Cognitive Biases Affect the Acceptance of Tradeoff Studies

Eric D. Smith[1], Massimo Piatelli-Palmarini[2], and A. Terry Bahill[3]

[1] Department of Engineering Management and Systems Engineering, University of Missouri at Rolla, MO 65409, USA erics@umr.edu
[2] Cognitive Science Program and Department of Management and Policy, University of Arizona Tucson, AZ 85721, USA massimo@u.arizona.edu
[3] Systems and Industrial Engineering, University of Arizona, Tucson, AZ 85721, USA terry@sie.arizona.edu

Summary. Tradeoff studies involving human subjective calibration and data updating are often distrusted by decision makers. A review of objectivity and subjectivity in decision making confirms that prospect theory is a good model for actual human decision making. Relationships between tradeoff studies and the elements of experiments in judgment and decision making show that tradeoff studies are susceptible to human cognitive biases. Examples of relevant biases are given. Knowledge of these biases should help give decision makers more confidence in tradeoff studies.

1 Introduction

Tradeoff studies provide a rational method for improving choice among alternatives. Tradeoff studies involve a quantitative consideration of all aspects of the decision, considering all evaluation criteria of the alternatives simultaneously. Without tradeoff studies, humans usually consider alternatives serially, and often fixate on one or a few less-than-optimal criteria.

Tradeoff studies are broadly recognized and mandated as the method for simultaneously considering many criteria and many alternatives. They are the primary method for choosing among alternatives given in the Software Engineering Institute's Capability Maturity Model Integration [7] Decision Analysis and Resolution process [9]. However, a 1999 INCOSE (International Council on Systems Engineering) International Symposium tutorial [12] reveals a much different truth:

> Over the past few years Bahill has worked with several major aerospace companies ... and asked for examples of tradeoff analyses that had been done there. He has not yet found one.

Given that multicriterion decision analysis techniques (such as tradeoff studies) are mandated for rational decision making, why do so few decision

makers use them? Perhaps, because (1) they seem complicated, (2) different techniques have given different preferred alternatives, (3) different life experiences produce different preferred alternatives, and (4) people do not think that way. The goal of this chapter is to inform the reader about common and ever-present biases that produce some of the just-mentioned variability. This variability of results hinders proactive use of tradeoff studies in industry, where tradeoff studies are often written only when required, such as in a project proposal presentation.

This chapter is organized as follows. It starts with a description of tradeoff studies, and then it describes a dozen biases that affect human decision making. (In this chapter, for simplicity, we group together cognitive illusions, biases in the canonical definition, and the use of heuristics and call them collectively biases.) The objectivity and subjectivity section of this chapter discusses rational decision making and presents some descriptive models for how humans actually make decisions. The next section presents a dozen biases that especially affect tradeoff studies. Finally, the discussion section suggests how humans can make better decisions if they understand cognitive biases.

2 Components of a Tradeoff Study

Problem statement. Problem stating is often more important than problem solving. The problem statement describes the scope of the problem and the key decisions that must be made.

Evaluation criteria are derived from high-priority tradeoff requirements. Each alternative will be given a value that indicates the degree to which it satisfies each criterion. This should help distinguish between alternatives.

Weights of importance. The decision maker should assign weights to the criteria so that the more important ones will have more effect on the outcome.

Alternative solutions must be proposed and evaluated. Investigation of a broad range of alternatives increases the probability of success of a project and also helps to get the requirements right.

Evaluation data can come from approximations, product literature, analysis, models, simulations, experiments, and prototypes. Evaluation data are measured in natural units, and indicate the degree to which each alternative satisfies each criterion.

Scoring functions (utility curves) transform the criteria evaluation data into normalized scores. The shapes of scoring functions should ideally be determined objectively, but usually subjective expert opinion is involved in their preparation. A scoring function package should be created by a team of engineers and re-evaluated with the customer with each use [8,51].

