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From Consumer Preferences Towards Buying Decisions - Conjoint Analysis as Preference Measuring Method in Product Recommender Systems

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Conjoint Analysis as Preference Measuring Method in Product Recommender Systems

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Abstract

This paper briefly introduces the conjoint analysis as a method to measure consumer preferences. Based on the introduction the conjoint analysis is suggested as preference measuring method in product recommender systems. The challenges and limits in applying the conjoint analysis to product recommender systems are analysed and discussed. In the end we present a set of adaptations to the traditional conjoint analysis which address the mentioned challenges and limits.

Keywords: product search engine, conjoint analysis, product recommender systems

1 Introduction

In recent years the internet has been used to conclude more and more sales contracts. Consumers can find billions of products in the internet. There are product recommender systems for a lot of different product types to help finding products which fits the preferences of consumers (Schafer et al., 1999; Montaner et al., 2003).

Major recommender systems can be divided into two categories, collaborative-based and content-based (Hung, 2005; Ahn, 2006). While collaborative-based recommender systems suggest products which are bought by consumers with similar preferences, content-based recommender systems try to find products based on syntactic properties of the products (Burke, 2002; Wei et al., 2007). Some authors also define a third category which consists of those recommender systems which are using both approaches (Montaner et al., 2003; Choi et al., 2006).

However, preference measurement is vital for all product recommender systems. The preferences will either be compared to those of other consumers or to product descriptions. In recent decades there has been research of preference measurement in the context of consumer behaviour. In 1967 Fishburn reported on 24 methods to measure consumer preferences (Fishburn, 1967). Besides early self-explicated approaches and the conjoint analysis, there was a dozen of hybrid approaches which have been developed and applied (Wittink and Cattin, 1989; Sattler and Hensel-Boerner, 2007). It is obvious that these approaches should be applied in product recommender systems. But considering current systems, self-explicated approaches are implemented merely (Guttman, 1998; Chun and Hong, 2001; Choi et al., 2006; Cao and Li, 2007), the conjoint analysis is not implemented at all. Due to their high predictive validity conjoint analysis and hybrid approaches would be more suitable for product recommender systems.

In this paper we briefly introduce and discuss the conjoint analysis as a method to measure consumer preferences for product recommender systems.

The paper is organised as follows. In section 2 we briefly introduce the conjoint analysis. In section 3 we discuss the challenges and limits arising in applying conjoint analysis to product recommender systems. Some suggestions how to handle these challenges and limits are depicted in each subsection. We conclude the paper in section 4 reflecting on open research tasks.

2 Conjoint Analysis

The conjoint analysis has originally been developed in the context of mathematical psychology in the 1960s (Luce and Tukey, 1964). The conjoint analysis was first applied to consumer behaviour questions by Green and Rao in the early 1970s (Green and Rao, 1971). The basic concept of the conjoint analysis is to estimate preference values for partial aspects of objects by measuring the preference for whole objects. In case of product recommendation the objects are products and the partial aspects are the attributes of the products.

In following consumer theory products are objects consisting of a finite set of attributes. If preference values for all attributes of a product class are estimated, it is possible to calculate the preference value for each existing product of this class. The itemised steps of a conjoint analysis are summarised in the following figure (Green and Srinivasan, 1990; Backhaus et al. 2005):

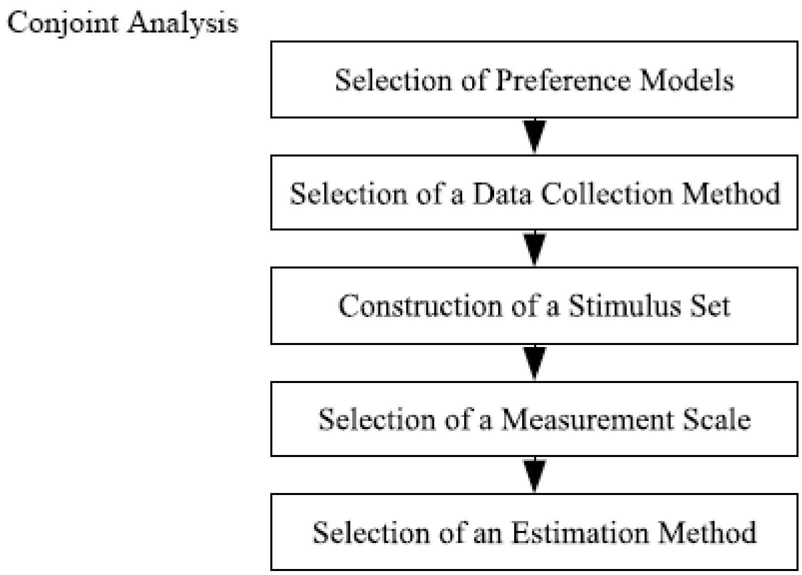

Figure 1: Steps of the conjoint analysis

Each step of the conjoint analysis will be explained in one of the following sections. Afterwards, the challenges and limits using conjoint analysis to preference measuring in product recommender systems will be discussed.

