# Persuasive Recommendation: Serial Position Effects in Knowledge-Based Recommender Systems

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**Abstract.** Recommender technologies are crucial for the effective support of customers in online sales situations. The state-of-the-art research in recommender systems is not aware of existing theories in the areas of cognitive and decision psychology and thus lacks of deeper understanding of online buying situations. In this paper we present results from user studies related to serial position effects in human memory in the context of knowledge-based recommender applications. We discuss serial position effects on the recall of product descriptions as well as on the probability of product selection. Serial position effects such as primacy and recency are major building blocks of persuasive, next generation knowledge-based recommender systems.

**Keywords:** persuasive technologies, recommender systems, knowledge-based recommendation, human memory, interactive selling.

## 1 Introduction

Recommender systems are among the most successful applications of Artificial Intelligence technologies. The major purpose of recommender systems is to improve the accessibility of complex and large product assortments for online customers. There are basically three different types of recommendation approaches. One of the most frequently used one is C*ollaborative Filtering* [16, 29]. It implements the idea of word-of-mouth promotion where a buying decision is predominantly influenced by the opinions of friends and benchmarking reports. For instance, if two customers have bought similar books in the past and have rated those books in a similar way, positively rated books bought by only one of them, are recommended to the other customer. *Content-based Filtering* [26] is an information filtering approach that exploits item features a user has liked in the past to recommend new items. In contrast to collaborative approaches, content-based filtering cannot provide serendipitous recommendations. It recommends all items based on purchase information available from the current user. Both approaches are based on long-term user profiles and do

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not exploit deep knowledge about the product domain. Thus, they are excellent techniques supporting recommendation processes for simple products such as movies, compact discs or books. Compared to users purchasing simple products, those purchasing complex products such as financial services or digital cameras are much more in the need of information and in the need of intelligent interaction mechanisms supporting the selection of appropriate items. *Knowledge-based approaches* [6,9] make use of an explicit representation of product, marketing and sales knowledge. Such deep knowledge allows (a) the recommendation of items which fulfil certain quality requirements, (b) the explanation of recommended items, and (c) the support of users in situations where no solution can be found. In contrast to word-of-mouth promotion implemented by collaborative filtering, knowledge-based recommendation implements explicit sales dialogs which support users in the item selection process. In this paper we focus on knowledge-based recommender technologies that determine recommendations on the basis of explicit sales dialogs where users are confronted with questions related to their wishes and needs (preference elicitation phase – e.g., the tent recommender in Fig. 1). Elicited preferences are in turn used for calculating recommendations for the current user. After the completion of a sales dialog, a product comparison page is presented to the user which contains a set of alternative items (see Fig. 1). The simplified tent recommender depicted in Fig. 1 has been used as the basic stimulus/framework for user studies which are presented in the following sections.

