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Improving Decision Quality Through Preference Relaxation

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Abstract. In online shopping scenarios, it can be difficult for consumers to process the vast amounts of information available and to make satisfactory buying decisions. Interactive decision aids are a potential solution to this problem. However, decision aids that filter a very large set of alternatives based on initial preferences may eliminate potentially valuable alternatives early in the decision process and possibly negatively impact decision quality. To address this issue we introduce a new kind of decision aid that enables consumers to consider high-quality alternatives they initially eliminated. We develop a model of such a decision aid and evaluate it on a set of 2650 car advertisements gathered from popular used car advertiser website. We discuss the potential impact of our decision aid on decision quality and consideration sets parameters, and give an overview of implications of our study for practitioners and researchers.

Keywords. Decision Making, Preference Relaxation, Decision Performance, Soft Preferences, e-Commerce

Introduction

Consumers often face a task to select a best option from a large set of alternatives, such as choosing a car to buy, an apartment to rent, or an unforgettable trip to book. E-commerce sites often provide search functionality, usually by asking a user to fill in a form asking about the requirements that a desired product has to satisfy (preferences). This process is used, for example, when searching for a used car (http://carzone.ie/), or a flight (http://orbitz.com/) on popular websites, and is referred to as preference-based search [1] or parametric search [2]. Although such choice-based approaches are prevalent, both users and retailers can find them unsatisfying [3] as users are often not able to correctly transform their preferences into requirements using online forms, and thus they are rarely provided with the information they need [1].

On the other hand, consumers making purchase decisions in online shops are often unable to evaluate all available alternatives in great depth, and so seek to reduce the amount of information processing involved [4]. Häubl & Trifts [5] discuss a staged

\footnotesize{\textsuperscript{1} The work presented in this paper has been funded in part by Science Foundation Ireland under Grant No. SFI/08/CE/I1380 (Lion-2).}
process in the context of online shopping and argue that interactive decision aids that provide support to consumers are particularly valuable in helping to determine which alternatives are worth further, detailed consideration. However, many factors, such as the number of available products as well as the precision of information preference elicited can affect performance of decision aids (e.g. recommender systems) [6]. Utility theory provides a solid mathematical foundation for recommendations of products [7], however, it assumes complex preference models that cannot be elicited in e-commerce scenarios because of lengthy and effortful preference elicitation procedures. Furthermore, customers are typically not familiar with the available products and their characteristics [8] and their preferences are constructed while learning about the available alternatives [9]. It is therefore important to enable users to explore the space of possible options while expressing their preferences.

In this paper we study the impact of a preference relaxation mechanism on consumer decision making. We argue that during the process of filtering (providing their preferences for attribute values) an initial, very large, set of product alternatives (the ‘Universal Set’ [10]) by providing preference on attributes and attribute values, consumers can eliminate products they might later consider valuable. We introduce a decision aid that uses ‘preference relaxation’ to extend the initial value preference specified by a consumer and thus incorporating selected alternatives (of potential high utility) for further consideration. Thus, a consumer is able to revise his criteria, consider more products and choose a configuration he finds the most suitable, but which does not fully fit his initial preference. We describe a model for such a decision aid, and present results of a study using 2650 car advertisements gathered from one of the most popular used car websites in Europe.

We first provide an overview of literature on decision aids and recommender systems in the context of e-commerce. Later we present a model of a preference relaxation mechanism and discuss potential impacts of preference relaxation on consumer decision making. We develop our research hypotheses, and present the design and results of a simulation-based experiment. We conclude the paper with a discussion of current findings and summarise the directions for future research.