2.1 Selection of Preference Models

A conjoint analysis can not be conducted until the attributes for which preference values should be estimated are selected. This is due to the circumstance that the number of stimuli is heavily increasing if the number of attributes increases. Therefore, there has to be a restriction.

Thereafter a preference model has to be selected for each attribute. According to the different possibilities of describing the relationship between attribute values and preference values three main preference models are conceivable: the vector model (linear), the ideal point model (linear and quadratic) and the part-worth function model (piecewise linear) (Green and Srinivasan, 1990). While the vector model and the ideal point model are only applicable to metric or ordinal attributes like the price or the processor clock of notebooks. The part-worth function model can be used with cardinal as well as ordinal and metric attributes.

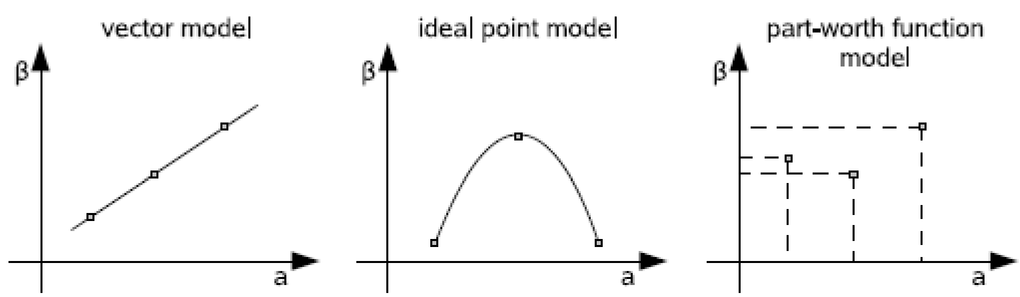

Figure 2: Preference models

The vector model is suitable if the part-worth of an attribute increases constantly according to the attribute level. If the part-worth of one level surpasses the partworth of each other levels the ideal point model has to be applied. In all other cases the application of the part-worth function model is obligatory. Figure 2 illustrates the connection between part-worth β and attribute level a for each of the three main preference models.

The more general the model the more parameters have to be estimated. Therefore, the vector model requires the lowest number of parameters while the part-worth function model requires most (Gustafsson et al., 2007).

2.2 Selection of a Data Collection Method

After determining adequate preference models for each attribute it is necessary to select an adequate method to get preference data from consumers. Following the argumentation in literature two methods of data collection can be distinguished -- the full-profile method and the trade-off method (Green and Srinivasan, 1990; Gustafsson et al., 2007; Härdle and Simar, 2007).

Figure 3: Example of full-profile method

While stimuli for the trade-off method consist of only two attributes stimuli for the full-profile method encompass all defined attributes. Thus, the full-profile method is more realistic but requires more concentration of consumers than the trade-off method. Furthermore, using the trade-off method the number of stimuli increases exponentially with the number of attributes.

