Title	Modelling preference relaxation in e-commerce.
Author(s)	Dabrowski, Maciej; Acton, Thomas
Publication Date	2010-09-23
Publication Information	Dabrowski, M., & Acton, T. (18-23 July 2010). Modelling preference relaxation in e-commerce. Paper presented at the Fuzzy Systems (FUZZ), 2010 IEEE International Conference on.
Publisher	IEEE
Item record	http://hdl.handle.net/10379/1416

Modelling Preference Relaxation in e-Commerce

Maciej Dabrowski and Thomas Acton

Abstract—**In multi-attribute decision choice scenarios, although decision-makers desire access to very large sets of possible choice options (alternatives), their cognitive resources are limited. They may simply be unable to process vast amounts of information available and to make a satisfactory decision. Interactive decision aids, are a potential solution to this problem. Decision aids that filter a very large set of alternatives based on initial decision-maker preferences may eliminate potentially good alternatives early in the decision process, lead to a poor quality consideration set, and possibly negatively impact decision quality. The decision aid we propose here modifies the filtration criteria provided and thus, allows decision makers to reconsider selected alternatives they initially eliminated. We propose a model of such a decision aid, give an overview of its different configurations, and provide an illustrative example of use in the apartment selection decision problem. We also hypothesize about the impact of the proposed decision aid on decision quality and consideration set size and quality. We conclude the paper with an overview of potential directions for future research and a discussion of benefits of application of preference relaxation.**

I. INTRODUCTION

MULTI-ATTRIBUTE decision-making (MADM) refers to the problem of choosing the best option from the set of items (alternatives) described with a number of attributes [1]. Making decisions based on a large set of alternatives is challenging. This problem is recognized in many domains, for example in online shopping, where consumers making purchase decision are often unable to evaluate all available alternatives in great depth, and tend to use two-stage decision process to reach their decisions [2]. Payne [3] suggests that decision makers seek to reduce the amount of information processing involved in complex decision making, as minimization of effort related to decision making is one the most important factors that influence the decision process [4]. Thus, decision makers tend to adopt a stage decision process: "At the first stage, consumers typically screen a large set of available products and identify a subset of the most promising alternatives" [2]. Consequently, they are able to evaluate the resulting subset in more depth, perform relative comparisons across alternatives or their important attributes leading to a decision. Häubl & Trifts [2] discuss the stage process in the context of online shopping,

proposing that "interactive tools that provide support to consumers in the following respects are particularly valuable: (1) the initial screening of available products to determine which ones are worth considering further, and (2) the in-depth comparison of selected products before making a purchase decision". Although the positive influence of a decision aid increases with the problem size [4], in some decision problems the initial number of alternatives can be very high and thus difficult to grasp. Even pre-exposure to attribute levels [5], although proven to be beneficial to a decision maker, does not fully eliminate this problem.

The key contribution of this work-in-progress paper is a model of a soft-boundary decision aid that utilizes a preference relaxation mechanism and scenario of application in a common multi-attribute decision-making problem. We argue that during the process of filtering of the initial, very large, set of alternatives by providing preference on attributes and attributes' values decision makers (e.g. customers in ecommerce platforms) can unconsciously eliminate alternatives they could later consider. For example, a customer, who is willing to pay between €280,000 and €300,000 for an apartment, may, after consideration of all options, decide to buy a particular apartment for €302 000, because he finds the location and the size worth paying additional €2,000. However, when a customer specifies the price range, all apartments not in this range are removed from the set and cannot be considered. A soft-boundary decision aid may extend the value range specified by the customer (e.g. price range preference to €275,000 - 305,000). Thus, a customer is able to choose an option (apartment) he finds the most attractive, however, which does not fully fit his initial price preference. In this paper we introduce a model of a soft-boundary filtering decision aid and discuss its impact on decision quality and consideration set formation.

The paper is organized as follows. First, we provide an overview of the relevant literature on decision making and decision aids in the context of multi-attribute decision-making. Later, we develop a set of hypotheses regarding how we expect the decision aid we propose to affect a number of variables of the decision (e.g. quality). Finally, we discuss the impact of the soft-boundary filtering decision aid and propose directions for future research.

II. RELATED WORK

Multi-attribute decision-making (MADM) involves tradeoffs among alternative performances over multiple attributes. The decision information generally consists of attributes' values (also called alternative performance

measures) and attributes' weights. The better the fit of an attribute value of a given alternative to the decision maker's preference (utility), the higher the preference for the alternative. The overall utility of a given alternative maker is a combination of the levels of utilities of its attributes (utility function). Usually, in the process of decision making, attributes' values are not precisely known, but value ranges can be obtained or expressed in various formats [6, 7], such as linguistic variables or value ranges.

In this section we briefly discuss different aspects of multi-attribute decision-making and elicitation of user preferences.