Scores. The numerically normalized 0 to 1 scores obtained from the criteria scoring functions are easy to work with. Assuming that the weights of importance are also normalized, combining these scores leads to a rankable set of scores for the alternatives that preserves the normalized 0 to 1 range.

Combining functions. The weights and scores must be combined in order to select the preferred alternatives [8]. The most common combining functions are:

$$
\begin{aligned}
\text{Sum Combining Function} &= x + y \\
\text{Product Combining Function} &= x \times y \\
\text{Sum Minus Product Combining Function} &= x + y - x \times y \\
\text{Compromise Combining Function} &= [x^p + y^p]^{1/p} \ .
\end{aligned}
$$

One must be careful to choose a combining function appropriate to the situation.

Preferred alternatives should arise from the impartial parallel consideration of the scores for the evaluation criteria. The alternative ratings will allow a ranking of alternatives. Care must be taken, however, to eliminate human tendencies that draw the study to a result that is merely subjectively preferred.

Sensitivity analysis identifies the most important parameters in a tradeoff study. In a sensitivity analysis, you change a parameter or an input value and measure changes in outputs or performance indices. A sensitivity analysis of the tradeoff study is imperative.

The tradeoff study components. Evaluation criteria are derived from a problem statement and possible alternatives are selected. Evaluation data for each evaluation Criterion are normalized with a scoring function, and combined according to the weights of importance and combining functions, yielding a rating for each alternative. A sensitivity analysis is conducted to determine robustness, and a list of preferred alternatives is written. The relationships of these components are shown in Figure 1.
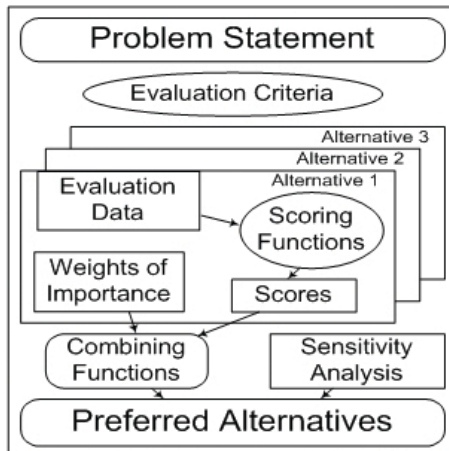

Fig. 1. Components of a tradeoff study.

The *Pinewood Derby Tradeoff Study* is a real-world tradeoff study that also serves as a reference. It has been implemented in Excel with a complete sensitivity analysis, and is available at [34].

3 Inevitable Illusions and Biases

When examining human decision making, the presence of cognitive biases and irrationalities can never be ruled out. (Note: In this chapter, we use the term *rational* as it is used in the field of decision analysis: meaning agents or decision methods that are guided by the aim of maximizing expected value. Our use of the term irrational is therefore technical and does not reflect on any person's ability to reason, or sanity.) The universality of biases in human decision making is the central tenet of the "heuristics and biases" research program inaugurated and developed by Kahneman and Tversky, which produced the now widely accepted prospect theory [27] to explain how people respond to choices made under risk and uncertainty. Deeply ingrained human biases and predictable misinterpretations of certain classes of external circumstances, such as the framing of choices, can compromise the rationality of decisions and plans. It is important to note that subjects maintain a strong sense that they are acting rationally while exhibiting these biases. One of us (Piattelli-Palmarini), in the book *Inevitable Illusions*, introduces the subject this way:

> The current term for these biases is "cognitive" illusions, to indicate that they exist quite apart from any subjective, emotional illusion and from any other such habitual, classical, irrational distortion by a particular subject. The pages that follow provide ample documentation, and contain suggestions as to how we may take urgent and sensible precautions against these illusions.

> It never ceases to surprise me that, more or less 20 years after these illusions were first discovered, and after dozens of books and hundreds of articles have been printed on the subject of cognitive illusions, almost no one except for a select circle of specialists seems to have taken this discovery seriously.

