The performance of recommender systems in online shopping: a user-centric study

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Abstract. This research investigates the effects of preference relaxation on decision-making performance of users in online preference-based product search contexts. We compare four recommender systems based on different preference relaxation methods in extensive user experiments with 111 subjects that use two real-world datasets: 1818 digital cameras and 45278 used car advertisements gathered from popular e-commerce websites. Our results provide new insights into the positive impact of the soft-boundary preference relaxation methods on decision-making quality and effort. The paper extends previous studies on this topic and demonstrates that decision aids based on preference relaxation techniques can effectively enhance preference-based product search in online product catalogues and help alleviate common disadvantages of form-based filtering mechanisms.

Keywords: Recommender Systems, Decision Theory, Preference Relaxation, E-Commerce.

Abbreviations: NR – No Relaxation, SR – Standard Relaxation, SBR – Soft-Boundary Preference Relaxation, SBR_{ADD} – Soft-Boundary Preference Relaxation with Addition, SBR_{REP} – Soft-Boundary Preference Relaxation with Replacement.

1 Introduction

Building upon and extending recent work by Dabrowski and colleagues (Dabrowski, Acton, & Van der Heijden, 2012) wherein various preference relaxation techniques were employed in a series of simulations, we evaluate their approach in a user study with a larger data set and compare our findings to the results of their simulations. Each of the 111 participants of our user experiment was asked to choose a car from a set of 45278 actual advertisements published by the biggest used car portal in Ireland. The experiment focused on user-centric measures of decision performance including decision quality and effort, in contrast to the set of simulations described by Dabrowski and Acton (Dabrowski et al., 2012), where the effect of decision quality and effort were measured without user participation. We show that our user experiment enhances that study by providing new insights to decision-making performance of preference relaxation in product search and accordingly, we suggest possible improvements to the method directly applicable to online retailers.

There has been a rapid growth in online consumer purchase transactions over the last decade, with the online product sales exceeding $140 billion in 2010 and predicted to reach $279 billion in 2015 (Wauters, 2011). Online product stores offer large numbers of products such as books[1], cars[2] or plane tickets, leading to difficulties for the consumers to find the product they want (Viappiani, Pu, & Faltings, 2007). Another issue with the availability of large numbers of products can also negatively impact usability and ease of use – two features of online product catalogues important for consumer retention (Chen & Macredie, 2005). Unfortunately, large quantities of product alternatives, as well as a large number of product attributes contribute to information overload (Todd & Benbasat, 1994) and lead to increased effort required to make a purchase decision (Parra & Ruiz, 2009). These problems typically result in consumers making compromises (i.e. choosing products that may only partially satisfy their needs) and may lead to lower choice satisfaction and affect consumer retention – a major issue for online retailers. On the other hand, such variety of products increases choice, and together with higher awareness of available alternatives may lead to higher satisfaction and better quality of purchase decisions. Theories, techniques, and tools that address the above issues, improve product search in online catalogues and guide consumers to the most suitable alternatives have been widely studied (Bergmann, Schmitt, & Stahl, 2002; Bridge, Goker, McGinty, & Smyth, 2005; Pu, Viappiani, & Faltings, 2006). Such tools have a direct effect on decision-making performance of online shoppers and can be assessed using various user-

[1] Amazon makes more than 32 millions of books available, see http://amazon.com/

[2] Autotrader is a website that offers about 2 millions of used cars on the USA market, see http://autotrader.com/

centric measures, which include decision quality and decision effort (see (Xiao & Benbasat, 2007) for a more complete overview). On one hand, existing studies (Todd & Benbasat, 1993, 1994) argue the importance of minimisation of decision effort, yet focus on quality of choice is crucial in high-risk choice tasks (e.g. shopping for a car or a house) (Spiekerman, 2001), where the cost of making low-quality decisions can be very high. In this paper we discuss how decision aids can support online shoppers in high-risk choice tasks and evaluate the impact of four different preference relaxation approaches on decision-making performance in online shopping focusing on two major factors: decision effort and quality.

1.1 Motivation

Decision support systems, typically implemented as web-based decision aids in online stores address a number of choice-related issues attributed to large number and variety of available products and offer assistance for consumers in making satisfactory and quality purchase decisions. Such support mechanisms span a multitude of functionalities, for example, filtration of large amounts of data based on preferences or historical activity, visual aids to identify good options, or recommender systems based on a variety of heuristics. Ultimately, the goal of these systems is to elicit consumers' preferences and help them identify subsets of relevant products facilitating accurate decisions (Zhang & Jiao, 2007), possibly with lower effort. This process of searching online product catalogues to locate the product(s) that best match consumer's product needs is often referred to as *preference-based search* (Viappiani, Pu, & Faltings, 2008) and involves frustrating, iterative refinement of preferences to filter out unwanted products (Hagen, Manning, & Paul, 2000). However, consumers faced with a purchase decision tend to construct their preferences when they browse available offers (J W Payne, Bettman, & Johnson, 1992) and often are unable to express their actual requirements using available search parameters with the form-filling interfaces used by major retailers (Klenosky & Perkins, 1992) such as Amazon or eBay. Moreover, search parameters tend to be exclusive and non-compensatory, and remove alternatives that do not conform to strict parameters, a process typically referred to as logical product filtration. Filtration can eliminate choice alternatives only based on one unsuitable attribute value (for example, slightly high weight of a camera) even if all other attributes (e.g. price, quality, size, and other attributes), with that camera becoming 'invisible' to the consumer, and destroying any opportunity for its selection. As such, there may be a need for support systems that can provide online consumers with lists of products that do not necessarily *fully* match their stated preferences – so called *suggestions* or *recommendations* (Kim, Kim, & Cho, 2008; Lee, Liu, & Lu, 2002), but that can recognise high quality alternatives even where particular attribute values might suggest otherwise. Preference-based search tools intent on improving consumer decision making performance (Kim et al., 2008) are referred to as recommendation agents (RAs) (Xiao & Benbasat, 2007).

In this paper we focus exclusively on preference-based search and apply it in an extensive user study, with particular emphasis on the recommendation agent that uses various preference relaxation approaches to improve consumer choice in high-risk scenarios where there are large numbers of potential product alternatives. Examples of such scenarios include purchasing a digital camera or a used car from an online shop where there are many makes and models available, each with varying characteristics and the cost of low-quality decisions is very high. Our approach (see Section 3) primarily focuses on reducing the number of erroneously filtered-out products by intelligent relaxation of preferences provided by a consumer. Secondly, many of the existing methods for the computation of product suggestions require prior knowledge or history of user interactions and preference models, which are not required in our approach. Therefore, the preference relaxation approaches discussed in this paper are easily applicable to any e-commerce platform that employs form-based product filtration mechanisms.

