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Comparing Techniques for Preference Relaxation: a Decision Theory Perspective

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Abstract. This research proposes a decision aid based on a novel type of preference relaxation, which enables consumers to easily make quality choices in online multiattribute choice scenarios. In contrast to filtering and recommendation mechanisms that are a potential solution to this problem, our method combines decision theory with preference relaxation and enables consumers to consider high-quality alternatives they initially eliminated. We compare our approach with existing methods using a set of 2650 car advertisements gathered from a popular advertiser website. We discuss the potential impact of our method on decision quality and give an overview of implications for practitioners and researchers.

Key words: Decision Theory, Recommender Systems, Preference Relaxation, eCommerce

1 Introduction

Online stores tend to provide large numbers of products with a variety of features. Consumers making purchase decisions are often unable to evaluate all available alternatives in great depth, and so seek to reduce the amount of information processing involved[1]. To prevent information overload online retailers provide product search and filtering functionality, usually by requesting users to fill in a form asking about the requirements that a desired product has to satisfy (their 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* [2] . Although such choice-based approaches are prevalent, both users and retailers can find them unsatisfying. One of the major reasons is that users are often not able to correctly transform their preferences into requirements using online forms [2], and thus they are rarely provided with the information they need.

In this paper we study the impact of a preference relaxation mechanism on consumer decision making, and implement it as a decision aid. We argue that during the process of preference-based filtration of an initial, very large, set of product alternatives consumers can eliminate products they might later consider valuable. We introduce a method that uses preference relaxation to extend the initial value preference and to include initially filtered out alternatives of potential high utility for further consideration. As such, a consumer is able to revise her criteria, consider more products and choose a configuration she finds the most suitable, but which may not fully fit her initial preference. In this paper we describe a model of a decision aid implementing our method, and present results of a simulation-based study using 2650 car advertisements gathered from one of the most popular websites in Europe.

2 Theoretical Background

2.1 Information Filtering and Recommender Systems

Information Filtering techniques typically perform a progressive removal of non-relevant content based on the information in a user profile acquired either in an implicit (e.g. studying user behavior) or an explicit (e.g. asking user to state his preferences) manner. These techniques provide a theoretical foundation for building recommender systems [3] that enable content personalization - an important stream of research in e-commerce.

Numerous studies [4, 2] use recommendations to improve consumer decision-making. Providing a consumer with a relevant (similar to their stated preferences) yet diverse (so that they can discover new opportunities and adjust their preference model) set of alternatives has become an important research problem [5]. According to the *Look-ahead* principle [2],"suggestions should not be optimal under the current preference model, but should provide high likelihood of optimality when an additional preference is stated". Furthermore, dynamism in user preferences [6] is a problem recognized in Recommender Systems research.

2.2 Preferences in Decision Theory

Assumptions that the decision maker can accurately state (and indeed bound) which levels within an attribute are acceptable versus unacceptable is a fundamental to a self-explicated approach [7]. Decision-makers (DM) 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 further consideration. Product search and filtering mechanism offered online adhere to that approach, and filter out all products that do not fully fulfil stated requirements. However, previous research indicates that decision makers tend to fail to fully adhere to the self-explicated approach. Klein [8] found that decision makers often fail to reject alternatives with attribute levels which they themselves had previously described as unacceptable, and showed that significant numbers of participants can choose an alternative described with at least one attribute level they initially indicated as completely unacceptable. Preference relaxation mechanisms may assist in alleviating this problem. Further, a decision aid supporting preference relaxation can be seamlessly integrated with the existing online shopping websites to improve consumer decisions. The rigidity of typical preference elicitation (filtering) mechanisms is a well-established problem [9] that can potentially lead to the elimination of all available products from consideration. Over-specification of consumer requirements leading to an empty result sets motivated research on similarity based-retrieval [10] and query (preference) relaxation [11]. The process of filtering involves the application of filtering rules (or restriction on attributes) to the items in the set to be filtered [11, 9]. Consumer 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. Mirzadeh and Ricci proposed a mechanisms for preference relaxation for failing queries (producing an empty result set) [11]. However, they do not investigate the impact of the extent of relaxation on decision maker behaviour, and their method is applicable primarily to failing queries.

Our research differs 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 impact decision making.

