cards with respect to the perceived utility of the items described on the cards. Third, special algorithms are applied to derive the customer's utility function (i.e. preferences) based on the order of the conjoint cards, regarding the selected item attributes.

As already mentioned, classic conjoint analysis is rarely used in recommender systems due to the substantial customer input required (i.e. ordering conjoint cards in regard to their perceived utility). Nevertheless, it 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 the possibilities to minimize customer input by applying a stepwise componential segmentation to the data of an ex-ante conducted conjoint analysis. Their proposed approach comprises 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 representative sample of customers.
2. *Model development*: From that data, build a preference model representing the relationships between customer characteristics, i.e. demographics and intended product usage, and customer preferences. Using a stepwise componential segmentation algorithm, cluster customers regarding the similarity of their preferences and identify an optimal set of corresponding most informative customer characteristics describing the clusters.
3. *Questionnaire-driven Recommendations*: When an individual potential customer browses the 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 user's preferences according to the preference model of the respective cluster.

We slightly adapted this described approach to fit the special characteristics of value-added services in B2B markets. The resulting steps and artifacts are shown in the procedure model in Figure 1, which we will explain in detail in the next sections.

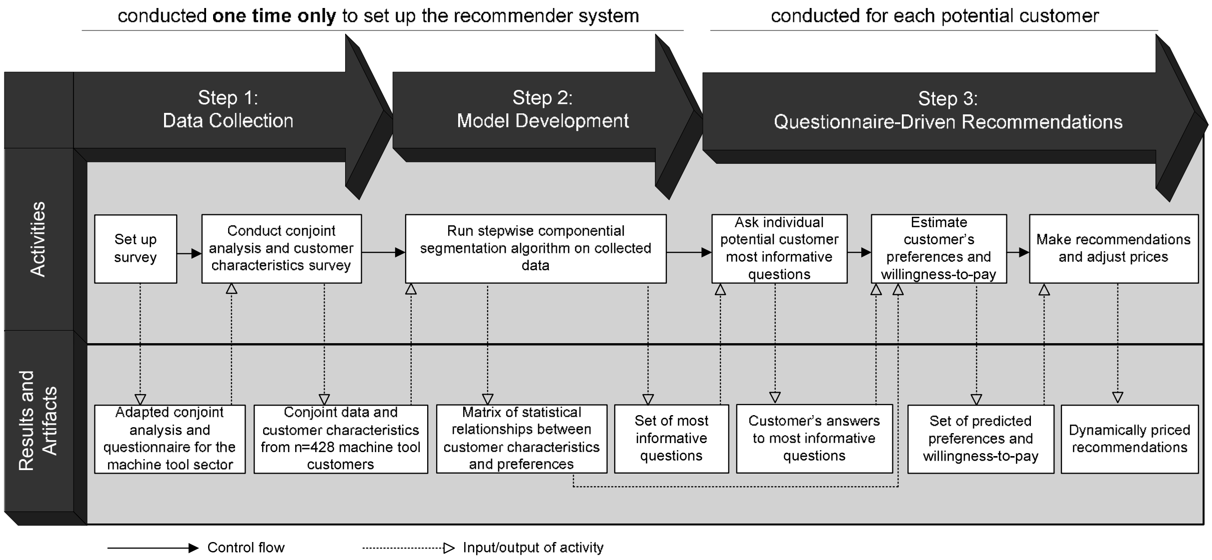

Figure 1. Overall procedure of the proposed approach

3.1 Data Collection

Adaptive conjoint analysis variants are particularly suitable for the context of industrial goods and services, which usually represent high-involvement purchases, characterized by a complex and individual decision-making process and a potentially large number of relevant attributes (Stremersch & Wuyts & Frambach 2001). The hierarchical individualized limit conjoint analysis (HILCA; Voeth & Herbst & Tobies 2007) is an adaptive method that can cope with large numbers of attributes, which is necessary to adequately describe complex physical goods and related services. However, to fulfill all our requirements some adaptations had to be made. Based on the original HILCA procedure, our modified conjoint method, which we call the ServPay-Conjoint Analysis (SPCA), comprises the following steps (see Figure 2):