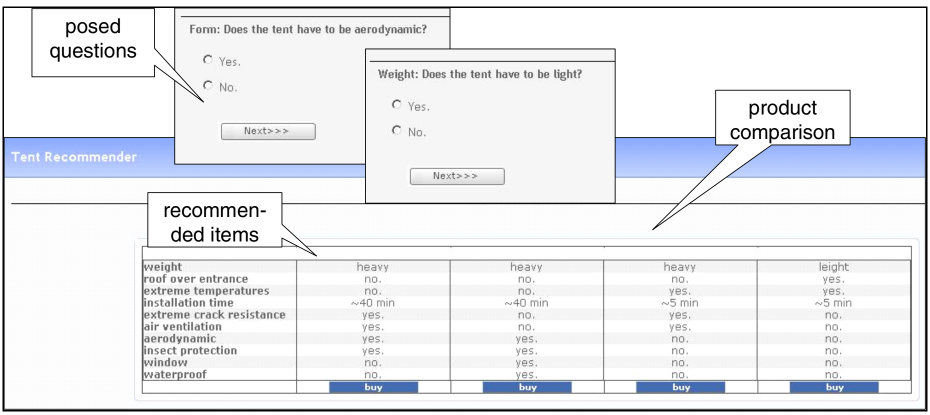


**Fig. 1.** Example Recommender Application

Knowledge-based recommender technologies have been successfully applied in different commercial environments, for example the recommendation of financial services [9] or restaurants [6]. A major reason for the successful deployment of those technologies is that users do not only receive recommendations but additionally are provided with a corresponding set of explanations as to why a certain item fits to the wishes and needs of a user. Features such as explanations significantly improve the trust of users regarding recommendations [9]. However, the development of recommender applications is still rather focused on an existing set of technical features. The effects of applying different theories about human memory in online buying situations have not been analyzed up to now. In this paper we present results of two empirical studies which investigate *serial position effects* [24] of human memory in the context of recommendation sessions. Primacy and recency as a specific form of serial position effects describe the phenomenon that information units at the beginning and at the end of lists are more likely to be remembered than those in the middle [10, 17]. Such effects may potentially occur in every situation where information is presented in list format. In knowledge-based recommenders, there are mainly three such listings: first, sequential product attribute questions in the dialog phase. Second, the order of product attributes on the product comparison page, and finally the order of products on the product comparison page.

In the relevant literature it has been argued that recommenders always persuade when recommending [14, 20, 35]. This interpretation is based on the fact that recommenders successfully support the effective identification of items which otherwise would not have been found by the customer and consequently not been purchased. We follow the definition of persuasion given in [10] where persuasion is defined as *the attempt of changing people's attitudes or behaviours or both*. Our overall hypothesis is that serial position effects can be successfully exploited for changing people's attitudes in the context of online buying situations. In contrast to [14, 20, 35] our approach actively exploits psychological theories for attaining persuasion effects. For this purpose, knowledge-based recommenders can constitute an ideal platform for installing persuasion technology. The deep understanding of persuasion mechanisms offers the possibility of exploitation and control. COHAVE[1] is an interdisciplinary research project at Klagenfurt University with the goal of building a general framework for exploiting persuasive mechanisms in knowledge-based recommendation. In this project, psychological theories from the areas of memory phenomena and decision theory are investigated, implemented and evaluated.

The remainder of the paper is organized as follows: in Section 2 an overview of related work is given and research questions are presented which are investigated in the follow-up sections. Section 3 and Section 4 present results of two studies investigating serial position effects in the domain of tents and digital cameras. The paper is concluded with Section 5 where an outlook on future work is given.

## 2 Persuasive Effects in Preference Construction

Position effects in human memory are one of the oldest phenomena investigated in experimental psychology [8, 19, 21, 24, 34]. Serial position effects are basic memory phenomena first discussed in 1878 [24]. The effect has originally been found in short-term memory tasks. It describes a specific order in the recall of a list of items, such as meaningless syllables [8], numbers [24] or names of common objects [19] which people had to learn by heart beforehand. In this context, recall accuracy of items from a list shows two patterns: a) items from the beginning of the list (primacy) and b) the items from the end of the list (recency) are better remembered than items from the middle of the list [13, 24]. Mostly, primacy and recency effects have been explained

[1] COHAVE is the acronym for Consumer Behavior and Decision Modeling for Recommender Systems funded by the Austrian Research Fund (FFG-810996)., see cohave.ifit.uni-klu.ac.at

as effects of the dual store account model of human memory [1], but there is also evidence for a serial position effect related to long-term episodic memory [23].

Order effects in persuasion and 'the motivation to think' have been discussed for example in [27]. It could be shown that under chunked conditions, participants who were highly motivated to think were more susceptible to primacy and recency effects than those low in motivation to think. There are numbers of studies dealing with both short- and long-term episodic memory tasks. The outcome of studies of long-term serial position effects [2, 17, 28, 30] using serial order reconstruction tasks show clear recency effects. [23] shows a corresponding effect in semantic memory tasks using verse hymns as stimuli, resulting in the first unequivocal demonstration of serial position effects in semantic memory. In contrast to most other work mentioned above we use meaningful product-features (questions) as stimuli which are used as information units in knowledge-based recommender systems. Information in knowledge-based recommender systems is usually presented in the form of ordered lists of questions, product attributes, and recommended products. Unlike meaningless material, this kind of information requires a higher level of semantic processing. The studies presented in this paper deal with primacy and recency effects in a semantic memory task and focus on the dialog and the product selection phase.

