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# Descriptive and Prescriptive Models of Decisionmaking: Implications for the Development of Decision Aids

ELKE U. WEBER AND OSMAN COSKUNOGLU

*Abstract* —Experimental investigations by psychologists have revealed significant deviations of actual human decision behavior from classical rational theories of judgment and decisionmaking. Weakening the assumptions of the latter has led to the development of new theories such as prospect theory or rank-dependent subjective expected utility theory. The first part of the paper reviews recent work in this area with an emphasis on its implications for prescriptive modeling. These implications manifest themselves at every step of the decision analytic process, potentially limiting the effectiveness of these tools, as discussed in the second part of the paper. Finally, it is proposed that it may be possible to enhance the effectiveness of decision analytic tools or numerical optimization if they are coupled with some symbolic reasoning capability. The third part of the paper discusses the relevance of artificial intelligence techniques for enhancing existing decision tools. The paper shows some links between the descriptive decision research of psychology, prescriptive models of operations research, and symbolic reasoning research of artificial intelligence. The paper argues for the necessity and usefulness of future coordination of research in these three areas.

## INTRODUCTION

Experimental psychology has uncovered many instances where decisionmakers consistently and persistently violate the postulates of classical normative theories. This paper reviews the main results of this literature, its implications for prescriptive approaches and resulting demands on decision aiding tools. Finally, it demonstrates the potential use of artificial intelligence techniques that may help in meeting some of these demands.

Disciplines like operations research or the decision sciences that are concerned with developing normative or prescriptive models of decision and choice often dismiss the empirical results and models of behavioral decision theory as purely descriptive and thus irrelevant. The focus of these disciplines is on decisionmakers, for example in organizational environments, who do not and should not have the liberty of violating normative rules as a consequence of cognitive limitations or to minimize, for example, psychological regret. However, this paper argues that even decisionmakers willing to follow normative decision procedures are, often unknowingly, still subject to the influences described by behavioral decision theory. One goal of the paper is thus to lay a foundation for the development of flexible decision aids that will minimize the impact of psychological biases and shortcomings on prescriptive procedures.

Some 35 years ago, psychologists started to discover that newly developed normative theories of judgment and choice (e.g., expected utility theory or Bayesian probability revision) often failed to describe human performance in risky choice situations [14]. The ensuing behavioral and cognitive study of human decision processes developed at least partially as a dialectic between behavioral data and normative theories. This approach of measuring observed performance against prescriptive models has been deplored by some [36] but accepted as fruitful and productive by most [42]. The following sections will discuss two different solutions to the observed discrepancy between behavior and normative theory. It is argued that these approaches have different implications for prescriptive recommendations or decision aiding.

## DESCRIPTIVE MODELS—NONEXPECTED UTILITY MODELS

Whereas the normative/prescriptive status of expected utility models has been firmly established since von Neumann and Morgenstern's [60] classical axiomatization and other subsequent axiomatic developments (e.g., [49]), the status of (subjective) expected utility ((S)EU) theories as *descriptive* models has always been more controversial. Early counterexamples ([2], [18]) and more recent data [33] have largely questioned the empirical validity of the substitution principle of EU theory (alternatively known as either independence axiom or monotonicity assumption). Several good reviews of this literature exist and need not be repeated here. (See [40], [48], [63].)

The response of economists and mathematicians to this discrepancy between axioms and behavior has been to successively modify or weaken the axioms of EU theory (especially the substitution principle) until the resultant model describes the observed behavior. Such models (e.g., [4], [8], [20], [30], [39], [64]) all relax the expectation principle of EU theory but differ in the constraining assumptions about the effects of probability on overall utility

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suggested in its stead. Luce and Narens ([37], [38]) take a slightly different approach (measurement theoretical rather than axiomatic) and explain both violations of the expectation principle as well as ambiguity effects with a theory that models uncertainty not in terms of risk, i.e., probabilities, but in terms of subjective decision weights that are not constrained by the laws of the probability calculus. Their dual-bilinear model is the most general type of interval-scaled utility model of which (S)EU theory and prospect theory are special, more restricted, cases.

While mathematically elegant, the theoretical and practical implications of these generalized utility models are somewhat unclear. Most of their originators are either silent or undecided on the prescriptive status of their models. As descriptive theories, these models offer little assistance for decision aiding. That is, they are silent on the question of why and through what processes people's decisions differ from those of EU theory and thus offer no guidance as to how to modify or correct people's perceptions or decision processes to bring them in line with prescriptive model(s) of choice. If, on the other hand, these models are intended as prescriptive models (currently a minority opinion, but see, e.g., [41]), then the present generation of decision-analytic technology will have to undergo complicating modifications of several orders of magnitude. (e.g., [4].)

