Association for Information Systems AIS Electronic Library (AISeL)

Wirtschaftsinformatik Proceedings 2009

Wirtschaftsinformatik

2009

ON THE RELATIONSHIP BETWEEN INTERACTIVE DECISION AIDS AND DECISION STRATEGIES: A THEORETICAL ANALYSIS

Jella Pfeiffer Johannes Gutenberg-Universität Mainz

René Riedl Johannes Kepler Universität Linz

Franz Rothlauf Johannes Gutenberg-Universität Mainz

Follow this and additional works at: http://aisel.aisnet.org/wi2009

Recommended Citation

Pfeiffer, Jella; Riedl, René; and Rothlauf, Franz, "ON THE RELATIONSHIP BETWEEN INTERACTIVE DECISION AIDS AND DECISION STRATEGIES: A THEORETICAL ANALYSIS" (2009). *Wirtschaftsinformatik Proceedings* 2009. 94. http://aisel.aisnet.org/wi2009/94

This material is brought to you by the Wirtschaftsinformatik at AIS Electronic Library (AISeL). It has been accepted for inclusion in Wirtschaftsinformatik Proceedings 2009 by an authorized administrator of AIS Electronic Library (AISeL). For more information, please contact elibrary@aisnet.org.

ON THE RELATIONSHIP BETWEEN INTERACTIVE DECISION AIDS AND DECISION STRATEGIES: A THEORETICAL ANALYSIS

Jella Pfeiffer¹, René Riedl², Franz Rothlauf¹

Abstract

Internet shops enable customers to easily compare a large number of products. During their buying decision, customers apply decision strategies which describe their way of choosing their preferred product. In order to support the customers, Internet shops offer interactive decision aids like sorting or filtering mechanisms. This paper answers the question, which types of interactive decision aids are necessary to apply specific decision strategies. Based on the analysis, web designers are advised to offer those decision aids that go best with the most commonly used decision strategies and make decisions easier and more precise.

1. Introduction

For years, the Internet has continuously attracted an increasing number of consumers. A recent study predicts that the number of Europeans who shop online will grow to 174 million in 2011 with a total net retail spending of 263 billion euro [9]. An easy acquisition of product information fuels this online shopping boom. A main difference between online shopping and traditional shopping is that customers can easily access and compare information on products and services on the Internet. In contrast, in the traditional way of shopping, consumers have to move physically from store to store, which results in time-consuming and costly search processes.

Since there is a positive correlation between the ease of information acquisition and the total amount of information considered in a particular choice situation [21], consumers process more information online than in traditional shopping. However, providing too much information may have negative effects for online stores [14]. In particular, an information overload may prevent online consumers from making a purchasing decision, thereby negatively influencing an Internet store's sales.

¹ Lehrstuhl für Wirtschaftsinformatik und BWL, Johannes Gutenberg-Universität Mainz

² Institut für Wirtschaftsinformatik – Information Engineering, Johannes Kepler Universität Linz

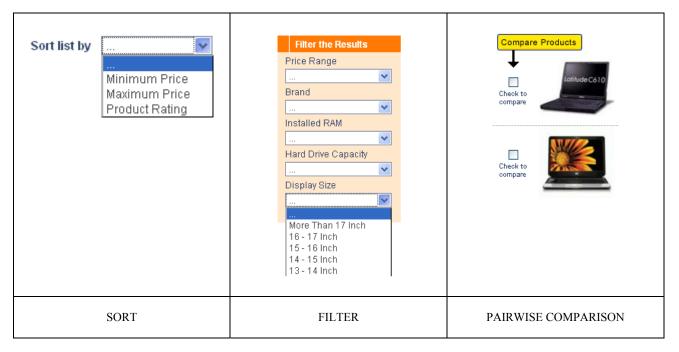


Figure 1: Examples of Interactive Decision Aids (taken from *activeshopper.com*)

Considering the importance of providing the appropriate amount of information (not too much, and not too little), it is crucial for Internet stores to present consumers with all information which might be relevant to make their purchasing decision. Unfortunately, presenting the appropriate amount of information to every single customer is not easy. On the one hand, a vast amount of information can be useful for a particular customer (depending, for example, on his/her prior experience in buying a particular product such as a digital camera). On the other hand, presenting unnecessary information might impede the customers' ability to make accurate decisions [4, 15, 22, 33]. Consequently, Internet stores face a serious dilemma: How to provide the appropriate amount of information?

The basic difficulty lies in the fact that online shop designers usually cannot know a priori what kind of information is needed for the individual customer [1]. Without this knowledge, the amount of information that is potentially relevant can be very large. In order to solve this difficulty, customers are provided with interactive decision aids which allow them to control their own information search [3, 37, 40]. The designers of *activeshopper.com*, for instance, provide several interactive decision aids for their customers. Figure 1 illustrates three of them: sort, filter, and pairwise comparison. It is important to note that other portals, such as *amazon.com*, use other sets of interactive decision aids and therefore decision aids may look different.