Research on consumer buying decision making argues that preferences are rather constructed spontaneously [3, 5, 25] than being stable. Following this interpretation, studies have recently shown several psychological phenomena that affect these short-term processes of preference construction. Through feature-based priming for instance, the background of an e-commerce site can guide the attention of customers towards specific product attributes [22]. The attention can also be influenced by the inclusion or exclusion of attributes in the dialog of a recommender system [15]. Both mechanisms contribute to the construction of consumer preferences and to the consideration of product attributes that otherwise may have been omitted. Taking into account these mechanisms can create a new possibility for product suppliers on e-commerce sites to emphasize on those product attributes with which they can outperform their competitors.

The major goal of this paper is to investigate to which extent serial position effects occur in the context of knowledge-based recommenders. Once serial position effects have been proven to work for such dialog systems, mechanisms for exploiting these effects can be implemented in knowledge-based recommender applications. The primacy and recency effect would thus influence the design of recommendation dialogs in terms of question ordering as well as the ordering of the product features. We assume that a supplier who tries to 'positively convince' (persuade) a customer of the quality of certain products should present the best attributes of her products at the beginning and at the end of product descriptions or result pages of a recommender-application. We examined our assumptions in two studies. Study 1 addressed the general question whether serial position effects occur for the recall of product attributes in the dialog phase of a recommender. In Study 2 we investigated whether serial position effects from the dialog phase directly influence product selection. In this context, we focused on answering the following research questions:

- Q1: Do serial position effects exist for sentences and product feature descriptions?
- Q2: Do serial position effects occur across different product domains?
- Q3: Do serial position effects influence the importance of attributes in a purchase situation?
- Q4: Do serial position effects in the dialog of a recommender influence product choices of customers?
- Q5: Are product choices influenced by the order of attributes or products on a product comparison page of a recommender?

## 3 Serial Position Effects in the Recall of Product Descriptions

The goal of the study 1 was to investigate serial position effects in the recall of product descriptions related to tents and digital cameras. In this study, 14 product attributes of tents as well as of digital cameras were collected. For each product attribute a corresponding explanatory sentence has been formulated (e.g., 'with a waterproof tent you can camp on rainy days' or 'the lowest capacity of memory cards for digital cameras is 16 megabytes'). Such explanatory sentences have been integrated in a MS PowerPoint presentation with one sentence per slide. Each slide has been presented for 15 seconds. First, participants had to read each explanatory sentence. Subsequently the participants had to recall as many attributes from the list as possible (after viewing the whole slideshow). Immediately after the recall task, participants were asked to rate the importance of each attribute they remembered would have in a real purchase decision as well as to estimate the overall familiarity of an average consumer with an attribute on a 5-point Likert scale.

In order to design orthogonal attribute orders, an a priori expert rating for the expected overall familiarity of customers with product attributes has been performed. Based on this rating, two different attribute sequences (lists) have been implemented for each product domain by categorizing the attributes as familiar salient and unfamiliar salient. In the familiar salient-list the most familiar attributes were positioned in the beginning and end of the lists while the less familiar attributes were put in the middle. In the unfamiliar salient-list the less familiar attributes were presented in the beginning and end of the lists. The experiment was conducted with four different groups of subjects. In each group participants were confronted with one list version for digital cameras and one list version for tents (see Table 1).

