Consumer Decision Making in Knowledge-Based Recommendation

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Abstract. In contrast to customers of bricks and mortar stores, users of online selling environments are not supported by human sales experts. In such situations recommender applications help to identify the products and/or services that fit the user's wishes and needs. In order to successfully apply recommendation technologies we have to develop an in-depth understanding of decision strategies of users. These decision strategies are explained in different models of human decision making. In this paper we provide an overview of selected models and discuss their importance for recommender system development. Furthermore, we provide an outlook on future research issues.

Keywords: Knowledge-based Recommendation, Interactive Selling, Consumer Buying Behavior, Consumer Decision Making.

1 Introduction

Traditional approaches to recommendation (collaborative filtering [1], content-based filtering [2], and different hybrid variants thereof [3]) are well applicable for recommending quality & taste products such as movies, groceries, music, or news. Especially in the context of high-involvement products such as computers, cars, apartments, or financial services, those approaches are less applicable. For example, apartments are not bought very frequently – consequently the corresponding items will not receive a critical mass of ratings needed for making reasonable predictions; for example, Bell and Koren [4] propose to use the 100 nearest neighbors in their collaborative filtering recommendation approach. Furthermore, a low frequency of user ratings would require to take into consideration a rather long time period of gathering ratings – this would make it infeasible for a content-based filtering algorithm to derive meaningful predictions.

Especially in domains where traditional recommendation approaches are not the first choice, knowledge-based recommendation technologies come into play [5,6]. Knowledge-based recommender applications are exploiting explicitly defined requirements of the user and additionally dispose of deep knowledge about the underlying product assortment. Thus, knowledge-based recommender applications exploit knowledge sources that are typically not available in collaborative and content-based filtering scenarios. A direct consequence of the availability of deep knowledge about the product assortment and explicitly defined customer requirements is that no ramp-up problems occur [5,6]. The other side of the coin is that – due to the explicit representation of recommendation knowledge in a recommender knowledge base – knowledge-based recommenders cause so-called knowledge acquisition bottlenecks: knowledge engineers and domain experts have to invest considerable time efforts in order to develop and keep those knowledge bases up-to-date. Beside this technical challenge it is also important to consider *consumer decision making strategies in the design of knowledge-based recommender systems* to improve the quality of the recommendation process and to increase customer satisfaction with recommendation results. In this paper we focus on the discussion of selected models of consumer decision making and their importance for the development of knowledge-based recommender applications.

The remainder of this paper is organized as follows. In Section 2 we introduce basic functionalities supported by knowledge-based recommender applications. We provide an overview of general models of consumer decision making in Section 3. In Section 4 to 7 we discuss related theories from decision psychology that can have a major impact on decision processes when interacting with knowledge-based recommender applications. With Section 8 we provide an outlook of relevant future research topics. The paper is concluded with Section 9.

2 Knowledge-based Recommendation

The major difference between filtering-based recommendation approaches and knowledge-based recommendation [5,6] is that the latter use explicit knowledge about customers, the product assortment, and the dependencies between customer preferences. The rules for the identification of a solution are explicitly defined and thus allow the derivation of intelligent and deep explanations regarding the recommendation results. Since advisory knowledge is represented in the form of variables and constraints we are able to automatically determine repair actions in situations where no solution can be found for the given set of customer requirements [7, 8]. Knowledge-based recommendation problems can be defined on the basis of simple conjunctive database queries as well as on the basis of so-called constraint satisfaction problems (CSPs) [9]. A knowledge-based recommender application typically guides a user (repeatedly) through the following phases:

1. *Requirements specification* (Phase I.): in the first phase users are interacting with the recommender application in order to identify and specify their requirements.
2. *Repair of inconsistent requirements* (Phase II.): in the case that the recommender application is not able to identify a solution, it proposes a set of repair actions (change proposals for requirements) that (if accepted by the user) can guarantee the identification of a recommendation.

3. *Result presentation* (Phase III.): if the requirements can be fulfilled, the recommender application presents a set of product alternatives. These alternatives are typically ranked on the basis of a utility function (for a detailed example see [6]) and are either presented as an ordered list or on a product comparison page.
4. *Explanations* (Phase IV.): For each of the identified and presented product alternatives the customer can activate a corresponding *explanation* as to why this product has been recommended. Each explanation consists of *argumentations* that relate specified user requirements with the corresponding product properties.

Figure 1 presents the requirements specification phase in RECOMOBILE, a knowledge-based application implemented for the recommendation of mobile phones [10]. Examples of such requirements in the mobile phones domain are *I want to hear music with my mobile phone*, or *the recommended phone should have an integrated camera*.

Figure 1: Phase I. requirements specification – personalized defaults are presented in order to proactively support users. These defaults are determined on the basis of the information from already completed recommendation sessions [10]

In Figure 2 a simple example of the RECOMOBILE repair mode is depicted. The recommender detects that no solution could be found, i.e., the defined set of customer requirements is inconsistent with the underlying recommender knowledge base. An example of such an infeasibility in the mobile phones domain is the combination of *the phone should have no web access* and *the phone should support sports tracking*. In such a situation, the system activates a repair component that identifies minimal sets of changes such that the retrieval of at least one solution is possible.

