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Abstract

In this study, an exemplar-based classifier was developed to predict which decision strategy may underlie an empirical ocular search behavior. Our rationale was mainly inspired by the exemplar-based models of categorization; that is, different decision strategies are conceived as different concepts, with the exemplar referring to the sequence of empirical fixations on decision information during a decision process. In order to ascertain the best exemplar of each strategy for our classifier, the Tabu search algorithm was applied. An eye-tracking based experiment was conducted to collect fixation data for training and validation. Our result showed that the classifier has significant accuracy in identifying underlying strategies, achieving an average hit-ratio of 76%. This indicated to us that the integration of the exemplar classifier with fixation data has certain applicable value for leveraging the adaptability of DSSs. Our result also has some important implications for the direction and methodology of behavioral decision research

Keywords

Multi-attribute decision making, eye-tracking approach, information search behavior, exemplar-based classifier, Tabu search

INTRODUCTION

Adaptive decision support systems traditionally have been of intense interest to researchers and practitioners alike (Fazlollahi et al. 1997; Norcio and Stanley 1989; Silver 1990; Tabatabaei 2002). In terms of the adaptability of such systems, the generally held view is that the systems should be capable of satisfying an individual's specific, personal cognitive demands arising during decision making, and/or guide the individual to use the default strategies preferred by organizations in the decision-making process. An essential requirement for the production of an ideal system is a broad range of knowledge from a variety of disciplines. Also vital is understanding of the following three fundamental principles: firstly, the cognitive demands that the system needs to support should be clarified before the design stage. Secondly, effective functionalities for supporting the conceptual cognitive demands should be ascertained. Finally, the systems should have the capacity to both identify instant demands and make appropriate automatic responses to those demands.

In the past, efforts have been made to develop DSS functionalities dedicated for the multi-attribute choice problem (Bettman and Zins 1979; Jarvenpaa 1989; Todd and Benbasat 1987; Todd and Benbasat 1991; Todd and Benbasat 1992; Todd and Benbasat 1994; Todd and Benbasat 1999; Todd and Benbasat 2000). In those studies, decision strategy has been considered the most important cognitive mechanism to be supported. This is due to its mediating role in decision making and its significant influence on various dimensions of decision outcome (Payne et al. 1993). Based on the existent behavioral decision making research into the descriptive models of decision strategies, researchers have conceptualized several functionalities for satisfying the demands of decision strategies. They have also further validated the effectiveness of the proposed functionalities. For example, in a series of studies, Todd and his colleagues developed a functionality which attempted to alleviate the computational effort required to execute elementary information processes during the decision process (Todd and Benbasat 1987; Todd and Benbasat 1991; Todd and Benbasat 1992; Todd and Benbasat 1994; Todd and Benbasat 1999; Todd and Benbasat 2000). Other researchers attempted to ease the execution of decision strategies by providing an information layout congruent with the demands of decision strategies (Bettman and Zins 1979; Jarvenpaa 1989). This brief overview of existing research in this field indicates a number of important directions necessary to pursue in order to further advance the adaptability capacity of DSSs. Research to date has focused on what cognitive demands should be targeted at and what are effective functionalities for those demands. However, an area neglected in studies on the necessary foundations for developing an adaptive DSS is automatic diagnosis of various demands from different decision strategies and the provision of appropriate support. In our view, of vital importance for adaptability is automatic identification of the type of strategy used by a decision-maker. In simple terms, if a DSS has the capability of diagnosing the particular strategy used by a decision-maker on the spot, support more closely aligned to that specific strategy can be provided. Such support will be more effective and efficient than those supports proposed in previous research, which are predetermined on the basis of generally adopted strategies