Our work contributes to theory and practice of recommender systems and online shopping through a user-focused evaluation of preference relaxation methods using a large real-world product dataset and online shopping site, which to this point have only been evaluated in a set of simulations with a smaller dataset and without user involvement. We present and compare four methods for preference-based product search with a focus on their impact on decision quality and effort, going beyond the focus of existing studies. This paper also includes a methodological contribution as we review results achieved in simulations based on a classical Information Retrieval approach and compare them to user experiments drawing from Information System theories. We show that the use of preference relaxation in product search is a valuable approach to product recommendation. Our user experiment demonstrates that classical approaches to preference relaxation (Mirzadeh & Ricci, 2007) fail to increase consumers' decision-making performance despite promising results achieved in previous work (Dabrowski et al., 2012). We show that although the results of previous studies suggest positive effects of the Standard Preference Relaxation (see Section 3) on decision performance, the strong negative effects on decision effort compromise the potential gain in decision quality. In contrast, our experiments show that the Soft-Boundary Preference Relaxation methods have a positive effect on decision quality and indicate lower decision effort. Finally, based on the information we collected in our study, we identify further areas of improvement and propose a set of extensions to the Soft-Boundary Preference Relaxation method that will further improve decision performance in online shopping.

2 Related work

2.1.1 Decision process in online shopping

Consumer choice studies show the existence of stages in the decision process, during which the number of brands and products decreases until a final choice is made (Roberts & Lattin, 1991). Prototypical choice process is based on "hierarchical or nested sets of alternatives" processed by the decision-makers prior to actual choice (Shocker, Ben-Akiva, Boccara, & Nedungadi, 1991) also referred to as *sequential choice*. In this process, the *universal set* is conceptualized as a set of all available products or services that can be obtained or purchased by any consumer under any circumstance, however may include items not relevant to a given consumer (Shocker et al., 1991). The universal set is often divided into a set of products that consumer does not have knowledge about and those that he or she is aware of (Roberts & Lattin, 1991) referred to as the *awareness set* consisting of products relevant for the consumer's purchase goal (Roberts & Lattin, 1991). For example, when shopping for the SLR digital camera using a large online product catalogue (such as amazon.com), all SLR cameras available for purchase constitute the awareness set for a given consumer. Wu and Rangaswamy (Wu & Rangaswamy, 2003) suggest that consumers do not choose products from a universal set of alternatives, but form a subset of all alternatives they are aware of by selecting only those which are both accessible and goal satisfying to form a *consideration set* (Holden, 1994). Consideration sets are also conceptualised as the set of alternatives a decision maker considers seriously for choice (Gilbride & Allenby, 2004) or that remain under consideration as potential choice selections after initial screening (G Häubl & Trifts, 2000). Thus, the size of this set tends to be small in comparison to the total number of alternatives available (Bearden, Hardesty, & Rose, 2001; Simonson, Nowlis, & Lemon, 1993). Consideration set formation is a fundamental stage of pre-choice decision-making (Aurier, Jean, & Zaichkowsky, 2000; M. D. Johnson & Lehmann, 1997) as only products that enter the consideration set can be selected for purchase in the final stage. Large numbers of potentially suitable products that cause information overload may lead to creation of low-quality consideration sets and negatively impact final decisions of online shoppers. Therefore, the tools that guide online consumers should alleviate the negative effects of information overload and facilitate construction of high-quality consideration sets.

2.1.2 Effects of information overload on decision performance

When consumers are not able to evaluate all available alternatives in detail due to high information processing effort required, they undertake a two-stage process, first screening and filtering available alternatives and then performing a detailed analysis of the reduced, more manageable (consideration) set (Parra & Ruiz, 2009). When a given product enters the consideration set of a consumer, its chances of being chosen increase even if the product is not the most preferred (Andrews & Srinivasan, 1995). When the number of available products is high, hence demanding high processing effort levels to examine them all or a large number of them, consumers tend to use simplifying heuristics (John W Payne, Bettman, & Johnson, 1993) such as 'screening' (Klenosky & Perkins, 1992). However, an alternative that is not included in the consideration set will not be chosen (Nedungadi, 1990). Another limitation lies in the lack of explicit incorporation the dynamics of consumer search process in consideration set formation is a limitation of existing consideration set models. Payne, Bettman, and Schkade (J W Payne, Bettman, Schkade, & Natl Sci, 1999) suggest that consumer choices should be based on careful consideration of a range of options and those objectives most critical to the individual. However, this is typically not the case in online product catalogues where consumers often erroneously filter out high-quality products based on inaccurate preferences (Klein, 1987). Also, consumers may believe that they have already sufficiently considered the important attributes when forming a consideration set, and may not pay enough attention to these key attributes when making their final choice, potentially leading to a lower quality of choice and lower satisfaction.

2.1.3 Drawbacks of popular approaches

A lot of research on decision aids for consumers shopping for products online has been conducted to address the challenges related to maximization decision quality and minimization of decision effort (Felfernig, Friedrich, Jannach, & Zanker, 2007; Komiak & Benbasat, 2006; Murray & Häubl, 2009; Pu & Faltings, 2000; Stolze, 2009). Such r*ecommendation agents* are designed to support consumers in making better purchase decisions, through increasing decision quality and/or reducing the effort required to make a product choice. Existing approaches can be classified into the following four categories: (1) similarity-based systems, (2) utility-based tools, (3) form-based interactive filtering tools, and (4) preference relaxation. Similarity-based systems (Resnick & Varian, 1997) are considered the most popular tools that utilize the concept of similarity of products for supporting consumers in their shopping decisions. These tools present consumers with suggestions of products that are similar, yet not fully adhere to their preferences (Stahl, 2006). However, the products most similar to stated consumer preferences are not always the best possible choices in a given context. In contrast, utility-based tools are based on the assumption that detailed models of consumer's preferences can be built. As such, additional steps are required in the product search process, for example pre-choice question answering, which lead to precise utility functions that score products based on all of their characteristics. Such approach allows for compensatory processing of alternatives, which positively impacts overall choice quality. The main drawback of utility-based approaches is related to the fact that determination of accurate utility functions is a lengthy and effortful process involving user input (Keeney & Raiffa, 1976). Similarly, form-based interactive filtering tools commonly used in current shopping sites acquire consumer preferences by using structured forms asking about product requirements. These requirements (hard-constraints) are used to filter out unwanted options that do not satisfy any of the product requirements and present consumers only with relevant products. Despite some advantages, form-based filtering tools often lead to erroneous elimination of quality products early in the choice process (Dabrowski & Acton, 2010a). Further, in standard product search tools supporting this paradigm, consumers are not guided by the system, for example with suggestions of potentially valuable products. Finally, in online product catalogues using hard-constraints for product filtration, when a consumer over-specifies requirements for his or her preferred product, no offers may match the request. In such cases it is difficult for consumers to realise which requirements cannot be met, what trade-offs need to be considered, and to decide on adjustment of their preferences. The fourth approach based on preference relaxation techniques can help consumers in cases of such empty failing queries by relaxing over-constrained preferences and suggesting potential compromises. The relaxation techniques focus both on repairing over-constrained product queries and on helping consumers avoid over-specification of requirements.

3 Preference relaxation methods

This section provides an overview of the preference relaxation mechanisms discussed in this study. We explain the details of each method using an example product search request: presume you intend to buy a compact used car for which you are prepared to pay between $8000 and $12000, you also expect that a reasonable mileage of a car in this price range would fall between 60000 mi and 100000 mi. Would you consider a car that is slightly more expensive ($12400) but with mileage lower than you expected (39000mi) and perhaps with additional features you haven't considered? Such alternatives increase consumers' awareness and may induce changes in their preferences as well as lead to more satisfying purchase decisions. The preference relaxation methods discussed here include such valuable alternatives in product search results and enable consumers to consider products that would ordinarily be eliminated early in the selection. Below we discuss our approach in more detail and contrast it with common product filtration and preference relaxation methods.