1. Theoretical background

1.1. Preferences, decision quality and the use of decision aids

Much research focuses on the elicitation of decision makers’ preferences. There is a growing consensus that preferences are typically constructed during the process of making a decision, and are influenced by the method of preference elicitation, the description of potential options, and the choice context. Despite many disadvantages of self-explicated methods for preference elicitation [11], there is some evidence [12] that if many attributes have to be handled, lower cognitive strain on the decision maker and lower chance for simplifying effect of self-explicated approaches may become crucial. However, Bond et al. [13] argue that decision makers tend to restrict their processing to a narrow subset of possibilities when faced with more than a few alternatives. They also explain that individuals generally fail to consider relevant information during the evaluation of alternatives, focusing only on that which is most salient.

Decision makers may be able to dynamically employ decision strategies as they progress in a decision process rather than selecting them “ex ante” [14]. A well-
designed decision aid can influence choice of decision strategy, by reducing the effort associated with high quality, accurate strategies compared with simpler, but less accurate, heuristics. Otherwise, a decision aid may only influence decision-making efficiency [15]. Indeed, decision behaviour can influence the quality of a decision. Payne et al. [11] propose that a well-constructed decision should be based upon consideration of a range of options and those objectives most critical to the individual. But decision makers often focus on a single option, a single objective or attribute, or a single assumed state of the world when reasoning about a decision problem, especially under stressful conditions such as high information overload or time pressure [16]. They suggest a remedy for this problem would be to explicitly encourage people to think of multiple alternatives, and multiple attributes or objectives.

Assumptions that the decision maker can accurately state (and indeed bound) which levels within an attribute are acceptable versus unacceptable is a fundamental to the self-explicated approach [17]. Decision makers often use a conjunctive evaluation of available alternatives in which all the alternatives that possess at least one attribute with unacceptable values are rejected from the further consideration. Product search and filtering mechanism offered online follow that approach and filter out all the products that do not fully fulfil stated preferences. However, previous research indicates that decision makers tend to fail to fully adhere to the self-explicated approach. Klein [18] found that decision makers often fail to reject alternatives with attribute levels which they themselves had previously described as unacceptable, and found that significant numbers of participants can chose an alternative described with at least one attribute level they themselves initially indicated as “completely unacceptable. When faced with more than a few alternatives, decision makers tend to restrict their processing to a narrow subset. Green et al. [19] argue that improving preference elicitation mechanisms can reduce the tendency to consider alternatives with “unacceptable” levels. In sum, much research has relied on a self-explicated approach, despite the fact that its assumptions are often violated by actual choice behaviour. Preference relaxation mechanisms may assist in alleviating such problems. Further, a decision aid supporting preference relaxation can be seamlessly integrated with the existing online shopping websites to improve consumer decisions.

1.2. Recommender Systems

Decision aids based on recommendations and suggestions have recently become an important stream of research in e-commerce. There are numerous studies that propose the use of recommendations to improve consumer decision-making [8, 20]. Providing a consumer with a relevant (similar to his stated preferences) yet diverse (so that he can discover new opportunities and adjust his preference model) set of suggestions has become an important research problem [21]. On the other hand, conversational recommenders with adaptive suggestions [8] emphasize the need for iterative preference construction enabling gradual improvements to the accuracy of suggestions. Pu et al. [22] propose to use critiquing as a methodology for mixed-initiative recommender systems, where users provide preferences with critiques on presented examples, thus selected of example products is important to stimulate their preference expression. According to the Look-ahead principle [1], “Suggestions should not be optimal under the current preference model, but should provide high likelihood of optimality when an additional preference is stated”. We contrast our research in a number of ways from these approaches. First, we primarily focus on reduction of type I
error by extending the preferences provided by a consumer (which, however, can lead to discovering alternatives that may lead to providing preference on additional attributes). Second, many of these approaches require prior knowledge or history of user interactions and preference models, which are not required in our approach. We argue that the decision aid proposed in this paper can increase the average quality of result sets presented to a user after filtration, and positively affect decision quality.

In the following section we discuss preference relaxation mechanisms and their application to decision-making problems.