In order to make online shopping as comfortable as possible, which in turn affects sales positively, software engineers develop and use interactive decision aids that support the users' buying decision. The buying decision is the result of a cognitive process in which the users screen and identify relevant products (the so-called consideration set) and then evaluate and compare the products in the consideration set to make a final choice. In the evaluation step, the consumers make use of their repertoire of decision strategies to identify the preferred product [27]. To our knowledge, a comprehensive study on the relationship between decision strategies and interactive decision aids, which support the consumers in choosing their preferred product, does not yet exist. Therefore, the objective and contribution of this article is to analyze this relationship. The results of the analysis help web site engineers provide online customers with proper decision aids.

The selection of a particular decision strategy depends on the effort of applying it [29]. Therefore, people hardly use strategies that systematically process all available information (because this is a time-consuming and costly process). Instead, they use simplifying heuristics that need less effort, but have an acceptable level of decision accuracy. This article studies how decision aids support the application of relevant decision strategies. Hence, if strategies with high effort (processing all information available) were supported by effective decision aids, then they would be used more frequently [37]. Hence, decision accuracy would increase. High accuracy positively influences customers' satisfaction, thereby making high sales for online shops likely.

The remainder of this article is structured as follows: In section 2, we summarize 13 important decision strategies as identified by a literature review. Then, we discuss three common characteristics of decision strategies and classify them on the basis of these characteristics. In section 3, we describe seven interactive decision aids as identified by a review of online shop portals such as *activeshopper.com* or *amazon.com* and literature. Afterwards, we analyze which of the decision aids offer support for which of the 13 strategies. We demonstrate that in some cases it is possible that only one decision aid supports the application of a particular strategy, whereas in other cases several aids have to be combined. In section 4, we discuss the factors that were found to influence the usage of decision strategies with the aim of drawing the attention to the circumstances which affect the usage of particular interactive decision aids. The final section outlines the implications of our analysis and promising directions for future research.

2. Decision Strategies

In close resemblance to Payne et al. [27], we define a decision strategy as a sequence of operations used to transform an initial stage of knowledge into a final goal state of knowledge in which the decision maker feels that the decision problem is solved. Therefore, a decision strategy guides decision makers in their choice between different options. Each option has several attributes which can take different values. The goal is to maximize the accuracy of the decision that is to select the option that maximizes the utility of the decision maker. The overall utility of an option is calculated using a utility function which usually sums up the weighted utilities of the attributes. Different decision strategies can be distinguished according to their characteristics [12, 17, 29]. For the purpose of this paper, we distinguish between three important characteristics (see Table 1). First, some decision strategies do not process all information available, whereas others do. Hence, strategies can be distinguished by the amount of information processed. Second, information processing is either option-wise or attribute-wise. In option-wise processing, the attribute values of a single option (e.g., a digital camera) are considered before information about the next option is processed. In attribute-wise processing, the values of several options on a single attribute (e.g., the price) are processed before any information about a further attribute is processed.

Characteristic	ADD	DOM	EBA	EQW	FRQ	LEX	LIM	LVA	MAJ	MAU	MCD	MDL	SAT
Information ignored? Yes (Y)/No (N)	N	N	Y	N	N	Y	N	N	Ν	N	N	Y	Y
Option-wise (O) vs. attribute-wise (A) search	Α	Α	Α	Ο	0	А	0	Ο	Α	Ο	Α	Α	0
Compensatory (C) vs. non- compensatory (N)	C	Ν	Ν	С	C	Ν	Ν	Ν	С	С	С	N	N

Table 1: Characteristics of Decision Strategies

Third, decision strategies can be distinguished by their ability of compensating for a low score on one attribute with a high score on another attribute. If so, such so-called compensatory strategies require trade-offs among attributes, whereas non-compensatory strategies do not.

The following list describes 13 decision strategies as identified by a literature review [12, 29, 32]. The items are sorted alphabetically. In addition, Table 1 compares the strategies on the basis of the three characteristics.

- 1. When using the *additive difference strategy (ADD)*, a decision maker compares two options at a time, attribute by attribute. Then, he/she sums up the differences of the utilities across the attributes to provide a single overall difference score across all attributes for that pair of options. The winner is then compared with the next option and so on. The chosen option has won all comparisons.
- 2. The *dominance strategy (DOM)* chooses the option for which the utility of each attribute is equal or higher than for any other option on all attributes and better on at least one attribute.
- 3. The *elimination-by-aspects strategy (EBA)* eliminates options with unacceptable values of attributes for the most important attribute. This elimination process is repeated for the second most important attribute. The processing continues until a single option remains.
- 4. The *equal weights strategy (EQW)* chooses the option with the highest overall utility. In contrast to MAU (see number 10 below), EQW simplifies decision making by ignoring attribute weights.
- 5. The *frequency of good and/or bad features strategy (FRQ)* starts with the development of cutoff values on the utility of attributes. Then a decision maker counts the number of attributes for each option, where the utility is above the cutoff value and chooses the option with the highest number of attributes with utility above the cutoff value, the lowest number of attributes with utility below the cutoff value, or both.
- 6. The *lexicographic strategy (LEX)* selects the option with the highest utility on the most important attribute. If there are more options, LEX proceeds with the second most important attribute and so on.
- 7. The *least important minimum heuristic (LIM)* first determines the lowest utility of the attribute values of each option and then chooses the option whose worst utility is on the least important attribute.
- 8. The *least variance heuristic (LVA)* chooses the option with the lowest variance across the utility of attribute values. LVA makes sense only for decision situations in which no dominant option exists.
- 9. The majority strategy (MAJ) chooses the option with the highest number of dominant attribute values.
- 10. The *multiattribute utility model (MAU)* chooses the option with the highest weighted overall utility score defined as the sum of the weighted attribute utilities. MAU is usually viewed as the normative rule.
- 11. The *majority of confirming dimensions strategy (MCD)* involves, like ADD (1.), processing pairs of options. The values of each of the two options are compared with reference to each attribute. The option with the majority of attribute values with higher utility is retained and then compared with the next option. The process of pairwise comparison stops as soon as all options have been evaluated and the final winning option has been identified.
- 12. The *minimum difference lexicographic strategy (MDL)* works like LEX (6.) with the additional assumption that there has to be a noticeable difference of values for each attribute. If several options are within this noticeable difference for an attribute, they are considered to be equal.
- 13. The *satisficing heuristic (SAT)* considers options sequentially, in the order in which they occur in the choice set. For each value of each attribute for a particular option it is considered whether the value is acceptable. If an attribute value is unacceptable, the option is rejected, and the next option is considered. The first option that satisfies the aspiration level for each attribute is chosen.