To avoid information overload, common techniques such as filtration are used to limit the number of products presented to consumers to only those items that fully match the preference criteria stated. In the example above, a consumer using such a product search tool, and who provided preferences on price ($7000 to $8000) and mileage (25000mi to 75000mi) would be presented with a *result set* with only those offers that fully satisfy all the stated criteria, that is, are both within the price and mileage range. This approach is often referred to as product filtration using hard-constraints or logical filtering (Mirzadeh & Ricci, 2007) and has many limitations acknowledged in the literature (Dabrowski & Acton, 2010b; Felfernig, Mairitsch, Mandl, Schubert, & Teppan, 2009; Mirzadeh, Ricci, & Bansal, 2004), addressed with recommendation method, for example through preference relaxation.

3.1 Standard preference relaxation

Preferences on numerical attributes are typically expressed using value ranges (a single value can be viewed as a special case of a value range where border values are equal). More formally, a preferred value range for an i^{th} attribute as $d_i = [d_{iL}, d_{iU}]$ where d_{iL} indicates the lowest, and d_{iU} the highest acceptable value for a given attribute. These hard constraints can be "softened" by the relaxation value e, and a relaxation factor δ (where $e_{ik} = \delta * d_{ik}$, k *in* $\{L, U\}$ and δ *in* $[0,1]$) causing the filtering rule to be less restrictive. The alternatives that satisfy the less strict preference $d_i^* = [d_{iL} - e_{iL}, d_U + e_{iU}]$ remain in the set and can be considered by the consumer. This approach, referred to as Standard Preference Relaxation (SR), often leads to a very large number of alternatives presented to the user (Dabrowski et al., 2012), resulting in information overload and increasing decision effort (Turetken & Sharda, 2004). This problem is addressed by the Soft-Boundary Preference Relaxation approach.

3.2 Soft Boundary Preference Relaxation

The Soft Boundary Preference employs the concept of an *Edge Set*: a set of alternatives that are close to border values for consumer preferences for a given attribute (e.g. a car that costs $6995 for a [$6000, $7000] preference). This applies both to higher and lower edges of the preference interval. For example, a price range preference p_{PRICE} = [$6000, $7000], relaxation factor $\delta = 0.05$, an *edge set* can be constructed: ES = $[\$5700, \$6300] \cup [\$6650, \$7350]$. Thus the *ES* will contain items that fall into [$5700, $6300] or [$6650, $7350] price range. The approach involves three steps: (1) creation of an *edge set* based on provided interval boundaries, (2) identification of non-dominated alternatives (Borzsonyi, Kossmann, & Stocker, 2001) that are in the value ranges specified by available edge sets, and (3) inclusion of the non-dominated alternatives that are members of edge sets, yet do not satisfy all hard-constraints specified by the user, as *suggestions* to the result set. This method is referred to as Soft-Boundary Preference Relaxation with *Addition*. Another variation of the method (Soft-Boundary Preference Relaxation with *Replacement*) for each identified suggestion removes one dominated (i.e. non-optimal) alternative from the edge set with the lowest utility, hence with lowest chance of being selected by the user. The goal of replacement is to further lower the decision effort at the same time increasing diversity and average quality of suggestions (see Figure 1~~Figure 1~~ for an example with seven used cars).

Available products

Car	Price	Mileage
1*	5750	90000
2	5800	110000
3	5900	93000
4	6100	95000
5	6450	91000
6*	7200	60000
7	7500	65000

preference: none

Logical filtering - no relaxation

Car	Price	Mileage
4	6100	95000
5	6450	91000

preference: €6000 < price < €7000

Standard Preference Relaxation

Car	Price	Mileage	
1*	5750	90000	s
2	5800	110000	s
3	5900	93000	s
4	6100	95000	
5	6450	91000	
6*	7200	60000	s

preference: €6000 < price < €7000
relaxation: €5700 < price < €7350

Soft Boundary Preference Relaxation with Addition

Car	Price	Mileage	
1*	5750	90000	s
4	6100	95000	
5	6450	91000	
6*	7200	60000	s

preference: €6000 < price < €7000
relaxation: €5700 < price < €7350
optimal suggestions added

Soft Boundary Preference Relaxation with Replacement

Car	Price	Mileage	
1*	5750	90000	s
5	6450	91000	
6*	7200	60000	s

preference: €6000 < price < €7000
relaxation: €5700 < price < €7350
optimal suggestions replace low utility items

Car - user car add
Price - price in €
Mileage - mileage in km
***** - optimal, non-dominated alternative
s- suggestion / recommendation

Figure 1 Example of result sets associated with each preference relaxation method

4 Experiments

The user experiment described in this paper provides additional insights to the study using a set of simulations recently carried out by Dabrowski and Acton (Dabrowski et al., 2012) using the *leave-one-out* approach (McSherry, 2004). Dabrowski and Acton's results showed that Standard Preference Relaxation might have a positive effect on decision quality, yet it can lead to a significant increase in the average number of alternatives in result sets, which negatively impacts decision-making effort. In these simulations, the Soft-Boundary Preference Relaxation methods positively impacted decision quality, however, the effect was smaller than that for the SR method. On the other hand, the SBR methods outperformed SR in terms of decision effort required, as the average size of result sets for the SBR methods was significantly lower than in case of the SR method. SBR required similar effort to the case when no relaxation was used, while providing consumers with a higher quality decision and increased product awareness. These promising results justified further studies of the SBR methods with real users focusing on consumer decision-making performance. Thus, in this paper we investigate the effects of preference relaxation methods on decision-making performance in a study with 100+ online shoppers.

4.1 Hypotheses

The following section outlines decision-making performance indicators for decision quality and effort, leading to the construction of a set of hypotheses examined in an experiment-based user study preceded by think-aloud sessions conducted to validate the software and the design of the experiment.

4.1.1 Decision Quality

The impact of recommendation agents (RAs) on decision quality has been investigated in many studies. For example, Pereira (Pereira, 2001) observed that query-based RAs improved both objective and subjective indicators of decision quality. Other studies (G Häubl & Trifts, 2000; Hostler, Yoon, & Guimaraes, 2005) demonstrated an assessment of decision quality through non-dominance (i.e. *pareto optimality*) of the selected alternative(s), also referred to as an "ideal selection" (G Häubl & Trifts, 2000). Indeed, such conceptualization of decision quality has been used as a measure of decision performance (Hostler et al., 2005). Häubl and Murray (Gerald Häubl & Murray, 2005) showed that the use of RA increases decision quality by reducing the likelihood of selecting a non-dominated alternative. Similar results were obtained by van der Heijden (Van der Heijden, 2006), who showed that the use of recommendation agent leads to a higher number of non-dominated alternatives in the consideration set. We expected that the use of Standard Preference Relaxation the objective indicators of decision quality should be positively affected in contrast to logical filtering approach:

H1: Standard Preference Relaxation (SR) leads to higher decision quality than logical filtering.

