EXPERT SYSTEMS AS COGNITIVE TOOLS FOR HUMAN DECISION MAKING

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INTRODUCTION

Research on judgment and decision making has produced two classes of theories, i. e., descriptive theories which specify how humans actually make decisions, on the one hand, and prescriptive theories on the other hand. Prescriptive theories are formal procedures which one supposedly ought to apply to determine the best decision under some well defined conditions. Such conditions are usually specified by a relatively small number of facts or variables. Prescriptive rules are based upon rationality principles such as consistency, transitivity of choices, or the maximization of subjective utility (Edwards, 1984).

For example, a decision task may be characterized by a set of alternative actions or alternatives, which we shall represent by the set {..x, y, z..}. Furthermore, it is assumed that every alternative x is described by its features x_i on some n attributes or dimensions, which are considered relevant. Presumably some subjective (utility) value $v(x_i)$ can be assigned to every feature x_i of every alternative x on each dimension i. Each dimension i is furthermore given some importance weight w(i). The particular alternatives, the relevant dimensions, the importance weights as well as the values $v(x_i)$ may all be subjectively specified by an individual. The multi-attribute utility (MAU) principle (Keeney, 1982) would then prescribe to maximize the subjective utility by selecting an alternative for which

$$\sum_{i=1}^{n} w(i) * v(x_i) \geq \sum_{i=1}^{n} w(i) * v(y_i) \quad \text{for all alternatives } y \in \{..x, y, z..\}.$$

Many years of research have shown that such prescriptive models do not adequately describe the cognitive decision process of humans in general nor of human experts in particular (Slovic, Fischhoff, & Lichtenstein, 1977). Instead, the empirical

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research of human information processing yielded the specification of descriptive theories of decision making. This research shows that contrary to prescriptive models humans use heuristics in decision making which yield violations of rationality principles and result in a number of biases (Kahnemann & Tversky, 1972). Supposedly, such heuristics are employed rather than prescriptive procedures because of processing limitations of the human mind. Let us consider, for example, the processing effort required to apply the multi-attribute utility rule in a simple binary choice situation, in comparison to some selective information processing rule.

EFFORT-QUALITY RELATIONS FOR COMPLETE AND SELECTIVE INFORMATION PROCESSING

Specification of binary choice task: Assume that the alternatives x and y are described by n dimensions. With respect to these n dimensions every alternative is described by the respective n features, $x = (x_1, \ldots x_i, \ldots x_n)$ and $y = (y_1, \ldots y_i, \ldots y_n)$. The attractiveness of every feature shall be specified by a positive integer $v \in [a, b]$. With $r := b - a$, a decision maker distinguishes $r + 1$ different attractiveness values.

For reason of simplicity it is assumed $w(i) = 1$ for all attributes i. Without loss of generality it may furthermore be assumed that by the MAU-rule

$$x \succsim y \Leftrightarrow \sum_{i=1}^{n} v(x_i) \geq \sum_{i=1}^{n} v(y_i).$$

For such binary choices the effort and quality of a decision can be defined in a rather simple way.

Definition. If the MAU-rule determines $x \succ y$, then the quality Q of a decision procedure p with respect to the choice pair (x,y) shall be given by

$$Q(p) = \begin{cases} 0 & \text{if } p \text{ determines } x \precsim y, \\ 1 & \text{if } p \text{ determines } x \succ y. \end{cases} \qquad (1)$$

If the MAU-rule determines $x \precsim y$ and $x \succsim y$, then $Q(p) = 1$ with respect to the choice pair (x,y) for all decision procedures

p. A choice which coincides with the choice of the MAU-rule will be termed an optimal choice. It is postulated that the processing of every feature requires a constant processing effort e. Since it is assumed that every feature is processed at most once, the decision effort for the application of some procedure p is:

$$E = 2 * \ell * e \tag{2}$$

where ℓ is the number of decision criteria considered. Thus for the MAU-rule $E = 2 * n * e$.

Decision procedures with reduced processing effort. We will consider two rules for reducing decision effort. For both rules it is assumed that the decision criteria are ordered with respect to the given choice situation, and the features of the choice alternatives are processed in the order of importance of the respective dimensions.

An effort reduction may simply be achieved by processing fewer dimensions, i. e., applying the MAU-rule only for $\ell < n$ criteria. In other words, a decision maker would process only the ℓ most important dimensions for deriving a decision. Since a decision would thus depend upon the constant number of dimensions, which a decision maker has specified for making a decision, this procedure will be termed dimension-dependent processing or DD-processing. While DD-processing may substantially reduce the decision effort, it cannot guarantee that the choice of the MAU-rule will be obtained.