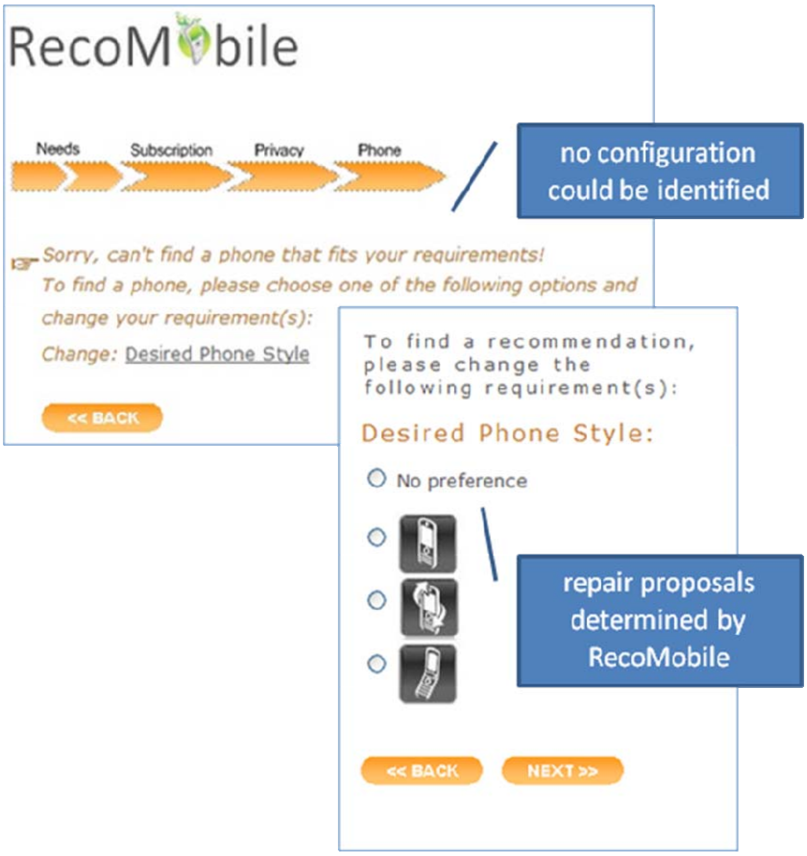

Figure 2: Phase II. repair of inconsistent requirements – a repair component identifies minimal sets of changes such that the retrieval of at least one solution is possible

The phone selection page (see Figure 3) enlists the set of phones that fulfill the given set of customer requirements. This set is ranked on the basis of similarity metrics, i.e., the similarity between the current customer requirements and the requirements of customers stored in logs of already completed recommendation sessions (for details see [10]).

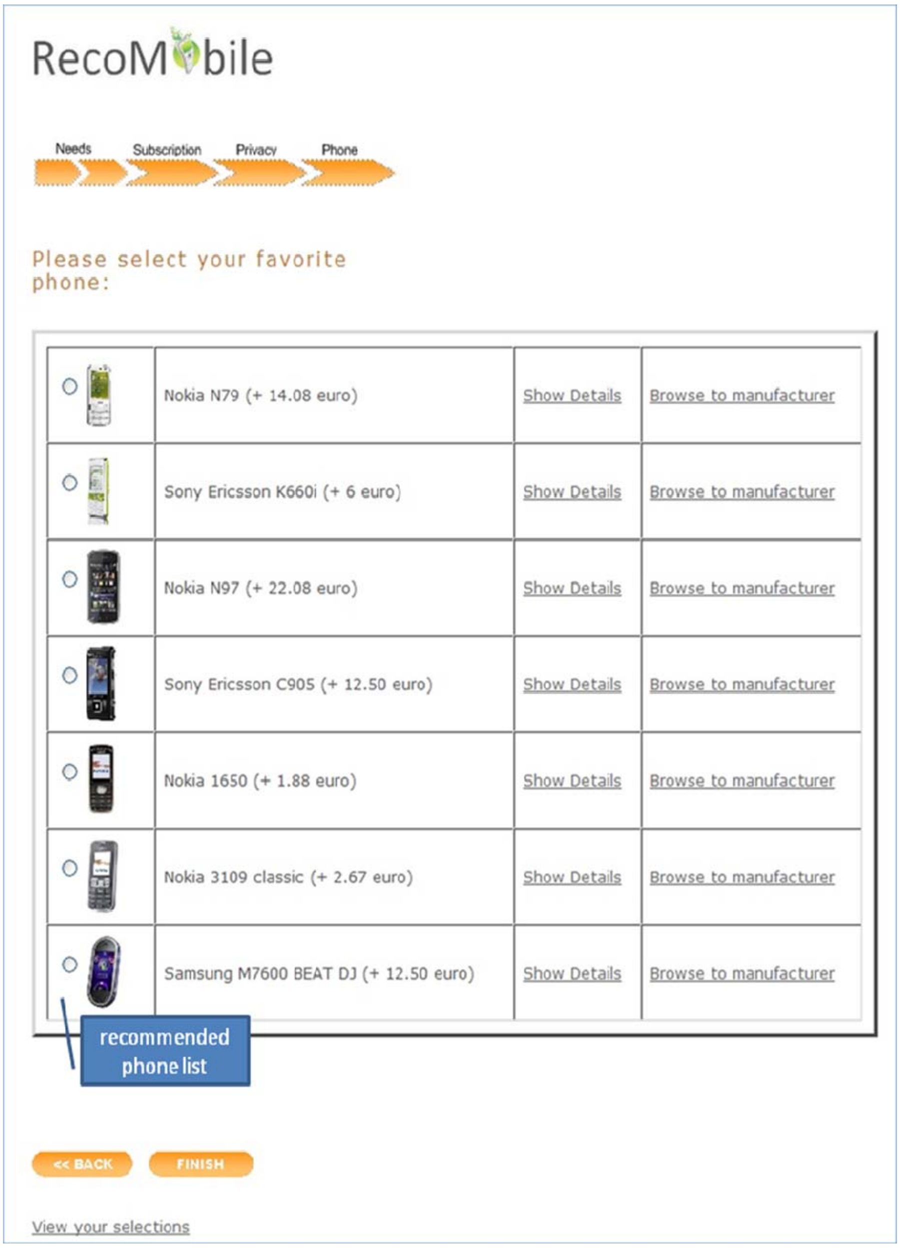

Figure 3: Phase III. result presentation – a set of phones that fulfill the specified requirements is presented to the user

For each mobile phone the user can activate a corresponding explanation page. In RECOMOBILE the explanations are presented in the form of a detailed enlisting of those user requirements which are fulfilled by the specific mobile phone (see Figure 4). Finally, the user can select the preferred mobile phone and finish the session.