Similar assumptions were made for the Soft-Boundary Preference Relaxation (SBR) methods. Dabrowski and Acton (Dabrowski et al., 2012) indicate that both SBR methods (with Addition and with Replacement) led to construction of better (in terms of decision quality indicators) result sets in comparison to no relaxation. In particular, SBR methods resulted in a higher average share of non-dominated alternatives in the set of alternatives returned as a result to a user product search query. The positive effects on the share of non-dominated alternatives were stronger than Standard Relaxation methods. Similarly, SBR methods with Addition led to a higher average utility of alternatives in result sets. Based on these initial findings, we expected the Soft-Boundary Preference Relaxation methods to have a positive effect on decision quality in contrast with logical filtration:

H2: Soft-Boundary Preference Relaxation (SBR) leads to higher decision quality than logical filtering.

4.1.2 Decision Effort

The level of effort required to make a decision is another common decision performance indicator (Bettman, Johnson, Luce, & Payne, 1993). Effort is directly related to the amount of information that needs to be considered by a user (Eppler & Mengis, 2004; Turetken & Sharda, 2004). Cognitive load imposed on the consumer to find the best offer among the list of products presented to him is considered an effort-related evaluation criterion for product selection tasks (Branting, 2002). Intuitively, preference relaxation mechanisms increase effort by relaxing rigid requirements, and therefore incorporating more alternatives for consideration by a user. Two other indicators directly influencing decision effort are the time taken to complete the task (Hostler et al., 2005) and the extent of product search (Moore & Punj, 2001). Decision effort is directly related to the amount of information that needs to be considered by a user (Eppler & Mengis, 2004; Turetken & Sharda, 2004) as a higher amount of relevant product information requires more information processing, which in turn demands more time. When product requirements are relaxed, in addition to alternatives that fully satisfy initial requirements, consumers are presented with a proportionally large number of product suggestions that should require significantly more time to make a decision in comparison to logical filtering. Therefore, we expected the use of Standard Preference Relaxation to negatively affect decision-making time. Further, larger sets of products often require users to perform additional actions such as further filtration or navigating to different product pages[3]. Indeed, some studies show that recommender system may lead to a larger number of products examined by a consumer (G Häubl & Trifts, 2000). However, each action that is performed by a consumer leads to an increase in decision effort. Overall, we expected that the use of Standard Preference Relaxation would lead to the exertion of higher decision effort:

H3: Standard Preference Relaxation (SR) leads to higher decision effort than logical filtering.

We expected that in contrast to the SR method, Soft-Boundary Preference Relaxation (SBR) approaches should not increase decision effort. First, the results of previous studies (Dabrowski et al., 2012) show that the SBR methods do not lead to an increase in the average number of alternatives in a result set. Although the SBR with addition led to a small increase that was not statistically significant, average result sets constructed using the SBR with Replacement approach were not larger than in the case of logical filtering. However, the fact that consumers shopping for products with a decision aid implementing the SBR method are receiving a small number of product recommendations may have

[3] Typical online product catalogues display only a small number of products at a time. When more products are available, software divides the set into a number of product subsets (so called *product pages*) that limit the amount of information displayed. When a consumer is interested in information about the products not displayed at a given moment he or she can navigate to the product page that contains the required information.

an effect on the time to make a decision. Therefore, the SBR methods may lead to a presumably small increase in the amount of product search. On the other hand, quality suggestions may allow consumers to quickly locate suitable products that at the same time are optimal (i.e. non-dominated) from the decision-making perspective. Overall, we expected that the SBR methods should not impact decision effort, as previous studies suggest (Dabrowski et al., 2012; Dabrowski & Acton, 2010b) that the number of products included in the result set is similar to the levels in the logical filtering approach. We expect, however, that the amount of necessary effort for SBR will be significantly lower than in case of Standard Relaxation, hence:

H4: Soft-Boundary Preference Relaxation (SBR) requires lower decision effort than Standard Preference Relaxation (SR).

4.2 Indicators

4.2.1 Decision quality

Decision quality is of major importance in assessing decision outcomes in the context of consumer decision-making performance (Fennema & Kleinmuntz, 1995). Two indicators of decision quality were used in Dabrowski and Acton's (Dabrowski et al., 2012) simulation-based study: share of the non-dominated alternatives and average utility, both for search results set. To enable a direct comparison and to build directly on that study, similar indicators were also adopted in the study here, in the assessment of decision quality with respect to final consideration sets constructed. Many studies show that both utility (Hostler et al., 2005; Pereira, 2001) and share of non-dominated alternatives in the consideration set (Van der Heijden & Sørensen, 2002) are good indicators of choice quality in evaluation of recommendation agents.

Overall, two indicators of decision quality were used in this user experiment:

a. Share of non-dominated products in the final consideration set
b. Average utility of the final consideration set

4.2.2 Decision Effort

Decision effort is a factor that often complements decision quality in assessing decision performance (G Häubl & Trifts, 2000). Larger amount of information increases the cognitive load (Sweller, Chandler, Tierney, & Cooper, 1990) imposed on a consumer searching for a product and can result in them spending more time analyzing available alternatives. Thus, higher level of effort necessitates more time to accomplish a given task (Hostler et al., 2005). Indeed, many studies use decision time as an indicator of decision effort (Hostler et al., 2005; McNee, Lam, Konstan, & Riedl, 2003; Olson & Widing, 2002). Further, the level of effort required to make a decision is strongly related to the amount of information that needs to be considered (Eppler & Mengis, 2004), and so the average number of alternatives in a result set can be considered a good indicator of decision effort. Finally, a larger number of alternatives in search result set may lead to more product search. The extent of product search refers to the number of products that have been returned in response to consumer's product searches and/or have been seriously considered for purchase (Xiao & Benbasat, 2007). The amount of product search is a widely used indicator of decision effort (Diehl, Kornish, & Lynch Jr., 2003; G Häubl & Murray, 2003) that is often defined as number of product information (pages) requested. This conceptualization is used here as an indicator of decision effort.

Overall, three indicators of decision effort are used:

a. Time taken to complete the decision making task (seconds)
b. Average number of items in the result set
c. Extent of product search

4.3 Method

We employed a three-step procedure following the one proposed by Todd and Benbasat (Todd & Benbasat, 1993):

1. A tutorial that demonstrated the use of software.
2. A practice task to familiarize participants with the system and the task.
3. A main task that was used to collect experiment data.

Following a well-defined and rigorous protocol, subjects performed two choice tasks (Wang & Benbasat, 2005) representing a widely used multi-attribute product selection (G Häubl & Trifts, 2000; Viappiani et al., 2008): the practice task (select a digital camera), and the main task (select a used car). These product domains were chosen as examples of high-risk products selection where focus on decision quality is vital (Spiekerman, 2001). The main task was based on the one used by Pereira (Pereira, 2001), and asked participants to select one or more used cars for a friend based on the description of generic preferences provided. The relaxation factor for the study was set to $\delta = 0.382$ what represents a maximum relaxation value according to the concept of perceived *closeness* (Bosc, Hadjali, & Pivert, 2009) and in line with Dabrowski and Acton's (Dabrowski et al., 2012) simulations that indicate best performance of preference relaxation algorithms for this value of the relaxation factor.