Instead of processing some predetermined number of dimensions, decision effort could also be reduced by allowing the number of processed dimensions to depend upon the particular choice pair. For example, only as many decision criteria may be processed as are necessary for yielding some predetermined overall attractiveness difference k between every two alternatives. A choice would thus depend upon some criterion k. Therefore, this decision procedure will be termed criterion-dependent processing, or CD-processing. For a given k and some choice pair (x, y), j_k dimensions will be processed, where

$$j_k := \begin{cases} \min \{ j : \mid \sum_{i=1}^{j} v(x_i) - v(y_i) \mid \geq k; \; j<n \} & \\ n & \text{else.} \end{cases} \tag{3}$$

It is clear that small k values reduce decision effort while large k values ensure decision quality. However, it remains to be examined whether some k reduces decision effort, while guaranteeing the quality of a decision as well. In order to investigate this issue, we will first examine the conditions for which a certain k may yield a choice, which differs from the choice of the MAU-rule. Assume that alternatives x and y can be evaluated by n dimensions and that the attractiveness evaluation of a feature yields one of r + 1 different attractiveness values. For example, $v \in [1,7]$. Non-optimal choices with j processing steps and a criterion value k, must satisfy the following conditions: In order to produce a choice at the barrier k

$$j * r \geq k, \tag{4}$$

and for yielding the optimal choice with the MAU-rule if processing were to be continued up to the n-th dimension:

$$(n-j) * r \geq k+1. \tag{5}$$

Therefore, if

$$(n-j) * r < k+1 \tag{6}$$

a binary choice must be identical to the choice of the MAU rule, even when less than n dimensions have been processed. In other words, if the accumulated attractiveness difference on r dimensions between x and y is very large, the direction of the difference cannot be changed by processing the remaining dimensions.

Theorem. For barriers $k \geq c = n/2 * r$, the CD-processing rule guarantees choices which coincide with the choices of the MAU-rule, while up to 50 percent of the decision effort may be saved.

Proof. From Eq. (4) and (6), we obtain $j * r = (n-j) * r$, and $j = n/2$. Inserting into Eq. (4) yields $c = n/2 * r$. Thus, for $k \geq n/2 * r$, the quality of a choice is guaranteed.

For example, when n = 20, for the choice pair with

$$\sum_{i=1}^{j_k} v(x_i) - v(y_i) = n/2 * r \text{ and } j_k = n/2 \tag{7}$$

a 50 percent reduction of processing effort will be saved. For choice pairs which do not satisfy Eq(7), but rather

$$\sum_{i=1}^{j_k} v(x_i) - v(y_i) \geq n/2 * r \quad \text{and } j_k = n/2 + 1 \tag{8}$$

a ((n/2-1)*100)/n) percent reduction of processing effort will be achieved, and so on. Finally, for choice pairs with $j_k = n-1$, (100/n) percent processing effort will be saved.

For more realistic versions of the MAU-rule, where the attractiveness differences of a dimension are weighted by the importance of that dimension, processing effort may be reduced by an even larger amount. For example, consider CD-processing with the weighted MAU-rule: For a given k and a choice pair (x,y), j_k dimensions will be processed, where

$$j_k := \begin{cases} \min \{ j : \left| \sum_{i=1}^{j} w(i) * (v(x_i) - v(y_i)) \right| \geq k \,;\, j<n \} \\ n, \qquad \text{else.} \end{cases} \tag{9}$$

Furthermore, assume that the importance weight of dimension i is defined by:

$$w(1) = n; \quad w(i+1) = w(i) - 1. \tag{10}$$

By this processing rule optimal choices are guaranteed by k-values which satisfy the following restrictions:

$$\sum_{i=1}^{j} w(i) * r \geq k, \tag{11}$$

$$\sum_{i=j+1}^{n} w(i) * r < k + 1. \tag{12}$$

We determine the lower boundary of the k-values, for which an optimal choice is guaranteed by:

$$\sum_{i=1}^{j} w(i) * r = \sum_{i=j+1}^{n} w(i) * r$$

By insertion of Eq. (10):

$$\frac{j * (n + n - j + 1) * r}{2} = \frac{(n - j) * (n - j + 1) * r}{2}$$

which yields:

$$j = 1/2 * (2n + 1 - \sqrt{2n^2 + 2n + 1} .$$

For $k \geq \sum_{i=1}^{[j]} w(i) * r$, the resulting choices necessarily coincide with the choices obtained by the MAU-rule. For example with $n = 20$, $k \geq 105 * r$ guarantees an optimal choice. Therefore with $n = 20$, in the best case only 6 dimensions must be processed.

Although the possible range of effort reduction was specified by Theorem 1, the expected effort-reduction for a sample of choice pairs depends upon the characteristics of the particular sample. In order to inspect how much effort reduction may be achieved on an average, under the assumption that the $r + 1$ attractiveness values are uniformly distributed between the two alternatives and among the n dimensions, we will calculate the expected effort reduction for some examples.

For instance, assume that a person distinguishes only between unattractive and attractive features. Unattractive features shall receive a value of 1 and attractive features shall receive a value of 2. Thus $v \in [1,2]$. If the (unweighted) MAU-rule is used and the alternatives are described by $n=2$ dimensions, a $k=1$ guarantees an optimal choice.

For the 2 attractiveness values and the 2 dimensions, 16 different choice pairs exist. For 11 of these pairs, the MAU-rule yields $x \succcurlyeq y$. For 4 of these pairs CD-processing according to Eq. (3) yields a choice with $j_k = 1$. On the average, a processing reduction of 18 percent is thus achieved in the given example. Similarly, for $n = 3$, $k = 2$ ensures an optimal choice and a processing reduction of 9.5 percent is obtained. For $n = 4$, $k = 2$ ensures the optimal choice, and processing effort is reduced by 29 percent on the average. In general, the number of choice pairs for which $k = n/2 * r$ is surpassed after $j_K \in [n/2, n/2 + 1, \ldots, n - 1, n]$ dimensions have been processed, may be specified by linear diophantine equations (Bose & Manvel, 1984). Although at least in some cases a substantial effort reduction may be achieved while preserving quality, a decision maker may even like to further reduce decision effort.