2. Preference Relaxation

Imagine you are planning to buy a second hand car. You would like to spend between €7000 and €8000 for a car that is well equipped (air conditioning, satellite navigation) and with reasonable mileage (between 25000 and 75000 km). These preferences are easy to input into forms provided by popular car advertising websites. However, would you be willing to pay slightly more (€8100) for a well-equipped car with a mileage lower than you expected (15000 km)? Perhaps, you would prefer a slightly cheaper car (€6950) with slightly higher mileage than initially expected (76000km)? A preference relaxation mechanism allows customers to consider some alternatives (e.g. cars) that were initially eliminated according to their preference in order to make better decisions.

2.1. Model of a decision making problem

Typically, preferences on numerical attributes are expressed using value ranges. Thus, we allow the consumer to specify his/her attribute value range preference for an i-th attribute as $d = (d_{\text{LOWER}}, d_{\text{UPPER}})$ where $d_{\text{LOWER}}$ ($d_{\text{UPPER}}$) indicates the lowest (highest) acceptable value for a given attribute. We now introduce relaxation variables $e_U$ (upper) and $e_L$ (lower), which cause the filtering rule to be less restrictive. Thus also the alternatives that satisfy the less strict preference $d^* = (d_{\text{LOWER}} - e_L, d_{\text{UPPER}} + e_U)$ remain in the resulting set of potential choices and can be considered by the decision maker.

Such relaxation can significantly increase of the number of alternatives presented to the user resulting in higher decision-making effort. However, because the size of such a result set can be large, display mechanisms such as pagination (i.e. displaying 30 most relevant products in the first result page) are used. Diehl [23] showed that when the products in the result set are ordered based on utility (from predicted best to worse utility), showing more items lowers choice quality. Moreover, Cai [24] showed that consumers tend to include products with higher quality in consideration sets when they are exposed to a descending list. Similarly, in our study we constraint the maximum number of items presented at once in the result set to 30 products with highest utility (“the first page of results”). Thus, for cases where both relaxed and not relaxed query produces a result set larger than 30 items, number of alternatives and related effort are constant.

There are many decision strategies applicable to preferential choice problems. However, only four prototypical forms [25] have been the focus of attention in empirical studies: additive-compensatory (AC), additive-difference (AD), conjunctive (CNJ), and elimination by aspects (EBA). Although the additive strategies require greater effort they are thought to lead to more accurate choices [26]. The additive-compensatory model (AC) is designed to evaluate a single alternative at a time based
on values of all relevant attributes. Total utility of an alternative is determined as a sum of products of each attribute's weight \((w)\) and utility \((u)\). The utility of each attribute is assessed with a utility function based on the attribute value and stated decision maker’s value preference. Three main models of utility functions are prevalent: the vector (linear) model, the ideal point model (linear and quadratic), and the part-worth function model (piecewise linear) [6]. For the purpose of this study we choose the linear model because of its simplicity and popularity. However, we note the preference relaxation method does not restrict the choice and any model can be used. When a utility function is introduced, overall utility value of a product can be represented as:

\[
x_j = \sum_{i=1}^{m} w_i f(g_{ij}, p_i) \quad j \in \{1...n\}
\]

where \(g\) is the value of particular attribute and \(p\) is the decision maker preference on the attribute values. Modelling overall value of alternatives requires a function for mapping its attribute values and user preferences into utility values. Utility evaluation is an important problem addressed by many researchers in different contexts and decision-making environments [27]. In general, one can identify cost (e.g. price) and benefit (e.g. quality) attributes in MADM problems [28]. Typically, the goal of a decision maker is to minimise the value of cost attributes and maximise the value of benefit attributes.

2.2. Preference relaxation during the filtration process

When the set of alternatives to consider is large, a decision maker suffers from information overload. High cognitive load influences strategy selection and can negatively impact decision quality [15, 23]. Filtering is one of the techniques used to limit the number of information items in the set presented to the user, reducing information overload. The process of filtering involves the application of filtering rules (or restriction on attributes) to the items in the set to be filtered [29]. User preferences are the key input for alternative pre-filtration as only alternatives that fully satisfy all provided preferences are presented to the user as a result to his query.