A. Decision Behaviour

Behavioural science contributes significantly to the decision-making theory. A lot of research is targeted on elicitation of the decision maker's preferences. An important aspect, from the point of view of our work, is differentiation between constructed and stable preferences [8]. Gilbride and Alenhy [8] comment on work of Simonson [9] and argue "constructive processes can lead to stable preferences as the outcome". There is a growing consensus that preferences are typically constructed when decisions are made and are influenced by the method of preference elicitation, the description of the options, and the choice context. Despite many disadvantages of self-explicated method for preference elicitation [10, 11], there is some evidence [12] that if many attributes have to be handled, lower cognitive strain on the decision maker and lower chance for simplifying effect of self-explicated approaches may become crucial. However, [13] pointed out that the decision makers tend to restrict their processing to a narrow subset of possibilities when faced with more than a few alternatives. They also explain that individuals generally fail to consider relevant information during the evaluation of alternatives, focusing only on that which is most prominent or salient.

Another important finding is related to minimization of decision-making effort. Todd and Benbasat in their work [14, 15] presented a model on how decision makers adopt the decision strategy under high cognitive load. Along with other research they point out that decision makers tend to trade off the quality of the decision for minimization of the decision-making effort. Payne [3] pointed out that people seek to reduce the amount of information processing involved in complex decision-making. Decision makers may be able to construct decision strategies as they progress in a decision process rather than selecting them "ex ante" [16]. A well-designed decision aid ("technological intervention" [17]) can influence choice of a decision strategy by making the strategy that leads to the more accurate decision at least as easy to employ as a simpler, but much less accurate, heuristic. Otherwise, a decision aid may only influence decision-making efficiency" [15].

Finally, decision behaviour can influence the quality of a decision in many ways. [11] conclude that a well-constructed decision should be based upon consideration of a range of options and those objectives most critical to the individual. But decision makers often focus on a single option, a single objective or attribute, or a single assumed state of the world when reasoning about a decision problem, especially under stressful conditions such as high information overload or time pressure [18]. They suggest a remedy for this problem would be to explicitly encourage people to think of multiple alternatives, and multiple attributes or objectives.

B. Consideration Sets in Decision Making

Consideration set is conceptualised as the set of alternatives a decision maker considers seriously for choice. When a given brand enters the consideration set of a consumer, it increases the chances that the consumer will choose that brand, but exclusion from the consideration set prevents the selection of the brand [1]. Consideration set theory is an important element of multi-attribute decision-making. The concept of consideration fits well with theory in consumer behaviour, which suggests that for complex decisions or those involving many alternatives a consumer is likely to employ a decision process that can be represented by a phased decision rule [2]. The consumer might undertake a two-stage process, first filtering available alternatives and then undertaking detailed analysis of the reduced set.

Wu & Rangaswamy [3] suggest that consumers do not choose products from a universal set of alternatives, but frequently form context-specific consideration sets from which they make their choices. An important limitation of existing consideration set models is that none of them explicitly incorporates the dynamics of consumer search process in consideration set formation. Payne et al. [4] suggest that a well-constructed preference should be based upon consideration of a range of options and those objectives most critical to the individual. Klenosky and Perkins [5] describe an approach, called the "screening" approach, in which respondents are shown full-profile choice alternatives (similar to those used in traditional conjoint studies) and are asked to decide which of three groups each alternative belongs to: (1) those the respondent would definitely consider selecting, (2) those he might consider selecting and (3) those he would definitely reject from further consideration. The important difference is that the screening approach allows capturing decision maker's preference in the different stage of the decision process; the derived utilities represent the importance (weights) "a subject placed on attribute levels during consideration set formation not during final evaluation and choice". However, when making a choice from larger consideration sets, "consumers may try to simplify the decision process by focusing on attributes that are more salient or easier to compare. If these attributes are less important, consumers make worse decisions" [6]. Moreover, consumers may incorrectly 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, thus leading

to worse choices. Next we discuss elicitation of decision makers' preferences in more detail.

C. Elicitation of preferences

Assumptions that the decision maker can accurately state which levels within an attribute are acceptable versus unacceptable is a fundament to the self-explicated approach [5]. Moreover, decision-makers use a conjunctive evaluation of available alternatives in which all the alternatives that posses at least one attribute with unacceptable value are rejected from the further consideration. However, previous research indicates that decision makers tend to fail to fully adhere to the self-explicated procedure. Klein [7] found that decision makers often fail to reject alternatives with attribute levels, which they themselves had previously described as unacceptable. The presented results show that 15 per cent of participants decided to finally choose the alternative described with at least one attribute level they themselves indicated as "completely unacceptable" (as cited in [5]). When faced with more than few alternatives, decision makers tend to restrict their processing to a narrow subset of possibilities [8]. In their study, Green et al. [9] argue that strengthening the instructions used to rate the attribute level desirability can reduce the tendency to consider alternatives with "unaccepted" levels. In sum, researchers rely on the self-explicated approach, despite the fact that its assumptions are often violated by actual choice behaviour."