3. Support of Decision Strategies by Decision Aids

The decision aids described in this article assist online shoppers in processing the information displayed in a comparison matrix. Such an nxm matrix consists of n options that are characterized by m attributes. For example, if laptops are the product to be purchased, price, brand, installed RAM, hard drive capacity, and display size may be relevant attributes for online shoppers (Figure 1, middle column). Comparison matrixes are commonly used in web shops to compare several options and to show differences to decision makers.

In this section, we will describe seven interactive decision aids as identified based on a review of online shop portals (SORT, REMOVE, FILTER, PAIRWISE COMPARISON), additional ones from a literature review (SCORE, SUM) [37], and a newly proposed one (MARK). Then, we

systematically analyze which of the decision aids can offer support for which of the 13 strategies. In some cases, only one decision aid supports the application of a particular strategy, in other cases, several aids have to be combined.

Table 2 summarizes the seven decision aids. First, the FILTER allows customers to specify cutoff values for an attribute (e.g., display size, middle column in Figure 1). As users might have different cutoff values for different attributes, we distinguish between a FILTER for one attribute (oneAttr) and for several attributes (sevAttr), where the latter allows for removing several attributes in one single step. A FILTER based on *markings* removes all options without a marked cell, where MARK allows coloring a cell which is unacceptable for the user, such as a particular brand. Third, the decision aid PAIRWISE COMPARISON allows to compare two options on one single screen (right column in Figure 1). Hence, the customer can access and compare relevant information more easily. Forth, the decision aid REMOVE enables decision makers to delete either an option or an attribute from the comparison matrix. Online shoppers will remove an option whenever it is no longer considered and they will remove an attribute if it is not relevant (any more) for the final decision. Fifth, the SCORE provides the possibility to write down a score or verbal note an online shopper associates with a particular option, an attribute or a particular cell. The technical implementation of this decision aid can be easily realized, because one simply has to offer a text field that can be filled in with any letters and numbers. Sixth, the decision aid SORT allows an online shopper to rearrange options and attributes in the comparison matrix on the basis of a particular criterion (e.g., minimum price, left column in Figure 1) or by manually changing the order by drag-and-drop. Finally, SUM sums up all values filled in by SCORE_{cell}. In the weighted version the SCORE_{cell} would first be multiplied with SCORE_{attr} (equivalent to calculating the overall utility of the option, see MAU).

Decision Aid	!	Description				
FILTER	oneAttr sevAttr markings	Remove all options that do not meet a minimum cutoff value/fall into a specified range on one or several attributes or which have eat least one marked cell.				
MARK		A cell is colored by clicking on it.				
PAIRWISE COMPARIS	ON	Display two options on one single screen.				
REMOVE	opt attr	Remove an option or attribute from the matrix, i.e., the option/attribute is no longer available on the screen.				
SCORE	opt attr cell	Provide a text field that can be filled in to write down information on options, attributes or single cells.				
SORT	opt attr	Rearrange options and attributes in the comparison matrix on the basis of a particular criterion (e.g., minimum price, assigned $SCORE_{attr}$, etc.).				
SUM	simple	Sum up all values listed in the $SCORE_{cell}$ for an option. In the weighted version it multiplies each attribute value with the $SCORE_{attr}$ first before summing all $SCORE_{cell}$				
weighted		up.				

Table 2: Description of Decision A	ids
------------------------------------	-----

Which of the seven decision aids can offer support for which of the 13 strategies? Decision makers using additive different strategy (ADD), for example, consider two options at a time (PAIRWISE COMPARISON) and sum up the differences of all attributes (SCORE_{cell} and SUM_{opt}). Then they remove the inferior option (REMOVE_{opt}) and compare the winner of the pairwise comparison with the next option until only one option is left. Decision makers applying the EQW strategy sum up all utilities for the single attributes of each option (SCORE_{cell} and SUM) and choose the one with the highest score. Table 3 demonstrates which decision aids support the application of which strategy.

 Table 3: Support of decision strategies by decision aid. (* Decision aid does not have to be used imperatively.)