Reducing decision effort at the cost of decision-quality. Decision effort may additionally be reduced by further lowering the k-value. Thereby, the average decision quality will possibly also be decreased. Also, the DD-processing rule may be applied for reducing decision effort. The relation between k and the effort as well as the quality of a choice is specified by the following definition:

Definition. Assume that for a choice pair (x, y), the MAU-rule determines $x > y$. The decision effort $E(k)$ of CD-processing with parameter k is given by:

$$k \longrightarrow E(k) := 2 * j_K * e$$

The quality $Q(k)$ of the respective decision is defined by:

$$k \longrightarrow Q(k) : \begin{cases} 0 & \text{if } \Sigma\, v(x_i) - v(y_i) \leq -k \\ 1 & \text{if } \Sigma\, v(x_i) - v(y_i) \geq k \\ 1 & \text{if } j_K = n. \end{cases}$$

Furthermore, we define:

$$E : = \{ E(k);\ k = 1 \ldots n\}$$

$$E^- : = \{ E(k) : \sum_{i=1}^{j_K} v(x_i) - v(y_i) \leq -k;\ k = 1, \ldots, n\}$$

$$E^+ : = E \setminus E^-, \text{ and}$$

$$Q(k) : = \mathbb{1}_{E+} (E(k)), \text{ where } \mathbb{1}_A(a) := \begin{cases} 1 & \text{if } a \in A \\ 0 & \text{if } a \notin A \end{cases}$$

For the DD-processing rule which assumes that some fixed $j \leq n$ dimensions are processed, quality and effort depend upon j. $Q(j)$ and $E(j)$ shall be defined accordingly.

While the mapping k ---> E(k) is monotonic for all pairs (x, y), k ---> Q(k) may violate monotonicity.

<u>Proof</u>: By definition $k_1 < k_2 \rightarrow E(k_1) \leq E(k_2)$.

For $v(x_1) = 2$, $v(x_2) = 1$, $v(x_3) = 6$,
$v(y_1) = 1$, $v(y_2) = 4$, $v(y_3) = 1$, and $k = 1$:

Q(1) = 1, Q(2) = 0, and Q(3) = 1.

<u>Definition:</u> Assume that for (x, y) the MAU-rule determines $x \succ y$. Then it is said that E^+ has a gap at position k if there exists a

$k' > 0$, $k' < k$: $E(k') \in E^+$ and $E(k) \in E^-$;
$L := \{ k \mid E(k) \in E^-$, and there exists $k' < k$ so that $E(k') \in E^+ \}$

It is assumed that a decision maker acquires information about the features of the alternatives, during the choice when he is processing these features. Since a decision maker does not have any prior information about the particular alternatives between which he is about to choose, the <u>average</u> quality and effort of a sample of choices pairs may be more important statistics than the respective values of a single choice pair. For some sample S of pairs (x, y), we define the average effort and the average quality as:

$$\bar{E}(k) := \frac{1}{|S|} \sum_S E(k),$$

$$\bar{Q}(\bar{E}(k)) := \frac{1}{|S|} \sum_S Q(k),$$

For a sample S the number ℓ of gaps for some given k is defined by:

$$\ell(k) := \sum_S \mathbb{1}_L (k)$$

<u>Lemma</u>. $\bar{Q}(\bar{E}(k))$ is monotonically increasing iff for $k < k'$: $\ell(k') \leq \ell(k)$.

<u>Conjecture</u>. If (r+1) values are uniformly distributed between the two alternatives and among the n dimensions in some population of choice pairs, the mapping $\bar{E}(k) \longrightarrow \bar{Q}(\bar{E}(k))$ is monotonically increasing.

<u>Evidence</u>. As a first step a simulation was performed. For n = 11, v = [1,7], and CD-processing by Eq(3), the results are shown in Figure 1. For CD-processing according to Eq. (9) and (10), the respective results are shown in Figure 2.

<u>Effort-Quality Trade-off</u>. A decision maker may desire to reduce decision effort at the cost of decision quality up to the point where the benefits of the effort reduction are smaller than the negative consequences (costs) of the respective quality reduction. Whether an effort-reduction is desirable at all, thus depends upon the utilities which a decision maker attributes to the various effort and quality levels as well as upon the functional relation between effort and decision quality. For the CD- and DD-processing rules, the functional relation between the average effort and the average quality of a decision may be characterized according to the following definition.