The online store explicitly developed for the experiment is a web-based application with the user interface based on Flex technology and the server layer using PHP (see Figure 2~~Figure 2~~). The application very closely resembled functionality and design of one of the biggest online retailers specializing in used cars (http://carzone.ie), with elements indicating purpose (A), result set size (B), user preferences (C), as well as a search refinement panel (D), number of items considered for purchase - a "shopping basket" (E), product attributes and result page navigation (G). The think-aloud sessions conducted with 10 subjects confirmed that subjects were familiar with the design and validated the experiment design. In addition, a pre-task questionnaire was administered to gather personal information. Participants included students, researchers and staff at an IT research institute directly associated with the university, and a mutually exclusive student population comprising final year business students at the same university. Out of the 111 participants, two subjects failed to abide by the experiment's documentation and adhere to the role presented in the task, further 8 participants did not complete the task. Four cases were identified as outliers and removed from further analysis leaving a valid N of 97 across four groups for further analysis: 25 for no relaxation (control), 24 for Standard Relaxation, 25 for Soft-Boundary Preference Relaxation with Addition and 23 for SBR with Replacement.

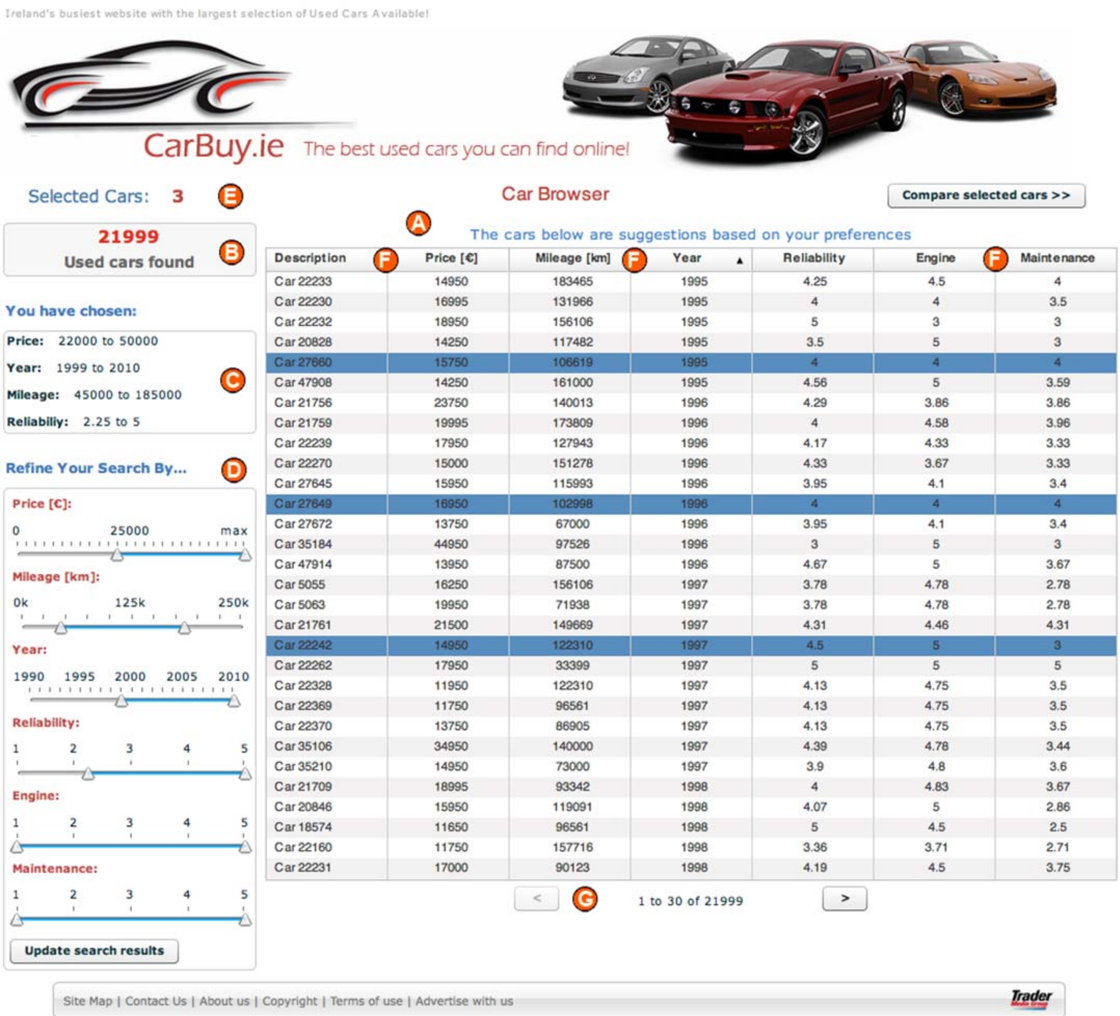


Figure 2 Main product search screen for the experimental system.

4.4 Datasets

Our experiments used two real-world datasets. The dataset in the practice task consisted of 1813 digital cameras extracted from the "Point & Shoot Digital Cameras" category on Amazon.com with information on: brand, model, price, zoom, screen size, resolution, and weight. The products were extracted using Java software and API provided by Amazon. These attributes were manually classified into cost-type (e.g. price) and benefit-type (e.g. resolution) categories. The second dataset included 45278 used car advertisements with information on price, mileage, and manufacturing year collected from an online car website, run and managed by the Autotrader media group. Additional attributes (i.e. maintenance cost, reliability, and engine quality ratings) that were not present in advertisements, were automatically generated using standard information extraction 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 relatively lowest maintenance cost).

4.5 Results

This section presents the results for six measures (see Table 1~~Table 1~~) used in the study for the four methods: logical filtering (control), Standard Preference Relaxation (SR), and Soft-Boundary Preference Relaxation with Addition (SBR$_{ADD}$) and Replacement (SBR$_{REP}$). Shapiro-Wilk's tests were conducted in all cases to assure the normality assumption and select a suitable method of statistical analysis.

	Decision Quality		Decision Effort		
Method	**Share of ND [%]**	**Avg. Util. [0-1]**	**Time [s]**	**Avg. Size [n]**	**Search [# actions]**
NR	50 (50)	.594 [± .12]	213.66	1261.69	4.08 (4.00)
SR	49 (54)	.637 [± .16]	329.39	3984.12	10.65 (7.00)
SBR$_{ADD}$	71 (100)	.640 [± .14]	248.33	1076.64	6.92 (7.00)
SBR$_{REP}$	71 (90)	.701 [± .08]	269.54	1876.95	6.21 (5.00)

Table 1 Overview of results for no relaxation (NR), Standard Preference Relaxation (SR), Soft-Boundary Preference Relaxation with Addition (SBR$_{ADD}$) and Replacement (SBR$_{REP}$). Values represent means with standard deviation in square brackets (Average Utility), means with medians in regular brackets (Share of ND, Search), and means for log-transformed data (Time, Average Size).

4.5.1 Decision Quality

Share of Non-dominated Alternatives in Consideration Set A Kruskal-Wallis test was conducted to evaluate differences among the four groups on median change in the share of non-dominated alternatives. The test showed statistically significant differences ($\chi^2(3,97) = 10.599$, $p = .014$) in average shares of non-dominated alternatives between the groups. Further analysis using follow up Mann-Whitney U tests revealed that there was no significant difference in the share of non-dominated alternatives in a consideration set between the groups using Standard Preference Relaxation and logical filtering with no relaxation (NR), $z = -.136$, $p = .951$, indicating rejection of hypothesis H1. On the other hand, there was a significant difference ($\chi^2(2,74) = 6.569$, $p = .037$) between the control group and both Soft-Boundary Relaxation methods. The difference was significant for both SBR_{ADD}, $z = -2.068$, $p = .039$, and SBR_{REP}, $z = -2.296$, $p = 0.022$. The effect size was medium for both SBR_{REP} ($r = .328$) and SBR_{ADD} ($r = .293$). As such, Soft-Boundary Relaxation led to a higher average share of non-dominated alternatives in a consideration set, indicating acceptance of hypothesis H2 for this factor.