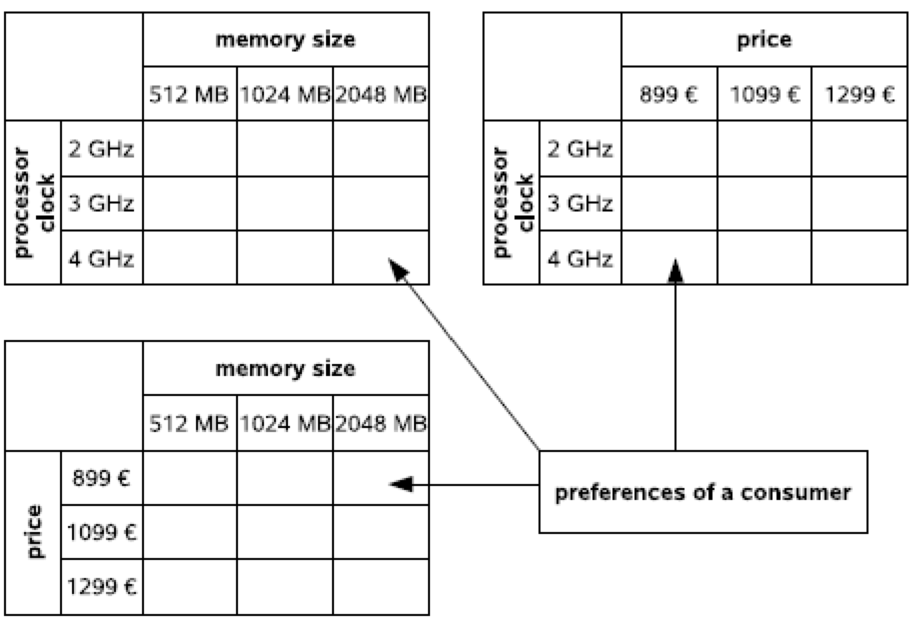

Figure 4: Example of trade-off method

Besides these two main methods a pairwise comparison of stimuli and hybrid forms is also discussed and applied (Wittink and Cattin, 1989; Hauser and Rao, 2004). To recommend one of the methods in general is not wise, but some surveys show that the full-profile method is applied more often than the trade-off method (Wittink and Cattin, 1989; Wittink et al., 1994).

2.3 Construction of a Stimuli Set

In the full-profile method only a few attributes and attribute levels result a high number of stimuli. We need 729 stimuli using the full-profile method for products with 6 attributes and 3 levels of each attribute. Consumers are not able to rate more than 30 stimuli at the same time though (Green and Srinivasan, 1978). Hence, fractional factorial designs are used to reduce the number of stimuli.

Several mathematical and heuristic methods like Addelman's basic plan or Hadamart matrices have been developed to generate a fractional factorial design (Addelman, 1962; Dey, 1985). There is no method which yields an optimal factorial design for each full design though. Using Addelman's basic plans we only need 16 stimuli for products with 6 attributes and 3 levels of each attribute.

Considering the example of notebooks with 3 attributes and 3 levels of each attribute we get the following fractional factorial design:

stimulus	*processor clock*	*memory size*	*price*
1	2 GHz	512 MB	899 €
2	3 GHz	512 MB	1099 €
3	4 GHz	512 MB	1299 €
4	2 GHz	1024 MB	1099 €
5	3 GHz	1024 MB	1299 €
6	4 GHz	1024 MB	899 €
7	2 GHz	2048 MB	1299 €
8	3 GHz	2048 MB	899 €
9	4 GHz	2048 MB	1099 €

Figure 5: Example of a fractional factorial design

The experimenter has to select a method of presentation before presenting the stimuli. It is also possible to present prototypes or real products as stimuli instead of plain text and images. Knoblich and Schubert have shown how to use fragrances in conjoint analysis (Knoblich and Schubert, 1989).

While stimuli consisting of plain text and images are very cost-saving for the experimenter they are often not suitable to describe all important attributes. Prototypes and real products are suitable to show non expressible attributes but they are often very expensive. Hence, the selection of a presentation method has to be done according to the objectives of the conjoint analysis.

2.4 Selection of a Measurement Scale

The stimuli generated in the previous step need to be evaluated by the consumers. The evaluations can be measured using a rating or a ranking scale. In a rating scale the consumers rank each stimulus with a value that lies within a predefined range (e.g. between 0 and 100). If a ranking scale gets used the consumers have to order the stimuli according to their preferences, while the rating scales provide metric data the ranking scales can only provide ordinal data. A ranking scale requires not as much concentration as rating scales though.

2.5 Selection of an Estimation Method

Based on the gathered data in the last step of conjoint analysis the utility function for the consumers will be estimated. This step is carried out to estimate each possible attribute levels part-worth.

The experimenter has to apply a metric or an ordinal estimation method depending on the type of data. The multiple regression analysis and the analysis of variance are recommended if the measurement in the previous step was based on a rating scale. The experimenter can use the monotone analysis of variance developed by Kruskal with ranking scales (Kruskal, 1965). Irrespective of the measurement scale an estimation method has to solve the following generic equation in case of part-worth function models for all attributes:

(1)
$$\alpha + \sum_{a=1}^{A} \beta_{ia} \cdot d_{ia} \longrightarrow \psi_{ia}$$

The estimated part-worth of attribute level *a* of stimulus *i* is denoted as β_{ia} here. The occurrence of attribute level *a* in stimulus *i* is determined by the dummy variable *d*. The utility value for a stimulus *i* is therefore calculated as the sum of all part-worth's and a constant utility value α. The estimation method has to calculate each β_{ia} in such a way that the value of each stimulus *i* has a minimal distance of the evaluation ψ_i.