## Descriptive Models—Behavioral Decisionmaking

There are many ways in which to classify the large body of empirical results in the field of behavioral decision making (see [14], [15], [17], [46], [47], [53] for reviews). The following discussion will focus on four topics: 1) Cognitive limitations of human information processing; 2) Restructuring of the problem representation by the decisionmaker; 3) Use of heuristics or simplifying processing algorithms; and 4) Instability of preference structures.

### *Cognitive Limitations of Human Information Processing*

Several limitations on human information processing capacity can be distinguished [28]. First, perception of information is selective because humans cannot process the multitude of incoming information. Secondly, processing usually occurs in a sequential manner or using simple procedures designed to reduce mental effort that may not always produce optimal results. The final limitation is on memory capacity. Unlike computers which can access all stored information in its original form, much of human memory works by a (less reliable) process of reconstruction. Realization of these constraints on human information acquisition and processing underlies Simon's conjecture of "bounded rationality" ([42], [52]) being the criterion for evaluating decision quality. The two phenomena discussed next, namely restructuring of the problem space and the use of heuristics, can be seen as procedures people develop over time and with experience to deal with their cognitive limitations. While adaptive and "boundedly rational" in the context of intuitive judgments, these processing styles can become so habitual or automatic that they will be applied even in situations where decisionmakers would prefer to use more formal or optimal procedures and where the use of heuristics can lead to serious biases.

### *Restructuring of Problem Representation*

One of the basic assumptions of the classical economic model of rational choice (e.g., expected utility theory) is the requirement that choice alternatives be evaluated in terms of their effects on final assets. That is, the outcomes of choice alternatives should be combined with current assets and that alternative should be selected that provides the most desirable final asset position. Continuously updating current asset levels and integrating those with the outcomes of every new choice set requires a significant amount of memory and cognitive effort. Therefore it is perhaps not surprising that people do not encode outcome information in this way, but instead in terms of gains or losses from the status quo or some other reference point. This is one of the central assumptions of Kahneman and Tversky's [29] prospect theory that (in conjunction with a value function that is concave for gains, convex for losses, and steeper for losses than for gains) accounts for a wide variety of decision behavior that no version of expected utility theory can explain. The reference point used to encode a particular outcome as a gain or a loss can be manipulated by normatively irrelevant changes in context or wording, often leading to reversals of preference between two choice alternatives. These "framing effects" are striking and robust, occur in natural environments, and for experts as well as naive decisionmakers (e.g., [4], [54], [57]).

### *Use of Heuristics*

The use of heuristics (i.e., simplified processing rules that provide the correct answer most but not all of the time) has been found extensively in people's judgments of the likelihood of uncertain events [56]. In making such judgments, people over time and experience learn certain regularities in their environment. One such regularity is the fact that similarity is an index of class membership. Estimating the probability that object $A$ belongs to class $B$ on the basis of $A$'s similarity to $B$ is an application of the representative heuristic. Another regularity is the fact that more probable events occur more frequently and thus produce more memories. Estimating the probability of an event by the ease with which instances or occurrences can be brought to mind is an example of the availability heuristic. These heuristics often lead to biased probability judgments because representativeness and availability are diagnostic but not exclusive determinants of probability. Use of the representative heuristic, for example, can under some circumstances lead to the neglect of base rates or prior probabilities [58]. Use of the availability heuristic can lead to overestimation of easily imagined events and to the perception of illusory correlations. Just as for framing effects, demonstrations of availability or representativeness biases have been reported both in the lab and in natural environments (e.g., [13]).

*Instability of Preference Structures*

Another assumption of the classical economic model of rational choice is that of procedure invariance, especially with respect to the elicitation of a decisionmaker's preference space. That is, his or her preference order for a set of outcomes or alternatives should not depend on the particular method by which it is assessed. However, empirical evidence is beginning to accumulate that suggests that people often may not have stable and well-defined preferences ([22], [24], [51]). In such situations, judged or revealed preference is not a reflection of the "true" internal preference structure, but is actually constructed during the elicitation process. Different elicitation procedures highlight different aspects of decision alternatives and may suggest different heuristics or different decision frames, thus giving rise to inconsistent responses [59]. Instability of revealed preference is an obvious problem for the utility elicitation stage of decision analysis. Pros and cons of different assessment procedures have been reviewed by [19], [27], [43]. Understanding the *processes* underlying changes in relative preference between elicitation procedures will allow decision analysts to select procedures in a more informed way as well as providing them with a vocabulary to explain and possibly resolve discrepancies between procedures to their clients.