We argue that preference relaxation would lower potential negative impact of dynamics in the decision makers’ preferences on attributes’ weights and values. Relaxation of preferences specified by a consumer causes a filtering rule to be less restrictive. Thus the products that satisfy the less strict filtration criteria, remain in the result set and can be further considered by the consumer (see Figure 1).

\[ X \] – set of all available alternatives  
\[ X_f \] – set after standard pre-filtration, contains only those alternatives that fully satisfy attributes’ values preference

Figure 1. Preference relaxation process.
The set of alternatives available for consideration is constructed based on the relaxed decision maker’s preferences. One can define a number of approaches for preference relaxation [30-32] proposing different methods to compute the extent of relaxation based on a relaxation factor $\delta$, in particular:

- **Relaxation proportional to preference range (value interval) (e.g. [30])** – relaxation is computed as a percentage of the size of the value range specified in consumer preference, $d^* = (d_L - \delta \times (d_U - d_L), d_U + \delta \times (d_U - d_L))$. For example, when $\delta = 0.1$ and preference on price $d_{\text{PRICE}} = (€7000, €8000)$ a relaxed preference would be equal, with $d^* = (€6900, €8100)$.

- **Relaxation proportional to preference values** – both lower and upper relaxation is proportional to lower and upper preference values (multiplied by $\delta$), $d^* = (d_L - \delta \times d_L, d_U + \delta \times d_U)$. For example, when $\delta = 0.1$ and preference on price $d_{\text{PRICE}} = (€7000, €8000)$ a relaxed preference would be equal to $d^* = (€6300, €8800)$. In this method the upper preference value is extended more than the lower limit, thus this method is more applicable in case of benefit-type attributes. In this study we concentrate on this method.

Selecting appropriate value of $\delta$ is not trivial, as it resembles closeness (similarity of values) and can differ among users [33]. However, some studies report that the maximum relaxation value $\delta_{\text{max}}$ should not be greater than $\frac{3-\sqrt{5}}{2}$ (~0.382) [32, 34]. Thus, the relaxation factor $\delta$ should be selected from the interval [0, ~0.382]. Although Mirzadeh and Ricci [30] report that relaxation parameters are attribute-dependent and should be tuned according to consumer sensitivity to changes in that feature, in our study we implemented the former relaxation approach to explore potential effects in the first instance, with a view towards possible expansion of parameters in future work. The fixed-interval relaxation approach is applicable to all types of attributes. We concentrated on numerical attributes in this paper as, following the literature [30], relaxation of binary and nominal (e.g. categorical) constraints is showed to be trivial as such constraints are typically discarded during relaxation process.

3. Hypotheses

We expect that the decision aid may impact various aspects of decision making, in particular decision quality and decision satisfaction. Consumers are typically not familiar with the available products and their characteristics [8], and their preferences are constructed while learning about the available alternatives [9]. We measured decision quality as the likelihood of selecting a non-dominated alternative. Häubl et al. [5] show that the share of considered products that are non-dominated indicates the quality of a consideration set, what positively impacts decision quality. Thus, we believe that increasing the share of non-dominated alternatives in a query result set will increase the likelihood of higher quality decisions in cases where the potential result set is large (more than 30 items) and small (less than 30 items). We propose the following hypotheses:

H1: Preference Relaxation increases the average share of non-dominated alternatives in the result set.
H2: Preference Relaxation increases the average utility of alternatives in the result set.