It is obvious that the utility of a product *p* can be calculated based on the partworth of each attribute of this product.

3 Conjoint Analysis in Product Recommender Systems

The conjoint analysis was originally developed to measure the preferences of a group of people. Product recommender systems are aim to support single consumers though. Another problem is the amount of stimuli when there are many attributes. Furthermore, product recommender systems have to be able to handle conjoint analysis for different products and hence different attributes. In this section the problems that arise when applying conjoint analysis to product recommender systems are discussed.

3.1 Individual Conjoint Analysis

The conjoint analysis has been developed to measure the preferences of an amount of consumers. Hence, in the traditional conjoint analysis the evaluation data is aggregated before the part-worth's are estimated. The fact that the estimation also works when some values are missing is the advantage of this approach. Furthermore, the experimenter selects attributes for the conjoint analysis for more than one consumer.

To adapt traditional conjoint analysis to individual preference measurement the estimation of the part-worth's has to be done independently for each consumer. Additionally, consumers need to have the opportunity to select the attributes they see as crucial to make a buying decision.

3.2 Number of Attributes

As mentioned in subsection 2.3 the number of stimuli depends on the number of attributes and the number of attribute levels as well as on the specified preference models. With fractional factorial designs we can reduce the number of necessary stimuli. It is doubtful whether the number of stimuli is low enough after all attributes which are relevant for a buying decision are considered in a conjoint analysis. As stated in some articles consumers are able to evaluate 30 stimuli at most (Green and Srinivasan, 1978; Gensler 2003). On the other side consumers do not use more than 10 attributes in average to make a buying decision (Jacoby et al., 1977; Kroeber-Riel and Weinberg, 2003).

The number of stimuli also depends on the number of parameters per attribute. If an attribute is scaled nominally the number of estimatable parameters is equivalent to the number of levels this attribute has. To estimate the part-worth of an attribute using a vector model only 2 parameters are necessary, due to its linear shape. Respectively set at least 2 attribute levels must occur in the stimuli. Similarly to estimate the part-worth of an attribute with an ideal point model which has a squared shape the stimuli set must include 3 levels of this attribute.

If products with attributes fulfilling the requirements of the vector model are considered only 24 stimuli for products with 20 attributes are needed (Dey, 1985). Implying that all attributes follow the ideal point model a conjoint analysis with 27 stimuli and 13 attributes can be done. If the part-worth function model is needed to describe some attributes the number of attributes can increase precariously. If there is a product with 5 attributes and 8 levels per attribute we for example need 64 stimuli.

Product recommender systems should therefore use fractional factorial designs to decrease the number of stimuli. Product recommender systems should furthermore restrict the number of attribute levels in case of part-worth function models to stay below a maximum of 30 stimuli.

3.3 Selection of Preference Models

The type of the preference models used in conjoint analysis is closely related to the number of attributes. The preference models briefly introduced in section 2.1 are discussed according to their applicability in the process of product recommendation using conjoint analysis.

Assuming we want to conduct a conjoint analysis for notebooks with the following attributes, brand (k_1), processor clock (k_2), memory size (k_3), weight (k_4), and price (k_5), as mentioned in section 2.1 we have to select an adequate preference model for each attribute. It is obvious that the part-worth function model is the only in case of attribute brand. For all other attributes we can try to use the vector model. If there is only a difference between all levels of an attribute (e.g. a price between 500 and 700 Euro) the vector model will fit the real preference function of a consumer well enough. If there is on the other hand a large difference between the attribute levels (e.g. a price between 500 and 3500 Euro) the vector model often underfits the real preference function as shown in figure 6.