## Prescriptive Models and Techniques—Implications of Behavioral Findings

Prescriptive techniques (e.g., decision trees or linear programming) employed in decision aiding are, implicitly or explicitly, based on certain normative assumptions about decisionmaking. The empirical results of behavioral research on decisionmaking reviewed in the previous section have raised profound questions about the validity of these assumptions, and, consequently, the validity of such prescriptive techniques is being challenged. Hence it is not an overdramatization when behavioral scientists, from their descriptive viewpoint, call "... the foundations of choice theory and decision analysis into question" [59]. In an effort to create new "foundations" and more general choice theories, the traditional normative assumptions are being relaxed, yielding the plethora of utility models discussed earlier. However, from a practioner's point of view, it is unclear which one to use when and how. Thus it seems not unrealistic to expect that "...another decade or two will pass before the shifting foundations settle" ([21], p. 79).

Experimental results demonstrating systematic and persistent deviations of human behavior from normative standards have turned decision theory into a newly controversial field from a theoretical point of view [50]. However, at the level of applications, decision analysts seem little perturbed. New utility models are either completely ignored [31] or categorically dismissed: "No principle other than maximizing SEU deserves a moment's consideration" [16, p. 7]. Empirical findings by behavioral scientists of human cognitive limitations and biases and of violations of the axiomatic foundation of SEU theory are also often sharply rejected as "...unwarranted generalizations from unrepresentative experiments" ([45], p. 537).

Even those who descriptively accept the findings of behavioral scientists do not necessarily agree that these findings invalidate the normative assumptions underlying their prescriptive techniques. According to one such viewpoint, human cognitive limitations and biases, even if they exist outside of the laboratory, do not have any significant effect on the quality of decisions [9]. The instances cited to support this position, however, seem to be restricted to decision situations with a flat criterion maximum.

According to another point of view, potential errors and inconsistencies raise only one necessary requirement, namely for the analyst to be careful and prudent ([61], [62]). This prevalent point of view is repeated in a recent article by some of the leading proponents of prescriptive and descriptive decision theory: "We can be glib in normative theories by hypothesizing the existence of decision agents who can think separately and distinctly about uncertainties and values and who can then integrate these deliberations jointly to determine preferences for actions. However, real behavior often does not conform to such an ideal.... The sophisticated prescriptive intervenor, who wants to help a real client to decide wisely, must be cognizant of these realities. The prescriptive analyst and client *must work carefully* to ameliorate some of these potential distortions" ([6, p. 22], emphasis added). Von Winterfeldt and Edwards [61, p. 385] go one step further and view the decisionmaker's errors and inconsistencies as "... an asset rather than a liability (which) forces both the analyst and the client to think hard and provides them with an opportunity to gain insights into the decision problem." Furthermore, they perceive some non-normative behavior as "creative stress" between the demands of a decision model and human intuition.

## Prescriptive Analysis as an Art

One widely accepted point of view sees the primary contribution of prescriptive decision analysis in the way in which it improves the decisionmaker's understanding and insight into the decision problem: "Such analysis might alter feelings as well as actions. Therapy through analysis" [6, p. 30]. This perception lies at the root of the current stress to view prescriptive analysis as an art requiring clinical skills. This point of view is inadequate for a number or reasons.

It is neither fair nor realistic to expect a practicing analyst to have the expertise, experience, and clinical skills that researchers like Edwards or von Winterfeldt may have in dealing with such conflicting situations. After all, practitioners, despite their professional training and ethics, operate under their own limitations, biases, and utilities. The suggestion that decision analysis should only be practiced after an internship with an expert [7] seems equally unrealistic. Consequently, the authors of this paper have observed analysts in practice performing blatantly erroneous analyses in order to release the "creative stress" through oversimplistic approaches rather than "thinking hard" or performing "therapy through analysis."

Even if the decisionmakers and analysts can manage to divorce themselves from their limitations, biases, and personal utilities, and instead judiciously and prudently think hard, *how* can they detect violation of normative principles by their clients (for example, violations of the independence axiom of EU)? If they do, what specific guidelines do they have to proceed? These and a host of other questions necessitate the development of sound theoretical principles and methodological tools.