We argue that there is a need for a soft-boundary filtering decision aid in order to reduce the negative effects of dynamics in attribute and attribute-level preferences of the decision-makers. We give an overview of the soft-boundary filtering decision aid in the next section.

III. THE DECISION AID

In the previous section we gave the general overview of the theoretical background of modelling user preferences in multi-attribute decision-making (MADM). In this section we present the model of the problem under our study and discuss it based on the relevant literature in the field. Later we explain the choice of the utility function for the purpose of this study. Finally, we discuss the consequences of incorporating the soft-boundary filtration decision aid in the general model and provide some illustrative examples.

A. Model of a decision-making problem

In this section we present and explain a model of the problem. The multiple-attribute decision-making problems under study can be described as follows. Let $X = \{x_1, x_2, ..., x_n\} (n \geq 2)$ be a discrete set of n alternatives available for a decision maker, $G = \{g_1, g_2, ..., g_m\} (m \geq 2)$ be a finite set of attributes describing alternatives, so that alternative $x_j \in X$ is described with a set of attributes' values: $x_j = \{g_{1j}, g_{2j}, ..., g_{mj}\}$, where g_{ij} is the value of i-th attribute describing alternative $x_j \in X$. Let $w = \{w_1, w_2, ..., w_m\}$ be the weight vector of attributes provided by a decision maker, and $P = \{p_1, p_2, ..., p_m\}$ be a set of preferences on preferred attributes' values expressed by a decision maker, where $p_i = [p_i^L, p_i^U]$, $p_i^L \leq p_i^U$ is a preference on attribute values in a form of an interval, expressed on the alternative $x_j \in X$ and with respect to the attribute $g_i \in G$. p_i^L and p_i^U denote the lower and upper limits of the value preference interval respectively. The importance weight of a given attribute $w_i \in w$ reflects the relative importance of the attribute g_i, $w_i > 0$, $i \in (1...m)$ where:

$$(1) \qquad \sum_{i=1}^{m} w_i = 1$$ Let $U = (u_{ij})_{n \times m}$

be the utility values matrix derived based on decision maker's preference on attributes' values, where $u_{ij} = f(g_{ij}, p_i)$ (a function assessing utility value for the alternative $x_j \in X$ and with respect to the attribute $g_i \in G$ - goodness of fit of the attribute value to the decision maker's preference). The general model of the overall value of the alternative $x_j \in X$ can be expressed as follows, presuming a summative linear arrangement:

$$(2) \qquad v(x_j) = \sum_{i=1}^{m} w_i u_{ij} \quad j \in \{1...n\}$$

Or, when a function for assessing utility level of values of attributes (u_i) is introduced:

$$(3) \qquad v(x_j) = \sum_{i=1}^{m} w_i f(g_{ij}, p_i) \quad j \in \{1...n\}$$

The decision problem can be thus presented as searching for the alternative with the maximum overall utility value (or maximum fit of the given alternative to the preferences of a decision maker).

B. Filtration of the set of alternatives

When the set of alternatives to consider is large, a decision maker suffers from information overload. High cognitive load [10] influences strategy selection and thus negatively impacts the decision quality [6, 11]. Filtering is one of the techniques used to limit the number of information items in the set presented to the user, thus allowing reduction of the effect of experienced information overload. The process of filtering involves application of filtering rules (or restriction on attributes) to the items in the set to be filtered [12]. Filtering rules are typically Boolean – if particular item does not satisfy any of the filtering rules it is removed from the set. Thus, users are able to significantly limit the number of alternatives they will examine in more detail with constructed filtering rules resembling their

information preference. User preferences on attributes' values are the key input in the process of filtration. If an alternative (information item) does not satisfy all the criteria specified by the user, it is removed from the set. Thus, a new set is constructed, that contains only the alternatives that fully satisfy users attributes' values preference:

$$(4) \quad \overset{*}{X} = \{x_1, ..., x_k\}(k \le n) \quad where \quad \underset{x_j}{\forall} \underset{p_i}{\forall} g_{ij} \in p_i$$

C. Utility values of attributes

As stated in the previous section, the model for overall value of the alternative requires a function for mapping the attributes' values and the user preferences into utility values. Utility evaluation is an important problem addressed by many researchers in different contexts and decision environments [5, 13, 14]. In general, one can identify cost and benefit attributes in MADM problems [13]. Typically, the goal of a decision maker is to minimize the value of the cost attributes and maximize the value of the benefit attributes (e.g. a customer is typically more happy with a bigger apartment (maximizing the benefit attribute) for the smaller price (minimizing the cost attribute)).
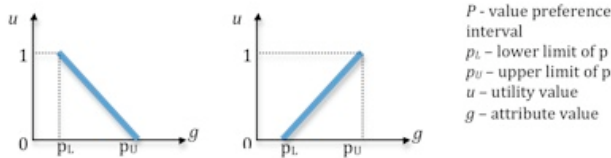

Fig. 1. Linear normalized utility function for a cost-type (a) and benefit-type (b) attribute.