4. EQW 5. FRQ FOR ALL OPTIONS DO SCORE _{opt} (number of good/ bad features) 6. LEX SUM _{simple} SUM _{simple} END SUM _{simple} ND SCORE _{cell} SORT _{attr} FOR ALL CELLS DO SCORE _{opt} (worst value) SCORE _{cell} END SCORE _{cell} FOR ALL OPTIONS DO SCORE _{cell} SCORE _{opt} (worst value) FOR EACH OPTION DO SCORE _{cell} SORT _{attr} FOR ALL OPTIONS DO SCORE _{cell} END FOR ALL OPTIONS DO SCORE _{cell} PAIRWISE COMPARISON FOR ALL ATTRIBUTES DO SCORE _{cell} (1 point if dominant) SCORE _{cell} SCORE _{cell} (1 point if dominant) END SCORE _{cell} (1 point if dominant) FOR ALL ATTRIBUTES DO SCORE _{cell} (1 point if dominant) SUM _{weighted} SUM _{simple}	<u>1. ADD</u> DO PAIRWISE COMPARISON FOR EACH CELL OF 2 OPTIONS DO SCORE _{cell} (with utilities) END SUM _{simple} REMOVE _{opt} UNTIL only one option is left	2. DOM DO FOR EACH OPTION DO *SCORE _{cell} *PAIRWISE COMPARISON REMOVE _{opt} UNTIL only one option is left	3. EBA *SORT _{attr} DO FILTER _{oneAttr} UNTIL only one option is	s left
SCORE cell SUMsimple SCORE opt (number of good/ bad features) SUMsimple DO *MARK REMOVE opt OR FILTERmarkings UNTIL only one option is left 7. LIM SORT attr 8. LVA FOR ALL CELLS DO SCORE cell 9. MAJ FOR ALL OPTIONS DO SCORE cell 9. MAJ FOR ALL OPTIONS DO SCORE cell 8. LVA FOR ALL OPTIONS DO SCORE cell 8. LVA FOR ALL CELLS DO SCORE cell 9. MAJ FOR ALL OPTIONS DO SCORE cell 10. MAU FOR ALL OPTIONS DO SCORE cell FOR EACH OPTION DO SCORE option SCORE cell 10. MAU FOR ALL OPTIONS DO SCORE cell 11. MCD DO *PAIRWISE COMPARISON FOR EACH CELL OF 2 OPTIONS DO SCORE attr 12. MDL SORT attr DO MARK REMOVE opt OR FILTERmarkings UNTIL only one option is left 13. SAT FILTERsevAttr				
SUMsimple ENDbad features) SUMsimple END*MARK REMOVE QINTIL only one option is left7. LIM SORT_attr8. LVA FOR ALL OPTIONS DO SCORE_cell9. MAJ FOR ALL CELLS DO SCORE_cell (1 point if dominant) SUMsimple END7. LIM SORT_attr8. LVA FOR ALL CELLS DO SCORE_cell9. MAJ FOR ALL OPTIONS DO SCORE_cell (1 point if dominant) SUMsimple7. LIM SORT_attr8. LVA FOR ALL OPTIONS DO SCORE_cell9. MAJ FOR EACH OPTION DO SCORE_cell (1 point if dominant)10. MAU FOR ALL OPTIONS DO SCORE_cell11. MCD DO SCORE_option END12. MDL SORT_attr DO MARK REMOVE_opt OR FOR ALL OPTIONS DO SCORE_cell (1 point if dominant)10. MAU FOR ALL ATTRIBUTES DO SCORE_attr END11. MCD DO SCORE_cell (1 point if dominant)12. MDL SORT_attr DO MARK REMOVE_opt OR FILTER_markings UNTIL only one option is left				
ENDUNTIL only one option is left7. LIM SORT_attr FOR ALL OPTIONS DO SCORE_opt (worst value)8. LVA FOR ALL CELLS DO SCORE_cell END9. MAJ FOR ALL OPTIONS DO SCORE_cell (1 point if dominant) SUM_simple END10. MAU FOR ALL OPTIONS DO SCORE_cell11. MCD DO SCORE_cell9. MAJ FOR ALL OPTIONS DO SCORE_cell (1 point if dominant) SUM_simple10. MAU FOR ALL OPTIONS DO SCORE_cell11. MCD DO POR EACH CELL OF 2 OPTIONS DO SCORE_attr END12. MDL SORT_attr DO MARK 	SUM _{simple}	bad features)		
7. LIM SORT_attr8. LVA FOR ALL OPTIONS DO SCORE_opt (worst value)9. MAJ FOR ALL CELLS DO SCORE_cell ENDB. LVA FOR ALL OPTIONS DO SCORE_opt (worst value)8. LVA FOR ALL CELLS DO SCORE_cell END9. MAJ FOR ALL OPTIONS DO SCORE_cell (1 point if dominant) SUM_simpleIO. MAU FOR ALL OPTIONS DO SCORE_cell11. MCD DO DO12. MDL SORT_attr DO13. SAT FILTER_sevAttrIO. MAU FOR ALL OPTIONS DO SCORE_cell11. MCD DO DO13. SAT FILTER_sevAttr13. SAT FILTER_sevAttrFOR ALL ATTRIBUTES DO SCORE_attr END FOR ALL OPTIONS DO SCORE_cell (1 point if dominant)11. point if dominant)13. SAT FILTER_sevAttrFOR ALL ATTRIBUTES DO SCORE_attr END FOR ALL OPTIONS DO FOR ALL OPTIONS DO11. point if dominant)13. sat FILTER_sevAttrFOR ALL OPTIONS DO SCORE_cell (1 point if dominant)11. mCD DO SCORE_cell (1 point if dominant)13. sat FILTER_sevAttr	END	1		