## Prescriptive Analysis as Science and Technology

The empirical findings by behavioral scientists and resulting new behavioral models discussed at the beginning of the paper seem to have either been dismissed by prescriptive analysts or are perceived as placing additional demands on the *art* and skills of the analyst. The impact of these findings and models on the science and technology of decision tools does not seem to have received much attention.

What then is the impact of nonnormative behavior of a decisionmaker on decisionaiding tools? A prescriptive approach to decision aiding goes through four principal stages: 1) problem formulation, 2) solution, 3) post-solution analysis (e.g., sensitivity analysis, reiteration, etc.), and 4) implementation (i.e., actual execution of the solution). The formulation stage takes into consideration the nature of the problem and may lead to a representation of the problem in form of a decision tree or a linear program. Formulation can further be subdivided into the following three components: identifying the variables, options, parameters, and objectives; establishing the relationships between them (e.g., constraints in a linear program, consequences of options and their probabilities in a decision tree); and determining the preference (value) structure of the decisionmaker (i.e., the objective function, composed of a multiattribute utility function, to be maximized). Potentially, all of these steps in the prescriptive procedure can be affected by nonnormative behavior. Elicitation of probabilities and utility assessment, for example, can be affected by certainty and framing effects (among others). The certainty effect, in turn, violates the independence principle and hence the solution procedure of folding back the decision tree. This suggests two, complementary, approaches to solving the problem: the first one is to change the nonnormative behavior and the second to modify the decision tools.

## Rectifying Nonnormative Behavior

The key factors in rectifying any nonnormative behavior are 1) to anticipate the occurrence of such behavior, 2) to detect it, and 3) to make it explicit to the decisionmaker and others concerned. In order to appreciate the need for such procedures, one should recognize that in many decision environments, an individual operating within an organizational setting should not and will not want to knowingly violate rules that are normative from the organizational perspective. For example (adapted from [57]), a public health official may choose an immunization program that guarantees to save a particular number of lives in a population at risk over another program that offers some less than certain chance at saving an even larger number of lives in this population when the effects of the two immunization programs are presented in terms of lives saved, but may reverse his or her preference when the identical programs are described in terms of lives lost. From a public policy perspective, such inconsistency is unacceptable, and the only criterion to decide between the two immunization programs (all other things being equal) probably should be maximizing the expected number of lives saved (i.e., the final asset position), which is identical under the two formulations [35]. In their personal choices, decisionmakers may or may not want to represent alternatives in terms of their final asset position. However, in dealing with an organization's assets they should not have this latitude. In such situations, decisionmakers need to be reminded and encouraged to use a final assets perspective. (Machiavellian decision analysts, aware of the power and mechanisms of "framing effects," can of course also employ decision frames in such a way that the public official or employee will make decisions in line with the policies of his or her organization.)

Cases where a decisionmaker insists on knowingly violating a normative principle raise the question of whether some important factor has been overlooked in the formulation of the problem. For example, a quality control engineer may find a particular part out of tolerance after the machining operation. The part may not necessarily be defective, but its defectiveness will be revealed only in the actual assembly process. Should the engineer accept the part and send it to the assembly line, taking the risk of an expensive revelation of the defect should one exist, or should she scrap the part? The normative answer would, of course, depend on the probability that a part registering out of tolerance is actually defective as well as on the cost of revealing the defect on the assembly line. However, the quality control engineer will most likely insist on scrapping the part even in situations where this decision has smaller expected utility than the other alternative. Situations where a retained part turns out to be defective are not only costly, but also constitute an identifiable and visible error on her part. Regret theory [5] or some other multiattribute representation that incorporates the cost of making a wrong decision or accountability could perhaps explain the decision of the quality control engineer. However, the goal may not be to predict or justify her decision by some formal model, but to guide the decisions towards some organizationally acceptable standards. Hence, a decision tool should, in addition to traditionally desired qualities, be able to remove any contextual biasing effects or to make them explicitly known to all concerned if the decisionmaker insists on his or her nonnormative behavior. The latter case may, in fact, reveal a factor not considered in the original problem formulation which is of sufficient normative appeal to be included in future versions of the prescriptive model.

Similar arguments can be made for decision tools designed to elicit probability judgments. Awareness, understanding, and anticipation of the heuristics used to make such judgments and the conditions under which these heuristics will lead to biases, can actually help prevent their occurrence by suggesting effective countermeasures. Thus it has been shown, for example, that base rate neglect as a function of use of the representative heuristic can be significantly reduced by explicitly emphasizing the causal connections between events [3].