1. *Selection of relevant services:* In the first step the respondent receives a comprehensive list of attributes (in our case: services related to a machine tool, e.g. technical hotline service) described by different attribute levels (in our case: different service levels, e.g. availability of 8h, 12h or 24h a day). Usually, this list includes the attribute ‘price’ as well to measure a respondent’s willingness-to-pay for the solution. However, because our study is characterized by highly heterogeneous services and a respondent-specific evaluation task, finding appropriate price levels that are equally suited for all services is virtually impossible. Therefore, we exclude the attribute ‘price’ here. Accordingly, in the first step of our procedure, the respondent selects services that he or she deems relevant for purchase in addition to the respective core product (step 1 in Figure 2). All unselected services will not be considered in the further analysis.

2. *Rating of relevant services:* The services selected as relevant undergo a compositional evaluation process (step 2 in Figure 2). The HILCA procedure, in its basic form, applies a ratio scale to evaluate attribute levels. In our SPCA method, we replace the ratio scale with a dollar metric for two reasons. First, using the dollar metric makes it possible to derive the willingness-to-pay, even without modelling price as an attribute. Second, the dollar metric has the advantage of being interpreted equally by all respondents and is open-ended, which benefits the evaluation of heterogeneous items such as services (Albrecht 2000). To ensure consistent scaling across all respondents, the ratings are not conducted in absolute dollar terms but rather in percentages to represent the price premium for the value-added service, relative to the price of the core product. Price premiums of 0% on the dollar metric represent a no-buy option for that service.

3. *Rating of service bundles:* In the last step, the most important services, with the highest deviation between the best and worst individual rating, serve to generate service bundles, presented to the respondent for joint evaluation on the dollar metric in a conjoint task (step 3 in Figure 2)

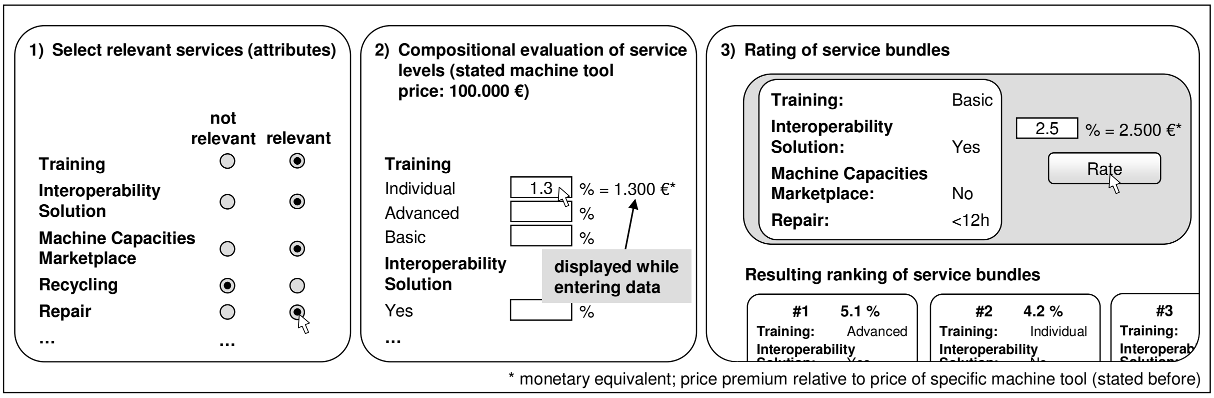

Figure 2. Steps of the ServPay-Conjoint Analysis

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 & Rogers & Albaum & Klein 2004, Fricker & Galesic & Tourangeau & Yan 2005), we performed a telephone-aided web survey for the one time data collection required to get our recommender up and running. 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 three years. The survey consisted of four parts. In the first part, participants became familiar with the study background; specifically, we asked them to put themselves into the situation of 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. In our attempt to ease the evaluation task, respondents first rated three selected services bundles – with the highest, lowest, and an average estimated value derived from the preceding step – which provides a mental bandwidth for subsequent evaluations of remaining service bundles, displayed one at a time in random order. To simplify the conjoint task we ensured that each customer rating (expressed as a relative dollar metric in percentage) translated immediately into an absolute dollar value (monetary equivalent; see Figure 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 are intended to help us 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 intended product usage derived from a widespread industrial buying behaviour model (Johnston & Lewin 1996). We recruited representatives from 428 potential machine tool customers to participate in the survey; the sample is nationally representative in terms of company size (number of employees), machine technology, and industry sector.