Recently, a new generation of eye trackers has achieved remarkable advancement in the capability of accessing real-time eye-movement data. This kind of objective eye tracker data has been traditionally considered by psychological researchers as observable, immediate cues to attention and cognitive process. The potential integration of DSSs with the modern eye tracker leads us to the possibility of exploiting decision-makers' fixation data to automatically diagnose the decision strategy. Specifically, in this study, we attempted to develop a classifier to predict the typical strategy to which an empirical search behavior might belong. Our rationale was mainly inspired by the exemplar-based models of categorization (Mantaras and Armengol 1998; Medin and Smith 1984; Smith and Medin 1981), which use a set of exemplars to represent each concept and then refer a new instance to the concept whose exemplars are most similar to the new one. In this study, the various decision strategies are conceived as the different intended concepts. The exemplar here refers to the sequence of empirical fixations on decision information during a decision process. To realize our exemplar-based classifier, we adopted the following approach. First, the Tabu Search algorithm was applied to ascertain the best exemplar for each strategy. This was done to reduce as far as possible the number of stored exemplars, thus improving classifier efficiency. Second, we validated the effectiveness of the classifier based on the best exemplars. We hypothesized that if the method is valid, the hit-ratio, i.e. percentage correctly predicted by this classifier, should be significantly higher than the percentage correctly predicted by chance.

To test the above hypothesis, we designed a laboratory experiment for the multi-attribute and multi-alternative choice problem. We used the modern eye tracker to collect empirical fixation data occurring in decision making in order to validate our proposed method.

LITERATURE REVIEW

Modeling decision strategies of a multi-attribute decision

A multi-attribute decision is characterized by a decision-maker's need to choose one brand out of a set of alternatives, where each alternative is described by a common set of attributes. This kind of decision-making problem is important in the fields of decision behavior and consumer behavior research because it is seen widely in daily life (Bettman et al. 1990; Bettman et al. 1998; Payne et al. 1993).

One approach to the study of decision making stems from the information processing perspective. From this perspective, decision making is viewed as a kind of problem-solving in which, given an initial problem state and goal, the decision-maker transforms the initial problem state into an array of temporal problem states step-by-step in the working memory until the goal state is achieved (Holland et al. 1986; Newell and Simon 1972; Payne et al. 1993). Therefore, the decision-making process can be subdivided into a set of elementary information processes (EIPs), such as read, compare, difference, add, product, eliminate, move, choose, etc. (Benbasat and Todd 1996; Bettman et al. 1990; Johnson and Payne 1985; Payne et al. 1988; Payne et al. 1993). They are responsible for transforming problem states, for example, EIP add represents the cognitive operation of "adding the values of an attribute in STM". Based on the set of EIPs, researchers are able to model a variety of widely accepted decision-making strategies, such as the weighted additive rule (WADD), the equal weight heuristic (EQW), the satisficing heuristic (SAT), the lexicographic heuristic (LEX), the elimination-by-aspects (EBA), the majority of confirming dimensions (MCD), etc. We use the following example to explain the above idea in more detail. Suppose that, as shown in Table 1, a decision-maker needs to choose one protection lotion among two alternatives, where each is described by two common attributes, such as SPF and Polished. The numbers in parentheses are labels used to identify each entry for the following explanation. Using the weighted additive rule, a decision-maker is expected to read the first weight (3) and then the rating on the first attribute (5). The two numbers are then multiplied and the resulting score of 2 is kept. The process is repeated on (4) and (6), and the resulting score of 15 is attained. For Protection Lotion 1, the total score is 17, achieved by adding 2 and 15. A similar process is applied to Protection Lotion 2, the total score for which is 18. Finally, the total scores for the two alternatives are compared. Protection Lotion 1 is eliminated and Protection Lotion 2 is chosen. More specifically, using the EIPs, the entire decision process detailed above can be modeled as the following sequence: read (3), read (5), product, read (4), read (6), product, add, read (3), read (7), product, read (4), read (8), product, add, compare, eliminate, choose. Further, based on the sequence of EIPs, the external information search behavior following the decision strategy should be observed in the following order: read (3), read (5), read (4), read (6), read (3), read (7), read (4), read (8). The main difference between the sequence of EIPs and the sequence of external information search behaviors is that the latter sequence excludes some unobservable cognitive operations from the former. In this way, if a decision strategy is well known, its hypothetical steps for external information search behaviors can be simulated. Here, we term such hypothetical behavioral steps as typical information search sequence (TISS). In contrast to TISS, the sequence of empirical external information search observed in decision making is termed empirical information search sequence (EISS). The rationale for the EIP model indicates that there is a somewhat immediate linkage between an abstract decision strategy and a series of observable external information search behaviors. As a result, EISSs are theoretically qualified for the instances of a decision strategy.