Decision aids designed to display large, more diverse numbers of alternatives may reduce decision makers' cognitive effort and improve decision quality by enabling individuals to make complex decisions with high accuracy [26]. However, as noted in this paper, such decision aids using filtering based on initial user preferences may prevent users from considering potentially interesting alternatives. Preferences Relaxation aims to provide alternatives of higher interest (utility) to the user, with minimum to zero effort gain. Decision aids allow decision makers to significantly reduce the amount of unnecessary information processed and may enhance the "quality" of the information that is processed, which, combined with reduced information quantity, should have a positive impact on decision quality [5]. Moreover, numerous studies indicate that decision aids that suggesting alternative products (e.g. recommendations) can significantly improve the quality of decisions [20, 22]. Thus, we argue that decision makers’ use of the preference relaxation aid suggesting high utility alternatives (with respect to stated preferences) will positively affect decision quality. In particular, we propose:

H3: Preference Relaxation increases the average share of non-dominated alternatives on the first page of results.

H4: Preference Relaxation increases the average utility of alternatives on the first page of results.

4. Evaluation

4.1. Dataset

The dataset in our studies consisted of 2650 used car advertisements collected from the most popular website in Ireland (http://carzone.ie/, a member of the Autotrader media group). Additional attributes for used cars in the set not present in advertisements, such as reliability, were automatically generated using standard information retrieval methods based on product reviews collected from various car reviews websites (e.g. whatcar.com). Generated attributes were classified as benefit-type and given scores ranging from 0 to 5 to resemble star ratings (e.g. 5 points for maintenanceCost describes the relatively lowest maintenance cost).

4.2. Method

Our experimental design is based on a common leave-one-out [35] approach in which we temporarily remove each alternative from the alternative library and use its description as a simulated user query. Based on user studies on importance of attributes in the used cars domain [36] and consisted with bounded rationality we chose 6 most popular attributes for our experiments. To best resemble user behaviour the preferences in our simulations were specified using a method resembling filtering interfaces of the popular websites, where value preference intervals were selected to resemble possible user entries. Every used car advert in the set was temporarily removed from the set and its values were used to create preference values (based on available preference
intervals). For example, a car at €3500 would be represented as a user search query with preference for price at (€3000–€4000). Simulations were run for combinations of 3, 4, 5, and 6 preferences and for relaxation factors ($\delta$) 0.05, 0.1, 0.2, and 0.3. Thus, for every simulation setup (a given number of preferences and a given $\delta$, a maximum of 2650 tests queries were issued (a case).

4.3. Results

Related samples non-parametric tests were carried out to compare average number of non-dominated alternatives in the result set for queries with and without the preference relaxation mechanism. For our analysis we included only the cases with non-empty result sets for at least one method (a total of 27221 cases). Thus, for the higher factor $\delta$ for a given setup, we observe a larger N (more relaxed query is less likely to return an empty set). Results show that on average, results set constructed using relaxation contained 24.35% of non-dominated alternatives in comparison to 15.94% for a non-relaxed case, representing a 52.76% improvement. The difference is statistically significant (p<0.001). There is significant improvement in the average share of superior solutions presented to a consumer when relaxation is present. As such, hypothesis H1 is supported.

Table 1. Average share of non-dominated alternatives (ND%), average utility (AvgUtil), and average result set size (ResSet) for relaxed (R) and not relaxed queries (NR) based on the relaxation extent.

<table>
<thead>
<tr>
<th></th>
<th>(\delta)</th>
<th>0.05</th>
<th>0.1</th>
<th>0.2</th>
<th>0.3</th>
</tr>
</thead>
<tbody>
<tr>
<td>ND%</td>
<td>R</td>
<td>24.97</td>
<td>24.81</td>
<td>24.37</td>
<td>23.42</td>
</tr>
<tr>
<td>ND%</td>
<td>NR</td>
<td>17.48</td>
<td>16.63</td>
<td>15.50</td>
<td>14.47</td>
</tr>
<tr>
<td>AvgUtil</td>
<td>R</td>
<td>0.354</td>
<td>0.373</td>
<td>0.395</td>
<td>0.416</td>
</tr>
<tr>
<td>AvgUtil</td>
<td>NR</td>
<td>0.206</td>
<td>0.196</td>
<td>0.183</td>
<td>0.171</td>
</tr>
<tr>
<td>ResSet</td>
<td>R</td>
<td>97.67</td>
<td>126.59</td>
<td>194.26</td>
<td>268.66</td>
</tr>
<tr>
<td>ResSet</td>
<td>NR</td>
<td>46.22</td>
<td>43.97</td>
<td>40.98</td>
<td>38.26</td>
</tr>
<tr>
<td>N</td>
<td></td>
<td>6205</td>
<td>6522</td>
<td>6998</td>
<td>7496</td>
</tr>
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</table>