> In simple and basic fashion, this book proposes to set out the recent scientific discovery of an unconscious ... that *always and unbeknownst to us* involves the cognitive; that is, the world of reason, of judgment, of the choices to be made among different opportunities, of the difference between what we consider probable and what we consider unlikely [32].

It is therefore proposed that tradeoff studies be re-examined with the goal of finding subtle biases and cognitive illusions. Below is a summary of common biases and irrationalities that may intervene, unbeknownst to the decider, in what is presumed to be rational decision making.

Because of cognitive illusions, biases, fallacies, and the use of heuristics, humans often make mistakes in doing tradeoff studies. Smith [43] discusses seven dozen biases from the psychology, decision-making, and experimental economics literature that can induce such mistakes. Many of these are also mentioned in [3,32,40] and in popular Web sites such as [29]. A matrix of relations between cognitive biases and tradeoff study elements is available at [34].

3.1 Judgment and Decision Making

The rich scientific literature on judgment and decision making details many cognitive biases, irrationalities, and inconsistencies in the way humans make judgments and decisions. In light of this, it may be cost effective to train decision-making personnel specifically in ways that reduce intangible cognitive biases. Training brings standardization and broadens decision-making abilities, breaking the situation where, "We are prisoners of our own experience."

Ambiguity Aversion, Comparative Ignorance, and Severity Amplifiers

The probability of someone accepting a bet can be lowered by the presence of nonrelevant ambiguous material, as in the Ellsberg paradox [16,17]. The decision to play a gamble can be influenced by the perceived intelligence of counterparts, even while the probability of winning remains the same [18,19]. Lack of control, lack of choice, lack of trust, lack of warning, lack of understanding, framing by man, newness, dreadfulness, personalization, and immediacy all amplify perceived severity [1,2].

Confirmation Bias

Humans will often try out several means to prove that their current favorite hypothesis is correct, until all efforts fail, and only then will they seriously consider the next hypothesis [50]. Shweder [42] showed a correlation between initially recorded data, and memories of subsequent data. The history of science offers many examples of this obstinacy, an example of which is the obdurate and exaggerated application of circular motion to the planetary orbits before Kepler introduced ellipses in 1609 in his *Astronomia Nova*. Symmetrically, a disconfirmation bias occurs when people exaggerate the severity of their critical scrutiny of information that contradicts their prior beliefs.

Individual Versus Group Decision Making

Individuals may be biased, but so may groups. Which is more biased? A prevalent thesis, backed by good data but by no means universally supported, is that groups are less easily biased than the individuals that compose them. However, there is no clear or general pattern. Complicated social models such as Davis's social decision scheme [10] give good, albeit complicated answers. In short, cognitive problems in decision making cannot always be solved by requiring group decision making.

3.2 Framing and Prospect Theory

This section and the next deal with objectively incorrect human subjective evaluations of value and probability, which are so ingrained in cognitive evaluation that experts employing their full attention find it difficult to recognize cognitive evaluations among objective evaluations. The effects of cognitive evaluations are thus subtle and difficult, in current untutored practice, to separate from objective assessment.

Framing—in a popular sense—is the act of "placing a picture frame" within the full reality of the decision situation, for the purpose of reducing processing effort, increasing mental assimilation and simplifying the decision. *Anchoring* is a psychological term that refers to focusing on the reference point when making decisions. For example, a shopper looking for a dog may anchor on the fact that a puppy is a Labrador Retriever, and ignore temperament, health, and price. Anchoring and then insufficient adjustment occurs when a decision maker chooses an anchor and adjusts his or her judgments myopically with respect to it. For example, a person may anchor on the first new computer she sees, and adjust insufficiently to consider fully the characteristics of other computers seen later.