Table 1. An illustrative multi-attribute and multi-alternative choice problem

	SPF	Polished
Cutoff	4(1)	1(2)
Weight	2(3)	5(4)
Protection Lotion 1	1(5)	3(6)
Protection Lotion 2	4(7)	2(8)

Eye Movement and Cognitive Processes

Previous research has suggested that eye movements are directly related to the underlying cognitive process, which is also known as the eye-mind assumption (Just and Carpenter 1976; Rayner 1998). Just and Carpenter, for example, suggested that eyes often fixate on the external referents whose corresponding internal representations are being processed. Various studies on tracking eye movements have produced evidence to illuminate the relationship between eye movement and cognitive processes in a variety of contexts, such as reading, perception, visual search, arithmetic education (Hegarty et al. 1992; Hegarty et al. 1995; Kuo et al. 2004; Laeng and Teodorescu 2002; Pomplug et al. 2001; Rayner 1998). In the field of behavioral decision making, the application of eye movements to infer decision strategies also has a long history. For example, Russo and Rosen (1975) recorded subjects' eye movements to observe how subjects solved a multi-attribute choice problem.

Modern eye tracking is also characterized by its active mode in use, which allows information systems to access eye-movement data in real-time. Based on this mode, a variety of innovative interface designs have been proposed; for example, attentive user interfaces (Vertegaal 2003), capable of adjusting the resolutions of each region of the screen according to the fixations of a user, or affective computing (Picard 1997), which uses eye movements to estimate the affective states of users and to make adaptive responses accordingly. Although the current applications seem not to be immediately relevant to DSS, they provide us with a promising way to improve the user interfaces and functions of DSS.

Exemplar-based classifier

Based on the theoretical assumptions that EISSs have certain implications for a decision strategy (as stated in 2.1) and that eye fixation serves as a cue for the empirical information search behavior (as stated in 2.2), our basic rationale for the exemplar-based classification in this study can be formalized in the following way. Suppose that there are n kinds of decision strategies ($d_1, d_2, d_3, \cdots, d_n$), and there are s EISSs ($e_{i1}, e_{i2}, e_{i3}, \cdots, e_{is}$, where i=1…n) to represent the decision strategy, d_i. In other words, decision strategy 1 to n is the intended concept and e_{is} is considered as an exemplar representative of concept i. Given a new EISS, x, we use the following algorithm to refer x to a specific concept.

For each $e_{ij} \in d_i$ do
  sim[e_{ij}]←$\mathrm{similarity}(x, e_{ij})$
end-for
  $e_{max} \leftarrow \underset{\substack{i=1\ldots n\\ j=1\ldots s}}{\mathrm{argmax}}\ \mathrm{sim}[e_{ij}]$
$d_x \leftarrow \mathrm{class}(e_{max})$

where $\mathrm{similarity}(x, e_{ij})$ is the similarity function which returns the Levenshtein distance between x and e_{ij} (Levenshtein 1966), and $\mathrm{class}(e_{max})$ is the function which assigns the decision strategy denoted by e_{max} to the new EISS, x. Our exemplar-based classification algorithm is similar to the simplest instance-based learning algorithm (Aha et al. 1991) and the nearest neighbor algorithm (Cover and Hart 1967). However, it differs from those two algorithms in four respects. Firstly, our algorithm only classifies a new instance and does not integrate the new one into its set of exemplars. Secondly, we consider only the Levenshtein distance between two objects and not the Euclidean distance in the n-dimensional space. Thirdly, the best exemplars for each concept are predetermined. Finally, a new instance is classified only according to the most similar exemplar rather than according to the majority vote of a set of its neighbor exemplars. To a limited degree, our method can be considered as a variant of the 1-nearest neighbor (1-NNR) classification algorithm.

Tabu Search algorithm and the best representative exemplars for the classifier

A basic challenge to most variants of the exemplar-based learning algorithm is what exemplars are worth retaining for use during generalization in consideration of the trade-off between representation vs. time complexity (and/or storage requirement) (Wilson and Martinez 2000). In other words, we aim to minimize the number of exemplars for each decision strategy (concept) without sacrificing the classification rate for new instances. The same aim applies also for training our classifier. In this study, the Tabu Search algorithm was applied to ascertain the best exemplars among the representative instances collected from our eye-tracking experiment.

