An Empirical Study on Consumer Behavior in the Interaction with Knowledge-based Recommender Applications

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***Abstract*— Knowledge-based recommender technologies provide a couple of mechanisms for improving the accessibility of product assortments for customers, e.g., in situations where no solution can be found for a given set of customer requirements, the recommender application calculates a set of repair actions which can guarantee the identification of a solution. Further examples for such mechanisms are explanations or product comparisons. All these mechanisms have a certain effect on the behavior of customers interacting with a recommender application. In this paper we present results from a user study, which focused on the analysis of effects of different recommendation mechanisms on the overall customer acceptance of recommender technologies.**

***Keywords*: knowledge-based recommendation, consumer buying behavior.**

I. Introduction

Recommender technologies are of extreme importance for improving the accessibility of product and service assortments for customers. These technologies are especially useful for customers with little product domain knowledge. Various application areas of recommender systems are discussed, e.g., in [18], [24], more details on the technological foundations of recommender systems can be found in [2], [3], [23], [27]. Basically, there are three main approaches to the development of a recommender application. First, collaborative filtering [15], [22] is based on the idea of exploiting product preferences of a large set of customers. New recommendations are derived from preferences of a group of customers with similar purchasing behaviors. Second, content-based filtering [20] calculates recommendations based on similarities between product descriptions and the preferences of the current customer. When a customer interacts with the recommender, products are proposed that are similar to those the customer has liked in the past. In this context, products are described by keywords (categories) stored in a profile if a customer buys a certain product. Finally, knowledge-based recommender applications (advisors) (see, e.g., [2], [8]) exploit deep knowledge about the product domain in order to determine solutions suiting the wishes and needs of a customer. Using such a representation of product, marketing and sales knowledge, the corresponding recommender applications can be equipped with intelligent explanation and repair mechanisms thus supporting more intuitive sales dialogs for customers [8], [12].

Although knowledge-based recommender technologies are frequently applied in commercial settings, the effects of the underlying mechanisms on consumer buying behavior have not been analyzed in detail up to now. Existing studies focus on specific aspects of the interaction with recommenders. E.g., [4] analyze different dimensions influencing the trustworthiness of a recommender application. [14] analyze the influence of different recommendation focuses (questions which are posed in different orders to customers) on the final product selection. Compared to, e.g., the work of [4], [14], we are interested in an integrated analysis of the effects of knowledge-based recommender technologies on consumer buying behavior. The extension of our knowledge-based recommender environment Koba4MS[1] [8] with relevant aspects of consumer buying behavior are the major goals of the project COHAVE.[2]

In this paper we focus on the presentation of the results of a study conducted within the scope of the COHAVE project which investigated explicit and implicit feedback of online customers to various interaction mechanisms supported by knowledge-based recommender applications. The results of the study are based on a data basis collected from 116 study participants. The study has been conducted on the basis of an Internet provider recommender application (see Figure 1). The findings of the study show interesting patterns of consumer buying behavior when interacting with knowledge-based recommender applications. In particular, there exist specific relationships between the type of supported interaction mechanisms and the attitude of the customer w.r.t. the recommender application. Major results of our study have been confirmed by an evaluation of the digital camera recommender deployed for geizhals.at [10].

In our study we analyzed the degree to which concepts such as explanations, repair actions or product comparisons influence the attitudes of online customers towards knowledge-based recommender technologies. Explanations are argumentations as to why a certain product suits the requirements articulated by the customer. Repair actions support customers in situations where no solution can be found by calculating proposals for minimal changes to a given set of customer requirements which in the following allow the calculation of a solution. Product comparisons help to highlight the major differences between the products part of a recommendation.

More specifically, we discuss results which give answers to, e.g., the following questions:

- To which extend do recommenders outperform simple product lists where customers have no additional support in identifying the product which best suits their wishes and needs?
- How does the provision of explanations for product recommendations influence the degree of perceived increase of domain knowledge and overall trust in the advisory process?
- How are product expectations and the process of preference construction in general influenced by the provision of explanations?
- What are the effects of product comparisons?

These and further questions will be discussed in the remainder of this paper which is organized as follows. In Section II we introduce the basic interaction mechanisms provided in our knowledge-based recommender environment. In Section III we discuss the design of our study and present the corresponding results. Section IV concludes the paper with a discussion of related work.