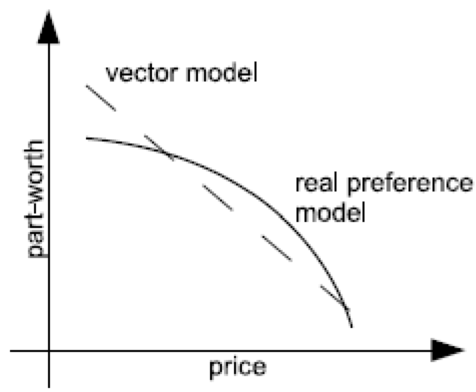

Figure 6: Problem of underfitting

According to real offered products there is often a large difference between attribute levels. Product recommender system must be suitable to handle a large difference between attribute levels due to the support of a plenty of products and a plenty of consumers. Hence, we need a more general preference model which is able to adapt to different shapes. But a more complex preference model also requires more estimation parameters. Thus, the more complex the preference model the more stimuli we need to estimate the model. Another general disadvantage of complex preference models or complex functions is the latent possibility of overfitting (Frees, 1996).

In case of overfitting the estimated function has local extrema which do not exist in the real the preference function. To address the problems of underfitting and overfitting in a balanced manner cubic models are recommended. To estimate a cubic part-worth function at least 4 levels are necessary. Thus, in the abovementioned example 4 levels of the attributes processor clock, memory size, weight, and price are needed in the stimuli set.

Considering the three preference models again it is apparent that the vector model as well as the ideal point model is special cases of the cubic model. The cubic model can therefore be used for each attribute having an ordinal or a metric scale. For attributes having a nominal scale the part-worth function model is indispensable.

3.4 Construction of a Stimuli Set

According to the selected attributes a stimulus set has to be constructed by the recommender system. To avoid excessive consumer demands it is advisable to fractionate a factorial design as shown in subsection 2.3.

As described in subsection 3.1 the attributes of the conjoint analysis are selected by the consumer. A product recommender system has therefore only to select the levels of each attribute for the stimuli set. The stimuli set should cover the range of attribute levels as good as possible. If an attribute fulfils the part-worth function model each attribute level must occur in the stimuli set. But if an attribute fulfils the cubic model only 4 levels are necessary to estimate the model. To select the levels there are 2 possible methods:

- select 4 levels at the raw level range
- select 4 levels at the distribution function of the level occurrences

The first method requires only the minimal and the maximal level of an attribute of real products. The minimal and the maximal level are the first two levels of the stimuli set. The other levels can be calculated by adding 33 or 67 percent of the difference between the minimal and the maximal level to the minimal level. For instance if there are notebooks between 499 and 3499 Euro the 4 points are 499, 1489, 2509, and 3499. So the stimuli either have a price of 499 Euro or 1489 Euro or 2509 Euro or 3499 Euro.

The advantage of this method is that the level can be selected easily. But it is not possible to generate a stimulus set which represents the set of real products, because there is no rectangular distribution of notebooks and prices. Maybe 70 percent of all real notebooks are cheaper than 1489 Euro, but in the stimuli set 50 percent of all notebooks would be more expensive than 1489 Euro.

This disadvantage can be eliminated using the second method to select levels. In this method the frequency of occurrence of attribute levels is also important. The minimal and the maximal level are still used in the stimuli set, but the other two levels are calculated using the distribution of the respective attribute. Thus, the third level is at the 33 percentile and the fourth at the 67 percentile of the distribution. Due to more realistic results the second method to select attribute levels is recommend for conjoint analysis in product recommender systems.

3.5 Selection of an Estimation Method

As concluded in subsection 3.3 attributes can be described either using the partworth function model or the cubic model. Hence, an estimation method is mandatory to handle these models in all conceivable combinations.

Considering the notebook example of subsection 3.3 again, the part-worth of an attribute with the cubic model, e.g. the price, is as follows:

$$\alpha + \beta_1 \cdot k^3{}_5 + \beta_2 \cdot k^2{}_5 + \beta_3 \cdot k_5 \tag{2}$$

In contrast to attributes with a cubic model the part-worth function model (e.g. for the attribute brand) will be described using the following equation:

$$\alpha + \sum_{a=1}^{A} \beta_{k1a} \cdot d_{k1a} \tag{3}$$

In both equations α is the constant part-worth and the equation behind α describes the part-worth in dependence of the attribute level. The utility of a notebook with the 5 abovementioned attributes consists of the part-worth of the attribute brand and the part-worth's of the attributes processor clock, memory size, weight, and price. For a product having n attributes fulfilling the cubic model and m attributes fulfilling the part-worth function model, an estimation method is needed which is suitable to solve an equation containing n-times equation 2 and m-times equation 3.