Availability and Typicality

People employ a mental availability heuristic when they evaluate the likelihood or frequency of an event based on how quickly instances or associations come to their own mind. For example, people who have friends that smoke usually overestimate the smoking population. Typicality occurs when items with greater family resemblance to a category are judged more prevalent. Tversky and Kahneman [47] give this example of typicality.

Subjects were told: imagine an individual X, who was extracted at random from a large population. Estimate the following probability.

- *Group 1:* That X has suffered already at least one heart attack
- *Group 2:* That X is over 50 years old and has suffered already at least one heart attack

Subjects who were shown the Group 2 statement gave, on average, higher estimates than subjects who were shown the Group 1 statement.

Loss Aversion

Figure 2 shows that people more strongly prefer to avoid losses than acquire gains. Would you rather get a 5% discount, or avoid a 5% surcharge? Most people would rather avoid the surcharge. The same change in price framed differently has a significant effect on consumer behavior. Economists consider this to be irrational. It is important in the fields of marketing and finance.

A delay–speedup asymmetry occurs when people will pay more to get rid of a delay than they would to speed up the schedule by the same amount
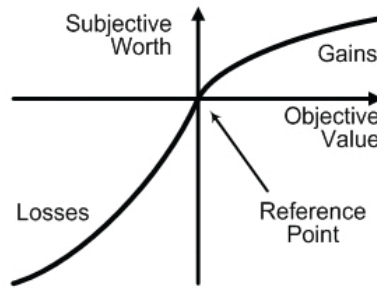
Fig. 2. Subjective worth versus numeric value according to prospect theory.

of time. The explanation for the asymmetry comes from the subjective value function of prospect theory shown in Figure 2. The delay–speedup asymmetry obviously has applications towards schedule and risk requirements, which often refer to money available either for ameliorating a delay or paying for a schedule speedup.

Loss/Gain Discounting Disparity

Losses are discounted less (and forgotten later) than gains, making humans susceptible to the "sunk costs effect," or a tendency to hold on to manifestly losing investments. This effect explains long-held grudges, and even mental illness stemming from an inability to forget past traumas. Perhaps remembering losses more than gains is a good way to focus on learning from mistakes, but the practice is not part of an objective probabilistic stance inline with rational decision making. For example, project managers should not over-emphasize aspects of a project related to a previous project failure.

Figure 2 also shows the reference point, which is important as demonstrated in this example from Hammond et al. [25]. Would you accept a 50–50 chance of either losing $300 or winning $500? Many people would refuse this bet. Now let us change the reference point. Assume you have $3000 in your checking account and you are asked, "Would you prefer to keep your checking account balance of $3000 or accept a fifty-fifty chance of having either $2700 or $3500?" Most people would take this bet.

3.3 Subjective Probability and Illusions

To the consternation of believers in human probability judgments, one can take practically any of the axioms of probability, including the one that says $0 \leq p \leq 1$, and design an experiment that shows that peoples' spontaneous intuitions violate it.

> There is always an appeal to "simple" explanations for probabilistic and other illusions. The data can allegedly be explained in terms

of absent-mindedness, linguistic ambiguity, skewed implicit presup-
positions, lack of memory, lack of attention, lack of motivation, etc.
However, the best papers in [cognitive psychology] show that this is
not the case. [33]

The following examples show subjective violations of the axioms of probability.

Frequency Illusions

Clausen and Frey [6],and Gigerenzer and Selten [20,21] proposed that humans
are better calibrated when using frequency of occurrence of events, instead of
probabilities. For the same reason professionally chosen stock portfolios may
do no better than those composed of stocks picked at random.

Conjunction Fallacy

The probability of two independent events happening simultaneously will al-
ways be less than the probability of either event happening alone: ($P(a) \times
P(b) \leq P(a)$ and $P(a) \times P(b) \leq P(b)$).