II. Interacting with Recommenders

The first step when building a recommender application (advisor) is the construction of a knowledge base which consists of two different sets of variables (V_C, V_{PROD}) and three different sets of constraints (C_R, C_F, C_{PROD}).

- Customer Properties (V_C) describe possible customer requirements. Examples for customer properties are the maximum price of the internet connection (*maxprice*), the *downloadlimit*, the average

[1] Koba4MS is the acronym for Knowledge-based Advisors for Marketing and Sales (FFF-808479).

[2] COHAVE is the acronym for Consumer Behavior Modeling for Knowledge-based Recommender Systems and is financed by the Austrian Research Fund (FFF-810996).

online time per day (*avgonlinetime*) or the major customer applications (*goals*), e.g., *games*, *films*, *email* etc.

- Product Properties (V_{PROD}) are a description of the properties of a given set of products. Examples for product properties in our example domain are the *region* of an internet provider or the offered *downloadrate*.
- Constraints (C_R) are restricting the possible combinations of customer requirements, e.g.,

```
CR={
    c1:¬(maxprice= <10 ∧
            downloadlimit = 5GB),
    c2:¬(maxprice = <10 ∧
            avgonlinetime = 3h)}.
```

  Confronted with such combinations of customer requirements, the recommender application indicates the incompatibility and tells the customer to change his/her requirements.

- Filter Conditions (C_F) establish the relationship between customer requirements and an available product assortment. An example for a filter condition is *customers wanting to see films or play games, definitely need a product with a high download rate*, i.e.,

```
goal=films ∨ goal=games ⇒
            downloadrate=high.
```

  A filter constraint is said to be *active* if its precondition is consistent with a given set of customer requirements.

- Allowed instantiations of product properties are represented by constraints (C_{PROD}) which define restrictions on the possible instantiations of variables in V_{PROD}. All these instantiations represent products part of the offered assortment.

Given a set of customer requirements, we can calculate a recommendation. We denote the task to identify a set of products for a customer as recommendation task.

Definition (Recommendation Task): A recommendation task can be defined as a Constraint Satisfaction Problem [29] (V_C, V_{PROD}, $C_C \cup C_F \cup C_R \cup C_{PROD}$), where V_C is a set of variables representing possible customer requirements and V_{PROD} is a set of variables describing product properties. C_{PROD} is a set of constraints describing available product instances, C_R is a set of constraints describing possible combinations of customer requirements and C_F is a set of constraints describing the relationship between customer requirements and available products (also called filter conditions). Finally, C_C is a set of concrete customer requirements (represented by unary constraints). □

Definition (Recommendation Result): A recommendation result is an instantiation of the variables in $V_C \cup V_{PROD}$ which is consistent with the constraints defined in $C_C \cup C_F \cup C_R \cup C_{PROD}$. □

A customer interacts with a recommender by answering a set of questions related to his/her wishes and needs. Depending on the given answers, the recommender application (advisor) determines the relevant set of additional questions [13]. After a customer has answered all relevant questions, a corresponding recommendation is calculated based on the definition of the filter conditions in C_F. An example user interface of an Internet Provider recommender is depicted in Figure 1. This recommender has been developed for the purposes of our experiment which is presented in Section III. Examples for questions posed to customers are the *online time per day* and the *ratio between business time and spare-time application of the internet connection* (see Figure 1a). In some situations, the customer imposes requirements which are incompatible with the existing definitions in the recommender knowledge base. In such a situation, the recommender application proposes a set of repair actions (a minimal set of changes to a given set of customer requirements which can guarantee the identification of a solution). In our example in Figure 1b,