Result sets constructed using preference relaxation had an average utility of 0.386, with 0.188 for the not-relaxed case (a 105.32% improvement). The difference was statistically significant (p<0.001). Preference relaxation resulted in an improvement of the average utility of alternatives presented to a consumer, and so hypothesis H2 is also confirmed (for details see Table 1).

Table 2. Average share of non-dominated alternatives in the result set (ND%) and average utility (AvgUtil), for relaxed (R) and not relaxed queries (NR) for result sets larger than 30 items based on the relaxation extent.

<table>
<thead>
<tr>
<th></th>
<th>(\delta)</th>
<th>0.05</th>
<th>0.1</th>
<th>0.2</th>
<th>0.3</th>
</tr>
</thead>
<tbody>
<tr>
<td>ND%</td>
<td>R</td>
<td>24.84</td>
<td>26.09</td>
<td>26.49</td>
<td>26.63</td>
</tr>
<tr>
<td>ND%</td>
<td>NR</td>
<td>16.89</td>
<td>16.01</td>
<td>15.34</td>
<td>14.82</td>
</tr>
<tr>
<td>AvgUtil</td>
<td>R</td>
<td>0.519</td>
<td>0.466</td>
<td>0.434</td>
<td>0.413</td>
</tr>
<tr>
<td>AvgUtil</td>
<td>NR</td>
<td>0.277</td>
<td>0.217</td>
<td>0.185</td>
<td>0.165</td>
</tr>
<tr>
<td>N</td>
<td></td>
<td>6205</td>
<td>6522</td>
<td>6998</td>
<td>7496</td>
</tr>
</tbody>
</table>
The second group of hypotheses was related to situations where the result set is very large and initially only part of the result set can be presented to a user (product pagination). As stated earlier, we used a threshold of maximum 30 alternatives filtered for presentation at the “first page” of results. Results showed that there is a significant difference in the average share of non-dominated alternatives in the result set with preference relaxation (25.99%) and without preference relaxation (15.89%). This difference is statistically significant (p<0.01), and so hypothesis H3 is accepted. With respect to the average utility of alternatives, results showed a 115.34% increase (from 0.215 to 0.463) when preference relaxation is present, confirming the hypothesis H4. The difference is statistically significant (p<0.01). These results indicate that preference relaxation allows consumers to initially screen alternatives of greater potential utility, thus increasing the likelihood of higher decision quality (see Table 2).

![Figure 2. Relative increase (%) of the share of non-dominated alternatives and the average share of the non-dominated alternatives in a result set based on the number of specified preferences.](image)

As stated before, our results indicate higher average share of non-dominated alternatives in result sets constructed using preference relaxation than in results sets constructed without using preference relaxation. Moreover, our findings indicate that the preference relaxation increases the average utility of alternatives in a result set. Furthermore, we note that higher numbers of specified customer preferences (more detailed information on decision maker’s preference) lead to higher benefits of using preference relaxation (see Figure 2).

5. Discussion

Our simulation-based experiments provide evidence that preference relaxation can facilitate consumers making higher quality decisions. Specifically, this research suggests that the relaxation of initial preferences provided by a consumer used for filtering products in online consumer scenarios can result in higher average utility of displayed alternatives. In scenarios where the whole result set can be displayed (that is, where there are up to 30 alternatives satisfying the filtering criteria), the average number of high quality alternatives is higher using preference relaxation. Further,
preference relaxation can compensate for any potential overspecification of user filtering criteria in product search [37]. In our study we performed simulations for 3, 4, 5, and 6 stated preferences. Our results confirm that preference relaxation enables retention of more high quality values in the result set (see Table 3).