However, most people are influenced by the "typicality" or "ease of repre-
sentation" of some conjoined circumstances, and so wrongly judge that spe-
cific conditions are more probable than general ones. Consider this example
by Tversky and Kahneman [47]:

Linda is 31 years old, single, outspoken and very bright. She majored
in philosophy. As a student, she was deeply concerned with issues of
discrimination and social justice, and also participated in anti-nuclear
demonstrations. Which is more likely? (1) Linda is a bank teller, or,
(2) Linda is a bank teller and is active in the feminist movement.

85% of those asked chose option 2.

The Sure-Thing Principle

If you are going to perform an action regardless of the appearance of an
unrelated outcome, then you should not wait to see the unrelated outcome
[38]. A response pattern violating the sure-thing principle would look like this:

- I will do A, if I know that S the case.
- I will do A, if I know that S is not the case.
- However, because I do not know the state of S yet, I will wait to do A.

An example is choosing a project whether or not a certain employee comes
on board [49]. Humans seem to avoid complex disjunctive choices, and opt
for decisions that hypothetically will assure less undesirable outcomes. This
occurs even when they are told that the outcome, not yet known to them,
has already been irrevocably determined. Consequently, most people seem to
prefer to settle for "sure" key attributes before advancing into an analysis of
other important, but conflicting, attributes.

Extensionality Fallacies

Extensionally equivalent true descriptions of an event should all map onto the same numerical probability. But they do not. Two groups of subjects were shown the following insurance policies.

- *Group A.* How attractive do you find an insurance that covers hospitalizations due to any cause whatsoever?
- *Group B.* How attractive do you find an insurance that covers hospitalizations due to diseases or accidents of any sort?

On the average, subjects of Group B found their insurance more attractive than did subjects of Group A [26]. One can imagine that a specialized weapon system adapted against two or three specifically ominous threats could be preferred to a more general-purpose system with more capabilities.

Certainty Effect

People prefer reducing chances of something bad happening from something to nothing, more than reducing chances of something bad happening by the same amount but not to zero. Plous [35] cites economist Richard Zeckhauser: "Zeckhauser observed that most people would pay more to remove the only bullet from a gun in Russian roulette than they would to remove one of four bullets." Notice that the reduction in their probability of being shot is the same in both cases.

3.4 Objectivity and Subjectivity; Prospect Theory

The definitions of value versus utility, and the objective versus the subjective, must first be settled in order to gain a clear understanding of decision theory as it applies to human decision making. Edwards [14] created Figure 3, which differentiates the four variations of the expected value model.

In the upper left is the rational, normative, prescriptive, mathematical theory of expected values, where objective probabilities and isomorphic values of rewards are considered. Isomorphic here means preserving an identical value—determined by a normative rational theory—despite the opinion of any individual. The lower right quadrant represents the subjective, behavioral, "biological," descriptive theory of subjective expected utility, where subjective probabilities and nonisomorphic utilities are considered. This terminology is clarified in Figure 4, in which cross-hatching indicates the areas of subjective utility and probability.

It is seen that there are two models (or views, or theories) of human behavior: the normative and the behaviorally descriptive. The normative, or prescriptive, model arises from the view that humans should make decisions according to rational calculations, for example, when the sum of objective probabilities multiplied by corresponding objective values gives the overall
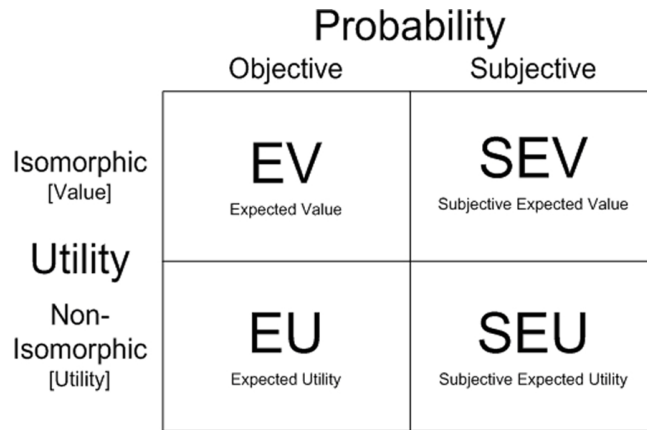
Probability

	Objective	Subjective
Isomorphic [Value]	**EV** Expected Value	**SEV** Subjective Expected Value
Non-Isomorphic [Utility]	**EU** Expected Utility	**SEU** Subjective Expected Utility

Fig. 3. Four variations on the expected value model, from Edward [14].