<u>Definition</u>. The function $\bar{Q}$ is said to be negatively (positively) accelerated at the point of some barrier k, if

$$\frac{\bar{Q}(\bar{E}(k)) - \bar{Q}(\bar{M}(k))}{\bar{E}(k) - \bar{M}(k)} \; \underset{(<)}{>} \; \frac{\bar{Q}(\bar{m}(k)) - \bar{Q}(\bar{E}(k))}{\bar{m}(k) - \bar{E}(k)} \qquad (13)$$

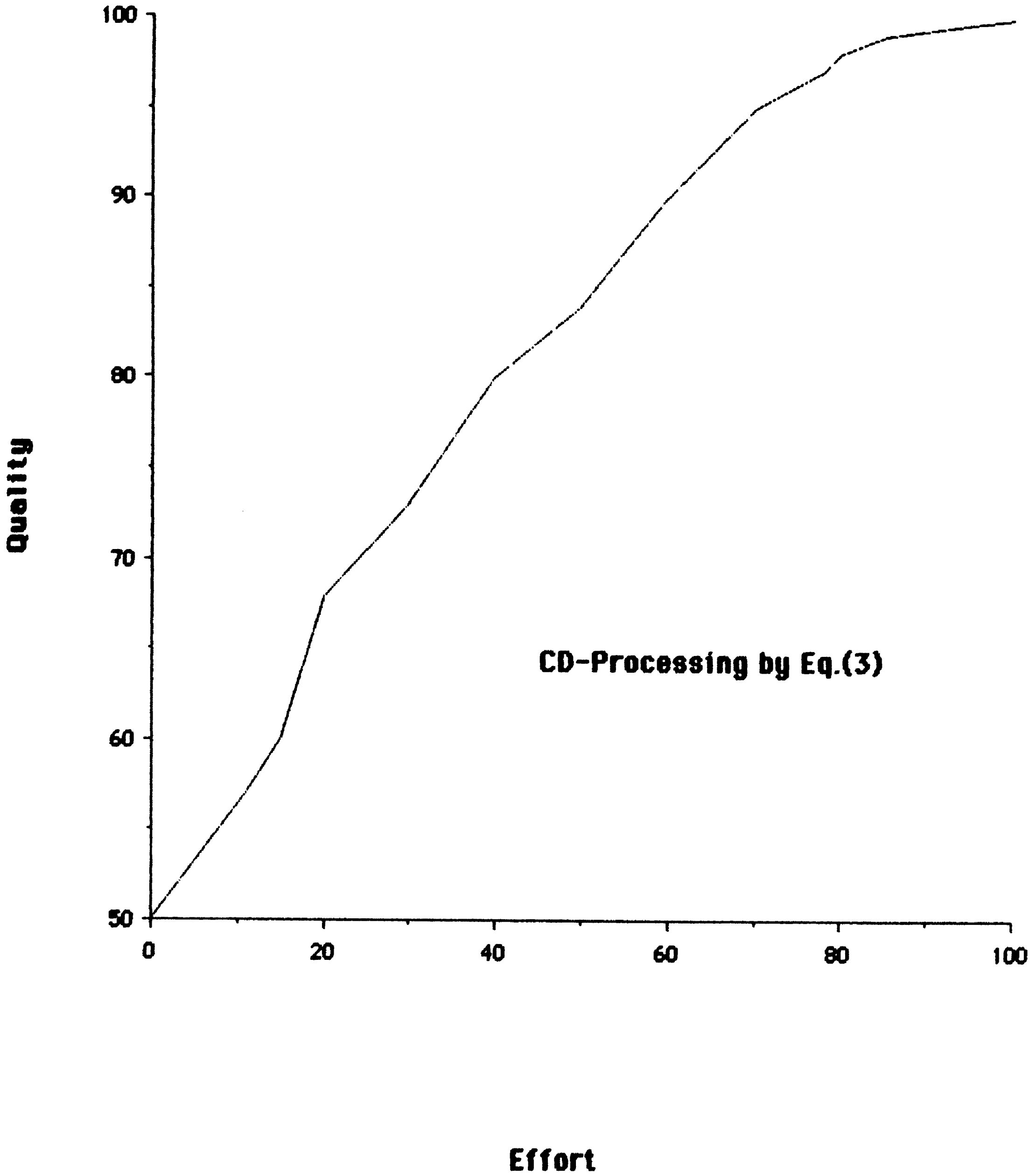
$$\text{where } M(k) = \sup_{\ell} \{ \bar{E}(\ell) \mid \bar{E}(\ell) < \bar{E}(k) \},$$

$$\bar{m}(k) = \inf_{\ell} \{ \bar{E}(\ell) \mid \bar{E}(k) < \bar{E}(\ell) \},$$

$\bar{E}(0) := 0$; $\bar{Q}(0) := .5$; and for $\bar{E}(k) = 2 * n * e$ the right side of Eq (13) is defined to be zero. If a function $\bar{Q}$ is negatively (positively) accelerated in every single point which is specified by a k-value, the function is said to be negatively (positively) accelerated. For the DD-processing rule negatively and positively accelerated is defined accordingly for all values

$j \in [1 \, . \, . \, ., n]$.