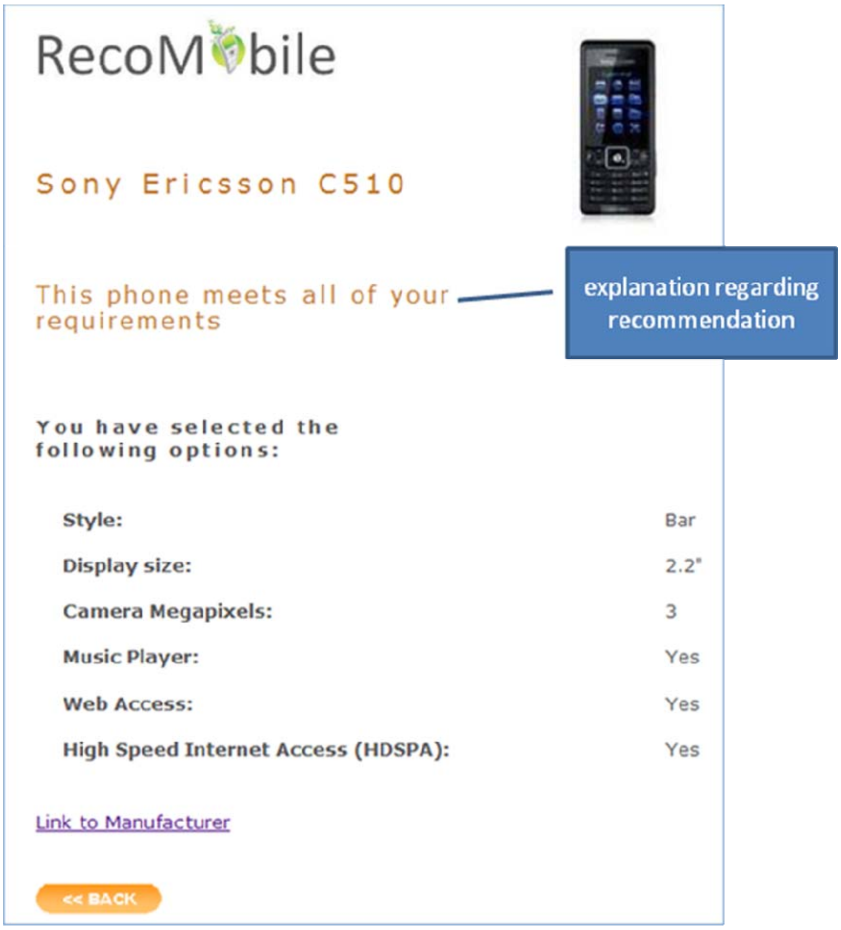

Figure 4: Phase IV. a simple form of explanation - an enlisting of those user requirements which are fulfilled by a specific mobile phone

To increase the user satisfaction with the recommendation process, it is not only important to implement algorithms that provide good recommendations, but also to establish an adequate format for presenting the recommendations. Research on consumer decision making has shown that consumers are influenced by the format of the information presented and as a consequence use different decision-making strategies in different contexts [see e. g. 11, 12, 13, 14, 15, 16]. In order to better assist consumers in buying decisions, recommender systems require the integration of basic algorithms with deep knowledge about human decision making. An overview of selected models of consumer decision making is provided in the next section.

3 Models of Consumer Decision Making

History. In the 18th century, economics began to explore knowledge about consumer decision-making processes. Nicholas Bernoulli developed the first consumer decision making theory. The basic assumption of this theory was that consumers make buying decisions based on the expected results of their purchases [17]. According to Bernoulli, consumers select that option which will provide maximum satisfaction. *Bernoulli's Utility theory* was later extended by John von Neumann and Oskar Morgenstern [18]. In their *Expected Utility Theory* they introduced four axioms which define a rational decision maker: *completeness* (a decision maker has well defined preferences), *transitivity* (preferences are consistent), *independence* (preferences hold independently of the outcome) and *continuity* (given a middle option there is a "tipping point" between being better than and worse than this reference option). Von Neumann and Morgenstern stated that the preferences of a rational decision maker can be represented by a utility function. In the 1950s, Herbert Simon developed an alternative model of consumer decision making: "*Satisficing*" [19]. This model takes into account the fact that consumers stop the decision making process when they have found a product they consider as "good enough", rather than to identify the best solution. Simon argued that the idea of the rational decision maker requires cognitive information processing skills that people do not possess. According to Simon, decision makers lack the ability and resources to arrive at the optimal solution and typically operate within a *bounded rationality*. Since 1960s various consumer decision-making models have been developed [20]. In the following we will discuss selected models with a special relevance in the context of recommender applications.

Traditional Economic Models. Based on the rationality aspects of Utility Theory [18], traditional economic models are assuming that all users are able to take decisions that are optimal and that have been derived on the basis of rational and formal processes. Consumers were considered as rational decision makers who seek to maximize utility. Due to their wide ranging scope, these models are often labeled as "grand models" [21]. Among the best known are the Nicosia Model [22], the Howard-Sheth-Model [23], and the Engel, Kollat & Blackwell-Model [24]. An assumption of economic models is that preferences remain stable, i.e., are not adapted within the scope of a decision process. However, it is a fact that preferences can be extremely unstable, for example, a customer who buys a car first sets the upper limit for the overall price to 20.000€. This does not mean that the upper limit is strict since the customer could change his/her mind and set the upper limit for the price to 25.000€ simply because he/she detected additional technical features for which he/she is willing to pay the higher price, for example, high-quality headlights, park-distance control, satellite navigation, and rain-sensor for the windscreen wipers. Solely on the basis of this simple example we immediately see that preferences could change over time, i.e., are not stable within the scope of a recommendation session. This insight led to the development of new decision models – see, e.g., [25, 26]. The most important ones will be discussed in the following.