Probability

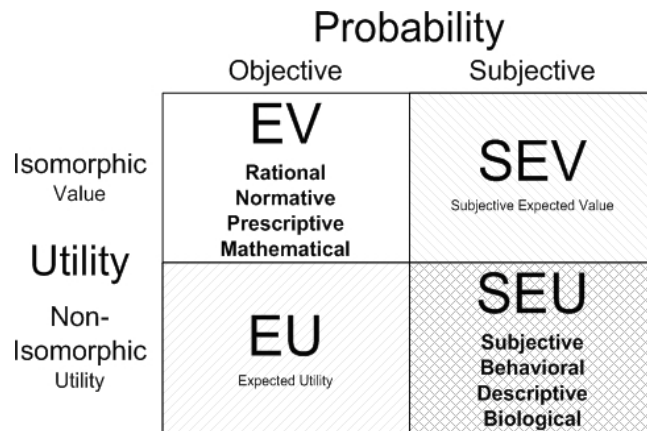|	Objective	Subjective
Isomorphic Value	**EV** Rational Normative Prescriptive Mathematical	**SEV** Subjective Expected Value
Non-Isomorphic Utility	**EU** Expected Utility	**SEU** Subjective Behavioral Descriptive Biological

Fig. 4. Objective and subjective value and probability models.

expected value of a choice. On the other hand, descriptive models of human decision making seek, rather, to describe and explain human behavior as it is.

The most accepted descriptive theory is prospect theory [27,48], which explains the nature of the subjective human decision-making process in terms of the heuristics and biases employed in assessing information, and the common deviations from rational decision making that result.

Framing and Subjective Utility

Prospect theory breaks subjective decision making into a preliminary screening stage, and a secondary evaluating stage. The effect of these two stages is that values are considered not in an absolute sense (from zero), but subjectively from a reference point established by the subject's perspective on the

situation, based on his self-estimated wealth and his evaluation of the best and worst outcomes before the choice is made. Within prospect theory, the establishment of a subjective reference point is formally called framing. This reference point can be predictably altered by presenting a same choice situation under different, although equally truthful, descriptions. The key graph that shows how objective values translate into subjective worth is shown in Figure 2. Note the significant disparity in magnitude with which gains and losses are subjectively valued; losses can have absolute magnitudes of about 2.25 to 2.5 times that of gains, depending on the human subject.
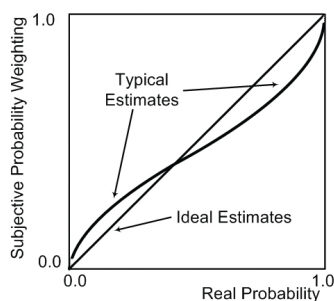

Fig. 5. The probability weighting function of cumulative prospect theory [36,48].

The probability weighting function of Figure 5 shows the subjective probability weight (how much the stated probability weighs in real-life decision making) as a function of the real probability. The diagonal represents the normative ideal case of a perfectly calibrated, perfectly rational decision maker. In several mathematical models the two curves cross at $1/e \approx 0.37$.

Subjective Probability

Prospect theory describes the subjective evaluation of probabilities according to the experimentally obtained graph in Figure 5. People overestimate events with low probabilities, such as being killed by a terrorist or in an airplane crash, and underestimate high probability events, such as adults dying of cardiovascular disease. The existence of state lotteries depends upon such overestimation of small probabilities. An effective method of forcing the visualization of how small the probability of winning any such large-stakes lottery consists of computing how many lotteries one should be playing until the chance of winning at least one approaches 50%. The typical figure is one new lottery every minute for thousands of years. At the right side of Figure 5, the probability of a brand new car starting every time is very close to 1.0. But many people put jumper cables in the trunk and buy memberships in AAA.