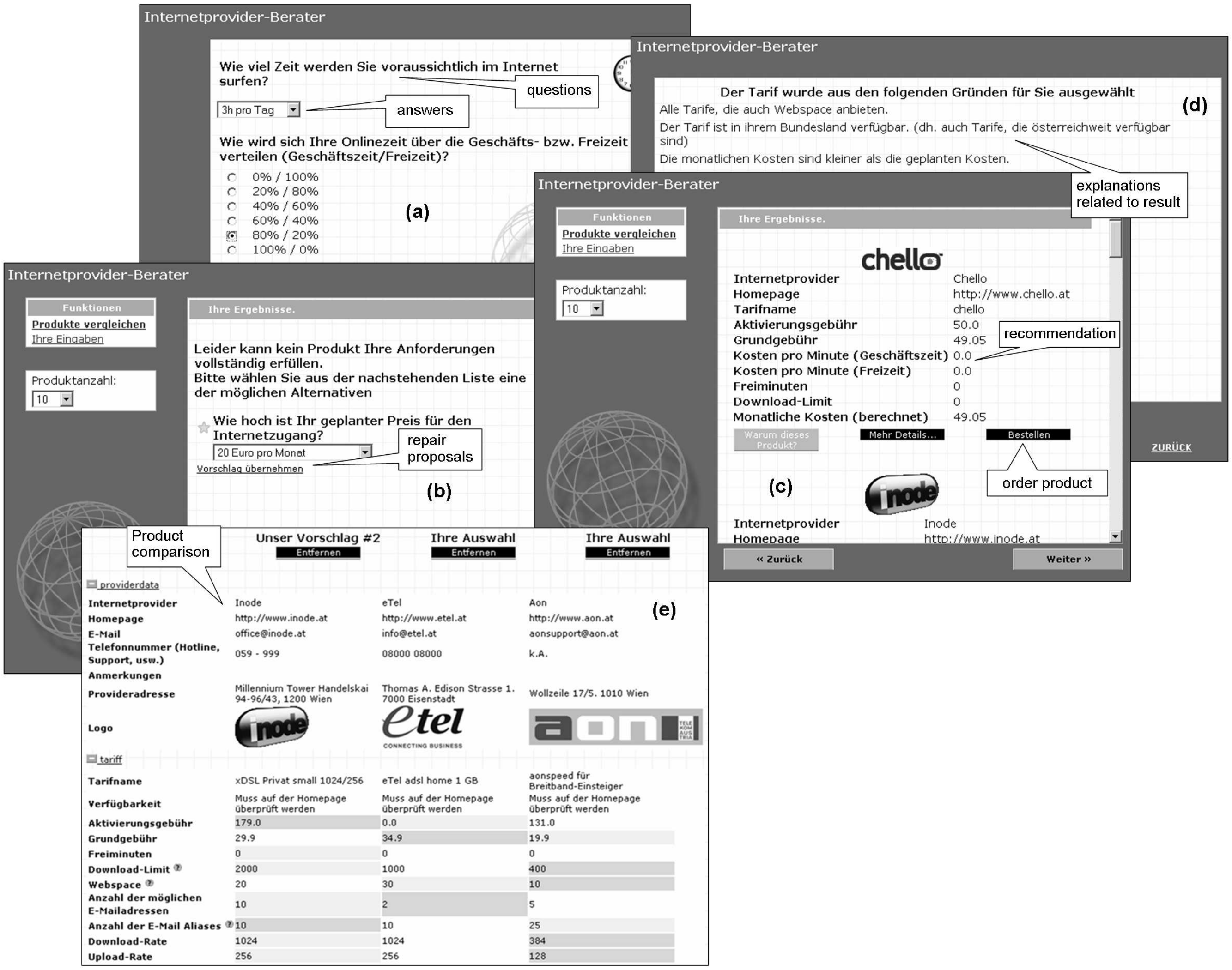

Fig. 1. Example user interface of an Internet Provider recommender application.

the customer has to change his/her requirements related to the upper bound of the price per month. The technical approach behind the calculation of repair actions is an application of model-based diagnosis (MBD) [9], [21]. Having identified a recommendation (see, e.g., Figure 1c), each product part of the recommendation has related explanations as to why it suits the specifications provided by the customer. Explanations are directly derived from *active* filter conditions. An example for such explanations is depicted in Figure 1d. Note that explanations can be formulated in a positive as well as in a negative way. We derive positive explanations directly from satisfied filter conditions. Negative explanations are derived from those filter conditions which can not be satisfied for the given customer specifications. These filters are relaxed in order to allow the calculation of a solution. Finally, product comparisons provide mechanisms to compare different products part of a recommendation result. Parts of our product comparison component are depicted in Figure 1e. The product comparison component is based on the definition of rules defining under which conditions an argumentation for/against a certain product should be displayed, e.g., if the price of component A is significantly higher than the price of B then the comparison component should display a hint.