Effort Accuracy Framework. Following this model developed by Payne, Bettman, and Johnson [25], users are taking into account cost-benefit aspects. This basic assumption is similar to Simon's Satisficing theory [19]. A decision process is now characterized by a trade-off between the effort to take a decision and the expected quality of the decision. The effort-accuracy framework is based on the fact that users (customers) show an adaptive decision behavior and select from an available set of different decision heuristics depending on the current situation. Criteria for the selection of a certain heuristic are on the one hand the needed decision quality and on the other hand the (cognitive) efforts needed for successfully completing the decision task. This framework clearly differs from the above mentioned economic models of decision making. In those models, optimality plays a dominant role and the efforts related to successfully completing a decision task are neglected. However, especially the effort for completing a decision task has to be taken into account as an important factor that determines whether the user is willing to apply the recommender application or chooses a different provider.

Construction of Preferences. The concept of preference construction in human choice has been developed by Bettman, Luce, and Payne [26]. The basic idea of preference construction is that users tend to identify their preferences within the scope of a recommendation session but only in rare cases are able to state their preferences before the beginning of the decision process. Thus decision processes are more focused on *constructing* a consistent set of preferences than *eliciting* preferences from the user which is still the predominantly supported type of decision process in many existing knowledge-based recommender applications. Since user preferences are constructed within the scope of a recommendation session, the design of the user interface can have a major impact on the final outcome of the decision process.

In order to improve the applicability of recommender applications we must integrate recommendation technologies with deep knowledge about human decision making. Such an integration can help to improve the perceived quality of the recommender application for the user as well as the predictability of decision outcomes (see the discussions in the following sections). In the remainder of this paper we will review selected theories from decision psychology with respect to their potential impact on preference construction processes. These theories have already shown to be of relevance for recommender applications – an overview is provided in Table 1.

Table 1: Selected theories of decision psychology.

theory	explanation
decoy effects	inferior products added to a result set can significantly change the outcome of the decision process [27, 28, 29].
primacy/recency	information units at the beginning and the end of a list are analyzed and recalled significantly more often than those in the middle of a list – this has an impact on a user's selection behavior [30, 31, 32].
framing	the way in which we describe a certain decision alternative can have a significant impact on the final decision [12, 34, 35, 37].
defaults	pre-selected decision alternatives have the potential to significantly change the outcome of a decision process [10, 39, 40, 41, 42].

4 Decoy Effects

Decoy products are items that are inferior to other items in a given set of recommended products.[1] In this context, the inferiority respectively superiority of items is measured by simply comparing the underlying properties of items with regard to their distance to the optimal value. For example, *robot X* dominates *robot Y* in the dimensions *price* and *reliability* if it has both a lower price and a higher reliability. The inclusion of such decoy products can significantly influence the outcome of the decision process and therefore has to be taken into account when implementing recommender applications. The phenomenon that users change their selection behavior in the presence of additional inferior items is denoted as *decoy effect*. Decoy effects have been intensively investigated in different application contexts, see, for example [27, 28, 29, 43, 44, 45].

In the following subsections we will discuss different types of decoy effects and explain how those effects can influence the outcome of decision processes. Note that the existence of decoy effects provides strong evidence against the validity of traditional economic models of choice [22, 23, 24] that suppose rational and optimal strategies in human decision making.

4.1 Compromise Effects

Compromise effects denote one specific archetype of decoy effects which is shown in Table 2. It is possible to increase the attractiveness of robot X compared to robot Y by adding robot D to the set of alternatives. Robot D increases the attractiveness of robot X since, compared to robot D, X has a significantly lower price and only a marginally lower reliability (this effect is denoted as *tradeoff-contrast*). This way, X is established as a compromise between the alternatives Y and D. By the insertion of decoy robot D the comparison focus of the user is set to XD since D is more similar to X than to Y (*similarity effect*). Note that the compromise of choosing X can as well be explained by the aspect of *extremeness aversion*, a concept proposed by Simonson and Tversky [28]. Their research has shown that adding an extreme alternative to a choice set will result in people favoring the "middle" choice, where attribute values are positioned between the values of the other alternatives.

Table 2: Compromise effect.

product (robot)	X 	Y 	D 
price [0..10.000€]	3.000	1.500	5.000
reliability [0..10]	9	4.5	10

[1] Note that we use the *robot product domain* in the following examples.

More formally, we can explain decoy effects as follows. Under the assumption that the probability of selection for item X out of the item set {X,Y} is equal to the probability of selection of Y out of {X,Y}, i.e., P(X,{X,Y}) = P(Y,{X,Y})), the addition of D causes a preference shift to X, i.e., P(Y,{X,Y,D}) < P(X,{X,Y,D}).

4.2 Asymmetric Dominance Effects

The second archetype of decoy effect is called asymmetric dominance (depicted in Table 3). In this scenario, robot X dominates robot D in both attributes (price and reliability) whereas robot Y dominates robot D in only one dimension (the price). The addition of robot D to the set of {X,Y} can help to increase the share of X. In this context the comparison focus is set to XD (D is more *similar* to X than Y) which makes X the clear winner in the competition, i.e., P(Y,{X,Y,D}) < P(X,{X,Y,D}).