In our model, the user's preference on attribute value can be expressed using an interval. Thus, we define a simple utility mapping function as follows. For the convenience of calculation and simplicity, we propose a linear utility function (see Fig. 1) that provides values from the interval [0,1] for a given preference $p_i \in \left[p_i^L, p_i^U \right]$ (1 being ideal, and 0 being none preference for the particular value of a given attribute g_{ij}). Thus, the linear utility function has the form of:

$$(5) \quad u_{ij} = \begin{cases} a g_{ij} + b & g_{ij} \in p_i \\ 0 & g_{ij} \notin p_i \end{cases}$$

with the following coefficients for a give attribute type:

a. $\quad a = \dfrac{1}{p_i^U - p_i^L}, \quad b = \dfrac{p_i^L}{p_i^L - p_i^U}$ (benefit)

b. $\quad a = \dfrac{-1}{p_i^U - p_i^L}, \quad b = \dfrac{p_i^U}{p_i^U - p_i^L}$ (cost type)

Example utility values derived based on such a function for both types of attributes, where the price is the cost type attribute, and the size is the benefit type attribute, are presented in Table 1. Decision makers' preference of attribute values is p_1=[200 000,400 000] (price in €) and

p_2=[60,80] (size in m²). Based in these assumptions and using (5) we calculate utilities of attributes' values in case of price (utility 1) and size (utility 2) of the apartment.

TABLE 1
EXAMPLE SIMPLE DECISION PROBMEL AND UTILITY VALUES

	Price [€]	Size [m²]	Utility 1	Utility 2
X_1	6000	70	1	0.5
X_2	7000	75	0.5	0.75
X_3	8000	80	0	1

D. Soft-boundary preference decision aid

One of the contributions of this research in progress paper is the soft-boundary filtration decision aid. We propose a decision aid that would limit the negative effects of the dynamics in the decision makers' preferences on attributes' weights and values. We propose a modification to filtration process by introducing "soft-boundary variables" e_i^- and e_i^-, $i \in \{1...m\}$. Appearance of these variables modifies the filtering rules built based on attributes' values preference $p_i = [p_i^L, p_i^U]$ causing the filtering rule to be less restrictive. Thus the alternatives that satisfy the less strict criteria $\overset{*}{p_i} = [p_i^L - e^-, p_i^U + e^+]$ remain in the set and can be considered by the decision maker:

$$(6) \quad \overset{**}{X} = \overset{*}{X} + X_e \quad , \quad \underset{x_j \in X_e}{\forall} \underset{i}{\exists}(g_{ij} \in \overset{*}{p_i} \wedge g_{ij} \notin p_i)$$

In other words, the set of alternatives $\overset{*}{X}$ constructed based on the decision maker's attributes' values preferences (filtration rules) is extended with the set of alternatives X_e suggested by the soft-boundary decision aid. One can define a number of approaches for calculation of the soft-boundary variables e_i^- and e_1^+ (relaxation).

Firstly, relaxation variables can be computed in relation to the size of a preference range p_i proportionally to its size - where $e_i^- = e_i^+ = \delta \times (p_i^U - p_i^L)$ for $\delta \in R$, e.g. for δ = 0.5 we calculate $e_i^- = e_i^+ = 0.5 \times (p_i^U - p_i^L)$, so $\overset{*}{p_i}$ is twice larger than initial range p_i (e.g. [15]).

Secondly, relaxation can be computed as percentages of the values specified in consumer preference, then $e_i^- = \delta * p_i^L$ and $e_i^+ = \delta * p_i^U$ for $\delta \in R$, thus $e_i^+ > e_i^-$. For example, when δ = 0.1 and preference on price p_{PRICE} = (€7000, €8000) a relaxed preference would be equal $p*$ = (€6300, €8800).

Finally, extent of preference relaxation can be computed using the distribution and clustering of the attribute values – e_i^- and e_1^+ are calculated based on maximum allowed number of suggested items and within the preference interval distribution of attribute values.

For the purpose of this study we use the first method with

k=0.5, so that $e_i^- = e_i^+ = 0.5 \times (p_i^U - p_i^L)$. We present an example of application of the soft-boundary filtering decision aid in such a configuration in the following section.

E. Illustrative example

In the following example we use a multi-attribute decision-making problem of apartment selection (adapted from [16]) to illustrate the potential benefits of soft-boundary filtering decision aid. A customer is willing to choose an apartment to buy from the set of four apartments $x_j(j=1,2,3,4)$. Each apartment is described using the set of three following attributes:

- g_1: Price (in €) to pay for the apartment
- g_2: Distance to the office (in minutes)
- g_3: Size (in square meters)

Among these attributes, g_3 is of benefit type (the higher value the better) and g_1 and g_2 are of cost type (the lower value the better). Before examination of the initial set of alternatives (see Table 2), decision maker provides the importance level of attributes (Weights) and his preference on attributes' values (Preferences) (see Table 3).