A number of commercial applications have been implemented on the basis of Koba4MS, e.g., financial service recommenders for the Wuestenrot and the Fundamenta building and loan association (www.wuestenrot.at, www.fundamenta.hu) [11], [12], the Hypo-Alpe-Adria bank (www.hypo-alpe-adria.at), recommenders for www.quelle.at, one of the leading online selling environments in Austria, and the recommender which supports students at the Klagenfurt University (www.uni-klu.ac.at) in the identification of additional financial support opportunities (e.g., grants).

III. Empirical Findings regarding User Acceptance

In this section we focus on the presentation of the results of a user study (n=116) which investigated explicit and implicit feedback of online users to various interaction mechanisms supported by knowledge-based recommender applications. The findings of the study show interesting patterns of consumer buying behavior when interacting with knowledge-based recommender applications. In particular, there exist specific relationships between the type of supported interaction mechanisms and the attitude of the user w.r.t. the recommender application. In the study we analyzed the degree to which concepts such as explanations, repair actions, and product comparisons influence the attitudes of online users towards knowledge-based recommender technologies. In the scenario of the study the participants had to decide which online provider they would select for their home internet connection. To promote this decision, 8 different versions of an *Internet Provider* recommender application have been implemented. The participants of the study had to use such a recommender application to identify the provider which best suits their needs and to place a fictitious order. Each participant was randomly assigned to one version of the implemented recommender applications (an overview of the provided versions of recommender applications is given in Table I). Before and after interacting with the advisor, participants had to fill out an online questionnaire (see Table IIa, IIb). Participation was voluntary and a small remuneration was offered. We were interested in the frequency, participants used a recommender application to order products or as an additional information source (Table IIa-1). Self-rated knowledge and interest in the domain of internet connection providers (Table IIa-4,5) was assessed on a 10-point scale before interacting with the recommender application. After solving the task of virtually buying a connection from an Internet Provider, the participants had to answer follow-up questions as well assessed on a 10-point scale (Table IIb) except IIb-10 where a probability estimate had to be provided. Additional variables have been extracted from interaction logs (Table IIc). The inclusion of the variables depicted in Table II is based on a set of hypotheses which are outlined in the following together with the corresponding exploratory results.

The participants of the user study were randomly assigned to one of the Internet Provider advisors shown in Table I. If a participant was confronted with the advisor version (a) or (b) and answered the question related to his/her expertise with *expert* than he/she was forwarded to a path in the recommender process which was designed for the advisory of beginners (and vice-versa) - we denote this as *switched expertise*. This manipulation was used to test the hypothesis that a dialog design fitting to the knowledge level of the participants leads to a higher satisfaction with the recommender application. Note that *positive explanations* provide a justification as to why a product suits a certain customer, whereas *negative explanations* provide a justification for the relaxation of certain filter constraints. *Product comparisons* were supported in two different ways: first, comparisons had to be explicitly activated by participants, second, the result page was automatically substituted by the product comparison page. Finally, a *pure product list*, i.e., product selection without any advisory support, was implemented by automatically navigating to the result page and displaying all available products.

Advisor versions
(a) switched expertise, positively formulated explanations, with product comparisons.
(b) switched expertise, without explanations, without product comparisons.
(c) positively formulated explanations, without product comparisons.
(d) negatively formulated explanations, without product comparisons.
(e) positively formulated explanations, with product comparisons.
(f) without explanations, with product comparisons.
(g) pure list of products (without any recommendation functionalities).
(h) positively formulated explanations, with product comparisons (automatically activated).

TABLE I
DIFFERENT VERSIONS OF *Internet Provider* ADVISORS.

(a) Questions posed before advisor has been started
1. previous usage (for buying purposes, as an information source)
2. satisfaction with recommendation processes (advisory support) up to now
3. trust in recommended products up to now (products suit personal needs)
4. knowledge in the Internet Provider domain
5. interest in the domain of Internet Providers
(b) Questions posed after completion of advisory session
1. knowledge in the Internet Provider domain
2. interest in the domain of Internet Providers
3. satisfaction with the recommendation process (advisory support)
4. satisfaction with the recommended products
5. trust in the recommended products (products suit personal needs)
6. correspondence between recommendations and expectations
7. importance of explanations
8. competence of recommender application
9. helpfulness of repair actions
10. willingness to buy a product
(c) Data derived from interaction log
1. session duration
2. number of visited web pages
3. number of inspected explanations
4. number of activated product comparisons
5. number of clicks on product details
6. number of activations of repair actions

TABLE II
VARIABLES ASSESSED IN THE STUDY.