In marketing experiments the multiple regression analysis is because of its robustness most common for metric as well as for ordinary measurement scales (Wittink and Cattin, 1981; Mishra et al., 1989). To estimate the parameters of the conjoint analysis the multiple linear regression is recommend due to the possibility of transforming equation 2 as well as equation 3 into a linear equation.

4 Discussion

The overall conclusion that can be drawn from the above discussed issues is the general suitability for measuring individual preferences within product recommender systems.

To overcome the amount of data to be processed the presented method has to be implemented in a software. Furthermore, the creation of fractional factorial designs as well as the estimation of part-worth’s requires a lot of time if it is not done by efficient computer based algorithms. Another issue militating in favour of a software implementation is the high amount of available product descriptions on the internet. To implement such a product recommender system some further issues have to be considered:

- Product recommender systems based on conjoint analysis are particularly suitable for search goods but not for experience and credence goods.

- Products have to be described in a unique structure. On each producer web site the products are described in another structure which complicates an automatic data collection.
- Conjoint analysis provides part-worth's enabling the calculation of each products utility. But there is no possibility to calculate a threshold which divides relevant from irrelevant products.
- It is wise to calculate the internal validity for each search process. This is due to review the quality of the systems estimation. In case of low quality the consumer can be warned by the system.

A prototype which is based on conjoint analysis and contains the suggestions of this paper can be reviewed at http://132.231.35.113/ipse. Before using the prototype in real buying processes the preparation of product descriptions has to be automated.

5 Future Research

In this paper the conjoint analysis has been briefly introduced and adapted according to the theory of consumer behaviour for application in product recommender systems. The suggestions in this paper are implemented in a product recommender system. Following the process of research an evaluation of the prototype is necessary to revise the prototype as well as the adapted conjoint analysis.

Due to the circumstance that the core of the prototype is a measuring instrument we can proof the reliability and the validity of the prototype. A measuring instrument is reliable if it delivers the same results as another instrument measuring the same objects (here preferences). Hence, we can test the reliability in a multi-method test.

The validity of conjoint analysis can be proofed using the predictive validity (Hensel-Börner 2000). Therefore, the estimated results of the product recommender system have to be compared with those results created by an external criterion (e.g. a real purchase). Furthermore, the internal validity can be evaluated by comparing the estimated results with the rated stimuli (Hensel-Börner 2000). To judge the external validity the prototype has to be applied in real buying processes. Due to the pre-stable version of the prototype field-tests are not possible at that time.

The abovementioned criteria will be tested in laboratory experiments with students. After an introduction each student has to fulfil some search tasks. Based on a following survey the preferences are collected again to evaluate the reliability and the validity. The detailed methodology as well as the results of the experiments will be published in forthcoming papers.

References

Addelman, S., (1962): Symmetrical and asymmetrical fractional factorial plans, Technometrics, Vol. 4, No. 1, pp. 47 - 58.

Ahn, H., (2006): Utilizing popularity characteristics for product recommendation, International Journal of Electronic Commerce, Vol. 11, No. 2, pp. 59 - 80.

Backhaus, K., Erichson, B., Plinke, W., and Weiber, R., (2005): Multivariate Analysemethoden - Eine anwendungsorientierte Einführung. Springer, Berlin et al.,11th edition.

Burke, R., (2002): Hybrid recommender systems – survey and experiments, User Modeling and User-Adapted Interaction, Vol. 12, No. 4, pp. 331 - 370.

Cao, Y. and Li, Y., (2007): An intelligent fuzzy-based recommendation system for consumer electronic products, Expert Systems with Applications, Vol. 33, No. 1, pp. 230 - 240.

Choi, S. H., Kang, S., and Jeon, Y. J., (2006): Personalized recommendation system based on product specification values, Expert Systems with Applications, Vol. 31, No. 3, pp. 607 - 616.

Chun, I.-G. and Hong, I.-S., (2001): The implementation of knowledge-based recommender system for electronic commerce using java expert system library, In Proceedings of the Industrial Electronics (ISIE) 2001, Vol. 3, pp. 1766 - 1770.

Dey, A., (1985): Orthogonal Fractional Factorial Design, John Wiley & Sons, New York et al.

Fishburn, P., (1967): Methods of estimating additive utilities, Management Science, Vol. 13, No. 7, No. 435 - 453.

Frees, E. W., (1996): Data Analysis Using Regression Models – The Business Perspective. Prentice Hall, Upper Saddle River.