TABLE 2
INITIAL SET OF ALTERNATIVES FOR CONSIDERATION

	Price [€]	Distance [min]	Size [m²]
X_1	98 000	5	60
X_2	99 000	4	60
X_3	101 000	2	80
X_4	120 000	3	70

TABLE 3
INITIAL SET OF PREFERENCES ON ATTRIBUTES AND WEIGHTS

	Price [€]	Distance [min]	Size [m²]
Weights	0.8	0.2	-
Preferences	[94500, 99500]	[0,5]	-

In other words, the most important criterion for the decision maker is the price ($w_1 = 0.8$) of an apartment, with $p_1 = [94500, 99500]$. Secondly, the apartment must be located in the close distance to the office (max 5 minutes), thus $p_2 = [0,5]$ with the importance $w_2 = 0.2$. Other attributes seem to be not important to the decision maker as $w_3 = 0$. These information preferences allow the construction of the filtration criteria, the reduction of the set of alternatives so that only alternatives of value to the decision maker are presented (see Table 4) and calculation of the utility values for price (utility 1), distance (utility 2) and size (utility 3) attributes (see Table 5).

TABLE 4
SET OF ALTERNATIVES AFTER FILTERING

	Price [€]	Distance [min]	Size [m²]
X_1	98 000	5	60
X_2	99 000	4	60

TABLE 5
UTILITY VALUES FOR VALUE PREFERENCES

	UTILITY 1	UTILITY 2	UTILITY 3
X_1	0.3	0.2	0
X_2	0.1	0.2	0

According to the utility values, with the assumption that the decision maker's preferences did not change and based on (2) we calculate the overall utility of both alternatives as follows:

- $v(x_1) = 0.8*0.3 + 0.2*0.2 = 0.28$
- $v(x_2) = 0.8*0.1 + 0.2*0.2 = 0.12$

According to user preferences, the first apartment is more attractive. However, user preferences are context dependent (they can change significantly when a decision maker is comparing alternatives). We now examine a scenario where a soft-boundary filtration decision aid is used. During the filtration phase, the soft-boundary filtration decision aid expands the interval resembling decision maker's attribute values preference from $p_1 = [94500, 99500]$ to $p_1^* = [92000, 102000]$, for k=0.5 and $e_1^- = e_1^+ = 0.5 \times (99500 - 94500) = 2500$. Thus, the decision maker is presented with the set of three (x_1, x_2, x_3) alternatives (see Table 6) instead of two when standard filtration is used.

TABLE 6
SET OF ALTERNATIVES AFTER FILTRATION USING RELAXED CONSTRAINTS

	Price [€]	Distance [min]	Size [m²]
X_1	98 000	5	60
X_2	99 000	4	60
X_3	101 000	2	80

TABLE 7
UTILITY VALUES ADJUSTED IN PREFERENCE RELAXATION

	UTILITY 1	UTILITY 2	UTILITY 3
X_1	0.4	0.2	0
X_2	0.3	0.2	0
X_3	0.1	0.6	1

Based on the presented set, the decision maker reassesses the importance levels of attributes as he finds price as important as the distance to the office ($w_1 = w_2 = 0.4$) and the size to be of some value ($w_3 = 0.2$). Decision maker's preferences regarding attributes' values also change regarding the size of apartment specified as $p_3 = [60,80]$ (see Table 7). Thus, overall utility values of the alternatives are calculated as follows (under assumption that utility value is assessed based on p_1 not p_1^*:

- $v(x_1) = 0.4*0.4 + 0.4*0.2 + 0.2*0 = 0.24$
- $v(x_2) = 0.4*0.3 + 0.4*0.2 + 0.2*0 = 0.2$
- $v(x_3) = 0.4*0.1 + 0.4*0.6 + 0.2*1 = \textbf{0.48}$!

This example illustrates how the use of a soft-boundary

filtration decision aid can prevent decision maker from filtering out the alternatives he may find attractive from the initial set, and lead to more confidence in decisions in the decision process where decision maker's preferences are dynamic. Using the typical filtration, the decision maker eliminates all alternatives that do not fully fit his preferences specified using attributes' values ranges. In contrast, when using the soft-boundary filtering decision aid, selected alternatives that do not fit initial decision maker's preferences are not removed from the set and can still be considered. Our example illustrates how the variation of the decision maker's preferences may lead to choosing an alternative initially removed from consideration (apartment x_3 in our example). Moreover, we show that the soft-boundary filtering decision aid may lead to the increase of the quality of a decision.