3.2 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 parthworths as linear combinations of their customer characteristics. In our example, this means that it is assumed that preferences for certain value-added services (e.g. hotline services with 24/7 availability, maintenance with response time < 6h) as well as the customer’s willingness-to-pay are expected to be a function of the customer’s demographics (e.g. industry sector, company size, market position) and customer’s intended usage of the core product (e.g. mode of production, processed materials, precision of end product). Whereas classic conjoint analysis methods compute those functions for each individual customer, stepwise componential segmentation approximates a customer’s preference parthworths 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 for certain services (columns of the matrix). This matrix is not specific to a particular customer, but estimated on the level of the entire population of customers in the B2B-market.

In order to identify the most informative customer characteristics, i.e. the most informative questions to be asked, and hence to minimize the required user input, 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. The procedure is stopped as soon as the inclusion of additional customer characteristics does not improve the adjusted R^2 of the predicted preference score and the self-reported preference score (known from the previous data collection phase) by at least 0.05 (which is an arbitrarily set value to describe a satisfactory level of saturation). The result is an optimal set of questions on customer characteristics to predict a customer's preference for a certain service by using the matrix of correlation coefficients between customer characteristics and preference scores.

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

(2a) $y_{ij} = (\beta_i \cdot X_{ij}) \rightarrow$ (2b) $\tilde{y}_{ij} = (\beta_i \cdot X_{ij})$

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

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 scores given by the i^{th} respondent to the j^{th} item profile
$\tilde{y}_{ij}$	predicted preference scores for the i^{th} respondent to the j^{th} item profile
β_i	vector of preference 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)

	Training				Interoperability		Machine Capacities
	Individual	Advanced	Basic	...	Solution	...	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 confident at all) and 3 (slightly not 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?"

Table 1. Elements of matrix Ψ representing the statistical relationships between customer characteristics (descriptors) and preferences for value-added services

More formally (De Bruyn et al. 2008): Stepwise componential segmentation distinguishes two effects in the estimation of preferences: a main attribute level effect that reflects the average partworth

(Moore 1980) caused by the attribute levels of an item pooled across all respondents, and additional interaction effects between attribute levels and descriptor variables (i.e. customer characteristics). Equation 1 models both effects, such that the preference 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 partworths and descriptors. In contrast with traditional conjoint analysis, for which all $ß_i$ vectors are modelled 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 (Equation 3) between the self-reported (y_{ij} calculated in Equation 2a) and predicted ($\tilde{y}_{ij}$ calculated in Equation 2b) preference scores, is minimized.

3.3 Questionnaire-driven Recommendations

The most informative customer characteristics derived from the stepwise componential segmentation algorithm form a set of questions that serves as the basis for our recommender. Once the recommender system is integrated on the manufacturer's website, 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 for each service with reference to the ex-ante computed preference matrix.

Table 2 illustrates the estimated preference scores of a potential customer who has answered the three most informative questions (see Table 1) as follows: 'agree' (which equals a score of 6 on a 7-point Likert scale, see Figure 3), 'not confident' (score = 2), and 'aerospace'. On the basis of these answers the system computes the preference and willingness-to-pay as the sum of the base value and the values of the three descriptors (if applicable) for each offered service.

	Training				Interoperability		Machine Capacities
	Individual	Advanced	Basic	...	Solution	...	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)**

Table 2. Example: Estimated preference scores of a potential customer

The system then displays the services with the highest estimated preference/willingness-to-pay in descending order. Moreover, as a dollar metric has been used in the conjoint analysis, the predicted preference scores at the same time represent the customer's estimated willingness-to-pay for each service. In the presented example, the willingness-to-pay for the interoperability solution would be an additional 1.94% compared to the machine tool price, the willingness-to-pay for an advanced training would be an additional 1.06% and the willingness-to-pay for a machine capacities marketplace would be an additional 0.77% compared to the machine tool price. This information may be used to instantly adjust displayed price information on the website or – more appropriate in our context – transfer this data to a sales representative so that it can be leveraged in subsequent price negotiations. Figure 3 shows the screen the user of the ServPay Recommender sees.