Table 3: Asymmetric dominance effect.

product (robot)	X 	Y 	D 
price [0..10.000€]	3.000	1.000	3.500
reliability [0..10]	9	5	8

4.3 Attraction Effects

The third archetype of decoy effects is called attraction effect. In this context, X appears to be only a little bit more expensive and simultaneously has a significantly higher reliability compared to robot D (*tradeoff-contrast* – see Table 4). In this scenario the inclusion of D can trigger an increased probability of selection for robot X since X appears to be more attractive than D, i.e., P(Y,{X,Y,D}) < P(X,{X,Y,D}). The attraction effect moves the comparison focus to the combination of items XD since D is more similar to X than to Y (*similarity effect*). Note that both compromise effects and attraction effects are based on the ideas of tradeoff-contrast and similarity. The difference lies in the positioning of decoy items. In the case of the compromise effect, decoy products are representing extreme solutions (see Table 2) whereas in the case of the attraction effect decoy products are positioned between the target and the competitor product (see Table 4).

Table 4: Attraction effect.

product (robot)	X 	Y 	D 
price [0..10.000€]	5.000	2.000	4.900
reliability [0..10]	7	3	5

Application of Decoy Effects in Recommendation Scenarios. If decoy items are added to a result set, this can change the selection probability for items that were included in the original result set. The occurrence of decoy effects have been shown in a number of empirical studies in application domains such as financial services, e-tourism, and even software agents (see, for example, [27, 28, 46]). The major possibilities of exploiting decoy effects in knowledge-based recommendation scenarios are the following:

- *Increased selection probability for target items*: as already mentioned, adding additional inferior items to a result set can cause an increased share of target items [43] (in our example denoted as item X). This scenario definitely has ethical aspects to be dealt with since companies can potentially try to apply decoy effects for selling products that are maybe suboptimal for the customer.
- *Increased decision confidence*: beside an increase of the share of the target product, decoy effects can be exploited for increasing the decision confidence of a user [44]. In this context, decoy effects can be exploited for resolving cognitive dilemmas which occur when a user is unsure about which alternative to choose from a given set of nearly equivalent alternatives.
- *Increased willingness to buy*: from empirical studies we know that a user's level of trust (confidence) in recommendations is directly correlated with the willingness to buy, i.e., increasing the level of trust directly means that the purchase probability can be increased as well [47].

The important question to be answered now is how to predict decoy effects within the scope of a recommendation scenario. Predicting the selection of products contained in the set of possible product alternatives (the consideration set CSet) requires the calculation of dominance relationships between the items contained in a result set. Exactly for this calculation different models have been developed [46, 48] – the outcomes of each of these models are dominance relationships between the items in CSet. The calculation of such dominance relationships can be based on Formula 1 which is a simplified version of the approach introduced in [46]. This formula allows the calculation of dominance relationships between different products in a consideration set, i.e., d(u, CSet) denotes the dominance of product u compared to all other items in CSet.

$$d(u,CSet) = \sum_{v \in CSet-\{u\}} \sum_{a \in properties} \sqrt{\left| \frac{diff(u_a,v_a)}{a_{\max} - a_{\min}} \right|} * sign(u_a,v_a) \ .$$

Formula 1: Calculating dominance value *d* for *u* in *CSet*: *diff*(u_a,v_a) = u_a-v_a if *a=reliability*, otherwise *diff*(u_a,v_a) = v_a-u_a. sign(u_a,v_a)=1 if $u_a \geq v_a$, -1 otherwise.

Applying Formula 1 to the product set {X,Y,D} depicted in Table 2 results in the dominance values that are depicted in Table 5. For example, product v_1 (Y) has a better price than product u (X; the target item) – the corresponding dominance value is -0.65, i.e., product u is inferior regarding the attribute price. The sum of the attribute-wise calculated dominance values, i.e., d(u,CSet), provides an estimation of how dominant item u appears to be in the set of candidate items CSet. The values in Table 5 clearly show a dominance of item X over the items Y and D.

Table 5: Dominance values for A ∈ CSet for Table 2.

	u	**v_1**	**v_2**	**Sum**	**d(u,CSet)**
	X	**Y**	**D**		d(X,{X,Y,D})
price		-0.65	0.75	0.10	
reliability		0.90	-0.42	0.48	
					0.58
	Y	**X**	**D**		
price		0.65	1.0	1.65	
reliability		-0.90	-1.0	-1.9	
					-0.25
	D	**X**	**Y**		
price		-0.75	-1.0	-1.75	
reliability		0.42	1.0	1.42	
					-0.33

The dominance relationships between items in a result set can be directly used by a corresponding configuration algorithm to calculate a choice set, such that the attractiveness of one option is increased [46]. If the recommendation algorithm determines, for example, 20 possible products (the consideration set) and the company wants to increase the sales of specific items in this set, a configuration process can determine the optimal subset of items that should be presented to the user such that purchase probability is maximized.

5 Primacy/Recency

In 1946 Solomon Asch conducted an experiment on formations of personality impression [11]. The results of this study showed that presenting adjectives describing a person in sequence, the same words could result in very different ratings of that person depending on the order in which the words were presented. A person described as "*intelligent, industrious, impulsive, critical, stubborn, envious*" was rated more positive by the participants than a person described as "*envious, stubborn, critical, impulsive, industrious, intelligent*". This phenomenon is known as primacy effect and is explained through a memory advantage that early items in a list have [49].

Murphy, Hofacker and Mizerski [31] explored the importance of an item's list position in an online environment. In their experiment they manipulated the serial position of links on the website of a popular restaurant. The results of this study showed that visitors tended to click the link on first position most frequently. But there was also an increased tendency to click on the links at the end of the list. This is known as recency effect. The results go along with the findings of Hermann Ebbinghaus who first documented the *serial position effect* [50] which describes the relationship between recall probability of an item and its' position in a list (see Figure 5).