We have tested 116 participants with a mean age of $\bar{x}$= 28.7 SD (standard deviation) = 9.78 (33,6% female). 42.2% were recruited from the Klagenfurt University and 57.8% were non-students. Explanations were used by 29.2% of the participants, repair actions have been triggered in 6.9% of the cases. Finally, a product comparison was used by 32.8% of the participants.[3] To assess the significance of correlations and differences, non-parametric tests were used [16]. Because the assessed variables were either ordinal-scaled or violated

[3]Note that the relative frequencies refer to participants who had the possibility to use the corresponding feature (explanations, repairs, product comparisons).

the assumptions of normal distribution or homogeneity of variance (visited pages, session duration), the Mann-Whitney U-Test was used to compare two groups and the Kruskal-Wallis-H Test to assess differences between more than two groups. In the following, only significant results are reported, with α set to 0.05 for all subsequent tests. The corresponding z-values are provided to show the size of the effects.

There were clear differences between the eight versions of recommender applications. The most positive ratings related to trust in the recommended products (Table IIb-5) and satisfaction with the recommendation process (Table IIb-3) were provided by participants interacting with the versions (e) and (h), i.e., advisor versions with positively formulated explanations and a product comparison functionality. Let us now consider the relationship between the features in the different advisor versions and the participants´ impressions in more detail.

Recommender application vs. pure product list. We have found recommender applications to be more advantageous with respect to most of the assessed variables (see Table IIb). Participants using a recommender application were significantly more satisfied with the recommendation process ($z = -3.872$; $p < 0.001$) (Table IIb-3) and had a significant increase in satisfaction due to the interaction with the Internet Provider advisor ($z = -2.938$; $p < 0.01$) (Table IIa-2, IIb-3). Participants' trust in that the application recommended the optimal solution was higher for those interacting with the recommender application compared to those confronted with a pure product list ($z = -3.325$; $p = 0.001$) (Table IIb-5). Furthermore, participants stated that the final recommendation better fitted to their expectations than when they were confronted with a simple product list ($z = -3.872$; $p = 0.001$) (Table IIb-6). Most interestingly, the increase of subjective product domain knowledge due to the interaction was higher when participants interacted with a recommender application ($z = -2.069$; $p = 0.04$) (Table IIa-4, IIb-1). The estimated (subjective) probability to buy a product in a purchase situation was higher for those interacting with a recommender application than for those interacting with a pure product list ($z = -2.1$; $p < 0.01$). Actually, this mean probability was only $p = 0.19$ for participants confronted with a product list, suggesting that these participants estimated a real purchase of the selected product as rather unlikely. Basically, these results related to the applicability of recommender technologies are confirmed by an online evaluation of the digital camera recommender deployed for geizhals.at [10], the largest Austrian price comparison platform. Users having applied the digital camera recommender more often successfully completed their product search (found what they were searching for).

Effects of providing explanations. The perceived correspondence between recommended products and expectations (Table IIb-6) as well as the perceived competence of the recommender application (Table IIb-8) were rated higher by participants provided with the *possibility to use* explanations ($z = -3.228$; $p < 0.01$ and $z = -1.966$; $p < 0.05$). Most importantly, these participants´ trust in recommended products clearly increased due to the interaction process ($z = -2{,}816$; $p < 0.01$) (comparing pre- to post-test, Table IIa-3, IIb-5). There is a tendency that providing explanations leads to more satisfaction with the recommendation process ($z = -1.544$; $p = 0.06$) (Table IIb-3). However, as hypothesized before the study, the increase in the rated knowledge from pre- to post-test did not differ significantly between both groups (Table IIa-4, IIb-1). Participants who have *actively* (!) inspected explanations express a higher correspondence between expected and recommended products ($z = -2.176$; $p = 0.01$) (Table IIb-6) and an increased interest in the product domain when comparing pre- to post-test ($z = -1.769$; $p < 0.05$) (Table IIa-5, IIb-2). On an abstract level, these results are confirmed by our evaluation of geizhals.at [10], where 57.6% of the interviewees rated explanations as a useful feature of the digital camera recommender application.

Interpreting interaction processes with advisors as processes of preference construction, as described by [19], we assume that explanations influence preferences by adjusting the expectations of customers. This influence may be simply due to the fact that an explanation contains product features to which customers are primed. As argued in [19], priming of features causes customers to focus attention to those features and thus possibly to compare the recommended products with their expectations mainly along the primed features. This provides an explanation as to why the perceived correspondence between recommended and expected products and trust is higher when providing explanations.