3 The Decision Aid

You intend to buy a car priced between €7000 and €8000 with reasonable mileage (25000 to 75000 km). Would you be willing to pay slightly more (€8100) for a car with mileage lower than you expected (11000 km)? The ability to locate cars with such attribute values which, albeit out of the boundary ranges specified, may provide consumers with a better awareness of possible choices. The method proposed here enables consumers to consider products that would ordinarily be eliminated early in the selection process by falling outside rigid preferences. In the subsections below we discuss our approach in more detail and contrast it with common simple preference relaxation methods.

3.1 Edge Sets

Typically, preferences on numerical attributes are expressed using value ranges. As such, we allow the decision maker to specify his/her attribute value range preference for an i-th attribute as $d = (d_L, d_U)$ where d_L (d_U) indicates the lowest (highest) acceptable value for a given attribute. We now introduce softening variables e_U (upper) and e_L (lower), and a relaxation factor δ (where $e_i = \delta * d_i$), which enhance the filtering rule (value range) built based on attribute value preference p causing the filtering rule to be less restrictive. The alternatives that satisfy the less strict preference $d^* = (d_L - e_L, d_U + e_U)$ remain in the set and can be considered by the DM. However, this approach, commonly referred to as Simple

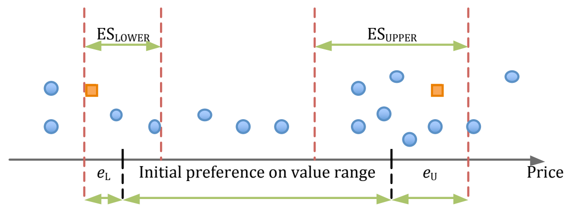

Fig. 1. An example of an Edge Set for a user price preference.

Preference Relaxation (SR), can significantly increase the number of alternatives presented to the user, resulting in information overload and increasing decision effort [12]. In order to prevent these negative effects we use approach based on a concept of Edge Set (ES). We conceptualize an Edge Set as a set of alternatives that fall into a value range based on the initial consumer value preference for a given attribute (see Fig. 1). For every preference value range two edge sets can be constructed (lower and upper), respectively: $ES_{LOWER} = (d_L - e_L, d_L + e_L)$ and $ES_{UPPER} = (d_U - e_U, d_U + e_U)$. We explain this concept using price range preference p_{PRICE} =(€3000, €4000). For example, assuming softening variables e_U =€200 and e_L = €150 (5% of respective preference interval boundaries' values) we can construct ES_{LOWER} =(€3000 - €150, €3000 + €150) resulting in ES_{LOWER} =(€2850, €3150) and ES_{UPPER} =(€4000 - €200, €4000 + €200) resulting in ES_{UPPER} =(€3800, €4200). Thus, ES_{LOWER} will contain cars that fall into the (€2850, €3150) price range.

3.2 Information Filtering Using Edge Sets

The inclusion of all alternatives satisfying the relaxed criteria would ordinarily increase the number of items presented to the DM, contributing to information overload. To address this issue we incorporate a selection mechanism into our relaxation method that includes only some of those cases (see Algorithm 1). First, we create edge sets (ES) based on relaxed preferences (e.g. $ES_{LOWER} = (d_L - e_L, d_L + e_L)$ for a lower preference boundary) using a selected δ (e.g. 0.05). Second, for every ES we identify the subset of all non-dominated alternatives (also referred to as the skyline [13]) that are part of this set. An item is non-dominated if no other item is better for any preference on attribute without being worse for at least one preference on other attributes [14]. If a non-dominated item is a member of an edge set and it does not satisfy the non-relaxed initial DM preferences (is not a member of $ResultSet_{NR}$) it is added to the set of *Suggestions*, as it may be found valuable. We define two methods for inclusion of *Suggestions* in the result set presented to a consumer. First, we propose to add