**Table 1.** Groups and Attribute Sequences

| group | attribute sequence 1 | attribute sequence 2 |
|---|---|---|
| 1 | digi_familiar_salient | tents_ familiar_salient |
| 2 | tents_unfamiliar_salient | digi_ unfamiliar_salient |
| 3 | digi_ unfamiliar_salient | tents_ familiar_salient |
| 4 | tents_ unfamiliar_salient | digi_ familiar_salient |

*N* = 72 students of the Klagenfurt University (36.1 % female) with a mean age of 23.3 years (*SD* = 5.1) were tested in group sessions. Out of the 14 product attributes subjects recalled 8.2 attributes of tents (*SD* = 4.0) and 8.0 attributes of digital cameras (*SD* = 3.38). This difference is not significant.

*Results for tents.* For the analysis, attributes were combined into pairs according to their position within each list. The results of a computed two-factorial ANOVA show that the position of an attribute pair has a clear effect on the frequency of recall ($F(6, 70) = 5.75$, $p < .001$, $\eta^2 = .08$, see Fig. 2). The list-version had no influence on the frequency of recall ($p = .34$). Descriptively, the slightly incremented recall for middle attribute pairs (3-5) in the unfamiliar salient list reflects the fact, that in this list more familiar attributes were presented in the middle.

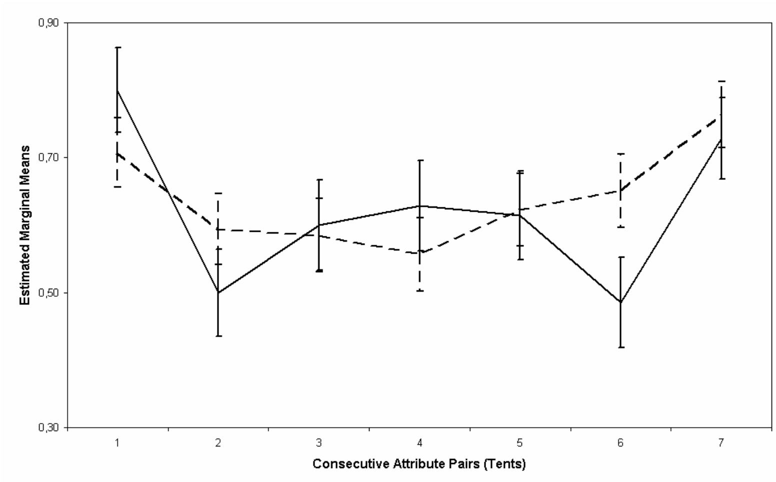


**Fig. 2.** Relative frequencies of recall for consecutive attribute pairs of tents (1-7). The continuous line corresponds to the results for the unfamiliar salient- and the dashed line to the familiar salient-list. The bars represent the standard errors in all figures.

The probability of recalling attributes from the first pair was .8 and the last pair .72. Combined over both lists we first tested the difference in recall between the first item pair and each of the remaining six pairs, and second, between the last pair and all the other pairs. The investigation of these specific contrasts results in a clear pattern: the probability to recall either the first (primacy) or last (recency) pair was significantly higher than the probability to recall any of the attribute pairs in the middle of the lists (five *F*-tests, all $p < .01$). At the same time the recall performance for the first and last pairs did not differ significantly. Combining the attributes in the middle into one group shows an even more pronounced position effect ($F(2, 70) = 13.28$, $p < .001$, $\eta^2 = .16$). The self reported knowledge about tents was coded into a dichotomous variable using a median split and has been included in the analysis. Subjects reporting higher knowledge were tending to recall more attributes. However, at least for tents serial position effects occurred independently of the self-reported product domain knowledge.