Effects of product comparisons. Participants using recommender applications supporting product comparisons were more satisfied with the recommendation process ($z = -2.186$; $p = 0.03$) (Table IIb-3) and the recommended products ($z = -1.991$; $p < 0.05$) (Table IIb-4) than participants using advisors without product comparison support. Furthermore, participants using advisors with product comparisons showed a significant higher trust in the recommended products ($z = -2.308$; $p = 0.02$) (Table IIb-5). Product comparison functionality leads to a higher perceived competence of the recommender application ($z = -1.954$; $p < 0.05$) (Table IIb-8). Interacting with advisors supporting product comparisons leads to a clear increase in trust ($z = 3.016$; $p < 0.01$) (Table IIa-3, IIb-5) and interest in the product domain (Internet Providers) ($z = 1.885$; $p < 0.05$) (Table IIa-5, IIb-2). Interestingly, these positive effects seem to be due to the offer of comparisons and not to their usage since only 32,8% of the participants actually used them. Those participants who actually used product comparisons, were more satisfied with the recommendation process ($z = 2.175$; $p = 0.03$) (Table IIb-3). On an abstract level, user feedback related to product comparisons corresponds to the feedback of interviewees of our geizhals.at study [10]: product comparisons were rated as the feature with the highest usefulness.

The multitude of positive influences that product comparisons offer (especially the increase in satisfaction) can be explained by the lower mental workload when products and product features are visually clearly presented to enable an evaluation of the recommended product set. Interestingly, taken together with the results on the explanation feature, some suggestions for the optimal design of product comparisons can be made. First, as already suggested by [7] it is useful for customers to visually highlight feature (settings) in the result that vary between the products (e.g., different color or font size). Also, assuming that a customers product evaluation will be rather based on features that she/he was primed to in the course of the interaction process through questions or an explanation feature, it should aid her/his purchase decision when primed features are highlighted as well. These implications will be tested in a follow-up study.

Effects of repair actions.[4] If we compare the participants who triggered repair actions (due to their inconsistent specifications) to those who did not trigger repair actions, we find that the first group stated to have less knowledge in the product domain ($z = -1.801$; $p < 0.05$) (Table IIa-4) and that they rarely used recommender applications before ($z = -1.645$; $p < 0.05$) (Table IIa-1). This is plausible since participants with higher product domain knowledge and more experience with recommender applications will have more realistic expectations regarding product features and costs and they will provide information to an advisor that will most likely generate a set of recommended products, which makes a repair action dispensable. Thus, participants who used repair actions indicated an increase in product

[4] In the present study only 6.9% of the participants triggered repair actions. For this reason we combined the data with a sample from a pilot study.

domain knowledge ($z = -1.730$; $p < 0.05$) (Table IIa-4, IIb-1) and rated repair actions as more useful ($z = -2.978$; $p < 0.01$) (Table IIb-9).

Effects of *switched expertise*. Participants who received switched versions showed less satisfaction with the recommendation processes ($z = -1{,}790$; $p < 0{,}05$) (Table IIb-3) and provided a lower rating for the competence of the advisor ($z = -2{,}997$; $p < 0{,}01$) (Table IIb-8). They regarded the helpfulness of repair actions as lower ($z = -2{,}379$; $p < 0{,}01$) (Table IIb-9) compared to participants not confronted with the switched expertise scenario. This may be interpreted as an indicator of lower interest in recommender applications that fail to put questions that appropriately incorporate the expertise or knowledge level of the customer.

Willingness to buy a product. We examined which of the assessed variables show a significant correlation with the willingness to buy a product. The highest correlation has been detected between the willingness to buy (Table IIb-10) and trust in the recommended products ($r = 0.60$; $p < 0.01$) (Table IIb-5).[5] Furthermore, the higher the fit between the suggested products and the expectations of the participants (Table IIb-6), the higher was the willingness to buy the recommended product ($r=0.54$, $p < 0.01$). Another interesting relationship exists between the perceived competence of the recommender application (Table IIb-8) and the willingness to buy ($r = 0.49$, $p < 0.01$) (Table IIb-10).