Input: $Products$, $Preferences$, δ, $Method$
Output: $ResultSet_{SBR}$
$SKYLINE \longleftarrow$ findSkyline($Products$);
$ResultSet_{NR} \longleftarrow$ filter($Products$, $Preferences$);
$PREF_{RELAXED} \longleftarrow$ relaxPreferences($Preferences$, δ);
$SUGGESTIONS \longleftarrow \emptyset$;
$EdgeSet \longleftarrow$ filter($Products$,$PREF_{RELAXED}$) ;
foreach $Product\ p \in EdgeSet$ **do**
    if $p \in SKYLINE$ *and* $p \notin ResultSet_{NR}$ **then**
        $SUGGESTIONS \longleftarrow SUGGESTIONS \oplus p$;
    end
end
if $Method = ADD$ **then**
    $ResultSet_{SBR} \longleftarrow ResultSet_{NR} \oplus SUGGESTIONS$;
end
if $Method = REPLACE$ **then**
    $LowUtilSet \longleftarrow$ findLowUtil($ResultSet_{NR} \cap EdgeSet$, $|SUGGESTIONS|$);
    $ResultSet_{SBR} \longleftarrow ResultSet_{NR} \ominus LowUtilSet$;
    $ResultSet_{SBR} \longleftarrow ResultSet_{SBR} \oplus SUGGESTIONS$;
end

Algorithm 1: The Soft Boundary Preference Relaxation Mechanism

suggestions to an initial result set constructed using a non-relaxed (NR) query. This method, further referred to as SBR_{ADD} (Soft Boundary Preference Relaxation with addition), may lead to increases in the size of result sets. To address this drawback and to prevent an increase in cognitive load we propose an alternative method. Instead of simple addition to the set, the method would replace dominated, low-utility items from a non-relaxed result set ($ResultSet_{NR}$) that belong to the EdgeSet, with high-utility alternatives. We refer to this method as SBR_{REP} (Soft Boundary Preference Relaxation with replacement). With this approach, the total size of the set is kept constant, and the alternatives with lowest utility according to current preference model (in this study we use the WADD model) are substituted with items from the skyline. We further refer to to these two mechanisms as SBR (Soft Boundary Preference Relaxation).

As indicated earlier, our method assumes variables e_U (upper) and e_L (lower), and a relaxation factor δ, which relax the value preference p. Selecting an appropriate value of δ is not trivial, as it resembles *closeness* (similarity of values) and can differ among consumers [15]. However, some studies [16, 17] report that the maximum relaxation value δ_{max} should not be greater than $(3 - \sqrt{5})/2$, that is 0.382. Thus, the relaxation factor δ should be selected from the interval $[0, 0.382]$ to satisfy the concept of closeness [17]. Although Mirzadeh and Ricci [11] 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 simpler relaxation approach to explore potential effects in the first instance, with a view towards possible expansion of parameters in future work. Although our approach is applicable to all types of attributes, in this study we investigate the methods that use numerical attributes as, commensurate with the literature [11], relaxation of binary and nominal constraints is trivial, as they are typically discarded during the relaxation process.

4 Hypotheses

Many dependent variables have been proposed as good indicators of the impact of decision aids on DM performance [18, 19, 1]. In our study we concentrate on three common measures, that is: decision quality, decision effort and diversity of a set of considered alternatives.

Previous studies [18, 14] assess decision quality as a match between actual DM's choice from a set of alternatives and the "ideal selection" (a *non-dominated* alternative [14]). Hostler et al. [18] and Häubl and Trifts [14] have used such conceptualization of decision quality as a measure of decision performance. Our Soft Boundary Preference Relaxation method leads to better decisions by facilitating the consideration of a larger number of high quality alternatives by DMs. Consequently, compared to non-relaxing methods, we propose:

H1.1: Simple Preference Relaxation increases decision quality.

Similarly, our method should allow consumers to locate products that more closely match their preferences further improving decision quality:

H1.2: Soft Boundary Preference Relaxation increases decision quality.

The level of effort required to make a decision is another common decision performance indicator [1]. Ideally, the better support offered by a decision aid, the lower the cognitive effort required by a DM to make a decision. Effort is directly related to the amount of information that needs to be considered by a DM [20, 12]. Intuitively, preference relaxation mechanisms increase effort by relaxing rigid requirements, and therefore incorporating more alternatives for consideration by a DM. We expect that our method will not lead to a significant increase in decision-making effort due to an increased number of products included for consideration. Compared to non-relaxing methods, we propose:

H2.1: Simple Preference Relaxation increases decision-making effort.
H2.2: Soft Boundary Preference Relaxation does not increase decision-making effort.