*Results for digital cameras.* We found a significant interaction between attribute position and attribute familiarity ($F(6, 70) = 6.05$, $p < .001$). Both serial position effects (primacy and recency) can only be found in the familiar salient-list which contained the more familiar attributes at the beginning and at the end (see Fig. 3). The pattern of results for specific contrasts is less clear than for tents: first and last attribute pairs were recalled significantly more often than the three pairs in the middle of the list but the differences to the second and last but one pair were not significant. Because there are no guidelines on how many items are to be involved in primacy and recency effects, the choice of pairs is arbitrary. Especially, for the pattern of results shown in Fig. 3, it seems more plausible to assume that all four attributes presented at the beginning of the list contributed to a primacy effect. For the unfamiliar salient-list it is noticeable that if no position effects occurred and only attribute familiarity influenced recall performance, the expected line in Fig. 3 should be inversely u-shaped. In this list, the most familiar attributes which were in the middle of the list, would be recalled more often than the less familiar attributes at the beginning and end of the list, which is not the case. A possible explanation would be that primacy and recency actually occurred in the unfamiliar salient-list and resulted in an improved recall performance on unfamiliar attributes.

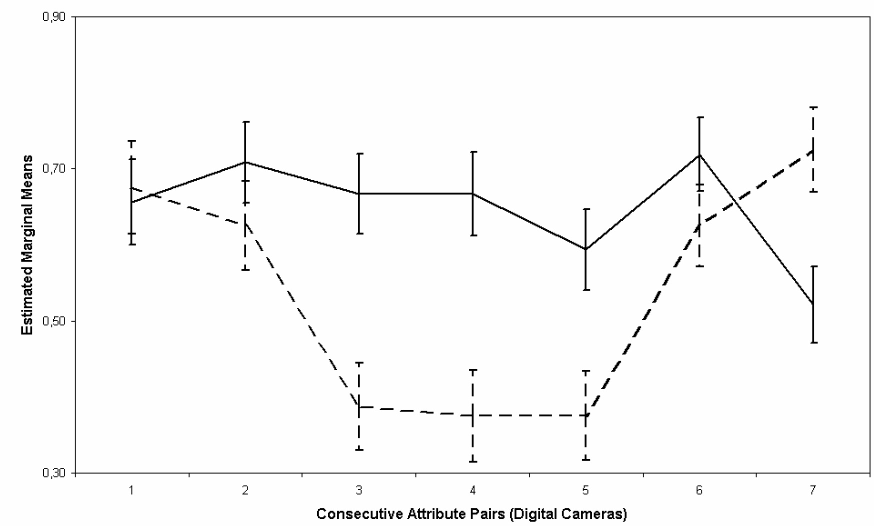


**Fig. 3.** Relative frequencies of recall for consecutive attribute pairs of digital cameras (1-7). The continuous line corresponds to the results for the unfamiliar salient- and the dashed line to the familiar salient-list.

Summarizing, serial position effects do exist for descriptions of product features presented subsequently (*Q1*). However, the effect was not as domain-independent as assumed manifesting itself less clearly in the domain of digital cameras (*Q2*). Also, the self reported domain knowledge did not suppress the effect. More knowledgeable participants also remembered attribute descriptions from the beginning and end of the lists more often then attributes in the middle.

Participants rated resolution and zoom of digital cameras to be the most important attributes in a real purchase situation and waterproofness and insect protection as the most important attributes of tents. In order to assess whether the position of attributes influenced the importance ratings (Q3), a two-factorial ANOVA for list-version and position was computed with three positions (beginning: first pair, middle: all five pairs in the middle and end: last pair). The importance ratings for digital cameras showed an interaction between list-version and position ($F(2, 56) = 21.26$, $p < .001$). The pattern does not seem to resemble an influence of serial position effects on importance ratings because more familiar attributes at the beginning and end were rated significantly more important than the attributes in the middle for the familiar salient-list and vice versa for the unfamiliar salient-list. This result shows that familiar attributes are rated as important. However, importance ratings of single attributes did differ according to our expectation depending on their position. For example additional lenses were rated significantly more important in the unfamiliar salient-list where this attribute was presented first than in the familiar salient-list where it was in the middle ($t(34) = -1.71$; $p = .04$). Importance ratings for attributes of tents varied depending on their position in the list. Attribute pairs at the beginning were rated more important than those in the middle ($F(1, 76) = 13.92$; $p < .001$; $\eta^2 = .16$) and also attribute pairs at the end were rated more important than those in the middle ($F(1, 76) = 4.85$; $p = .03$; $\eta^2 = .06$). The effect is larger for primacy than recency. This result implies that at least for tents the sequential order of product descriptions influences importance ratings and thus may influence actual product purchases. Among others, this question is pursued in the following study performed with an actual recommender (tent recommender application).