Tabu Search (Glover 1989; Glover 1990) is a metaheuristic strategy which guides a lower-level heuristic search procedure to escape the barriers of local optima. Tabu Search (TS) has exhibited many successful applications for complex combinatorial optimization problems. As indicated by its name, TS forbids reverse search directions to avoid revisiting trial solutions already seen in the historical search trajectories. This restriction embedded in the search procedure makes TS unique among other metaheuristics such as Genetic Algorithm.

The primal TS method proceeds in the following way. A random solution is used as the starting seed of the iterative TS procedure, where the seed solution is moved from place to place until a stopping criterion is satisfied. At each move iteration, a set of candidate moves is generated by exploring the neighbors of the seed solution. The candidate moves that will lead immediately to recently visited solutions are designated tabu active and made inaccessible. This mechanism is facilitated by tallying the recently performed moves in the tabu list, which is fixed in size and is implemented as a circular list. When the tabu list is full, the oldest element is removed before the new element can be inserted. Hence, each tabu move will recover its accessibility after some move iterations depending on the size of the tabu list. Another feature of TS is the use of an aspiration criterion which overrules the tabu restriction if a certain condition is met; for example, where the tabu move will lead to a solution with better objective value than the best one obtained so far.

In this study, we apply the TS algorithm for learning the best exemplars for the 1-NNR classifier. With the notations used in 2.3, we formulize the addressed problem as follows:

$$Min \sum_{i=1}^{n} \sum_{j=1}^{s} x_{ij}$$

s.t:

$$\sum_{j=1}^{s} x_{ij} \geq 1, \qquad \forall i$$

$$PR_{best} - PR_{TISS} \geq t$$

$$x_{ij} \in \{0, 1\}$$

where xij is a binary decision variable and xij = 1 indicates eij is selected as one of the exemplars for di and xij = 0 otherwise. PRTISS is the classification rate obtained by using TISSs as the representative exemplars for the classifier, while PRbest is the classification rate obtained by using the best representative exemplars learned by the proposed TS for the classifier. The objective of the learning problem is to minimize the number of representative exemplars learned by the TS subject to the constraint that at least one instance should be used to represent a particular decision strategy and the classification rate PRbest is greater than PRTISS by at least a threshold t. The reason for using PRTISS as a benchmark is that our previous study has demonstrated that the classifier with TISSs as exemplars has a good degree of accuracy in identifying underlying decision strategies.

METHODOLOGY

Participants

A total of 49 college students at the Southern Taiwan University of Technology, Taiwan, were recruited as participants, each of whom was paid a cash reward of NT$ 300 for their participation. In order to encourage them to make accurate decisions, an extra NT$ 100 reward was granted when subjects demonstrated their intention to apply correct decision strategies to trials.

Stimulus Materials and Apparatus

The decision information necessary for the multi-attribute choice problem was arranged and displayed in the shape of an alternative-attribute matrix, which has been widely used in previous research on decision making (Bettman et al. 1990; Bettman and Zins 1979; Payne et al. 1993). As Appendix A reveals, the information matrix consisted of four alternatives, each with four attributes. The layout of the information matrix was displayed in a medium resolution mode of 800*600 pixels.

An EyeLink II eye-tracking system (SR Research, Canada) with a sampling rate of 500 Hz was used to track and record the participants' eye movements (saccades and fixations) while they performed the decision-making task.

Design and Procedure

One within-subjects factor was manipulated in the experiment, i.e. typical decision strategy, which consisted of 6 levels: the weighted additive rule (WADD), the satisficing heuristic (SAT), the equal weight heuristic (EQW), the lexicographic heuristic (LEX), the elimination-by-aspects (EBA), and the majority of confirming dimensions (MCD). That is, each subject was required to finish six trials. In each a given strategy was applied to solve the choice problem. The order of the six trials presented for each subject was randomized by the experimental program. Our operational definitions of the decision strategies meticulously followed those of Payne et al. (1993).