Average Utility of Alternatives in Final Consideration Set The results of a one-way between groups analysis of variance showed statistically significant differences between groups in the average utility of products in final consideration sets ($F(3, 93) = 2.726$, $p = .049$). The effect size was moderate (Eta Squared = .081). Levene’s test indicated significant differences in variances among the groups ($F = 3.420$, $p = .020$), and so post-hoc analysis using the Games-Howell test was performed. The analysis indicated significant differences in the average utility of items in between the Standard Preference Relaxation and Soft-Boundary Preference Relaxation with Addition ($p = .028$). As no other differences were statistically significant, the results indicate rejection of hypothesis H1 for this factor. On the other hand, Soft-Boundary Relaxation with Replacement led to a higher average utility of products in consideration sets, thus providing support for hypothesis H2 for this factor.

1.1.1 Decision Effort

Time to Finish the Task First, the data were transformed using a logarithmic transformation to achieve a normal distribution, and confirmed with a normality test. Although the p-value for the SBR_{ADD} method might suggest a violation of normality ($p = .033$), analysis of Kurtosis = .530 (Std. Error = .485) and Skeweness = .266 (Std. Error = .245) indicated normality of the distribution. The Levene’s test indicated no significant differences in variances among the groups ($F = 1.620$, $df = 3$, $p = .190$). The results of the one-way ANOVA indicate significant differences between the groups [$F(3,93) = 2.934$, $p = .037$] in the average time to complete the task. The effect size was moderate (Eta Squared = .086). Post-hoc analysis using Tukey’s HSD test indicated that the subjects who used the Standard Preference Relaxation group took significantly more time to make a decision (M = 329.39) in comparison to NR (M = 213.66), p = .037. As no other differences were statistically significant, the results indicate acceptance of hypothesis H3 and rejection of hypothesis H4 for this factor.

Average Size of the Result Set The data were transformed using a logarithmic transformation to achieve a normal distribution. Shapiro-Wilk's test was conducted to assure the normality assumption. The results indicate that mean values for the average size of the result set followed a normal distribution (p = .0.59, p = .426, p = .417, and p = .240 respectively). The results of the one-way ANOVA showed statistically significant differences [F(3, 93) = 4.186, p = .008] in average size of the result sets between the groups. The effect size was large (Eta Squared = .119). Levene's test indicated no significant differences in variances among the groups (F = 1.606, df = 3, p = .193). Post-hoc analysis using Tukey's HSD test indicated that the subjects who used the Standard Preference Relaxation method dealt with significantly larger result sets than in the case of No Relaxation (p = .034) and Soft-Boundary Preference Relaxation with Addition (p = .007). These results indicate that the Standard Preference Relaxation method had a significant impact on the number of products in search result sets and contributed to higher decision effort, confirming hypothesis H3. On the other hand, no other comparisons in post-hoc tests were significant, thus no significant differences in the size of the result set between the SBR and the NR methods were detected, indicating acceptance of hypothesis H4.

Extent of Product Search The differences in amount of product search conceptualised as the average number of pages viewed by a consumer among the four groups (No Relaxation, Standard Relaxation, Soft-Boundary Relaxation with Addition, and Soft-Boundary Relaxation with Replacement) were assessed with non-parametric analysis. The number of information search queries did not follow a normal distribution. Therefore, a non-parametric Kruskall-Wallis test was conducted to compare the differences in the amount of product search among the four groups. There results of this test indicate that there is a significant difference in the median, $\chi^2(3,97) = 8.491$, p = .037. The effect size was moderate (Eta Squared = .088) for the impact of preference relaxation method on the amount of product search. Further analysis, using follow-up Mann-Whitney U tests with sequential Benferroni adjustment, revealed that there was a significant difference in the amount of product search between the Standard Preference Relaxation and logical filtering with no relaxation (NR), z = -2.571, p = .010, r = .357 (medium size effect), indicating support for hypothesis H3. On the other hand, similar Mann-Whitney U test analysis revealed that there were no significant differences between the NR and both Soft-Boundary Preference Relaxation groups, indicating support for hypothesis H4.

5 Discussion

This section presents the discussion of the impact of various preference relaxation methods on decision-making performance of online shoppers. We then conclude with an outline of the contributions of the research and an explication of the value of Soft Boundary Methods for online consumer activities.

5.1 Decision Quality

Results show that Standard Relaxation (SR) had no significant impact on decision quality both in case of the share of non-dominated alternatives in consideration sets as well as the average utility of products seriously considered for purchase (see Table 2~~Table 2~~). Relative to use of the logical filter tool, the consideration sets of SR users contained the same average share of superior alternatives than the NR group, and considering that the utility of alternatives of products in consideration sets was very similar, hypothesis H1 is rejected.

In contrast, results indicate the positive impact of the Soft-Boundary Preference Relaxation methods on decision quality relative to logical filtering. The share of superior alternatives both for the SBR with addition (Median = 1.00, or 100%) and SBR with Replacement (Median = 0.90, or 90%) was significantly higher (with $p < 0.05$) than for the logical filtering (Median = 0.50, or 50%). Results also showed statistically significant ($p < 0.05$) improvement in the average utility of products in the consideration sets constructed with SBR with Addition (M = .652, SD = .13) and SBR with Replacement (M = .701, SD = .08) compared to the non-relaxed group (M = .606, SD = .13). Strong positive effects on the objective indicators of decision quality provide support for hypothesis H2.

Hypotheses and measures of decision quality	**Result [Effect]**
H1: Standard Preference Relaxation leads to higher decision quality than logical filtering.	**Rejected**
• Share of non-dominated alternatives in a consideration set	[None]
• Average utility of alternatives in a consideration set	[None]
H2: Soft-Boundary Preference Relaxation methods lead to higher decision quality.	**Accepted**
• Share of non-dominated alternatives in a consideration set	[Higher]
• Average utility of alternatives in a consideration set	[Higher]

Table 2 Summary of effects on decision quality

5.2 Decision Effort

The user experiment showed a negative effect of Standard Preference Relaxation (SR) method on decision effort, confirming the results of simulations (see Table 3~~Table 3~~). Subjects using the SR method were presented on average with significantly ($p < 0.05$) larger result sets ($M = 3984.12$) that in case of logical filtering ($M = 1261.69$). Time to complete the product choice task was also significantly higher ($M = 347.15$ seconds) than for subjects using logical filtration ($M = 224.54$). Finally, the SR method had a negative effect on decision effort through the impact on the amount of product search ($p < 0.05$). In particular, subjects using the SR method issued almost twice more search queries (Median = 7.00) compared with no relaxation (Median = 4.00). Standard Preference Relaxation had a negative effect on decision effort, confirming hypothesis H3.