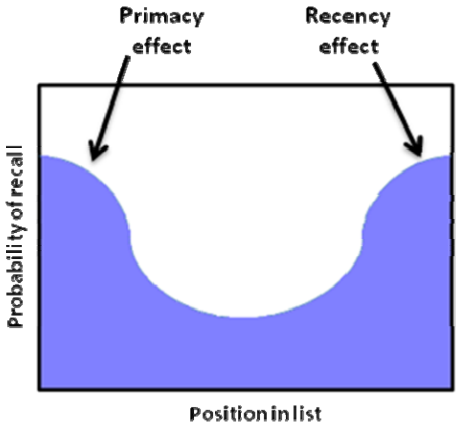

Figure 5: Serial position effect – a term coined by Hermann Ebbinghaus [50] that refers to the finding that items at the beginning and at the end of a list are more accurately recalled than those items positioned in the middle of a list

Application of Serial Position Effects in Recommendation Scenarios. Felfernig et al. [30] investigated serial position effects in knowledge-based recommendation scenarios, especially in the context of presenting product features. They conducted a study where participants were asked to choose a tent out of a set of tents (the tent, a participant would buy most likely in a real purchase situation). The position of product attributes used to describe the tents was varied. The results of this study showed significant changes in the product selection behavior that have been triggered by changed product attributes orderings.

The results of the studies [11, 30, 31] illustrate the importance of an item's position in an ordered list. E-Commerce retailers utilize product recommendations as a targeted marketing tool to personalize the shopping experience for each customer [64]. In this context serial position effects play an important role in the ordering of products on result pages. As a consequence, recommender applications must be aware of the fact that different item rankings can trigger different item selection behavior and as well can increase or reduce a users decision making efforts.

Based on the results of their research, Murphy, Hofacker and Mizerski [31] suggest to place the most important item on the first position and to place another important item on the last position of a list (the process should be continued with the order of importance). An approach to calculate personalized item rankings and to take into account primacy/recency effects in the presentation of result sets has been introduced in [32]. The authors of [32] utilize the concepts of Multi-Attribute Utility Theory (MAUT) [33] and derive the importance of interest dimensions from customer requirements. Product alternatives are then evaluated according to these dimensions.

We now want to discuss the concepts presented in [32] in more detail on the basis of the following example. Let us assume that *economy* and *quality* have been defined as example interest dimensions for the robot product domain introduced in Section 4. In Tables 6-7 example scoring rules are defined that describe the relationships between the robot attributes (*price* and *reliability*) and the corresponding interest dimensions. For example, Table 6 shows that an expensive robot has a low perceived value for interest domain economy and a high perceived value for interest dimension quality. Table 7 shows that a robot with low reliability has a high valence in interest domain economy and a low valence in interest dimension quality.

Table 6: Scoring rules for product attribute *price*

price	economy	quality
<= 2000	10	3
> 2000, <= 5000	6	5
> 5000, <= 8000	4	7
> 8000, <= 10000	2	10

Table 7: Scoring rules for product attribute *reliability*

reliability	economy	quality
<= 3	10	4
> 3, <= 6	6	7
> 6, <= 10	4	10

Given a concrete customer (*customer 1*) with a higher interest in the dimension economy (importance of 0,7) compared to the dimension quality (importance of 0,3 – assuming that the sum of importance values is 1), a personalized product ranking can be calculated on the basis of Formula 2. In this formula *contribution(r,i)* defines the contribution of product *r* to the interest dimension *i* and *interest(i)* shows the degree to which a specific customer is interested in dimension *i*.

$$productutility(r) = \sum_{i=1}^{n} contribution(r,i) * interest(i)$$

Formula 2: Calculating overall utility of a product *r* [32] - *contribution(r,i)* = the contribution of product *r* to the interest dimension *i*; *interest(i)* = the degree to which a specific customer is interested in dimension *i*

Applying the scoring rules of Tables 6-7 to the robots of Table 4 results in the item ranking shown in Table 8.

Table 8: Overall utilities of robots in Table 4

robot	economy	quality	overall utility
X	6+4=**10**	5+10=**15**	10*0,7+15*0,3=**11,5**
Y	10+10=**20**	3+4=**7**	20*0,7+7*0,3=**16,1**
D	6+6=**12**	5+7=**12**	12*0,7+12*0,3=**12**

This customer-specific ranking of products can now be used to identify an ordering of robots that takes into account primacy/recency effects. For this purpose a utility value has to be assigned to each list position. Based on the approach of Murphy, Hofacker and Mizerski [31] the first and last position will get a higher utility value as the middle position (see Table 9).

Table 9: Utilities of product positions

robot position	1	2	3
utility of position	3	1	2

In order to calculate a customer-specific product ordering taking into account primacy/recency effects, Formula 3 can be applied. In our simple example we have 3!=6 possible combinations of product sequences. We can use this formula to identify a corresponding product ordering.

$$orderutility_{r1...n} = \sum_{i=1}^{n} productutility(r_i) * positionutility(i)$$

Formula 3: Calculation of the utility of a product sequence with *n* products [32] - *productutility(r)* = the utility of a specific product for a particular customer; *positionutility(i)* = the utility of a specific position in the result list

In Formula 3, *productutility*(r_i) specifies the utility of a specific product r_i for a customer (in our case *customer 1* – see Table 8) and *positionutility(i)* defines the utility of a specific position *i* in the result list (see Table 9). As shown in Table 10, the listing with the highest utility is the one where robot Y is positioned at the first position (the most interesting option for the customer) and robot D is placed on the last position.