Now, with some understanding of the key differences between objective and subjective decision making, we apply Edwards' schema to the field of

decision making to give Figure 6 (note that prospect theory is not the only mathematical treatment of real-life decision making, but it is the most widely accepted as theoretically sound).
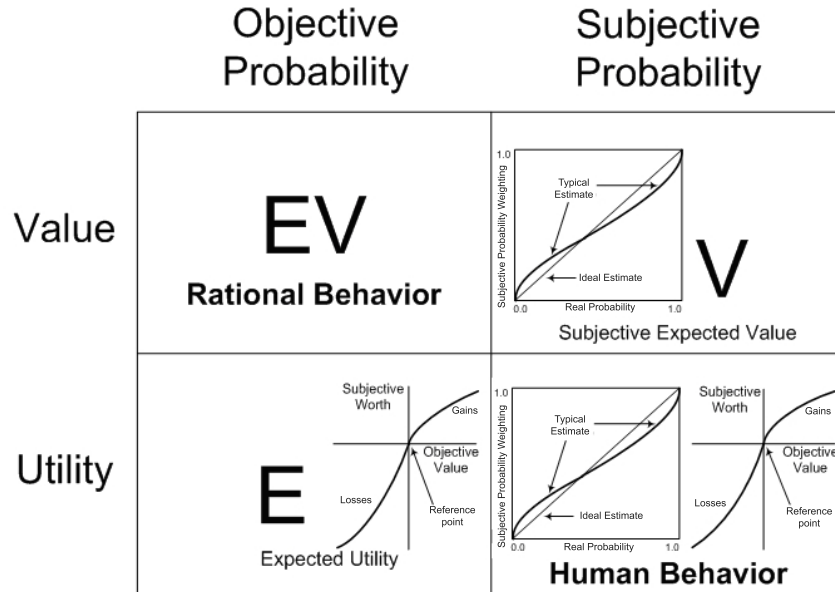

Fig. 6. Rational behavior versus human decision making.

When objective and accurate numerical values are available, tradeoff studies give an exact ranking of alternatives through numerical calculation. In the presence of subjective utilities, when a person expresses judgments or preferences, the best description for human decision making is prospect theory. Humans are far from ideal decision makers because of cognitive illusions and biases, and the use of heuristics. Using tradeoff studies judiciously can help people make rational decisions. We want to help move human decision making from the normal human decision-making lower-right quadrant to the ideal decision-making upper-left quadrant in Figure 6.

4 Biases That Inhibit Acceptance of Tradeoff Studies

Many aspects of tradeoff studies "turn off" human decision makers. Evidence for this is in the small number of tradeoff studies reported in the literature. This is a 1999 INCOSE International Symposium tutorial description [12]:

> When an engineer performs a tradeoff analysis and submits the results to his or her boss, the boss often says, "No, that is not the right

answer." In response to this, the engineer might change weights, values, scoring functions or tradeoff functions. Part of the reason that engineers do not do tradeoff studies may be that they have seen applications where similar analyses using similar techniques have given different preferred alternatives. Tradeoff analyses fall into the field of decision making under risk or uncertainty, often called utility theory or multicriterion decision making.

Perhaps the thought of having to delve into a combination of subjective utility theory and multicriterion decision making discourages human decision makers from performing tradeoff studies.

Overconfidence in Subjective Choice: Often Wrong, but Rarely in Doubt

Griffin and Tversky [24] have this to say about the weighing of evidence and the determinants of confidence:

> One of the major findings that has emerged [from cognitive science] is that people are often more confident in their judgments than is warranted by the facts. Overconfidence is not limited to lay judgment or laboratory experiments. The well-publicized observation that more than two-thirds of small businesses fail within 4 years suggests that many entrepreneurs overestimate their probability of success.