Although our user experiment indicated an absence of negative effects of SBR on decision effort (confirming the results of Dabrowski and Acton's (Dabrowski et al., 2012) simulations), the positive effect in contrast to Standard Relaxation was not statistically significant for most measures. SBR with Addition led to significantly ($p < 0.01$) lower average size of the result set ($M = 1076.64$) in comparison to Standard Relaxation ($M = 3984.12$). Although a similar trend was noticed for SBR with removal, ($M=1876.95$) the difference was not significant. Though subjects performing the product search task with the SBR tool took on average less time than the group using Standard Preference relaxation, the mean differences were not statistically significant. Similar results were observed for the amount of product search. Overall, Soft-Boundary Preference Relaxation led to an improvement in all measures, yet only differences in the size of the result set were statistically significant, and so we reject H4.

Hypotheses and measures of decision effort	**Result [Effect]**
H3: Standard Preference Relaxation leads to higher decision effort than logical filtering.	**Accepted**
• Time taken to complete the task	[Longer]
• Average number of items in a result set	[Higher]
• Extent of product search	[More]
H4: Soft-Boundary Preference Relaxation (SBR) requires lower decision effort than Standard Preference Relaxation (SR).	**Rejected**
• Time taken to complete the task	[Not sig]
• Average number of items in a result set	[Lower]
• Extent of product search	[Not sig]

Table 3 Summary of effects on decision effort

Overall, the Soft-Boundary Preference Relaxation method had a positive effect on consumers' decision-making performance. Both the simulations and the user experiment provided evidence of the positive effect of the SBR method on decision quality. Subjects selected products of higher utility and considered more optimal products than in case of logical filtering with no relaxation (80-100% improvement). Further, higher quality decision-making did not require more effort, as time taken to complete the task, the average number of alternatives in a result set, and the extent of product search were similar to the levels measured for the group with no relaxation. The SBR method did not lead to significant increases in the average number of items in a result set. Further, Soft-Boundary Preference Relaxation had a positive effect on product awareness through the increase in diversity of viewed (search result set) and considered (consideration set) products (50% improvement), as well as high share (50%) of accepted suggestions in the final consideration set. In contrast, the effects of the Standard Preference Relaxation method on consumers' decision-making performance included increased decision effort required and no effects on decision quality. Further, the experiments demonstrated that consumers accepted the product recommendations identified with the Soft-Boundary Preference Relaxation (the share of product suggestions in the set of products examined to make the final decision ranged 80-100%), which demonstrates the value of the method.

5.3 User experiment vs. simulations

The results collected in our user experiment extend the findings of simulations reported by Dabrowski and Acton (Dabrowski et al., 2012) and provide a more complete view of decision performance based on a larger number of measures. The user experiment revealed that the improvement of decision quality for SR method suggested by simulations is not present in actual user usage (see Figure 3). Although the positive effect was visible in the 13.60% improvement in the average utility of items in the result sets, our experiment showed no increase in quality indicators related to final consideration sets: not only the share of non-dominated alternatives was 2.00% lower in comparison to NR method, but also there was no statistically significant increase in average utility (+7.24%). We believe that these results can be attributed to the strong negative effect of increased decision effort (see Figure 4) and its effect negative effect on decision quality in line with other studies (E. J. Johnson & Payne, 1985; Todd & Benbasat, 1993, 1999).

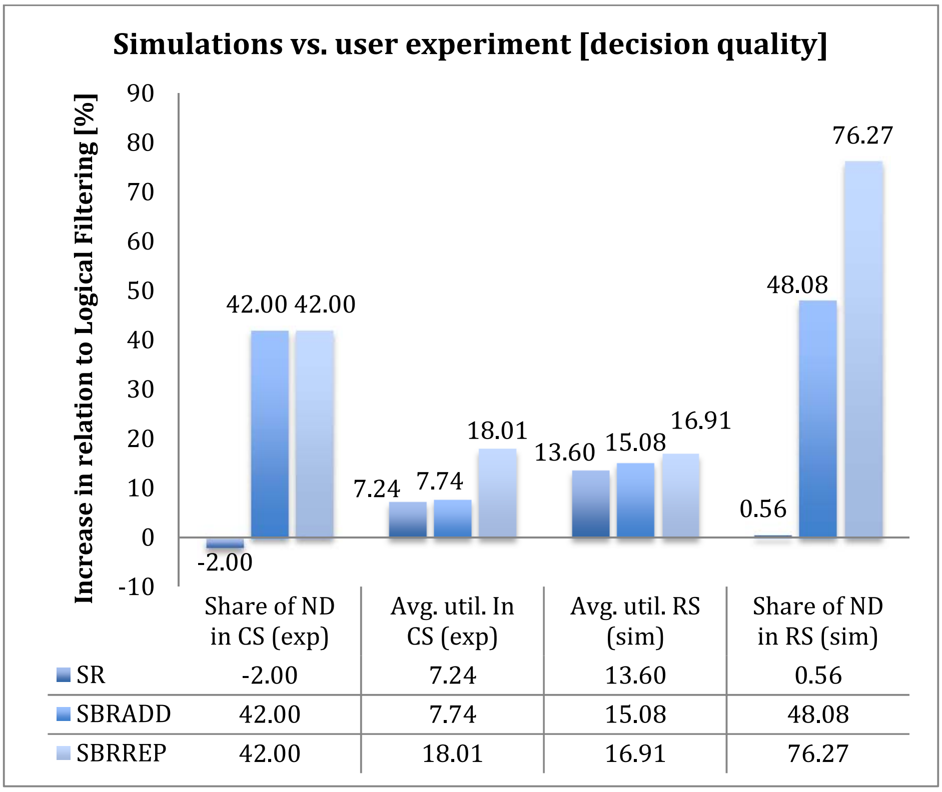
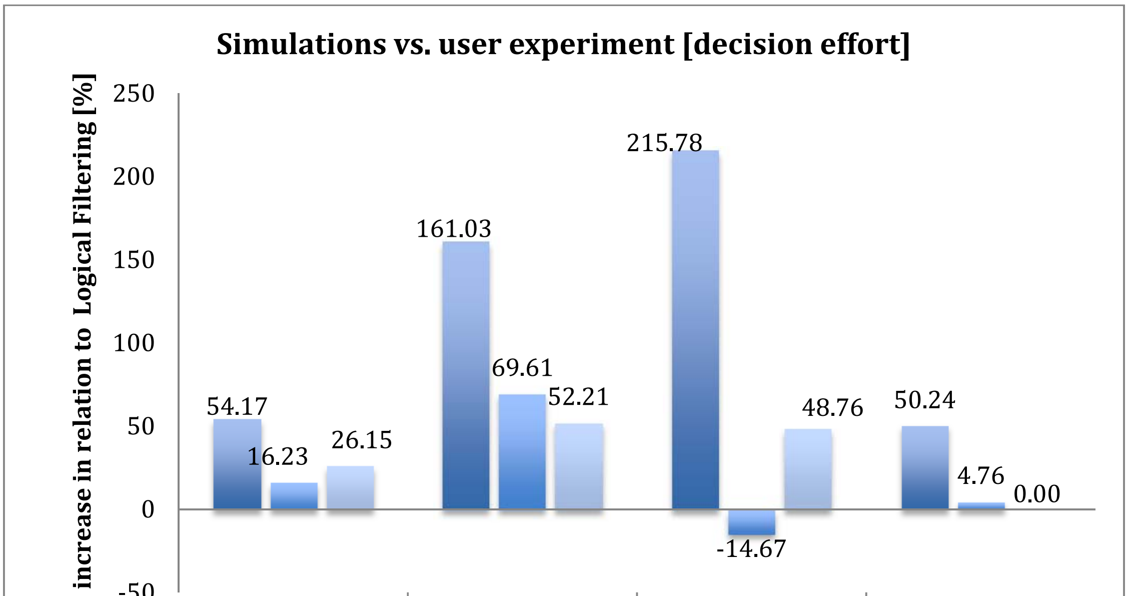