## Modification of Decision Tools

There are three major areas where decision tools will need to be modified. First, existing prescriptive techniques cannot satisfactorily handle the complexities created by dependencies between utilities and probabilities, and by nonlinearities introduced by some extended utility theories which relax the substitution principle. A preliminary effort towards developing an alternative to the standard decision tree fold-up procedure has recently been made ([4], [48]). However, the area is open for further algorithmic research.

The second point is more encompassing, namely the need to increase the effectiveness of existing tools through increasing their domain of application and their range of functions. The former necessitates relaxing rigid data and assumption requirements and the latter involves introducing reasoning and interactive explanatory capabilities (thus providing decisionmakers with the information necessary to justify the decision taken). Existing decision tools (e.g., procedures or algorithms such as the simplex or decision tree analysis) are rigid and they are opaque. If a single data point is missing in a linear program, the program will not run. A structural sensitivity analysis on a decision requires the tedious task of restructuring the complete tree all over. In existing decision aids that employ a conventional hierarchical programming structure, even a small structural modification is rather tedious (e.g., [34, p. 471]). Opaqueness of decision tools refers to the fact that most tools cannot explain, let alone justify, the reasoning process which led to the decision. Modifications will require to provide the tools with a knowledge base, an inference mechanism, and a set of procedural primitives (e.g., modus ponens for symbolic manipulation, a matrix inversion algorithm for numerical computations).

The third area of enhancement is to introduce anticipatory behavior into decision tools. Current technology allows for sequential execution of procedural steps with little flexibility in shifting the control from a predefined sequence of operations. There are three types of knowledge or information that may necessitate a change in control strategy as execution proceeds: knowledge about the problem domain, about the algorithm itself, and about the decisionmaker. These types of knowledge correspond roughly to the three components of the decisionmaking process: the decision problem, decisionmaking tools, and the decisionmaker.

In order to accomplish the second and third enhancements discussed above, a decision tool must have a flexible control strategy, a knowledge base, and an explanatory capability. Development of techniques and technologies supporting these features is at the core of the research in the field of artificial intelligence (AI). Consequently, the potentials of AI techniques have recently received much attention ([25], [26], [32], [34], [61]) amidst some cautionary remarks warning against excessive optimism ([12], [55]).

## Relevance of Artificial Intelligence

Issues and advances in a variety of areas of artificial intelligence (AI), including knowledge-base related research (e.g., knowledge acquisition and representation) and research on explanation, have important implications for designing decision tools. However, for the purposes of this paper (i.e., exposition and illustration of how AI techniques can incorporate some of the insights and overcome some of the shortcomings detected by descriptive research on human decisionmakers) we will concentrate on research on control strategies.

A computerized decision tool, like most nontrivial programs, is made up of many modules each carrying out a particular subtask (e.g., an algorithm, an operator, a macro, or any other procedure). How a given task can be divided into subtasks and how the execution of subtasks can be sequenced, is highly dependent on the control facilities offered by the programming language. In conventional languages these facilities are usually limited to conditionals (IF-THEN statements) and looping constructs (loop-exit tests). Such control structures are not adequate for designing a flexible program where the decisions on what module to execute when are preferred to be left to the program. If this flexibility is not built in, and if the conventional by programmed decision tool is to be implemented for a decision problem that is not well structured, then the inflexibility of the tool can only be alleviated by a large amount of judgmental input from the users (the analyst and the decisionmaker). This opens up the possibility of introducing the biases and limitations discussed earlier in this paper.

To illustrate this point let us consider an example. Airplanes arriving at an airport are assigned to certain gates. Each morning an optimal assignment of planes to gates is determined for the duration of the day, using some mathematical programming technique. However, this assignment may have to be revised during the course of the day if a delay in the arrival time of any airplane occurs. This revision is currently done manually by a separate human operator for each airline. The operator faces a multiattribute decision problem. For example, is it better to delay one airplane ten minutes or two airplanes five minutes each? Should an "important" airplane be kept on schedule at a cost of delaying another flight by twenty minutes, etc.? Furthermore, if there are several delays and the time span for the revision of the assignment becomes longer than one hour, then the decision problem becomes a risky one because of the uncertainties involved in projecting the arrival time of planes more than an hour into the future.