IV. Related Work

Recommender Technologies. In contrast to collaborative filtering [15], [23], [25] and content-based filtering [20] approaches, knowledge-based recommendation [2], [12], [17], [28] exploits deep knowledge about the product domain in order to determine solutions suiting the customers wishes and needs. Using such an approach, the relationship between customer requirements and products is explicitly modelled in an underlying knowledge base. Thus, ramp-up problems [2] are avoided since recommendations are directly derived from user preferences identified within the scope of the requirements elicitation phase. The main reason for the choice of a knowledge-based recommendation approach stems from the requirements of domains such as financial services where deep product knowledge is needed in order to retrieve and explain solutions. [17] embed product information and explanations into multimedia-enhanced product demonstrations where recommendation technologies are used to increase the accessibility of the provided product descriptions. Using such representations, basic recommendation technologies are additionally equipped with a level supporting the visualization of calculated results. [28] focus on the integration of conversational natural language interfaces with the goal of reducing system-user interactions. A study in the restaurant domain [28] clearly indicates significant reductions in efforts related to the identification of products (in terms of a reduced number of interactions as well as reduced interaction times). Natural language interaction as well as visualization of results are currently not integrated in the Koba4MS environment but are within the scope of future work. Compared to other existing knowledge-based recommender approaches [2], [17], [28], Koba4MS includes model-based diagnosis [9], [21] concepts allowing the calculation of repair actions in the case that no solution can be found and provides a graphical development environment which makes the development of recommender applications feasible for domain experts [12].

User Acceptance of Recommender Technologies. [26] evaluates navigational needs of users when interacting with recommender applications. A study is presented which reports results from an experiment where participants had to interact with recommender applications providing two different types of products (digital

[5] For the computation of correlation measures, the Spearman correlation r for ordinal scale variables was used.

cameras and jackets offered in a digital store). It has been shown that different types of products trigger different navigational needs. The major factors influencing the navigational behavior is the product type, e.g., compared to digital camera shoppers, jacket shoppers spent significant less time investigating individual products. The study of [26] focused on the analysis of different navigational patterns depending on the underlying product assortment. The results presented in this paper report experiences related to the application of basic recommender technologies in online buying situations. The investigation of differences related to different product domains is within the scope of future work. [19] analysed the impact of personalized decision guides to different aspects of online buying situations. An interesting result of the study was that consumers choices are mostly driven by primary attributes that had been included in the recommendation process which clearly indicated the influence of personalized decision guides on consumer preferences. Compared to the work presented in this paper, [19] did not investigate effects related to the application of knowledge-based recommender technologies such as explanations of calculated results or repair actions. Furthermore, no detailed analysis has been done on psychological aspects of online buying situations such as trust, subjective perceived increase of domain knowledge, or the probability to buy a product. [5] analyse different dimensions of the users perception of a recommender agents trustworthiness. The major dimensions of trust which are discussed in [5] are systems features such as explanation of recommendation results, trustworthiness of the agent in terms of, e.g., competence and finally trusting intentions such as intention to buy or intention to return to the recommender agent. Where the results are comparable, the study presented in [5] confirms the results of our study (explanations are positively correlated with a user's trust and well-organized recommendations are more effective than a simple list of suggestions).

There are a number of approaches exploiting design guidelines from social psychology in Collaborative Filtering applications. [1] focus on social psychological aspects motivating customers to increase their average level of product ratings. A consequence of this approach is increased preciseness of prediction generation by the Collaborative Filtering system. [6] show the influence of making explicit already conducted ratings on the execution of future ratings. Both, [1] and [6] focus on the improvement of Collaborative Filtering approaches, whereas our goal is to analyze and improve the acceptance of knowledge-based recommender technologies.

V. Conclusions

In this paper we have presented a study related to the application of knowledge-based recommender technologies in online buying situations. This study has been conducted within the scope of the COHAVE (Consumer Behavior Modelling for Knowledge-based Recommender Systems) project. The study provides major guidelines which should be taken into account when building knowledge-based recommender applications, e.g., product comparisons should be used as default for the presentation of recommended products. Based on the results presented in this paper, the focus of future work is to integrate psychological variables influenced by the recommender application in a corresponding structural equation model which will include trust, satisfaction and willingness to buy as key latent constructs.

VI. Acknowledgements

We want to thank P. Bleiweiß, H. Merl, E. Petutschnig, and D. Pohl for their valuable contributions in this study.

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