Figure 3 Summary of percentage differences in measures of decision quality used in simulations (*sim*) (Dabrowski et al., 2012) **and in our user experiment (*exp*) in contrast to the control group (No Relaxation) for consideration sets (CS) and results sets (RS), using non-dominance (ND).**

On the other hand, our experiments confirmed the positive effect of SBR methods on decision quality both for utility and share of non-dominated alternatives in the consideration set. We found a consistent improvement in the share of non-dominated alternatives (42.00%), yet there were small discrepancies in the average utility of considered alternatives, with only 7.74% improvement for SBR_{ADD} (in contrast to 15.08% in simulations) and 18.01% for SBR_{REP} (in contrast to 16.91%). The lower improvement of average utility of products together with 42.00% increase in the share of non-dominated alternatives in the consideration set suggest that subjects using the site with SBR_{ADD} made quality choices yet with less thorough consideration (indicated by shorter task time and higher search extent as indicated in Figure 4).



	Task time (exp)	Search extent (exp)	Avg. RS size (exp)	Avg. RS size (sim)
SR	54.17	161.03	215.78	50.24
SBRADD	16.23	69.61	-14.67	4.76
SBRREP	26.15	52.21	48.76	0.00

Figure 4 Summary of percentage differences in measures of decision effort used in simulations (*sim*) (Dabrowski et al., 2012) **and in our user experiment (*exp*) in contrast to the control group (No Relaxation), including various measures for results sets (RS) and tasks.**

In terms of the impact of on decision effort, our results also show strong negative effect of SR with 215.78% larger results sets in contrast to only 50.24% increase in simulations. This is confirmed with 54.17% longer average task completion time and 161.03% more product search actions. There results are in line with the simulations, however, the negative effect is much stronger than expected, what may explain no improvement in decision quality for the SR method. On the other hand, we noticed a number of differences in case of SBR methods. Although the simulations showed no significant impact of the SBR methods on decision effort (with less than 5.00% increase in the result set size), our results show that users dealt with 14.67% smaller result sets for SBR_{ADD}, yet SBR_{REP} presented them with 48.76% more products. Further, SBR methods required 16.23% (SBR_{ADD}) and 26.15% (SBR_{REP}) more time to make decisions, with 52.21% (SBR_{ADD}) to 69.61% (SBR_{REP}) more search. Although these differences were 2-4 times lower than in case of NR, we found no statistically significant differences in the effects on decision effort between SBR and SR methods. We expect that this lack of statistically significant differences may be related to the effects of information presentation on information processing (Swearingen & Sinha, 2001). In particular, the composition and presentation of the list of recommendations may have a significant impact on user performance (Komiak & Benbasat, 2004; Xiao & Benbasat, 2007).

6 Conclusion

This research extends and builds upon a previous study in the journal of Expert Systems with Applications (Dabrowski et al., 2012), and explores the effects of preference relaxation on consumers' decision-making performance in product search in an extensive user study. We extend previous work focusing on consumer decision-making performance of preference-based product search in online product catalogues (Xiao & Benbasat, 2007). Overall, this work compares two novel preference relaxation methods (Soft-Boundary Preference Relaxation with Addition and with Replacement) with Standard Preference Relaxation and logical product filtering with no relaxation commonly used in online shopping. The paper includes theoretical, methodological, and practical contributions with direct relevance to intelligent systems for online product search.

This work contributes to existing theory with two major findings related to preference relaxation and consumers' decision-making performance in preference-based product search. First, we show that both logical filtering and Standard Preference Relaxation are outperformed by the Soft-Boundary relaxation methods in an experiment with actual users. We show that our results shed new light on previous experiments with those methods that were based purely on simulations. Second, This study extends previous work on the effects of sorting of recommendation lists and number of recommendations on decision effort and quality. In particular, the results of experiments here support findings of Aksoy and Bloom (Aksoy & Bloom, 2001). Further, Basartan (Basartan, 2001) found that an RA that provides too many recommendations may increase the users' cognitive effort and decrease their evaluations' of use. The study here confirms these findings, as the inclusion of large number of recommendations in the Standard Preference Relaxation method led to a significant increase in decision effort indicators that counterbalanced potential positive effects of using recommendations on decision quality.

The second contribution is related to methodology and comparison of the results of simulations and user studies. Although valuable, the results of the simulations (Dabrowski et al., 2012) were limited in terms of the indicators of decision performance related to the actual use of the system, such as the extent of product search or task completion time - direct indicators of decision effort. Finally, simulations used a small set of 2650 used car adverts, which may have given an incomplete view of the effects of preference relaxation. To address this limitation of simulations, in this work we employed a second research method in a triangulatory approach: a controlled user experiment that involved a product selection task using a real-world dataset and shopping site. The user study enabled measurements of objective decision-performance indicators based on actual use of the system related to decision quality (i.e. share of the non-dominated alternatives and average utility of alternatives in a final consideration set) and decision effort (i.e. time to complete the task and extent of product search). The results of our experiment indicated that user studies are a more valuable and accurate method for assessment of actual effects of a given system on decision-making performance than simulations. Combined use of simulations followed by user experimentation provided more comprehensive understanding of the studied effects on decision performance. This was possible as similar, real world datasets were used in the described experiments: a digital camera datasets collected from the Amazon[4] website that contained 1813 products, and a used car dataset comprising a total of 45278 used car advertisements collected from the Carzone[5] website (2650 similar cases were used in simulations). The study illustrates the successful use of a large real world datasets in a multi-attribute decision-making task that involved product selection and was performed in a controlled environment.

Considering implications for online stores, this work outlines the effects of a recommendation agent based on a novel preference relaxation technique, and shows its positive effects on consumer decision-making performance. This method contributes to the class of feature-based recommendation agents that explicitly elicit consumer's preferences for different product features, which are then used to filter and/or order the available products to facilitate selection of the item that best meets consumer's needs (Murray & Häubl, 2002). Secondly, the paper explains the effect of the application of preference relaxation methods in preference-based product search contexts, which is a common scenario in online product catalogues. Thirdly, on a generic level the results of this work improve the understanding of the effects of various characteristics of recommendation agents on consumers' objective performance and subjective evaluations of use of the RA.

Finally, this paper extends the previous work on preferences relaxation and we call for further development of recommendation agents exploiting Soft-Boundary Preference Relaxation. The results of our experiments showed that SBR methods lead to significantly higher decision quality, yet not statistically significant improvement in decision effort. We believe that potential areas of improvement lay in further personalization of product search results. In future work we plan to extend the methods discussed here with contextual relaxation that incorporates user feedback and clustering methods that would present only best products among a number of similar optimal alternatives.

[4] http://amazon.com/

[5] http://carzone.ie/

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