Before the actual experiment was conducted, participants were taught to use the six strategies in two training courses for a total of two hours. Then the participants were tested individually in the actual experiment.

In the experiment, the experimenter first put the eye tracker's leather-padded headband on the participant's head and calibrated the eye tracker. Then, an experimental program designed for the study was launched. The program showed six trials randomly. Each trial consisted of two sections: first, the instruction screen was presented to instruct the participant on how to solve a follow-up choice problem with a typical, assigned decision strategy, and to encourage him/her to arrive at a decision as quickly and as accurately as possible. Second, an information matrix for a choice problem was shown. The main theme of the choice problem was to select one brand out of four protection lotion brands, each of which was described with the same set of four attributes. The information matrix was kept on the screen until the subject arrived at a decision and keyed in his/her choice. In addition, the participant's fixations were recorded by the eye tracker through the whole section, with the duration time of the section and his/her final choice also being recorded by the program.

RESULT AND DISCUSSION

Summary of data

In the experiment, each subject utilized six different strategies, and a total of 294 EISSs (6*49) were collected. In other words, we had six intended concepts, i.e. the decision strategies, each of which had 49 representative instances. Before analysis, preparation work had to be undertaken. First, it was necessary to recode the fixation sequences. The raw data on a fixation only provides the coordinates on the screen. In order to interpret what information a fixation is intended for, the coordinates need to be further mapped to the stimulus (i.e. decision information matrix). To map fixations, we used the following method: first, the decision information matrix was divided into regions, i.e. areas of interest (AOIs), each covering a piece of decision information. Each region was assigned a character or a number. Second, fixations were re-coded in the character or number code for the AOI at which each fixation was located, and successive fixations falling in the same AOI were represented by one code exclusive to that AOI (Brandt and Stark 1997; West et al. 2006). In this way, we re-coded sequences of raw fixations into sequences of AOI codes, which explicitly indicated the sequence of decision information being processed during the decision-making process. These re-coded sequences were viewed as EISSs, i.e. instances.

Prediction accuracy analysis

The goal of our analysis was to test whether the TS-learned exemplars are able to produce prediction accuracy that is comparable to that achieved by using the full set of instances. The implication of the analysis is that we can perform the classifier with a much smaller number of exemplars in practice, making possible a significant reduction in the time incurred. In the following experiment, the entire procedure involved two steps, the first of which was to ascertain the best exemplars for each strategy using the proposed TS algorithm. The second step was to evaluate the hit-ratio of the classifier with the exemplars identified in the first step. In order to reach a reliable estimation of the hit-ratio, 10-fold cross-validation was conducted, in which the instances belonging to each strategy were split into 10 subsamples. In each analysis, one subsample of each strategy was put together as the validation data for testing the classifier. The remaining 9 subsamples of each strategy were put together as the training data for the TS algorithm to ascertain the best exemplars for each strategy. In total, ten analyses were conducted.

In the analysis experiment, the Levenshtein distance was used to measure the similarity between two instances (Levenshtein 1966). With respect to the Levenshtein distance, there are three important parameters which considerably influence the analysis result: scores for insertion, deletion, and substitution operations. Here, all the operations were scored as 1.

Table 2. Averaged similarity between EISS groups and the best exemplars learned by the TS algorithm

EISS	TS exemplars								
	WADD01	WADD02	SAT01	SAT01	EQW01	MCD01	LEX01	EBA01	EBA02
WADD	0.323	0.297	0.191	0.121	0.191	0.207	0.092	0.267	0.194
SAT	0.258	0.296	0.380	0.276	0.289	0.237	0.153	0.244	0.280
EQW	0.272	0.219	0.286	0.185	0.365	0.281	0.128	0.214	0.214
MCD	0.280	0.206	0.170	0.113	0.192	0.305	0.091	0.230	0.178
LEX	0.130	0.127	0.172	0.228	0.184	0.088	0.443	0.155	0.175
EBA	0.280	0.262	0.211	0.151	0.209	0.199	0.157	0.408	0.372