Selection of a product is considered context dependent, as the relative value of an option depends not only on the characteristics of that option, but also upon characteristics of other options in the choice set [21]. According to behavioral decision theory [1, 22] the existence of such context impacts the perceived quality of available products. Indeed, Tversky [22] pointed out that in such contexts, DMs tend to adjust their initial preferences based on available choices, in contrast to maximizing pre-computed preferences. Further, the diversity of an RS is important in Recommender Systems research [23]. Consequently, we argue that preference relaxation mechanisms will increase the diversity of a result set.

H3: Soft Boundary Preference Relaxation increases result set diversity.

5 Evaluation

5.1 Dataset

The dataset consisted of 2650 used car advertisements collected from the most popular website in Ireland (http://carzone.ie/, a member of 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 car review 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).

5.2 Method

Our experimental design was based on a *leave-one-out* (LOV) [10] approach in which we temporarily removed each alternative from the dataset and used its description as a DM preference. Based on user studies on importance of attributes in the used cars domain [24], and consistent with bounded rationality we chose 6 most popular attributes for our experiments. To best resemble user behaviour the preferences in our simulations were constructed similarly to filtering interfaces of the popular websites, where value preference intervals were selected to simulate possible user entries. Using the LOV approach, 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 1 to 6 stated preferences and for relaxation factors 0.05, 0.1, 0.2, 0.3 and 0.382 (δ_{max}). Thus, for every set of parameters a maximum of 2650 *non-failing relaxed* queries were issued and relevant result sets were constructed for all four investigated methods: non-relaxed (NR), Simple Preference Relaxation (SR), Soft Boundary Preference Relaxation with Addition (SBR_{ADD}), and with Replacement (SBR_{REP}). Particular characteristics of these constructed result sets (see the next section) were assessed and compared to evaluate the methods under investigation.

5.3 Indicators

In our study a number of indicators were used to evaluate the four methods: non-relaxing (NR), Standard Preference Relaxation (SR), Soft Boundary Preference Relaxation with addition (SBR_{ADD}), and with replacement (SBR_{REP}).

Decision quality is a common indicator of performance. Häubl et al. [14] showed that the share of considered products that are non-dominated indicates the quality of a set of products considered by a consumer, which positively impacts decision quality. Conversely, we measured decision quality using a share of non-dominated alternatives present in the result set. Further, we note that decision quality is directly related to fulfilling particular DMs criteria for product selection (preferences) that can be measured by the utility of selected alternatives [4]. The higher the average utility of alternatives presented for choice, the more suitable options can be considered. Thus, we propose to measure decision quality using the average utility of a result set (where $AvgUtil \in [0, 1]$).

Information overload is an important factor that increases decision making effort and leads to changes in strategies employed by decision makers when selecting a product [20]. Following [21], we propose to measure decision making effort by the number of alternatives presented for consideration by a DM (that is, the size of a result set).

Vahidov [25] has indicated the importance of result set diversity in decision making. In our study we use a common conceptualization of normalized diversity ($diversity(ResultSet) \in [0, 1]$) that is inversely proportional to similarity, following the relation presented by Smyth and McClave [5]. We compute similarity using a law proposed by Shepard [26] stating that perceived similarity of items is related to their distance via an exponential function $sim(A, B) = e^{-distance(A,B)}$.

5.4 Results

We used related samples non-parametric tests to compare the average share of nondominated alternatives in the RS for queries using the preference relaxing mechanisms discussed in this study, with no preference relaxation. Results show that on average, RS constructed using relaxation contained significantly more non-dominated alternatives than the result sets constructed using no relaxation. In particular, we observed on average 23.92% (SR) of non-dominated alternatives in contrast to only 15.58% in case of non-relaxing methods (NR) (see Table 1). Similar results were obtained for average utility of alternatives in a RS ($AvgUtil_{NR} = 0.1879$ and $AvgUtil_{SR} = 0.3957$)). These differences were statistically significant ($p<0.001$) thus confirming the hypothesis H1.1. Similarly, our results indicate that the use of the SBR mechanism improves the share of non-donimated alternatives in a result set in contrast to both non-relaxing (NR) and simple relaxation (SR) methods. We observed 58.65% (SBR_{ADD}), and 68.65% (SBR_{REP}) of non-dominated alternatives in contrast to 23.92% (SR) and 18.79% (NR). These differences were statistically significant ($p < 0.001$). Although the average utility of alternatives in a RS was similar to all preference relaxing methods with 0.3975 (SR), 0.3730 (SBR_{ADD}), and 0.3747(SBR_{REP}) the extent of improvement in the average share of non-dominated alternatives in a RS provides evidence for accepting H1.2.