SORT attr FOR ALL OPTIONS DO SCORE opt (worst value)FOR ALL CELLS DO SCORE cellFOR ALL OPTIONS DO SCORE cell (1 point if dominant)ENDFOR EACH OPTION DO SCORE optionSUMsimpleIO. MAU FOR ALL OPTIONS DO SCORE cell11. MCD DO SCORE DO12. MDL SORT attr13. SAT FIL TER sevAttrIO. MAU FOR ALL OPTIONS DO SCORE cell11. MCD DO SCORE OPTIONS DO SCORE cell11. MCD DO ND12. MDL SORT attr13. SAT FIL TER sevAttrFOR ALL OPTIONS DO SCORE cell*PAIRWISE COMPARISON FOR EACH CELL OF 2 OPTIONS DO SCORE attrMARK REMOVE opt OR FIL TER markings UNTIL only one option is left13. SAT FIL TER sevAttr	7. LIM			
FOR ALL OPTIONS DO SCORE_opt (worst value)SCORE_cell ENDSCORE_cell ENDSCORE_cell (1 point if dominant) SUM_simpleENDFOR EACH OPTION DO SCORE_optionSUM_simple10. MAU FOR ALL OPTIONS DO SCORE_cell11. MCD DO12. MDL SORT_attrFOR ALL OPTIONS DO SCORE_cell*PAIRWISE COMPARISON FOR EACH CELL OF 2 OPTIONS DO SCORE_attr13. SAT FILTER_sevAttrFOR ALL ATTRIBUTES DO SCORE_attrOPTIONS DO SCORE_cell (1 point if dominant)13. SAT FILTER_sevAttrFOR ALL ATTRIBUTES DO FOR ALL OPTIONS DO SCORE_attrOPTIONS DO SCORE_cell (1 point if dominant)MARK FILTER_markings UNTIL only one option is leftFILTER_markings Intervention				
ENDFOR EACH OPTION DO SCORE optionEND10. MAU FOR ALL OPTIONS DO SCORE cell11. MCD DO12. MDL SORT attr13. SAT FILTER SORT DO10. MAU FOR ALL OPTIONS DO SCORE cell11. MCD DO12. MDL SORT Altr13. SAT FILTER SORT DOFOR ALL ATTRIBUTES DO SCORE attr0PTIONS DO SCORE cell (1 point if dominant)MARK FILTER MARK REMOVE UNTIL only one option is left13. SAT FILTER sevAttr	FOR ALL OPTIONS DO	SCORE _{cell}	SCORE _{cell} (1 point if o	dominant)
SCORE eNDSCORE end10. MAU FOR ALL OPTIONS DO SCORE cell11. MCD DO12. MDL SORT attr13. SAT FILTER SORT DOSCORE cell*PAIRWISE COMPARISON FOR EACH CELL OF 2 OPTIONS DODO MARK FILTER markings UNTIL only one option is left13. SAT FILTER sevAttr				
END10. MAU FOR ALL OPTIONS DO SCOREcell11. MCD DO12. MDL SORTattr13. SAT FILTER SORTattrEND FOR ALL ATTRIBUTES DO SCOREattr*PAIRWISE COMPARISON FOR EACH CELL OF 2 OPTIONS DO SCOREcell (1 point if dominant)DO MARK FILTER REMOVEopt OR FILTER MARK FILTER It comparison MARK FILTER SCOREcell (1 point if dominant)13. SAT FILTER SORTattr DO MARK FILTER SUPTIONS DO SCOREcell (1 point if dominant)	END		END	
FOR ALL OPTIONS DO SCORE cellDOSORT attr DOFILTER sevAttrEND FOR ALL ATTRIBUTES DO SCORE attrOPTIONS DO OPTIONS DO SCORE dominant)MARK FILTER markings UNTIL only one option is leftFILTER sevAttr				
FOR ALL ATTRIBUTES DOOPTIONS DOREMOVE_opt ORSCORE_attrSCORE_cell (1 point if dominant)FILTER_markingsENDdominant)UNTIL only one optionFOR ALL OPTIONS DOENDis left	FOR ALL OPTIONS DO SCORE _{cell}	<i>DO</i> *PAIRWISE COMPARISON	SORT _{attr} DO	
END FOR ALL OPTIONS DOdominant)UNTIL only one optionis left	FOR ALL ATTRIBUTES DO	OPTIONS DO	REMOVE _{opt} OR	
		,	UNTIL only one option	
SUM _{weighted} SUM _{simple}			is left	
END REMOVE _{opt}		REMOVE and		
UNTIL only one option is left				