In the first step, it was also necessary for several parameters of the TS algorithm (as previously noted in Section 2.4) to be configured. Preliminary experiments were conducted to determine the empirically best values of these parameters. Accordingly, the neighborhood size was set at 20, the length of Tabu list was 7, aspiration probability was 0.2, and the number of maximal move iterations was 20000. The gap threshold t between PRbest and PRTISS was set at 10%. We executed the proposed TS algorithm with the empirical parameter values to establish the minimum number of best exemplars for each strategy. Fig. 1 shows the dynamic nature of the reduction in the number of best exemplars learned by the TS algorithm. Observable is the dramatic reduction in the number of best exemplars through the initial period, demonstrating the learning efficiency of the TS algorithm. There is then a more gradual reduction in the number of best exemplars before the reduction reaches its minimum when the TS algorithm converges. It should be noted that the classification capability of the classifier does not deteriorate through the reduction. This is due to our TS learning model (see Section 2.4), which stipulates that the classification rate using the TS learned exemplars should be greater than that using the TISSs by at least a threshold t.

In the second step, we first computed the similarity (using the Levenshtein distance) between each EISS instance and the best exemplar learned by the TS algorithm. Then we averaged the similarity scores for each EISS group. As shown in Table 2 each TS-learned best exemplar was associated with the correct EISS group with the highest average similarity score. This phenomenon indicates that the best exemplars learned by the proposed TS algorithm have preserved the decision strategy features contained in the whole EISS set.

Finally, we applied the 1-NNR classifier with the best exemplars learned by the TS algorithm to classify each EISS instance to appropriate decision strategy and to calculate the classification hit-ratio. The hit-ratio was calculated using the following formula: $\frac{\text{number\_correctly\_classified}}{\text{total\_number\_of\_observations}} \times 100\%$ (Hair et al. 1998)[pp.267]. We then computed Press's Q statistic to assess whether our accuracy ratio was significantly better than that correctly predicted by chance. The Press's Q statistic is calculated by means of the following formula: $\frac{[N-(nK)]^2}{N(K-1)}$, where N=total sample size, n=number of observations correctly classified, and K=number of groups. The calculated value is then compared with a critical chi-square value for 1 degree of freedom at the desired confidence level (Hair et al. 1998)[pp.270]. Our analysis results indicate that the hit-ratios of the ten independent trials of the TS-algorithm are all significantly higher than those gained by chance, and the averaged hit-ratio is 0.76. Second, with the exception of the LEX, one additional best representative EISS was derived for each decision strategy.

As a descriptive illustration, Table 3 tabulates the average number of correctly classified EISSs using the TS-learned exemplars and average hit ratio for each decision strategy. It is seen that, with the exception of the EISSs collected for the SAT decision strategy, at least 85% of the EISSs for each decision strategy were correctly classified using the TS learned exemplars.

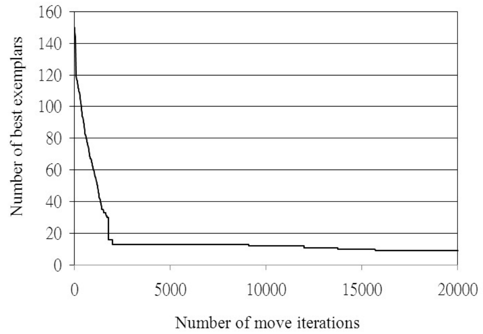

Figure 1: The dramatic reduction in the number of best exemplars learned by the TS algorithm

Table 3. The average number of correctly classified EISSs using the TS-learned exemplars and average hit-ratio for each decision strategy

Actual group	Predicted group						Actual group size	Hit-ratio
	WADD	SAT	EQW	MCD	LEX	EBA		
WADD	46.0	0.0	2.0	1.0	0.0	0.0	49	0.94
SAT	0.0	28.0	2.5	0.5	14.0	4.0	49	0.57
EQW	1.0	0.5	41.5	1.0	2.0	3.0	49	0.85
MCD	2.0	0.0	2.5	42.5	2.0	0.0	49	0.87
LEX	0.0	2.5	1.0	2.0	41.5	2.0	49	0.85
EBA	0.8	0.5	3.8	1.0	0.5	42.3	49	0.86
Predicted group size	60.0	53.3	51.3	31.5	49.8	48.0	294	0.82

CONCLUSION

From our cross-validation experimental results, we conclude that, based on the best representative empirical exemplars derived from the Tabu search, our classifier has a significant accuracy in identifying decision strategies underlying fixation sequences. This has a number of important implications for behavioral decision research and DSS interface design.