Gensler, S., (2003): Heterogenität in der Präferenzanalyse – Ein Vergleich von hierarchischen Bayes-Modellen und Finite-Mixture-Modellen. Deutscher Universitäts-Verlag, Wiesbaden.

Green, P. and Rao, V., (1971): Conjoint measurement for quantifying judgemental data, Journal of Marketing Research, Vol. 8, No. 3, pp. 355 - 363.

Green, P. and Srinivasan, V., (1978): Conjoint analysis in consumer research – issues and outlook, Journal of Consumer Research, Vol. 5, No. 2, pp. 103 - 123.

Green, P. and Srinivasan, V., (1990): Conjoint analysis in marketing – new developments with implications for research and practice, Journal of Marketing, Vol. 54, No. 4, No. 3 - 19.

Gustafsson, A., Herrmann, A., and Huber, F., (2007): Conjoint Measurement – Methods and Applications, chapter Conjoint Analysis as an Instrument of Market Research Practice, pp. 3 - 30, Springer, 4th edition.

Guttman, R., (1998): Merchant differentiation through integrative negotiation in agent-mediated electronic commerce, Master's thesis, School of Architecture and Planning, Program in Media Arts and Sciences, Massachusetts Institute of Technology.

Härdle, W. and Simar, L., (2007): Applied Multivariate Statistical Analysis, Springer, 2nd edition.

Hauser, J. and Rao, V., (2004): Market Research and Modeling – Progress and Prospects, chapter: Conjoint Analysis, Related Modeling, and Applications, pages 141 - 168, Springer Science+Business Media.

Hensel-Börner, S., (2000): Validität computergestützter hybrider Conjoint-

Analysen, DUV.

Hung, L.-P., (2005): A personalized recommendation system based on product taxonomy for one-to-one marketing online, Expert Systems with Applications, Vol. 29, No. 2, pp. 383 - 392.

Jacoby, J., Szybillo, G., and Busato-Schach, J., (1977): Information acquisition behavior in brand choice situations, Journal of Consumer Research, Vol. 3, No. 4, pp. 209 - 216.

Knoblich, H. and Schubert, B., (1989): Marketing mit Duftstoffen, Oldenbourg Verlag, München, Wien.

Kroeber-Riel, W. and Weinberg, P., (2003): Konsumentenverhalten, Verlag Vahlen, München, 8th edition.

Kruskal, J., (1965): Analysis of factorial experiments by estimating monotone transformations of the data, Journal of the Royal Statistical Society, Series B (Methodological), Vol. 27, No. 2, pp. 251 - 263.

Luce, R. and Tukey, J., (1964): Simultaneous conjoint measurement – a new type of fundamental measurement, Journal of Mathematical Psychology, Vol. 1, No. 1, pp. 1 - 27.

Mishra, S., Umesh, U., and Stem, D., (1989): Attribute importance weights in conjoint analysis: Bias and precision, Advances in Consumer Research, Vol. 16, pp. 605 - 611.

Montaner, M., Lopez, B., and de la Rosa, J. L., (2003): A taxonomy of recommender agents on the internet, Artificial Intelligence Review, Vol. 19, No. 4, pp. 285 - 330.

Sattler, H. and Hensel-Boerner, S., (2007): Conjoint Measurement – Methods and Applications, chapter: A Comparision of Conjoint Measurement with Self-Explicated Approaches, pp. 67 - 76, Springer, Berlin et al.

Schafer, J. B., Konstan, J., and Riedl, J., (1999): Recommender systems in e-commerce, In Proceedings of the 1st ACM Conference on Electronic Commerce, pp. 158 - 166.

Wei, K., Huang, J., and Fu, S., (2007): A survey of ecommerce recommender systems, In 2007 IEEE International Conference on Service Systems and Service Management, pp. 1 - 5.

Wittink, D. and Cattin, P., (1981): Alternative estimation methods for conjoint analysis – a monte carlo study, Journal of Marketing Research, Vol. 18, No. 1, pp. 101 - 106.

Wittink, D. and Cattin, P., (1989): Commercial use of conjoint analysis – an update, Journal of Marketing, Vol. 53, No. 3, pp. 91 - 96.

Wittink, D., Vriens, M., and Burhenne, W., (1994): Comercial use of conjoint analysis in europe – results and critical reflections, International Journal of Research in Marketing, Vol. 11, pp. 41 - 52.