In this section we discussed the model of the problem under study and introduced the soft-boundary filtering decision aid. We argue that the soft-boundary filtering decision aid has significant impact on characteristics of the decision made. We continue discussion and elaborate the hypotheses to be tested, in the next section.

IV. RESEARCH PLAN AND HYPOTHESES

In the previous section we discussed the model of the soft-boundary filtering decision aid. In this section we debate the potential impact of such a decision aid on decision quality and consideration sets. Moreover based on the discussion in the previous sections we develop hypotheses to be tested in the future studies.

A. Dependent variables

We expect that the soft-boundary decision aid will have an impact on various aspects of multi-attribute decision-making, in particular: decision quality, consideration set quality and size. We discuss our expectations in more detail further in this section.

Decision quality is conceptualized as a decision maker's degree of confidence in a correctness of his decision (discussed in the context of online shopping by [17]). We propose to measure of objective decision quality by how often decision makers change they initial decision when they are offered this opportunity. Switching indicates low quality of the initial decision. More measures will be used when required by the experiment setup.

Consideration set is defined as a set of alternatives that a decision maker seriously considers as his final choice. We argue that both the quality and the size of the set are affected by the use of the decision aid we propose. The size of the consideration set is simply the number of alternatives that a decision maker is seriously considering. The quality of the consideration set can be assessed by the average overall utility value of alternative seriously considered by a decision maker.

B. Decision Quality

Research on decision support systems indicates that decision aids designed to screen large numbers of alternatives may reduce decision makers' cognitive effort [10] and improve decision quality by enabling individuals to make complex decisions with high accuracy [18]. Decision aids allow decision makers to significantly reduce the amount of unnecessary information processed. Moreover, the ability to screen alternatives in an efficient manner enhances the "quality" of the information that is processed, which, combined with reduced information quantity, should have a positive impact on decision quality [17]. Moreover, some results [19] suggest that "electronic decision formats based on weighted average scores for alternatives lead to less switching after initial choice". Thus, we argue that decision makers' use of the soft-boundary filtering decision aid will have the positive effects on the decision quality. In particular, the following hypotheses are to be tested:

H1: Use of the soft-boundary decision aid positively influences quality of the alternative being selected

H2: Use of the soft-boundary filtration decision aid leads to a higher degree of confidence in the decision.

C. Consideration Set Quality

The soft-boundary filtering decision aid prevents filtering out the alternatives that do not fully satisfy the initial attributes' values preferences expressed by the decision maker. Thus, it increases the probability that more alternative of potential high-value will be examined and perhaps considered by the decision maker. We expect that the average quality of the alternatives in the consideration set will increase when using the soft-boundary filtering decision aid.

H3: Use of the soft-boundary decision aid leads to the increase of the average overall utility value of the alternatives in the consideration set.

D. Consideration Set Size

Model of consideration set size [2] suggest that the decision maker will continue to search for alternatives to consider "as long as the expected returns from search (in terms of making a choice of higher expected utility) exceed the cost of further searching". [17] pointed out that the use of screening reduces the size of the consideration set, as the decision aid used provides information about the relative utility of available alternatives prior to processing specific product information and thus "the marginal benefits of including additional products reduces much more rapidly than in a situation where the consumer has not prior information about the relative utility of alternatives". The soft-boundary filtering decision aid may have similar, however less intensive, effect on the size of a consideration set at it increases the number of alternatives considered by a decision maker.

H4: Use of the soft-boundary decision aid leads to

reduction number of items in consideration sets in comparison to no aid.

H5: Use of the soft-boundary decision aid prior to screening will increase the number of high-quality alternatives considered by the decision maker in comparison to no standard filtration decision aid.

E. Dataset for Experimentation

In order to evaluate our research hypotheses, we plan to conduct a set of simulations and user based studies in various scenarios including housing market and used car market. For simulations in the used car domain we collected 56915 car advertisements that were posted and available for browsing. Each advert was described using the following types of attributes: 5 numerical (e.g. price, mileage), 11 descriptive (e.g. color, body type), and 24 binary (indicating features of a car e.g. "Driver Airbag", "Air conditioning"). One image per advert was collected where available. The data allowed us to perform experiments in a controlled environment using an authentic dataset. Many decision aids (e.g. recommender systems) are evaluated using good quality datasets, often designed and prepared by the researchers. Thus, researchers often point out that the quality of the support provided by the various decision aids is highly dependant on the quality of data and is difficult to predict when dealing with real data. Inconsistencies, uncertainty and large number of alternatives are challenging characteristics of existing choice datasets. Thus, we believe that results of our experiments will be of value to both researchers and practitioners.

F. Proposed research method

We propose to evaluate the above propositions through a controlled user-based laboratory experiment. The apparatus will consist of a website that will provide users with access to 26915 available car adverts with pictures we gathered from an existing used car advertising web page, and task the users to buy a car. The website will be implemented to functionally resemble popular used-car advertisement websites[1] (e.g. range filtering, sorting). We will create two implementations: the treatment website offering a soft-boundary decision aid, and a control website with no decision aid, following the approach suggested in Viappiani et al [20].