Table 10: Overall utilities of possible robot sequences

robot sequence (r_1-r_2-r_3)	overall utility
X-Y-D	11,5*3+16,1*1+12*2=**74,6**
X-D-Y	11,5*3+12*1+16,1*2=**78,7**
Y-X-D	16,1*3+11,5*1+12*2=**83,8**
Y-D-X	16,1*3+12*1+11,5*2=**83,3**
D-X-Y	12*3+11,5*1+16,1*2=**79,7**
D-Y-X	12*3+16,1*1+11,5*2=**75,1**

6 Framing

Framing effects occur when one and the same decision alternative is presented in different variants [34]. Tversky and Kahnemann [12] presented a series of studies where they confronted participants with choice problems using variations in the framing of decision outcomes. They reported that "*seemingly inconsequential changes in the formulation of choice problems caused significant shifts of preference*" [12]. An explanation for such choice reversals is given by prospect theory developed by Kahnemann and Tversky [51]. In this theory a value function is introduced for explaining decision making under risk, where negative outcomes have a higher impact compared to the positive ones (see Figure 6).

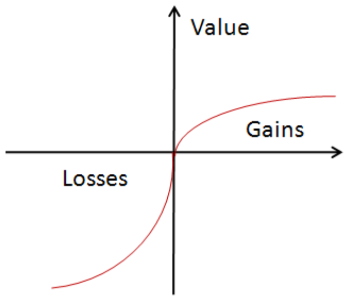

Figure 6: Prospect theory's value function [51] – evaluating losses and gains

Levin, Schneider and Gaeth [35] introduced three dimensions in which framing manipulations can differ: what is framed, what is affected, and how is the effect measured. Based on this distinction the authors identified three different types of framing effects (see Table 11).

Table 11: Framing types defined by Levin, Schneider and Gaeth [35]

Framing type	Information framed
risky choice framing	risk level of options
attribute framing	one attribute of an object
goal framing	goal of an action/behavior

The form of framing introduced by Tversky and Kahneman [12] is categorized as *risky choice framing*, based on the fact that given options in a choice problem differ in level of risk. The same decision problem can be described as a choice between one sure and one risky loss (loss frame) as well as a choice between one sure and one risky gain (gain frame) [36]. Research has identified a general preference shift from more risky choices (with more gains) to choices that avoid losses [35]. The most famous example of this framing type is the *Asian disease problem* [12] where participants of a study were confronted with the situation that 600 individuals are infected with a deadly disease. Two options with a different risk level to combat the disease where presented. Participants were divided into two groups. One group had to choose between options described in terms of lives saved (*positive frame*) and the other group had to choose between options based on a description of lives lost (*negative frame*). The results of this study showed that participants preferred the risk-free alternative when the problem was framed positively ("200 people will be saved" is preferred to the option "600 people will be saved with 1/3 probability and all people will die with a 2/3 probability"). In contrast, participants in the negative frame tend to choose the risky alternative ("1/3 probability that no one will die and 2/3 probability that all people will die" is preferred to "400 people will die").

The second framing type is called *attribute framing*. Here only one attribute or characteristic of an object is framed. For example in a study conducted by Levin and Gaeth [54] a beef product labeled as "*75% lean*" was evaluated more favorable than a beef product labeled as "*25% fat*".

The third type of framing termed by Levin, Schneider and Gaeth [35] is *goal framing* where the information which is framed is the goal of an action or behavior. Ganzach and Schul [38] reported three experiments where the goal of the decision was framed either as acceptance or rejection. The participants were asked to choose one out of two candidates which they would accept/reject. The results of the experiments showed that goal framing influences the extent of processing of positive vs. negative information. If the decision problem was framed as an *acceptance decision*, participants were more likely to rely on positive information whereas participants confronted with a *rejection decision* focused on the evaluation of negative information. An explanation for this phenomenon is given by the *confirmation bias*, a term coined by Peter Wason [52]. Confirmation bias is a tendency to make frame-compatible features more important in a choice problem.

Price framing. Another occurrence of framing is price framing, where the granularity of the presented price information (price information presented in one attribute or distributed over several attributes) is framed. Since only one attribute of the object is framed, price framing can be seen as a subclass of attribute framing in the categorization of Levin, Schneider and Gaeth [35]. Bertini and Wathieu [53] conducted a series of studies to investigate the effect of this framing type. They found that price format influences users in the evaluation of product attributes. If the price information is provided for different subparts of a product, users tend to focus on evaluating those subparts with corresponding price information. If the product price on the contrary is represented by one attribute, users focus on evaluating other technical attributes.

Application of Framing Effects in Recommendation Scenarios. The framing of options or characteristics of options in a choice set can result in a shift of selection probability for items [12, 34, 35, 37]. The implications of the above-mentioned framing types on user decision behavior are the following:

- *Risky choice framing:* Levin, Schneider and Gaeth [35] pointed out that in risky choice framing a positive frame typically enhances risk aversion. For example, a fund with a 95% probability of no loss is interpreted as a better solution compared to the same product described with a 5% probability of loss. In the context of recommender systems this framing type plays an important role in the presentation of product alternatives as well as in the presentation of repair proposals for inconsistent requirements since the way in which those alternatives are presented can significantly change a user's selection behavior.

- *Attribute framing:* a positive framing of an attribute of options leads to a more positive judgment of the options compared to negative frames. For example Marteau [37] demonstrated that people were more likely to attend medical procedures described by their survival rate rather than their mortality rate. In this context as well, attribute framing has to be taken into account when designing result (product) presentations in a recommender application.
- *Goal framing:* in goal framing a negatively framed message is more likely to lead to a negative response than a comparable positively framed message, as results of the research of Ganzach and Schul [38] shows. In recommender systems this fact is relevant in the requirements specification phase. For example, if the interface is requesting decisions regarding the inclusion of items, users will rather take into account positive properties and vice-versa if items should be excluded, uses will rather take into account negative (less preferred) item properties.
- *Price framing:* In the context of recommender systems, this framing type has to be considered in the product presentation since price framing can lead to a shift of a user's evaluation focus from quality attributes (e.g., technical attributes of a digital camera) to price attributes and thus could significantly change the outcome of the decision process. This effect is, for example, exploited by discount airlines which typically give a separate listing for air fares and fees.