## 4 The Influence of Serial Position Effects on Product Choice

In order to test whether positions of product attributes in the dialog and product comparison page influence product choice we have constructed six versions of a tent recommender with 10 attributes. In a two-factorial ANOVA we first varied three different attribute orders in the dialog (random order, fixed order 1 and fixed order 2) and combined it with two different orders of attributes on the product comparison page. In both orders of attributes in product comparison the first four attributes listed were the same as the first and last two in the corresponding dialog (see Table 2).

To be able to compare product choices over all six versions we presented to each participant the same set of four tents on the comparison page. The four tents were defined by using the attribute importance ratings from study 1 (see Section 3). The multi-attribute utility value was about the same for each tent. Two of the tents were defined as 'target products', because they outperformed all others when judged on the first and last two attributes from the corresponding dialog only. If serial position effects from the dialog influence the perceived importance of attributes (as shown in study 1), participants should choose the target product more often when interacting with the recommender with fixed order 1 in the dialog compared to any other order. The order of products on the product comparison page was random for each participant. The task of the participants was first to choose the tent they would buy most likely in a real purchase situation and second, to rank all four tents' attractiveness. Participants were recruited from students of the Klagenfurt University. The possibility of winning 1 x €100 and 2 x €50 has been offered. Participants were randomly assigned to one of the six versions of a tent recommender. Finally, 650 valid sessions could be extracted from the log files. Mean age of participants was 25.3 years (*SD* = 6.48), 63 % of them were female. The median time to complete the dialog was ~2.5 minutes and it took ~1.8 minutes to choose and rate products.

**Table 2.** Dialog and Product Comparison Orderings

| Comparison Ordering 1 | Dialog Ordering 1 | Dialog Ordering 2 | Comparison Ordering 2 | |
|---|---|---|---|---|
| **1** | **1** | **6** | **6** | 1 -waterproof |
| **10** | **2** | **7** | **5** | 2 -insect protection |
| **2** | **3** | **8** | **7** | 3 -air ventilation |
| **9** | **4** | **9** | **4** | 4 -installation time |
| **3** | **5** | **10** | **8** | 5 -roof of entrance |
| **8** | **6** | **1** | **3** | 6 -weight |
| **4** | **7** | **2** | **9** | 7 -extreme temperatures |
| **7** | **8** | **3** | **2** | 8 -extreme crack resistance |
| **5** | **9** | **4** | **10** | 9 -aerodynamic |
| **6** | **10** | **5** | **1** | 10 -window |

*Results*. Across all six recommender versions target product 1 was preferred more than any of the three other products $\chi^2(3, N = 650) = 636.54$; $p < .001$). It is noticeable that tent 1 outperformed all other tents in the set on two attributes rated as the most important ones. However, at the same time it showed worse quality on six attributes compared to one of the other tents. Taken together with the fact that products were generated with similar multi-attribute utility based on 'real' importance ratings (derived from study 1) this result suggests that participants based their choice only on a few important attributes rather than using all available information to decide. Support of this interpretation may be found in articles suggesting heuristic decision models like the lexicographic strategy or elimination by aspects [32, 33].

A two-factorial ANOVA with kind of dialog (three levels: random dialog, dialog 1 and dialog 2) and kind of product comparison (two levels: comparison 1 and comparison 2) was computed to determine effects on the relative frequency of booking the target product. Opposed to our expectations (*Q4* in Section 2), the frequency of booking the target product was not affected by the order of attributes in the dialog ($F(2, 643) = .44$; $p = .65$) but by the order of attributes on the product comparison page ($F(1, 643) = 9.76$; $p = .002$). 74 % of subjects interacting with product comparison 1 chose the target product but only 62 % of subjects interacting with product comparison 2 (see Fig. 4). The choice of the target product was not biased by subjective domain knowledge.