Measuring the quality of purchase decisions and consideration sets is a very ambitious task. In e-commerce contexts, decision (purchase) quality can be conceptualized as "the degree of match or fit between heterogeneous consumer preferences and differentiated products" [17]. However, as an individual's preferences are not subject to direct observation, and indeed dynamic throughout decision-making tasks, it is impossible to accurately measure decision quality in uncontrolled real-world settings. Häubl and Trifts [17] used prepared sets of products constructed in a way that

allowed, irrespective of the individual's utility function, assessment of whether the purchase of a particular alternative was a good decision. Choices of dominated alternatives in their controlled study resemble suboptimal real-world purchase decisions, "given particular utility functions of an individual and the set of given products, irrespective of whether or not any of the alternatives are objectively dominated" [17].

In our proposed experiment we plan to draw the participant sample from students of different programs at a university. Although the reliance on college students has been criticized by many studies in applied research, it was shown that it is appropriate to use student subjects in evaluation tasks that do not require prior knowledge, e.g. accommodation-to-rent search [21]. Moreover, we found out that many valuable research studies in e-commerce proposed students as a representative sample of the Internet users [11, 20, 22]. Todd and Benbasat [11] conducted their study using fifty-two undergraduate university students enrolled in business, arts, or engineering programs that volunteered for participation in the experiment. Hostler et al. [23] carried out a study on the impact of the Internet agents on end users' performance measured with decision quality and confidence using a sample of 69 undergraduate students.

V. DISCUSSION AND FUTURE WORK

This work-in-progress paper introduces the concept of a soft-boundary filtering decision aid used in multi-attribute decision-making. We argue that during the process of filtering of the initial, very large, set of alternatives, decision makers eliminate alternatives they could consider by providing preference on attributes and attributes' values. In this paper we introduce a model of such a decision aid and hypothesize about its impact on decision quality and consideration set formation.

We plan to investigate validity of the hypotheses presented in this article through a set of experiments. Apart from the discussion presented in this paper, we plan to investigate the effects of usage of the soft-boundary decision aid not only in filtering of alternatives but also during other stages of the decision process. We expect, for example, that interesting results may be gathered when the decision problem is viewed as a search and browsing issue. Thus, we will examine how the decision aid would enhance the process of exploration of a very large sets of alternatives, in comparison to various mechanisms explored in other studies [24]. Moreover, future experiments will investigate application of the research on filtration interfaces [25] and query previews [26, 27] for search in very large databases in the context of decision-making.

If the decision aid described here increases the overall quality of the consideration set, and enables alternatives to be retained in that set that would otherwise be lost in an early elimination stage, decision quality may be increased. Furthermore, if it impacts the decision quality, the decision

---

[1] http://www.carzone.ie/

aid would result in higher degree of confidence in the decision and lead to higher decision makers' satisfaction. Moreover, increased average quality of the alternatives considered by a decision maker would reduce his decision-making effort. This would have a direct relevance for online consumers, as well as having value to e-commerce providers.

E-commerce is one of the possible applications of the soft-boundary filtering decision aid. One of the characteristics of electronic shopping environments is the lack of physical constraints on product display. Although consumers desire access to a very large number of products, their cognitive resources are limited. They may simply be unable to process vast amounts of information about very large numbers of products and to make a satisfactory purchase decision. Häubl and Trifts [17] point out that sophisticated interactive decision aids are a potential solution to this problem. The soft-boundary filtering decision aid we propose in this paper may be of benefit for consumers in online stores and thus may be of value for the online shopping service providers.

REFERENCES

[1] R. L. Andrews and T. C. Srinivasan, "Studying consideration effects in empirical choice models using scanner panel data," *Journal of Marketing Research,* vol. 32, pp. 30-41, 1995.

[2] J. H. Roberts and J. M. Lattin, "Development and testing of a model of consideration set," *Journal of Marketing Research,* vol. 28, pp. 429-440, 1991.

[3] J. Wu and A. Rangaswamy, "A Fuzzy Set Model of Search and Consideration with an Application to an Online Market," *Marketing Science,* vol. 22, pp. 411-434, Summer 2003.

[4] J. W. Payne, J. R. Bettman, and D. A. Schkade, "Measuring constructed preferences: Towards a building code," in *Symposium on Elicitation of Preferences*, Berkeley, California, 1999, pp. 243-270.

[5] D. B. Klenosky and W. S. Perkins, "Deriving attribute utilities from consideration sets: An alternative to self-explicated utilities," *Advances in Consumer Research,* vol. 19, pp. 657-663, 1992.

[6] K. Diehl, "When Two Rights Make a Wrong: Searching Too Much in Ordered Environments," *Journal of Marketing Research,* vol. 42, pp. 313-322, 2005.