FIGURE 1


100
90
80
70
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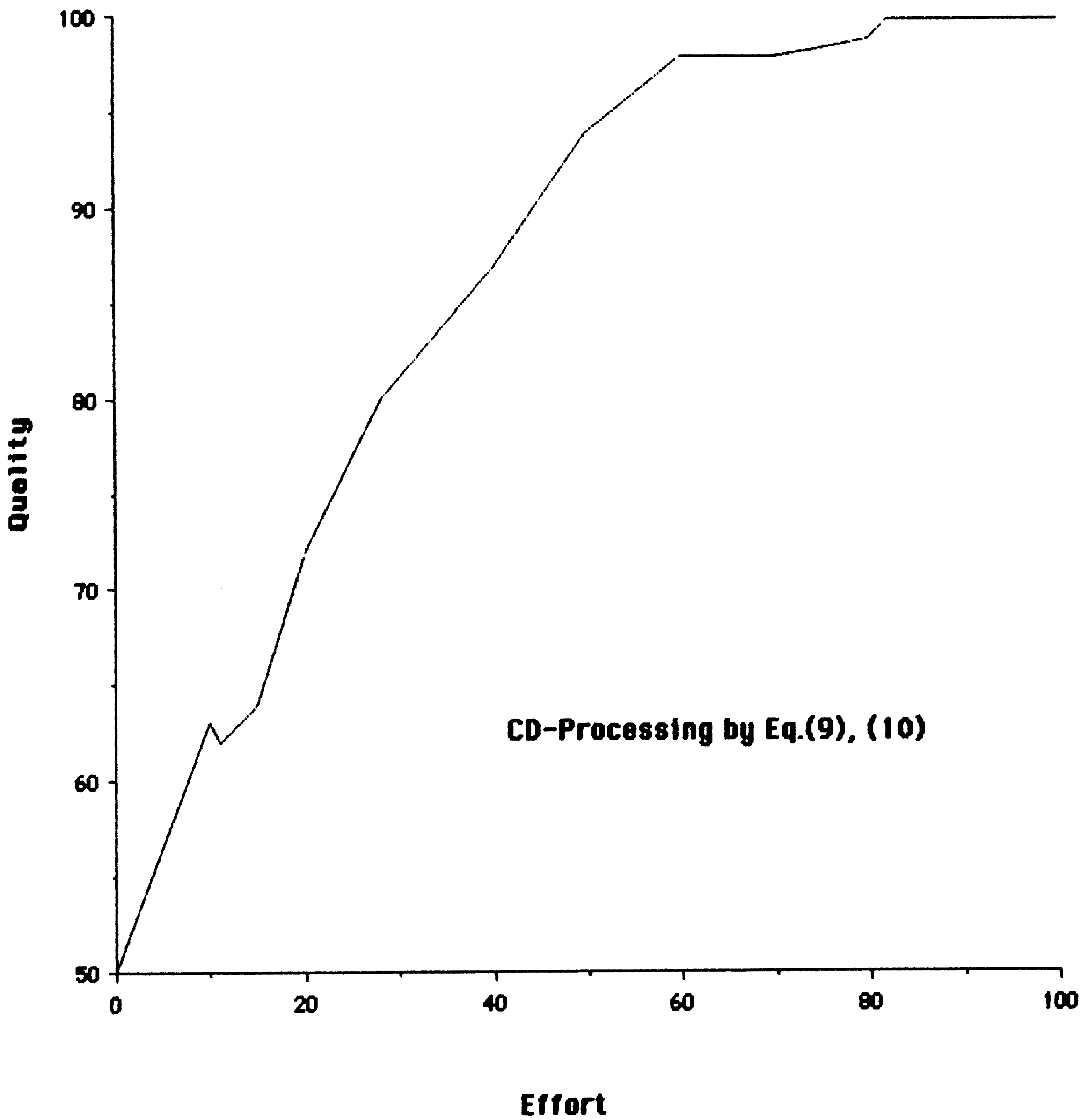
50
Quality
0
20
40
60
80
100
Effort
CD-Processing by Eq.(3)

FIGURE 2


100
90
80
70
60
50
Quality
0
20
40
60
80
100
Effort
CD-Processing by Eq.(9), (10)

<u>Conjecture</u>. If (r+1) values are uniformly distributed between two alternatives and the n dimensions, the CD-processing rule (Eq. 3) will produce a negatively accelerated function $\overline{Q}_{CD}(\overline{E}_{CD}(k))$.

Furthermore, if $\overline{E}_{CD}$, $\overline{E}_{DD} > .50$, $\overline{E}_{DD}(j) \leq \overline{E}_{CD}(k)$ implies

$$\overline{Q}_{DD}(\overline{E}_{DD}(j)) < \overline{Q}_{CD}(\overline{E}_{CD}(k)),$$

for all $j \leq n$ and k, where the indices DD and CD denote the dimension-dependent and criterion-dependent processing respectively.

<u>Evidence</u>. Simulation results with the CD- (Eq. 3), as well as with the DD-processing rule are shown in Figure 3. Again, n = 11, $v \in [1,7]$. These results seem to indicate that the CD-processing rule is superior for all decision efforts exceeding some critical effort (say E = 50).