The second group of hypotheses relates to the decision-making effort measured by a number of items from which DM has to select. For the methods investigated, we observed on average 229.73 (SR), 68.94 (SBR_{ADD}), and 57.54 (SBR_{REP}) items in the result set in contrast to only 51.10 items on average in a result set for non-relaxed queries (NR). These differences are statistically significant ($p<0.001$), confirming H2.1 and indicating rejection of H2.2. Finally, results indicate that the diversity of sets of alternatives generated using preference relaxation methods are more diverse than when no relaxation is used. In particular, we observed an average diversity of 0.1455 (SBR_{ADD}), 0.1463

Table 1. Average: utility (AvgUtil), share of non-dominated alternatives in the result set (%ND), and result set size ($|RS|$) for relaxed (SR), non-relaxed (NR), SBR with addition (SBR_{ADD}) and replacement (SBR_{REP}) for number of stated preferences N.

	N	1	2	3	4	5	6	Avg
AvgUtil	NR	0.3414	0.2792	0.2197	0.1851	0.1638	0.1498	0.1879
	SR	0.4533	0.4263	0.4123	0.3981	0.3869	0.3784	0.3975
	SBR_{ADD}	0.4892	0.4460	0.4029	0.3721	0.3509	0.3360	0.3730
	SBR_{REP}	0.5056	0.4541	0.4064	0.3735	0.3513	0.3357	0.3747
%ND	NR	12.25%	17.26%	16.62%	15.65%	14.91%	14.36%	15.58%
	SR	12.10%	18.87%	22.54%	24.18%	25.05%	25.57%	23.92%
	SBR_{ADD}	21.16%	43.77%	54.77%	59.48%	61.87%	63.27%	58.65%
	SBR_{REP}	25.37%	54.27%	65.46%	69.60%	71.47%	72.46%	68.65%
$\|RS\|$	NR	673.31	201.97	78.46	39.82	23.97	16.13	51.10
	SR	1057.82	494.97	291.61	213.15	175.39	154.08	229.73
	SBR_{ADD}	712.17	231.31	99.63	56.93	38.86	29.64	68.94
	SBR_{REP}	673.33	205.92	84.14	46.20	30.68	23.02	57.54
Diversity	NR	0.1560	0.1212	0.0913	0.0839	0.0754	0.0694	0.0837
	SR	0.2503	0.2134	0.1735	0.1661	0.1585	0.1537	0.1669
	SBR_{ADD}	0.1963	0.1812	0.1526	0.1463	0.1375	0.1311	0.1455
	SBR_{REP}	0.1945	0.1838	0.1542	0.1468	0.1379	0.1316	0.1463

(SBR_{REP}, and 0.1699 (SR) in contrast to 0.0837 for a non-relaxing method (NR) (see Table 2). These differences were statistically significant ($p < 0.001$), confirming H3. Results of the study are summarized in Table 3.

5.5 Discussion

Our study highlights the benefits of using preference relaxation from a decision making perspective. First, we showed that preference relaxation methods lead to construction of RS with a higher average utility ('usefulness') and a greater share of non-dominated alternatives. Furthermore, we demonstrated the positive impact of our method on the diversity of alternatives in the result set, what (following [25], may lead to higher DM satisfaction. In addition, we showed that standard Preference Relaxation (SR) induces very significant growth of the size of a result set leading to unacceptable level of increase in the decision-making effort. We proposed two variants of our method (SBR) that addresses this disadvantage. We demonstrate that our methods outperform the SR method and minimize the additional decision-making effort. In particular, for a low number of explicated preferences ($N < 3$), the difference in the size of a result set for SBR_{REP} and no-relaxing method (NR) is not statistically significant (see Table 1). Furthermore, when comparing the (SBR_{REP}) and the non-relaxed method (NR), we observed 12.6% increase in the average size of a result set (57.54 and 51.10 respectively), however we found a large (340,6%) increase in the share of non-dominated alternatives (68,65% and 15.58% respectively). Moreover, we note that for low values of relaxation factor (e.g $\delta = 0.05$) we observed

Table 2. Average: utility (AvgUtil), share of non-dominated alternatives in the result set (%ND), and result set size ($|RS|$) for relaxed (SR), non-relaxed (NR), SBR with addition (SBR_{ADD}) and replacement (SBR_{REP}) for different values of δ.