7 Defaults

Internet users are facing an ever increasing amount of product information. For example, at Pandora[2], a popular personalized internet radio service, the characteristics of a song are specified by 400 attributes. Early research in the field of consumer behavior indicated that confronting the consumer with too much information can result in a decreased quality of decision performance [55, 56]. These traditional approaches studied the information overload effect by varying the number of alternatives in the choice set and the number of product attributes. The results of these studies showed an inverted-U-shaped relationship between the amount of information and decision quality (measured by the consumers' ability to make correct decisions among many different products [57]). Later research resulted in contrary results (see, e.g., [58, 59]). For example, Russo [58] reanalyzed the data of the research of Jacoby, Speller and Kohn [55] and found no overload effect. Contrary to the original conclusions, Russo's results suggested that more information can help the consumer in making choices. Consequently both aspects seem to be important, i.e., the user must not be overloaded with too many (often non-understandable technical) aspects but on the other hand must have available all the necessary information relevant for taking a

[2] www.pandora.com

decision. Huffman and Kahn [39] state that "*the key to customer satisfaction with the entire shopping interaction is to ensure that the customer is equipped to handle the variety*." A possibility to support users in the specification of their requirements is to provide *defaults* [10]. Defaults in recommender systems are preselected options used to express personalized feature recommendations. For example, if the user is interested in using GPS navigation with the mobile phone, the recommended phone should support web access. Thus defaults are a means to help the user identifying meaningful alternatives that are compatible with their current preferences.

Application of Defaults in Recommendation Scenarios. Especially for knowledge-based recommender applications defaults play a very important role since users tend to accept preset values compared to other alternatives [41, 42]. An explanation model for this phenomenon is that users often tend to favor the status quo over alternatives often of equal attractiveness. Samuel and Zeckhauser [42] have shown this effect, known as *status quo bias*, in a series of experiments. Kahnemann, Knetsch and Thaler [60] argue that the status quo bias can be explained by a notion of *loss aversion*. They explain that the status quo serves as a reference point and alternative options are evaluated in terms of gains and losses relative to the reference point. Felfernig et al. [10] conducted a study to investigate the impact of personalized feature recommendations in a knowledge-based recommendation process (see e. g. Figures 1-4). The nearest neighbors and Naïve Bayes voter algorithms were used for the calculation of defaults. The results of this research indicate that supporting users with personalized defaults can lead to a higher satisfaction with the recommendation process.

A major risk of defaults is that they could be exploited for misleading users and making them to choose options that are not really needed to fulfill their requirements. Ritov and Barron [41] suggest counteracting the status-quo bias by presenting the options in such a way, that keeping as well as changing the status quo needs user input. They argue that "*when both keeping and changing the status quo require action, people will be less inclined to err by favoring the status quo when it is worse*" [41]. Consequently, a recommender interface supporting such an interaction type has the potential to reduce biasing effects and also could help to increase a user's trust in the recommender application.

8 Further research issues

Until now we focused on the discussion of selected decision-psychological aspects relevant for the development of knowledge-based recommender applications. In the remainder of this paper we are going to discuss relevant topics for future research.

Repair actions. Repair actions help users to get out of the so-called "no solution could be found" dilemma [8] (see Section 2). If a given set of requirements does not allow the calculation of a recommendation there exist potentially many different alternative combinations of repair actions (exponential in the number of requirements [61]) that resolve the current conflict. As a consequence, it is not possible to present the complete set of possible repair actions and we have to select a subset that best fits with the requirements of the user. An approach to personalize the selection of repair actions has been introduced in [8]. A major goal for future work is to extend the approach of [8] by additionally taking into account different types of decoy effects that potentially occur in the repair selection process. Of special interest is the question whether there exist dependencies between decoy types. Serial position effects on result pages in the context of knowledge-based recommender systems have been demonstrated by Felfernig et al. [30]. We want to investigate whether such effects also occur when presenting repair actions. Finally, we are interested in the existence of decision biases when using defaults for the presentation of repair alternatives.

Result pages. Similar to the selection of repair alternatives we are also interested in general properties of decoy effects when presenting product lists. In this context we are interested in answering questions regarding the upper bound for the number of products such that decoy effects still occur. Furthermore, we are interested in interrelationship between item distances (typically calculated by different types of similarity metrics [65]) and the existence of decoy effects. A further question is whether we have to cluster target, competitor, and decoy items or whether decoy effects still occur if the positioning distance between items is increased. Another challenging question is whether there exists an interrelationship between different types of decoy effects, for example, do the asymmetric dominance effect and the compromise effect compensate each other or is there a kind of "synergy effect" in terms of even more significant selection shifts?

Compound critiques. Critiquing-based recommender applications [62, 63] often support the concept of compound critiques. Critiques are a natural way to support users in item selection processes without forcing them to explicitly specify values for certain item properties. Especially users who are non-experts in the product domain prefer navigation process where they are articulating requirements on a more abstract level such as *lower price* or *higher resolution*. In order to fasten the interaction with a critique-based recommender application, prototype systems have been developed that support the articulation of so-called compound critiques, i.e., critiques that include two or more change requests regarding basic product properties. An example of such a compound critique is *lower price and higher resolution*. A typical critiquing-based recommender presents a list of alternative compound critiques to the user. In this context, we are interested in answering the question whether decoy effects and serial position effects also occur in the selection of compound critiques.

9 Conclusions

We have presented a selected set of decision-psychological phenomena that have a major impact on the development of knowledge based recommender applications. A number of related empirical studies clearly show the importance of taking into account such theories when implementing a recommender application. We see our contribution as a first one on the way towards more intelligent recommender user interfaces that know more about the user and also know how to exploit this knowledge for improving the quality of applications in different dimensions such as prediction accuracy or overall satisfaction with the recommender applications.

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