If utility is a linear function of processing effort and decision quality, for a negatively accelerated function $\overline{Q}$, an optimal effort-quality trade-off would be achieved by the parameter k, for which

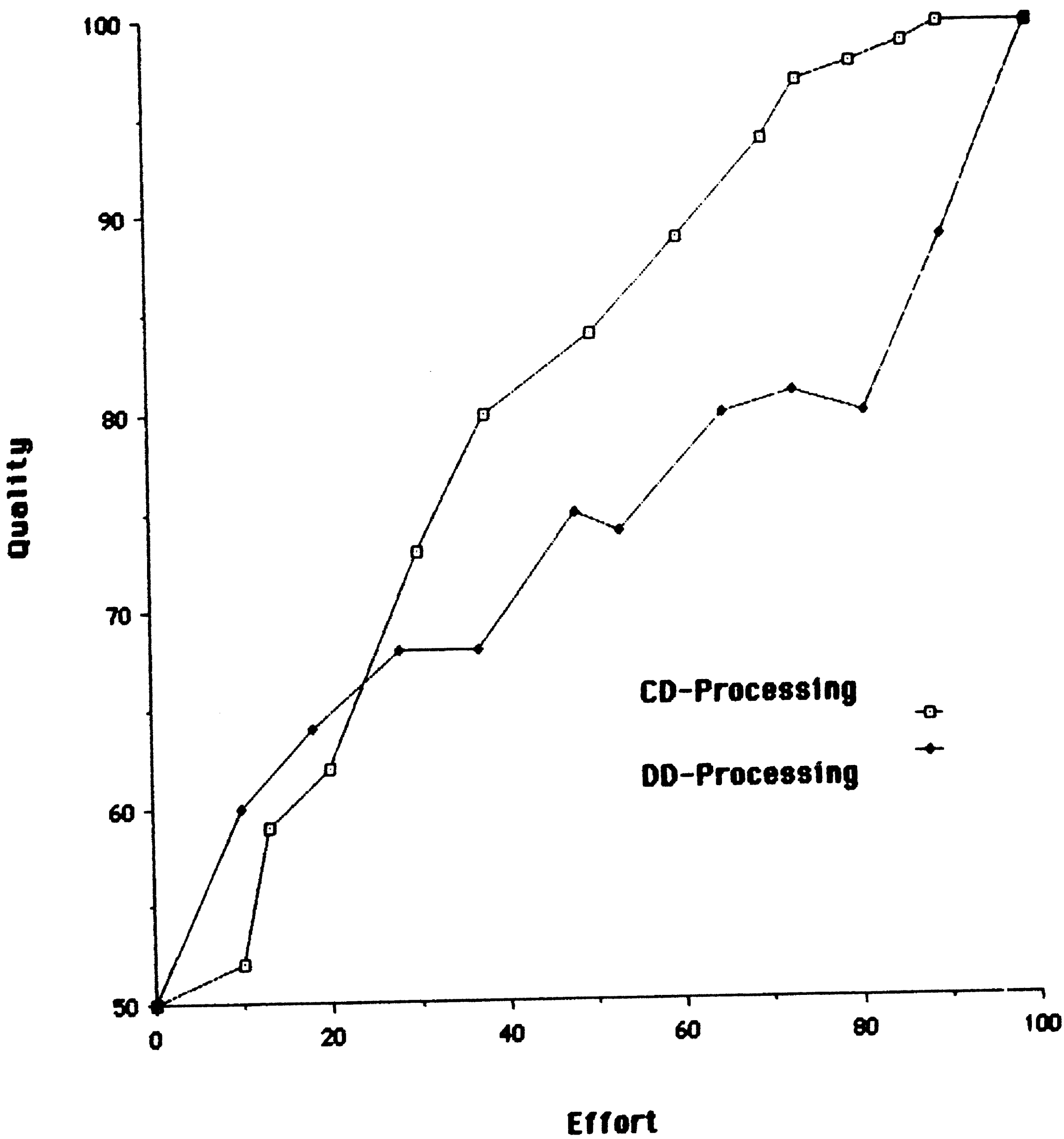
$$\frac{\overline{Q}(\overline{E}(k)) - \overline{Q}(\overline{M}(k))}{\overline{E}(k) - \overline{M}(k)} \geq 1, \quad \text{and}$$

$$\frac{\overline{Q}(\overline{m}(k)) - \overline{Q}(\overline{E}(k))}{\overline{m}(k) - \overline{E}(k)} \leq 1.$$

A decision maker, who attempts to achieve an operating point, which is close to an optimal trade-off between the effort and the quality of a choice, must therefore somehow determine the respective k-parameters.

<u>The approximate determination of a close to optimal k-parameter over a number of decisions</u>. Rather than postulating that a decision maker would perform a formal decision analysis for finding the optimal k-parameters, we assume that such parameters are specified by the experience from previous decisions. We assume that during the decision process the dimension number j, at which the sum

FIGURE 3



Quality
Effort
100
90
80
70
60
50
0
20
40
60
80
100
CD-Processing
DD-Processing

$$\sum_{i=1}^{j} v(x_i) - v(y_i)$$

changed from a positive to a negative value or vice versa will be remembered. We suppose that this information is used for adjusting the k parameter for the next decisions. One possible rule for adjusting the k parameter, which does not require any feedback about the quality of a choice would be: Initial value K = n * r, after every choice a new value k^* is specified.

$k^* := k + 1$ if $j_k - j \leq N_1$
$k^* := k - 1$ if $j_k - j \geq N_2$
$k^* := k$ else, where $N_1 < N_2$, and k^* denotes the new k-value. By an adaptive procedure of this kind optimal k - values could possibly be approximated (Treisman & Williams, 1984).