Table 3. Average share of non-dominated alternatives (ND%), average utility (AvgUtil), and average result set size (ResSet) for relaxed (R) and not relaxed queries (NR) based on the number of stated preferences.

<table>
<thead>
<tr>
<th>Number of stated preferences</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
</tr>
</thead>
<tbody>
<tr>
<td>ND% R</td>
<td>22.73</td>
<td>24.32</td>
<td>25.14</td>
<td>25.63</td>
</tr>
<tr>
<td>ND% NR</td>
<td>16.94</td>
<td>16.07</td>
<td>15.39</td>
<td>14.87</td>
</tr>
<tr>
<td>AvgUtil R</td>
<td>+1.65</td>
<td>+1.63</td>
<td>+1.39</td>
<td>+1.28</td>
</tr>
<tr>
<td>AvgUtil NR</td>
<td>.406</td>
<td>.389</td>
<td>.375</td>
<td>.365</td>
</tr>
<tr>
<td>ResSet R</td>
<td>251.10</td>
<td>176.51</td>
<td>140.79</td>
<td>120.73</td>
</tr>
<tr>
<td>ResSet NR</td>
<td>79.96</td>
<td>40.90</td>
<td>24.75</td>
<td>16.70</td>
</tr>
<tr>
<td>N</td>
<td>5853</td>
<td>10529</td>
<td>8383</td>
<td>2456</td>
</tr>
</tbody>
</table>

Häubl and Murray [38] argued that instead of having well-defined, stable preferences that are merely revealed when making a purchase decision, consumers tend to construct their preferences when they are facing a product selection task, or when they are forced to express an evaluative judgment [39]. Preference relaxation can increase the diversity of products screened by a decision maker and thus encourage adjustment of his/her preferences, and as such is typically used in recommendation agents [2, 40]. We showed that preference relaxation can not only increase the diversity of the products but also prevent overspecification of consumer preferences. Our results indicate that overall, larger relaxation factors perform significantly better for all queries while keeping additional decision effort low.

6. Conclusions

This paper investigated the impact of preference relaxation on decision making. We argued that during the process of filtering of the initial, very large set of products, consumers eliminate alternatives they could later consider, by providing inaccurate preferences for attributes and attribute values. In this paper we introduced a model for a decision aid based on preference relaxation that can limit the potentially negative effects of the dynamic preferences of consumers addressing the limitations of existing methods. Moreover, we discussed the results of our experiments that show potential positive effect of preference relaxation on consumer decisions.

We showed that preference relaxation enables alternatives to be retained in that set that would otherwise be lost in an early elimination stage. If it positively impacts decision quality, the decision aid might result in higher decision confidence. As such, it is worthy of study. We believe that the e-commerce application of such a decision aid can be highly beneficial to providers of online shopping services: increased confidence of consumers leads to higher customer retention and, typically, higher profits [41]. Moreover, increased average quality of the alternatives considered by a decision maker would reduce decision-making effort. This would have direct relevance to online consumers, as well as having value to e-commerce providers.
We expect that a decision aid using preference relaxation may impact various aspects of decision making, in particular decision quality, consideration set quality and size. We plan to carry out a series of user studies to measure decision quality by the degree to which decision makers select a non-dominated alternative. Regarding decision quality as a decision maker’s degree of confidence in the correctness of his decision (discussed in the context of online shopping by Häubl and Trifts [5]), we propose to examine decision confidence in light of how often decision makers change their initial decision when they are offered a switching opportunity. Furthermore, it is possible that both the quality and the size of consideration sets are affected by the use of decision aids such as that described here. The size of the consideration set represents the number of alternatives that a decision maker is seriously considering. The share of considered products that are non-dominated indicates the quality of a consideration [5].

References