4. Use of Decision Strategies

We discuss the factors that influence the use of decision strategies as observed in traditional retail and electronic commerce. Based on those factors, we are able to make more precise recommendations on the proper use of web-based decision aids for supporting decision strategies.

In 1990, Simon [34] pointed out that "Human rational behavior is shaped by a pair of scissors whose two blades are the structure of task environments and the computational capabilities of the actor". The *Theory of Adaptive Decision Making* [29] acts on this notion and hypothesizes that the choice in favor or against a particular decision strategy depends on both the characteristics of the decision maker and the decision problem. The most important characteristics of the decision makers are their product knowledge and their cognitive capacity, in particular the limited capacity of short-term memory [10, 13, 20]. The most important characteristics of the decision problem are (i) the complexity of the decision task, (ii) time pressure, and (iii) response mode.

The *complexity of the decision task* is determined by the number of options and attributes avaiable. Most studies have shown that the use of compensatory strategies (Table 1) decreases with an increasing number of options, whereas the use of non-compensatory strategies increases [10, 19, 29]. The results of the influence of the number of attributes on the use of decision strategies are more controversial [25]. However, as soon as the number of attributes reaches a certain level, decision makers tend to apply non-compensatory strategies [19, 29]. A meta-research study by Ford et al. [10] found that compensatory strategies are only applied when the number of options *and* attributes is small or after a number of options has been eliminated from the consideration set.

Time pressure is high when the available time to make a decision is short. There is empirical evidence that with an increasing time pressure, decision makers tend to use more non-compensatory strategies with an attribute-wise pattern of information search [28, 41, 43]. As indicated in Table 1, DOM, EBA, LEX, and MDL show such a combination.

Usually, two different *response modes* are used in experimental decision research studies [7]: Participants can either state one preferred option ("I choose option A") or rank options ("Option A is better than B, which in turn is better than C"). Empirical studies found that if participants are required to state one preferred option only (rather than a ranking), less information is considered and the information search is more attribute-wise [7, 39]. Since online shoppers' objective usually is the purchase of one preferred option, it is likely that—without any decision aids—they do not use strategies that (i) process all information available and (ii) imply an option-wise search (Table 1).

Considering the effects of the decision makers' characteristics on the applied strategy, it has been shown that experts with high product knowledge can process information about attributes better and therefore prefer non-compensatory strategies and attribute-wise search [5, 30]. Inexperienced decision makers applied first EBA to narrow down the consideration set and then ADD for the final choice [5]. Furthermore, Pereira [30] showed that decision makers with high product class knowledge react more positively, both on decision aids supporting EBA and WADD such as SORT, FILTER, SCORE, and SUM.

Because of one's *limited capacity to keep attribute values in short-term memory* [23], it is almost impossible—without having any decision aids—to apply strategies that process all information available (Table 1). Consider, for example, the MAU strategy which maximizes the utility. Using this strategy, a decision maker evaluates one option at a time for all attributes. Each attribute gets a weighting, with larger weights indicating a higher importance. For a particular option, the decision maker reads the first attribute value. The utility of that attribute value is then combined with its weight. This process is repeated for each attribute of the option. A score for each option is determined by summing up the products of the attribute utilities and weights. Once these computations have been completed for each option, the one with the highest weighted score is selected. Obviously, MAU demands a lot of the (limited) short-term memory.

A recent experiment with a combination of 4 vs. 8 options and 4 vs. 8 attributes found out that people hardly use strategies that process all information available in a comparison matrix [31]. For example, the usage of MAU (3%), EQW (1%), ADD/MCD (1%), and LVA (1%) is almost non-existent. Instead, people use heuristics such as SAT (36%) and EBA/LEX (38%). Support for the decision makers can therefore best be achieved by offering SORT, MARK, REMOVE, and FILTER. Since the authors found that ADD and MCD are hardly applied, this indicates that PAIRWISE COMPARISON is of less importance to the decision maker. All in all, this study provides empirical evidence that people apply both strategies with attribute-wise and options-wise search patterns (Table 1), but seldom do they process all information provided.

In principle, it is possible that people exactly follow *one* particular strategy. However, decision makers are usually not purists [8, 18, 24, 35], but sequentially apply different information acquisition patterns during the decision process. For example, Payne [26] discovered that in the case of choice tasks involving a large number of options, decision makers usually start with an attribute-wise information acquisition pattern (to reduce the set of options), and then shift to an option-wise pattern to make a final decision (see also [2, 5, 6, 10, 11, 16, 25, 36, 42]). This means that online customers would start using a decision aid that helps them to exclude options (e.g., FILTER, SORT_{attr}, SCORE_{attr}, and REMOVE) and then continue with a decision aid that directly compares options (e.g., SORT_{opt}, REMOVE_{opt}, PAIRWISE COMPARISON, SCORE_{opt}, and SUM).

Therefore, online shop designers must assume that customers use different strategies during one particular shopping transaction. A variety of interactive decision aids must be provided to support a broad range of strategies. Table 4 summarizes which decision aids can offer the best support in which decision environments. It is important to note that both effortful strategies (all information is processed and they are compensatory, Table 1) and simple heuristics should be supported.