First, even under the constraint that PRbest needs to exceed PRTISS by 10%, our Tabu search did find that some of the empirical cases (i.e. EISSs) qualified. To a limited degree, it revealed that some of the empirical instances (i.e. EISSs) are better representatives than the hypothetical exemplars (i.e. TISSs) derived from the theoretical inference. With regard to behavioral decision research, this leads us to a theoretical question as to why the empirically-derived exemplars accommodate cases in reality better than the theoretically hypothetical model does. The reason for this phenomenon might be that the defined set of EIPs missed some cognitive operations which were performed in empirical decision-making, thus rendering the inferred TISS incomplete. At the same time, the empirically-derived model might be inherently full of all EIPs defined and undefined; that is, it might be self-contained. Therefore, as compared with the inferred TISS, the empirical model may better represent the empirical cases which are also inherently whole. Moreover, in similar vein to a data-mining approach, our method contributes to the decision-making research by providing an innovative methodology to mine out potential variants of a target decision strategy. That is, the best empirical representative exemplars derived by the Tabu search can be interpreted as the variants for an intended concept. For example, the subjects in our study had learned each target decision strategy in the same manner. However, after decision making, there was found to be one more best representative instance for each decision strategy respectively; for example, the WADD had at average of 2.1 best representative exemplars, the SAT had 2.2,…, and so on (see Table 2). To some extent, this indicates the emergence of different variants for each strategy.

Secondly, with regard to the design of adaptive DSSs, our result demonstrated that the integration of the exemplar classifier with fixation data has applicable value for leveraging the adaptability of DSSs. In addition, our method is especially suitable to the application context where the application goal is to map fixation sequences to certain concepts without consideration of detailed features of fixation sequences. An example of such a context is when decision-makers' fixation sequences are used to distinguish between decision-makers who have mastered a kind of decision problem and those who have not.

Limitation and Future Research

When interpreting our results, the reader should be aware of certain limitations. First, the decision information layout was based on the tradition of behavioral decision making. This simplified the actual purchase information environment in order to exclude irrelevant confounding factors. In spite of the benefits of this more abstract approach, it would be of value for future research to be undertaken in a more realistic environment. Secondly, future research might adopt the data-mining perspective as suggested in our Conclusion to further explore the best representative exemplars found for each strategy. From this, suggestions could be made with respect to possible supplementation of or revision to the current behavioral decision-making theory and the current set of EIPs.

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APPENDIX A

	SPF	Polished	Moisture	Fresh
Cutoff value	$4_{AOI(21)}$	$1_{AOI(22)}$	$3_{AOI(23)}$	$2_{AOI(24)}$
Weight	$2_{AOI(17)}$	$5_{AOI(18)}$	$4_{AOI(19)}$	$1_{AOI(20)}$
Protection Lotion 1	$1_{AOI(01)}$	$3_{AOI(02)}$	$2_{AOI(03)}$	$4_{AOI(04)}$
Protection Lotion 2	$4_{AOI(05)}$	$2_{AOI(06)}$	$3_{AOI(07)}$	$1_{AOI(08)}$
Protection Lotion 3	$4_{AOI(09)}$	$1_{AOI(10)}$	$4_{AOI(11)}$	$3_{AOI(12)}$
Protection Lotion 4	$2_{AOI(13)}$	$1_{AOI(14)}$	$3_{AOI(15)}$	$4_{AOI(16)}$

The choice problem was presented in the experimental trial using the WADD strategy. The dashed rectangles represent the areas of interest, AOIs, and the numbers in parentheses are labels used to identify each AOI. With respect to this choice problem, two TISSs based on the WADD strategy were modeled:

17,1,18,2,19,3,20,4,17,5,18,6,19,7,20,8,17,9,18,10,19,11,20,12,17,13,18,14,19,15,20,16.

1,17,2,18,3,19,4,20,5,17,6,18,7,19,8,20,9,17,10,18,11,19,12,20,13,17,14,18,15,19,16,20.

In the above sequences, number denotes AOI code.

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