[7] N. M. Klein, "Assessing Unacceptable Attribute Levels in Conjoint-analysis," *Advances in Consumer Research,* vol. 14, pp. 154-158, 1987.

[8] T. J. Gilbride and G. M. Allenby, "A choice model with conjunctive, disjunctive, and compensatory screening rules," *Marketing Science,* vol. 23, pp. 391-406, Sum 2004.

[9] P. E. Green, A. M. Krieger, and P. Bansal, "Completely Unacceptable Levels in Conjoint-Analysis - A Cautionary Note," *Journal of Marketing Research,* vol. 25, pp. 293-300, Aug 1988.

[10] P. Todd and I. Benbasat, "The Influence of Decision Aids on Choice Strategies - An Experimental Analysis of the Role of Cognitive Effort," *Organizational Behavior and Human Decision Processes,* vol. 60, pp. 36-74, Oct 1994.

[11] P. Todd and I. Benbasat, "Inducing compensatory information processing through decision aids that facilitate effort reduction: An experimental assessment," *Journal of Behavioral Decision Making,* vol. 13, pp. 91-106, Jan-Mar 2000.

[12] U. Hanani, B. Shapira, and P. Shoval, "Information filtering: Overview of issues, research and systems," *User Modeling and User-Adapted Interaction,* vol. 11, pp. 203-259, Aug 2001.

[13] Z. H. Xu, "Multiple-attribute group decision making with different formats of preference information on attributes," *Ieee Transactions on Systems Man and Cybernetics Part B-Cybernetics,* vol. 37, pp. 1500-1511, Dec 2007.

[14] I. T. Yang, "Utility-based decision support system for schedule optimization," *Decision Support Systems,* vol. 44, pp. 595-605, Feb 2008.

[15] N. Mirzadeh and F. Ricci, "Cooperative query rewriting for decision making support and recommender systems," *Applied Artificial Intelligence,* vol. 21, pp. 895-932, 2007.

[16] P. Todd and I. Benbasat, "The Use of Information in Decision-Making - An Experimental Investigation of the Impact of Computer-Based Decision Aids," *Mis Quarterly,* vol. 16, pp. 373-393, Sep 1992.

[17] G. Häubl and V. Trifts, "Consumer decision making in online shopping environments: The effects of interactive decision aids," *Marketing Science,* vol. 19, pp. 4-21, Win 2000.

[18] D. T. Singh and M. J. Ginzberg, "An empirical investigation of the impact of process monitoring on computer-mediated decision-making performance," *Organizational Behavior and Human Decision Processes,* vol. 67, pp. 156-169, Aug 1996.

[19] R. E. Widing and W. W. Talarzyk, "Electronic Information Systems for Consumers: An Evaluation of Computer-Assisted Formats in Multiple Decision Environments," *Journal of Marketing Research,* vol. 30, pp. 125-141, May 1993.

[20] P. Viappiani, P. Pu, and B. Faltings, "Preference-based search with adaptive recommendations," *AI Commun.,* vol. 21, pp. 155-175, 2008.

[21] E. J. Garrity, B. Glassberg, Y. J. Kim, G. L. Sanders, and S. K. Shin, "An experimental investigation of Web-based information systems success in the context of electronic commerce," *Decision Support Systems,* vol. 39, pp. 485-503, May 2005.

[22] P. Pu, P. Viappiani, and B. Faltings, "Increasing user decision accuracy using suggestions," in *Proceedings of the SIGCHI conference on Human Factors in computing systems* Montreal, Quebec, Canada: ACM, 2006.

[23] R. E. Hostler, V. Y. Yoon, and T. Guimaraes, "Assessing the impact of Internet agent on end users' performance," *Decision Support Systems,* vol. 41, pp. 313-323, Nov 2005.

[24] Y. Ka-Ping, S. Kirsten, L. Kevin, and H. Marti, "Faceted metadata for image search and browsing," in *Proceedings of the SIGCHI conference on Human factors in computing systems* Ft. Lauderdale, Florida, USA: ACM, 2003.

[25] C. Ahlberg and B. Shneiderman, "Visual information seeking: Tight coupling of dynamic query filters with starfield displays," in *Human Factors in Computing Systems, Chi '94 Conference Proceedings - Celebrating Interdependence*, B. Adelson, S. Dumais, and J. Olson, Eds. New York: Assoc Computing Machinery, 1994, pp. 313-317.

[26] E. Tanin, A. Lotem, I. Haddadin, B. Shneiderman, C. Plaisant, and L. Slaughter, "Facilitating data exploration with query previews: a study of user performance and preference," *Behaviour & Information Technology,* vol. 19, pp. 393-403, Nov-Dec 2000.

[27] E. Tanin, B. Shneiderman, and H. R. Xie, "Browsing large online data tables using generalized query previews," *Information Systems,* vol. 32, pp. 402-423, May 2007.