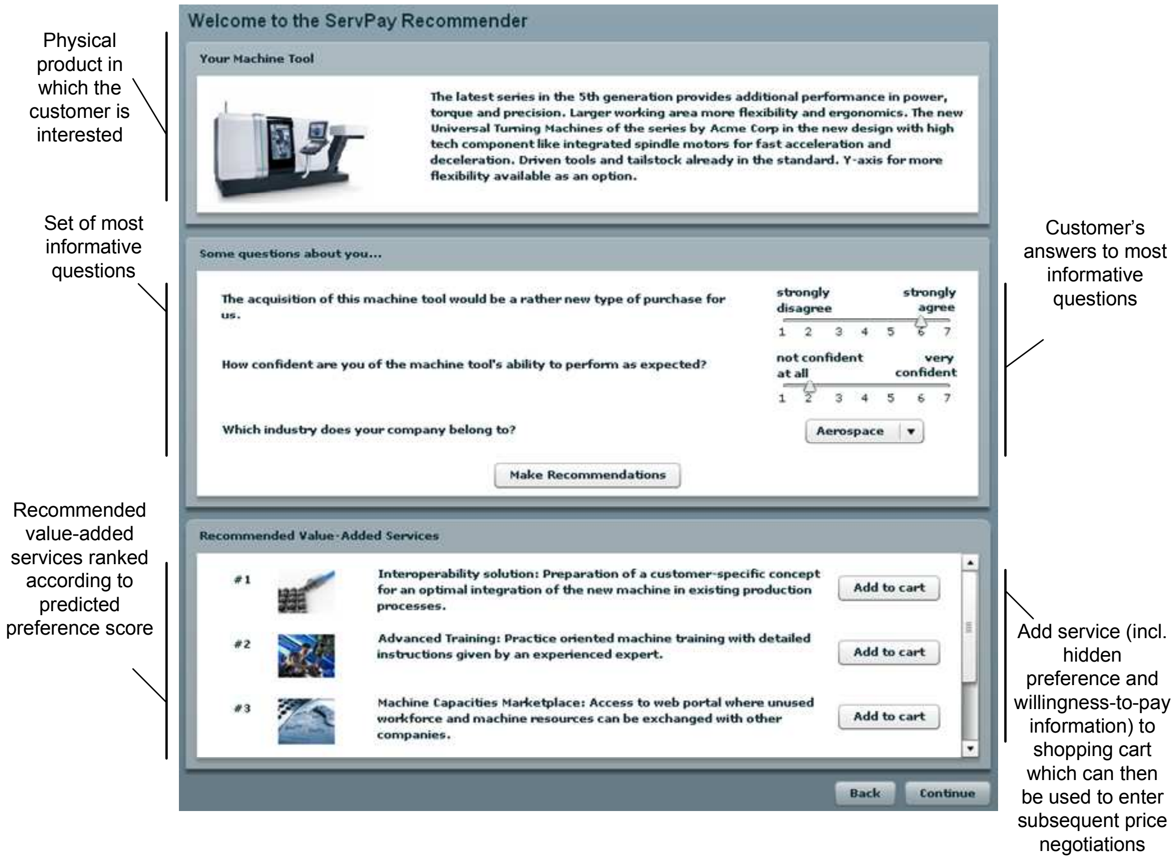

Figure 3. User interface of the ServPay Recommender

4 EMPIRICAL EVALUATION OF THE SPCA APPROACH

To evaluate the effectiveness of the derived preference matrix and the identified most informative customer characteristics, 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 preferences and customer characteristics from the conjoint analysis, we performed a componential segmentation for every training set and applied the stepwise algorithm to identify the most effective customer characteristics. From the estimated training set matrix we predicted the preferences 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 preference scores were recommended to the respondents in the testing set.