This problem, even though repetitive, is not a structured one. Hence it does not lend itself to a conventionally designed decision aid. A more flexible computerized system is currently under development using the reflective prolog language (RPL) [11], details of which will be reported elsewhere [10]. Two important features of RPL are (a) that it has meta level capabilities (metareasoning, metaknowledge, and metaevaluation) ([1]; [23, ch. 10]) and (b) that it has a procedural reflection mechanism ([23, pp. 255–261]).

Roughly, this decision system is organized in two levels. At the object (lower) level, in addition to knowledge about the problem (e.g., scheduled arrival times and planes, which gates can accommodate what type of plane) there also is a library of evaluation procedures (e.g., lexicographic analysis, decision tree approach, sensitivity analysis, deterministic search algorithm). The second, higher, level accommodates knowledge about the objects (problem specification, procedures) at the lower, object, level. This higher metalevel manipulates the soft constraints at the object level (e.g., relaxing certain preference constraints as necessary) and decides on which procedures to execute when during run time. Such a decision depends on knowledge of the current state of the problem (e.g., deterministic or probabilistic, whether a "good" solution already exists, presence of time pressure) and on the existing preference structure for choosing among different multiattribute alternatives.

Thus, the control structure of this decision system utilizes two lessons of behavioral decision theory. First, it flexibly uses a combination of procedures (including heuristics) to solve a given problem at a given point in time. Secondly, it avoids human judgmental inputs in defining the problem state during execution, thereby minimizing the potential for introducing biases such as "representativeness" or the potential for organizationally undesirable factors such as "regret." One may argue that such biases and factors may have been introduced into the decision system during the programming stage. However, after being programmed, any inconsistencies, incompleteness, or inaccuracies resulting from such biases or hidden agendas can be identified via simulations and resolved before implementation of the system.

It should be emphasized that the described decision system is not an expert system of gate assignment, in the sense that it does not try to emulate a human decision expert. Quite to the contrary, it tries to overcome the limitations and biases of human decisionmakers by automating the task as far as possible. At the same time, it utilizes AI techniques to rectify previous shortcomings of automation (e.g., inflexibility to changes in the problem environment). Doing so, the decision system draws on adaptive strategies and heuristics first identified by descriptive decision research of human decisionmakers and incorporates those into the decision repertory of the automated system.

## Conclusion

Prescriptive analysis used to be primarily preoccupied with mathematical and algorithmic aspects of decision tools with little or no attention to the environment within which the tool was intended to be used. Mounting disappointment and criticism of this focus coupled with the realization that individuals' behavior may not comply with classical normative axioms seems to have moved the pendulum to the other extreme. Decision aiding distanced itself from scientifically justifiable formalisms and has been increasingly perceived more as an art than as a science.

This attitude is not universal but prevalent enough to create some concern about the neglect of the scientific and technological basis of prescriptive decision analysis. This paper has argued that the experimental evidence on the decision behavior of individuals has demonstrated a need for decision aids significantly different from existing ones. Furthermore, we argued that it may be unfair and inadequate to leave the task of bridging the gap between necessary (or desirable) and existing decision tools to the skill and imagination of the decision analyst. We are more inclined to agree with the statement by the 16th Century Italian philosopher Vico: "Certum quod factum," i.e., "one is certain (only) of what one builds." Hence we discussed reasons and directions for strengthening and extending the capabilities of existing decision tools. It was suggested that necessary additional tools, techniques, and theories may be obtained from artificial intelligence, a field currently much interested in discovering how humans deal with problems of the type described by behavioral decision research and with ways in which problem solution procedures can be automated.

Thus the approach to decision aiding suggested in this paper is intermediate between the traditional (optimal yet inflexible) prescriptive models on the one hand and expert system models (flexible but emulating the human decisionmaker potentially with all of his or her shortcomings) on the other hand. Instead we propose that prescriptive and descriptive research should interact in two ways: 1) situations and decision stages during which descriptive research has demonstrated shortcomings of human decisionmakers (due to cognitive limitations and time pressure or due to conscious or unconscious hidden agendas or biases) need to be automated; and 2) automated prescriptive decision systems need to learn from descriptive research how to deal flexibly and efficiently with changing problem environments. Finally, AI techniques provide a way to instantiate any lessons and procedures gleaned from descriptive research on human decisionmaking flexibility.

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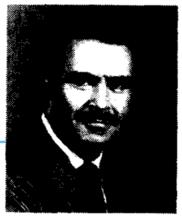

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