The conducted analysis shows that quite a substantial amount of processing effort can be saved by selective information processing without severely affecting choice quality. A number of empirical results show that human decision makers apply decision rules of the sort described by the CD-processing rule (Aschenbrenner et al. 1984; Busemeyer, 1985; Schmalhofer et al., 1986; Schmalhofer & Schäfer, 1986; Schmalhofer et al., 1987).

IMPLEMENTING PRESCRIPTIVE RULES WITH DECISION SUPPORT SYSTEMS

One possible reason why humans and human experts do not conform to prescriptive rules may thus be that prescriptive rules demand too much processing effort with respect to improvements in choice quality. Since the processing which humans are not willing to do could be performed by a computer the quality of human decisions could be improved by having a computer process all the information which is neglected by human decision makers. Decision support systems such as MAUD (Humphreys & McFadden, 1980) may enhance human decisions in this way. MAUD allows its user to enter any alternative as well as an arbitrary number of alternatives for consideration into the decision process. These alternatives may be characterized by whichever attributes a user considers to be relevant. After specifying the (utility) values of the different alternatives on the various attributes as well as importance weights for the attributes, a user is assisted by MAUD in making a decision according to the MAU principle.

Thereby, a number of rationality criteria such as consistency and transitivity of preferences will be satisfied.

Thus MAUD compensates for drawbacks which arise from selective information processing of humans, by performing a number of analyses which usually are too demanding for the human information processor. In summary it can thus be concluded, that decision support systems such as MAUD allow the human decision maker to derive a choice according to some prescriptive rule by taking the burden of the actual calculations away from the user. Decision support systems like MAUD thus derive decisions according to prescriptive rather than descriptive models. Prescriptive models rather than human information processing characteristics are thus taken as the first principle of such decision support systems.

According to this approach as well as according to the very simple expert system discussed by Mumpower (1987), humans are provided with assistance, so that they would adhere to certain -- sometimes quite general -- rationality principles.