Decision environment	Decision strategies	Decision aid
Large number of options	Non-compensatory strategies	PAIRWISE COMPARISON,
and attributes		REMOVE _{opt} , SCORE, SUM _{simple}
Time pressure or	Non-compensatory strategies	FILTER _{oneattr} , FILTER _{marking} , MARK,
decision maker is expert	with attribute-wise search	PAIRWISE COMPARISON,
		REMOVE, SCORE _{cell} ,SORT _{attr}
Ranking decision	No information ignored and	SCORE, SUM
	option-wise search	
First phase of decision	Attribute-wise search	FILTER _{oneattr} , FILTER _{marking} , MARK,
process		PAIRWISE COMPARISON,
		REMOVE _{opt} , SCORE _{cell} ,
		SORT _{attr} ,SUM _{simple}
Final phase of decision	Option-wise search	FILTER _{sevattr} , SCORE, SORT _{attr} ,
process		SUM

Table 4: Overview of which decision aids might support decision makers best in certain decision environments.

5. Implications and Directions for Future Research

As the access to information on the Internet is easy, online shoppers are usually confronted with a high number of products and product information. Due to their limited cognitive capacity, they strive for a reduction of the effort to process this information overload while still making a satisfactory decision. In this paper, we showed how interactive decision aids can help to apply different decision strategies. The motivation for assigning decision aids to decision strategies is twofold. First, the appropriate decision aid(s) for a particular strategy can reduce the effort of online customers in choosing a product. Second, decision aids can help the shopper to improve their decision accuracy [37]. Drawing upon our work, we suggest that Internet sellers first investigate the most frequently used search behavior of their customer empirically (e.g., by clickstream analysis). Then, sellers can tailor systems to incorporate those decision aids which best support the used strategies. Since the interactive decision aids presented in this article can be easily implemented, we consider our work to be highly relevant for Internet software engineers.

Promising directions of future work are to carry out more research along the lines of Todd and Benbasat [37, 38] who analyze the influence of decision aids on customer behavior (i.e., the use of

decision strategies and the final buying decision). Our analysis is a continuation of an ongoing investigation of the mediating role of effort in the relationship between decision aid usage and decision strategy. Several studies have demonstrated that effort constitutes an important mediator between decision aid use and decision strategy selection [33]. Therefore, it seems that the potential influence of decision aids on the decision quality cannot be understood without considering the way the decision aid affects the effort required to use alternative strategies. The research program of Todd and Benbasat suggests that decision makers use decision aids in such a way as to maintain a low overall level of effort expenditure and will employ a particular strategy if the decision aid makes it easier compared to competing alternative strategies. Thus, by studying the relationship between decision aids and decision-making effort, it becomes possible for a designer of decision aids to alter the way of processing information. Clearly, information processing can then be directed towards the main objectives of an internet store: satisfied customers and high sales.

6. References

[1] ARIELY, D., Controlling the information flow: Effects on consumer's decision making and preferences. Journal of Consumer Research, 2000. **27**(2): p. 233-248.

[2] BALL, C., A comparison of single-step and multiple-step transition analyses of multiattribute decision strategies. Organizational Behavior and Human Decision Processes, 1997. **69**(3): p. 195-204.

[3] BETTMAN, J. and M.A. ZINS, Information format and choice task effects in decision making. Journal of Consumer Research, 1979. **6**(2): p. 141-153.

[4] BETTMAN, J.R., E.J. JOHNSON, and J.W. PAYNE, *Consumer decision making*, in *Handbook of Consumer Behavior*, T.S. Robertson and H.H. Kassarjian, Editors. 1991, Englewood Cliffs: NJ: Prentice-Hall. p. 50-84.
[5] BETTMAN, J.R. and C.W. PARK, Effects of prior knowledge and experience and phase of the choice process on consumer decision processes: A protocol analysis. Journal of Consumer Research, 1980. 7: p. 234-248.

[6] BILLINGS, R.S. and S. MARCUS, Measures of compensatory and noncompensatory models of decision behavior: Process tracing versus policy capturing. Organizational Behavior & Human Performance, 1983. **31**: p. 331-352.

[7] BILLINGS, R.S. and L.L. SCHERER, The effects of response mode and importance on decision-making strategies: Judgment versus choice. Organizational Behavior and Human Decision Processes, 1988. **41**(1): p. 1-19.

[8] COOK, G.J., An empirical investigation of information search strategies with implications for decision support system design. Decision Sciences, 1993. **24**(3): p. 683-697.

[9] FAVIER, J. and M. BOUQUET. *Europe's e Commerce Forecast: 2006 to 2011*. Technographics Research 2006 [cited 2008 07/31]; Available from:

http://www.forrester.com/Research/Document/Excerpt/0,7211,38297,00.html.

[10] FORD, J.K., N. SCHMITT, S.L. SCHECHTMAN, B.M. HULTS, and M.L. DOHERTY, Process tracing methods: contributions, problems, and neglected research questions. Organizational Behavior and Human Decision Processes, 1989. **43**(1): p. 75-117.

[11] GENSCH, D.H., A two-stage disaggregate attribute choice model. Marketing Science, 1987. 6: p. 223-231.

[12] HASTIE, R. and R.M. DAWES, *Rational choice in an uncertain world: The psychology of judgment and decision making*. 2001, Thousand Oaks, CA: Sage.

[13] HENRY, W.A., The effect of information-processing ability on processing accuracy. Journal on Consumer Research, 1980. 7: p. 42-48.

[14] HORRIGAN, J.B., Online Shopping: Internet users like the convenience but worry about the security of their financial information, in Online Activities & Pursuits. 2008, Pew Internet & American Life Project.