To confirm the effectiveness of our out-of-sample recommendations, we referred to the results of the holdout task 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 & Vriens 2006). For comparison, we considered the in-sample predictive accuracy of the individual-level estimations (full scale conjoint analysis without stepwise componential segmentation).

Figure 4 shows the predictive accuracy of the individual-level estimation and the stepwise componential segmentation, 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. In contrast, the individual-level estimation would require answering 16 questions to achieve an in-sample first choice hit rate of 0.5977. From this data we can infer, that the stepwise componential segmentation algorithm offers the same predictive accuracy (predictive accuracy not statistically different for $p < 0.01$) as the individual-level estimation, i.e. a full conjoint analysis with 16 questions, with significantly less effort (3 questions) needed per customer.

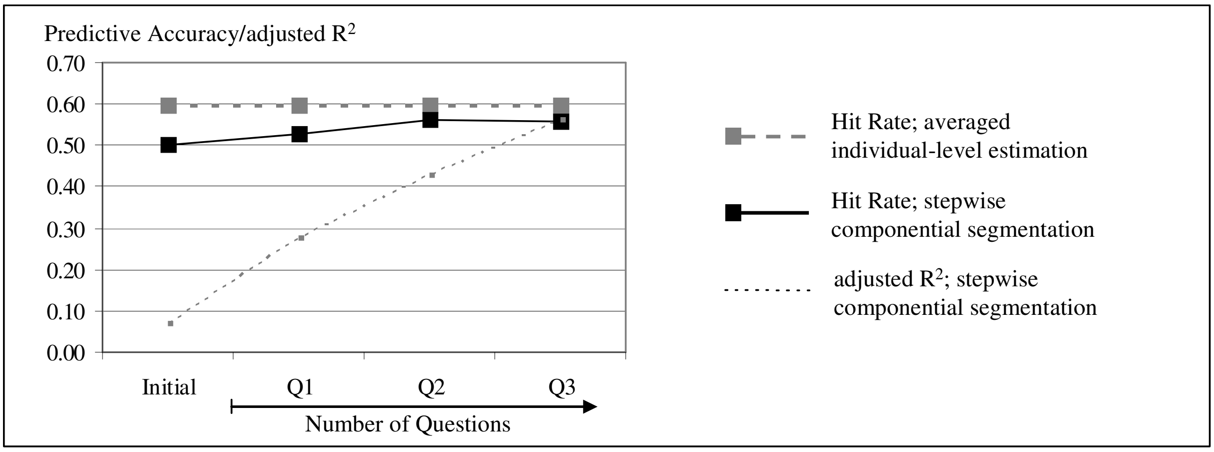

Figure 4. Results of the stepwise componential segmentation

5 CONCLUSIONS, LIMITATIONS, AND OUTLOOK

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

Traditionally, memory-based recommender systems in B2B settings often suffer from a lack of transactional data due to a low purchasing frequency. To avoid this cold-start problem, we presented a model-based recommendation approach based on preference data which was derived from a newly developed conjoint analysis variant, the ServPay-Conjoint Analysis. By calculating the statistical relationships between the collected preference data and additional customer characteristics in a stepwise componential segmentation approach, a preference matrix and a set of most informative customer characteristics has been derived. Combined, these two allow for giving recommendations of potentially interesting services to customer and at the same time estimating their willingness-to-pay for these services by asking only a hand full of questions. As we showed by presenting evidence from a field experiment with n=428 machine tool customers, our approach does not fall behind a full-scale conjoint analysis in terms of predictive accuracy.

Because customers’ preferences will likely change over time, our approach – though usable to initialise a recommender system – might require complementary memory-based collaborative filtering mechanisms to keep the recommendations up-to-date. Besides tackling this issue, our next steps will also include case study research to investigate the developed artifacts in their natural setting and assessing their utility for promoting and optimizing manufacturers’ portfolios of value-added services. Further research may also include applying the proposed approach to other domains to identify and compare preferences and the most discriminating customer characteristics in various settings.

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