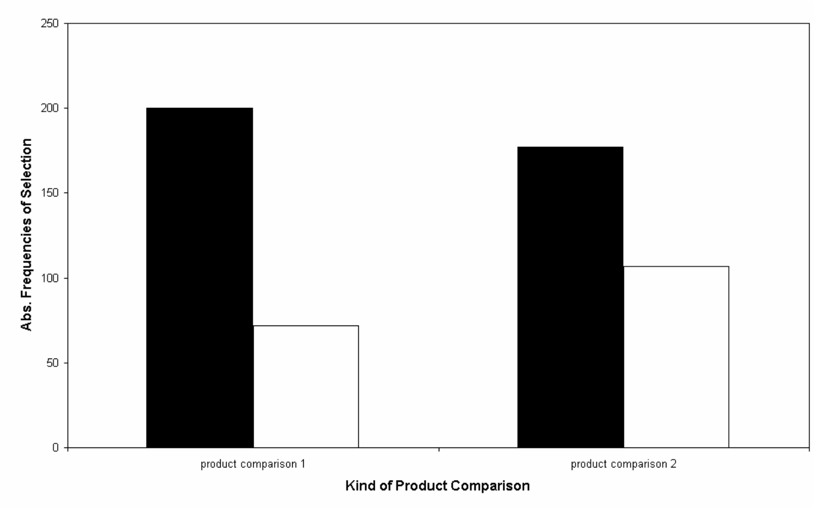


**Fig. 4.** Frequencies of product choice: tent 1 (black) vs. all other tents: (white)

To determine the relative impact of (a) *kind of product*, (b) *its position on the comparison page*, (c) *the question order in the recommender dialog*, and (d) *the attribute order in the product comparison page* on the choice behaviour of participants, a four-way frequency analysis was computed. The hierarchical log linear model describing the data best consists of two two-way interactions (position *x* product and attribute order *x* product) with likelihood ratio $\chi^2(76, N = 650) = 67.67; p = .74$. Especially the *attribute order* x *kind of product* interaction shows that depending on the kind of attribute order each tent was chosen more or less often than expected (see *Q5* in Section 2). While the target product was chosen more often than expected in product comparison 1 all other products were chosen more often than expected in product comparison 2. The second interaction (*product position* x *kind of product*) results from the fact that the target product was chosen more often than expected when it was presented as the first or last of all four tents, while there was an inverse trend for all other products. This implies that the order of products on product comparison pages has an influence on product choice. Summarizing, the order of attributes has an impact on product choice. Results of study 1 imply that attribute order in the dialog has an impact on the perceived attribute importance. Contrary to this result, no such impact of the dialog on product choices could be found in study 2 (a further clarification is needed in this context).

## 5 Conclusions and Future Work

The studies presented in this paper show that in the line of feature-based priming and inclusion effects serial position effects are another interesting cognitive phenomenon that can play a crucial role in the design of product comparison pages in recommender systems. This result generalizes beyond the dialog of knowledge-based recommenders and can be applied to a wide variety of product and service descriptions ranging from product fact sheets, package leaflets, motivational campaigns for the participation in health promotion or political engagement programs.

Based on the results reported in this paper, several challenges in the design of knowledge-based recommender applications emerge. It seems that long attribute lists are not necessary for users' decisions. Furthermore, algorithms are needed that provide as little information as necessary and as much as needed to not reduce a users' trust in the recommender application. In relation to the latter arguments, it does matter how attributes are ordered on product comparison pages and a corresponding recommendation to developers of recommender applications can be made to actively take into account serial position effects when designing result (product comparison) pages for recommenders.

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