[15] JACOBY, J., D.E. SPELLER, and C.K. BERNING, Brand choice behavior as a function of information load: Replication and extension. Journal of Consumer Research, 1974. **1**(1): p. 22-42.

[16] JOHNSON, E.J. and J.W. PAYNE, Effort and accuracy in choice. Management Science, 1985. **31**(4): p. 395-414.

[17] JUNGERMANN, H., H.-R. PFISTER, and K. FISCHER, *Die Psychologie der Entscheidung: Eine Einführung*. Vol. 2nd 2005, Heidelberg: Elsevier.

[18] KLAYMAN, J., Children's decision strategies and their adaptation to task characteristics.

Organizational Behavior and Human Decision Processes, 1985. 35(2): p. 179-201.

[19] LEE, B.K. and W.N. LEE, The effect of information overload on consumer choice quality in an on-line environment. Psychology & Marketing, 2004. **21**(3): p. 159-183.

[20] LINES, R. and J.M. DENSTADLI, Information overload on conjoint experiments. International Journal of Market Research, 2004. **46**: p. 297-310.

[21] LOHSE, G.L. and E.J. JOHNSON, A comparison of two process tracing methods on choice tasks. Organizational Behavior and Human Decision Processes, 1996. **68**(1): p. 28-43.

[22] MALHORTA, N.K., Information load and consumer decision making. Journal of Consumer Research, 1982. **8**(4): p. 419-430.

[23] MILLER, G.A., The magical number seven, plus or minus two: Some limits on our capacity for processing information. Psychological Review, 1956. **63**: p. 81-97.

[24] MONTGOMERY, H. and O. SVENSON, On decision rules and information processing strategies for choices among multiattribute alternatives. Scandinavian Journal of Psychology, 1976. **17**: p. 283-291.

[25] OLSHAVSKY, R.W., Task complexity and contingent processing in decision making: A replication and extension. Organizational Behavior and Human Performance, 1979. **24**: p. 300-316.

[26] PAYNE, J.W., Task complexity and contingent processing in decision making: An information search and protocol analysis. Organizational Behavior and Human Performance, 1976. **16**(2): p. 366-387.

[27] PAYNE, J.W., J.R. BETTMAN, E. COUPEY, and E.J. JOHNSON, A constructive process view of decision making: Multiple strategies in judgment and choice. Acta Psychologica, 1992. 80(1-3): p. 107-141.
[28] PAYNE, J.W., J.R. BETTMAN, and E.J. JOHNSON, Adaptive strategy selection in decision making. Journal of Experimental Psychology-Learning Memory and Cognition, 1988. 14(3): p. 534-552.

[29] PAYNE, J.W., J.R. BETTMAN, and E.J. JOHNSON, *The Adaptive Decision Maker*. 1993, Cambridge, UK: Cambridge University Press.

[30] PEREIRA, R.E., Optimizing human-computer interaction for the electronic commerce environment. Journal of Electronic Commerce Research, 2000. **1**(1): p. 23-44.

[31] RIEDL, R. and E. BRANDSTÄTTER, Die Strategie der Entscheidung: Alte Probleme und neue Lösungen. NeuroPsychoEconomics, 2007. **2**(1): p. 59-75.

[32] RIEDL, R., E. BRANDSTÄTTER, and F.ROITHMAYR, Identifying decision strategies: A process-and outcome-based classification method. Behavior Research Methods, 2008. **20**(3): p. 795-807.

[33] SCAMMON, D.L., Information load and consumers. Journal of Consumer Research, 1977. **4**(3): p. 148-155.

[34] SIMON, H.A., Invariants of human behavior. Annual Review of Psychology, 1990. 41: p. 1-19.

[35] SVENSON, O., Process descriptions of decision making. Organizational Behavior and Human Performance, 1979. **23**: p. 86-112.

[36] TODD, P. and I. BENBASAT, An experimental investigation of the impact of computer based decision aids on decision making strategies. Information Systems Research, 1991. **2**: p. 87-115.

[37] TODD, P. and I. BENBASAT, Inducing compensatory information processing through decision aids that facilitate effort reduction: An experimental assessment. Journal of Behavioral Decision Making, 2000. **13**(1): p. 91-106.

[38] TODD, P.A. and I. BENBASAT, The influence of decision aids on choice strategies und conditions of high cognitive load. IEEE Transactions on Systems Man and Cybernetics, 1994. **24**(4): p. 537-547.

[39] TVERSKY, A., Intransitivity of preferences. Psychological Review, 1969. 76: p. 31-48.

[40] WILKIE, W.L., New perspectives for consumer information processing research. Communication Research, 1975. **2**(3): p. 216-231.

[41] WRIGHT, P., The harassed decision maker: Time pressure, distractions, and the use of evidence. Journal of Applied Psychology, 1974. **59**(5): p. 555-561.

[42] WRIGHT, P. and F. BARBOUR, *Phased decision strategies: Sequels to an initial screening*, in *Research Paper No.* 353. 1977, Stanford University, Graduate School of Business: Stanford, CA.

[43] ZAKAY, D., Post-decisional confidence and conflict experienced in a choice process. Acta Psychologica, 1985. **58**(1): p. 75-80.