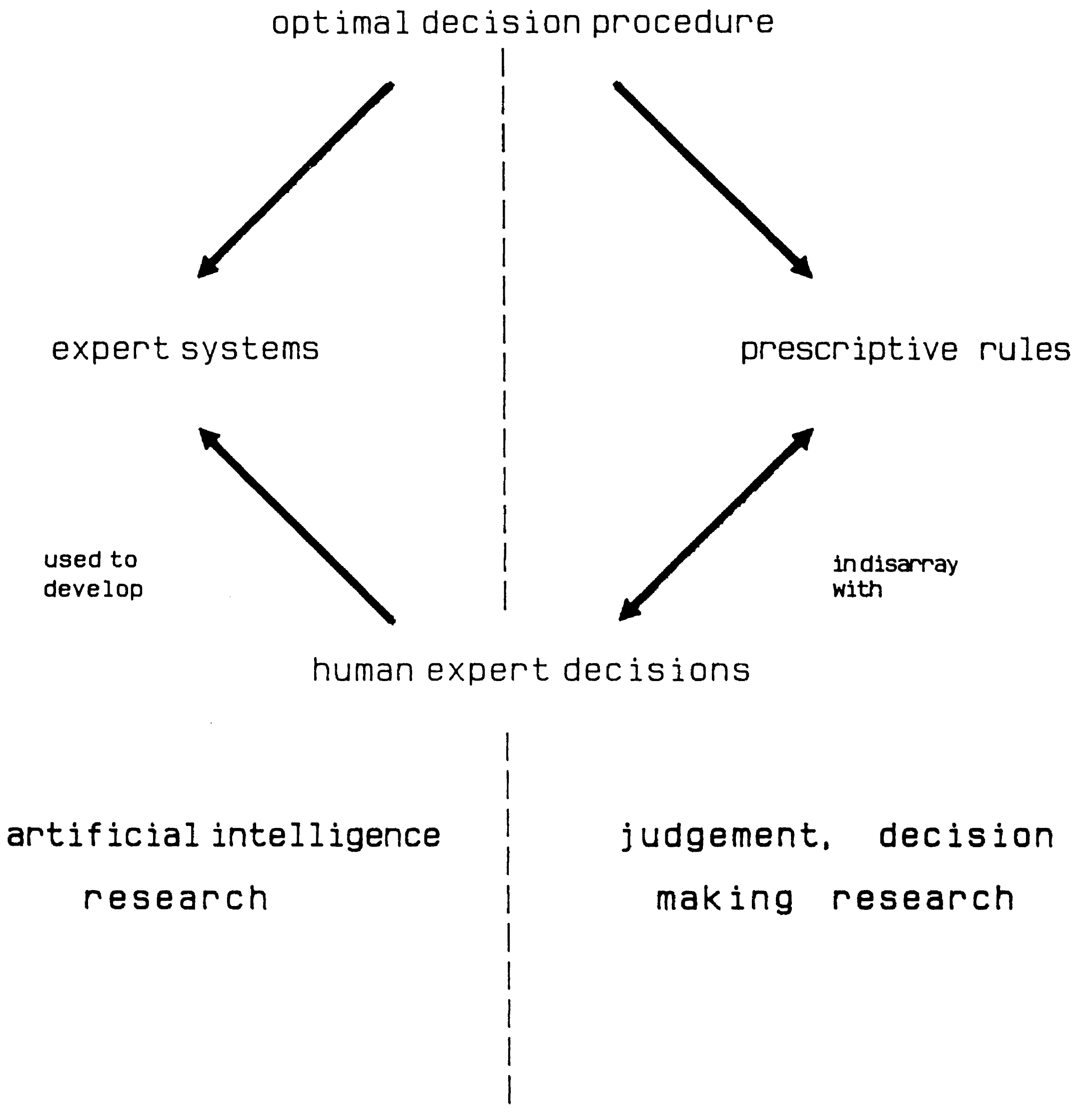
ANALYZING EXPERTS FOR DEVELOPING BETTER DECISION PROCEDURES

As Hammond (1987) has pointed out, the field of artificial intelligence (AI) takes quite a different approach. Despite the real or seeming inadequacies of human expert decisions AI researchers assume that expert systems are best designed by studying how human experts function. Rather than reducing a decision problem to some specification with a small number of variables, which can consequently be handled by some prescriptive rule, AI researchers assume decisions to be made on the ground of a large knowledge base.

Therefore, the question is whether the normative rules which have been studied in the judgment and decision literature should be used as "best procedure" or whether the information processing of human experts should be taken as guideline for developing expert decision systems. The relation between the JDM-approach and the AI-approach is shown in Figure 4.

JDM-research considers prescriptive rules from which they have found human behavior to deviate to be the best decision procedure. AI-researchers, on the other hand, analyze the behavior of human experts to develop expert systems, which they may then consider to be the best procedure. As Hammond has pointed out and as Figure 4 shows, the views of AI and JDM researchers disagree with one another.

FIGURE 4


optimal decision procedure
expert systems
prescriptive rules
used to develop
in disarray with
human expert decisions
artificial intelligence research
judgement, decision making research

Some doubts may be raised whether prescriptive rules really are the best decision procedure:

1. As the paper of Milton (1987) has again demonstrated, decision analyses which are based on prescriptive rules are only marginally successful or not successful at all in real decision domains.

2. Prescriptive rules do not agree with the decision rules of experts.

3. But, experts are rather successful in that they are respected as such and are paid accordingly for their job (Shanteau, 1987)

Contrary to the conclusions of Hammond, it may thus appear that the prescriptive rules analyzed by JDM-researchers are only optimal with respect to the artificial circumstances, which, however, do not exist in real life decision problems.

It may be suspected that some decision biases as well as other non-optimal behaviors of experts may have a functional value in natural environments. In order to reveal such functional values, we will consider two of the most prominent violations of prescriptive rules. On the one hand, decision makers are known to ignore relevant information, and on the other hand, it is also known that irrelevant information affects decisions. What are possible functions of this seemingly non-optimal behavior. It has already been pointed out that selective information processing may reduce processing effort by a great deal without deteriorating choice quality. In addition, selective information processing will yield a simpler justification for a choice than an all encompassing decision. A decision is thus easier to communicate.

On the other hand, irrelevant information may be processed in order to adjust to changes in the future. For example, consider a physician who has to decide which patient should be given an organ for transplantation. Furthermore assume that the particular type of organ transplantation would still be in an experimental phase. Under these conditions, transplantation of an organ may only be considered as an ultima ratio. Criteria such as age and projected life expectancy would thus be considered irrelevant because an organ transplantation should only be performed if the patient would die otherwise.

As the medical skills are further developed, however, organ transplantations should be performed earlier when the respective patient is still healthy, thereby improving the success rate. Criteria which have been considered irrelevant may now become relevant. An expert who processes irrelevant information may thus just be processing information which will be considered relevant in the future. Again such a choice can be justified more easily in the future, when everybody uses the new criteria.

The example may demonstrate that the prescriptive rules are much too simple and too static to capture all the complexities of expert decisions:

Rather than selecting the alternative, which maximizes the (subjective) utility, expert decisions should agree with the large body of expert opinions. In addition it must be possible to explain a decision in terms of the expert knowledge rather than quoting some prescriptive rule. An expert must also be capable of justifying a decision for the many different viewpoints which people may use for interrogating his decision. Consequently, expert decisions must be knowledge-based and cannot be reduced to the consideration of values.

Unlike human decision makers, prescriptive rules do not provide such adaptiveness and flexibility. Therefore, human decisions cannot be replaced by some prescriptive rule. Quite to the contrary, in order to assist human decision making, it seems advisable to emulate the dynamic decision processes of experts in computer systems. The best decision procedure should thus not only produce the same decisions as the human expert, but should derive the decision in the same way. In other words, an expert system should be a cognitive model (Schmalhofer & Wetter, 1987) of the human expert, so that the system is adjusted to the human user rather than the human user being required to adapt to an arbitrary artificial system. By adjusting the information processing of expert systems to the actual cognitive processes of humans, expert systems can be employed as a cognitive tool, which assists the human rather than replacing his competence by some "prescriptive model."

Expert systems which are designed as cognitive tools for a human user should receive a much higher acceptability than the so called prescriptive systems. If an expert system processes information similar to a human, a human user will be better able to understand, accept, and also justify the decisions which are derived with the assistance of the system.

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