	δ	0.05	0.1	0.2	0.3	0.382	Avg
AvgUtil	NR	0.2107	0.2009	0.1878	0.1758	0.1702	0.1879
	SR	0.3537	0.3752	0.3964	0.4171	0.4310	0.3975
	SBR_{ADD}	0.3327	0.3430	0.3623	0.3939	0.4204	0.3730
	SBR_{REP}	0.3369	0.3455	0.3637	0.3949	0.4206	0.3747
%ND	NR	17.47%	16.65%	15.57%	14.57%	14.12%	15.58%
	SR	24.65%	24.50%	24.07%	23.13%	23.49%	23.92%
	SBR_{ADD}	39.70%	46.05%	58.12%	69.16%	74.95%	58.65%
	SBR_{REP}	46.09%	54.65%	69.73%	80.92%	85.87%	68.65%
$\|RS\|$	NR	57.51	54.85	51.28	48.00	46.49	51.30
	SR	113.04	142.64	211.53	286.60	359.07	229.73
	SBR_{ADD}	63.34	63.59	67.22	71.50	77.06	68.94
	SBR_{REP}	58.33	56.38	55.50	56.76	60.48	57.54
Diversity	NR	0.0939	0.0895	0.0837	0.0783	0.0759	0.0837
	SR	0.1393	0.1497	0.1728	0.1808	0.1848	0.1669
	SBR_{ADD}	0.1182	0.1211	0.1445	0.1636	0.1718	0.1455
	SBR_{REP}	0.1169	0.1208	0.1461	0.1647	0.1743	0.1463

only 1.4% increase in the average size of the result set between SBR_{REP} (58.33 items) and NR (57.51 items) (see Table 2). On the other hand, results indicate a 163,8% increase in the share of non-dominated items (from 17.47% for NR to 46.09% for SBR_{REP}) and 59.9% increase in average utility (from 0.2107 for NR to 0.3369 for SBR_{REP}). As such, we highlight the strong positive impact of SBR_{REP} on our decision-making indicators, with minimum negative impact on effort compared with other relaxation methods (see Fig. 2), and show that, overall, our method outperforms standard preference relaxation mechanisms.

Table 3. The summary of results.

Hypothesis		Result
H1.1	Simple Preference Relaxation increases decision quality	supported
H1.2	Soft Boundary Preference Relaxation increases decision quality	supported
H2.1	Simple Preference Relaxation increases decision-making effort	supported
H2.2	SBR does not increase decision-making effort	not supported
H3	SBR increases result set diversity.	supported

6 Conclusions

This paper investigated the impact of preference relaxation on decision performance measures. We argued that during the process of filtering of the initial, very

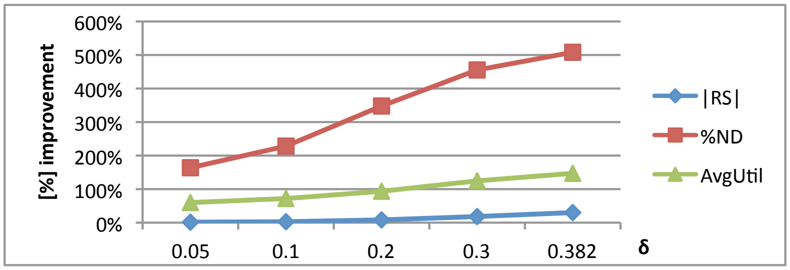

Fig. 2. Relative improvement in the size of a RS ($|RS|$), the share of non-dominated alternatives (%ND) and the average utility of alternatives in a set (AvgUtil) for SBR_{REP} compared with no relaxation (NR) for different values of δ

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. The e-commerce application of our method may be highly beneficial to providers of online shopping services: diverse result sets may lead to more consumer satisfaction and potentially higher customer retention [25]. 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.

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