Overall, people are too confident in their subjective opinion of the overall (presupposed) final result of a tradeoff study, even before they begin any calculations. They may therefore consider it a waste of time to proceed with the mechanics of a formal tradeoff study. However, there are other reasons for the uneasiness and reluctance to proceed with, and complete a tradeoff study. These reasons are described below.

Calibration

Griffin and Tversky [24] provide an answer to the question of uneasiness in conducting tradeoff studies: "Overconfidence is not universal. Studies of calibration have found that with very easy items, overconfidence is eliminated, and under confidence is often observed [28]." Because the process of completing a tradeoff study involves much calibration, underconfidence can easily occur, and possibly accumulate.

Consider the following two questionnaires depicted in Table 1, which were posed to experimental subjects. Half of the subjects got the first questionnaire and the other half got the second one [39].

The Xs show the average answer. On average, the subjects choose the answer near the center of the numerical range, regardless of its numerical value. Obviously, humans cannot be trusted with a problem of calibration, even when it pertains to their own personal experience. In this case, subjects seemed eager to calibrate a number in a way that seemed most compatible with the given range of scale.

Table 1. Experimental questionnaire [39].

Please estimate the average number of hours you watch television per week					
		X			
1–4	5–8	9–12	13–16	17–20	More than 20

Please estimate the average number of hours you watch television per week					
		X			
1–2	3–4	5–6	7–8	9–10	More than 10

Discriminability of Updated Information

Griffin and Tversky [24] reviewed the discrimination of a hypothesis against its updated hypothesis: "People seem to focus on the strength of evidence for a given hypothesis [or a favored hypothesis] and neglect how well the same evidence fits an alternate hypothesis." Furthermore, Griffin and Tversky note that "studies of sequential updating have shown that posterior probability estimates commonly exhibit conservatism or under confidence [15]." Thus, the sequential updating of information in a Bayesian fashion can be accompanied by inflexibility and lack of trust in the analyst's mind.

The lack of trust, in calibration and posterior probabilities, deals a double blow to progress within tradeoff studies. People would rather hold on to their false overconfidence in their preliminary subjective opinion of the alternatives.

Law of Small Numbers

The law of small numbers simply stated says, "There are not enough small numbers to meet the many demands made of them." For example, the function $\lceil e^{(n-1)/2} \rceil$ gives the sequence 1, 1, 2, 3, 5, 8, 13, 21, 34, 55, ... (i.e., the first ten Fibonacci numbers) for $n = 1, \ldots, 10$, although it subsequently continues 91, 149, ..., which are not Fibonacci numbers.

In tradeoff studies, this law could influence the estimation of weights of importance (or other parameters) whenever critical differences in weights are shrouded by the possibly small number of weight value options used. If aware of such limitations, a decision maker who considers tradeoff studies to be a large collection of "small numbers" may not want proceed with any extended analysis or effort.

In a another situation concerning the law of small numbers, someone charged with a decision may want to take some small indicator or data sample, place undue confidence in it, make the decision according to it, and "spare

himself the trouble of re-confirming the obvious." Tversky and Kahneman [46] wrote:

> In review, we have seen that the believer in the law of small numbers practices science as follows:
> 1. He gambles his research hypotheses on small samples without realizing that the odds against him are unreasonably high. He overestimates power.
> 2. He has undue confidence in early trends (e.g., the number and identity of significant results). He overestimates significance.
> 3. In evaluating replications, his or others', he has unreasonably high expectations about the replicability of significant results. He underestimates the breadth of confidence intervals.
> 4. He rarely attributes a deviation of results from expectations to sampling variability, because he finds a causal "explanation" for any discrepancy. Thus, he has little opportunity to recognize sampling variation in action. His belief in the law of small numbers, therefore, will forever remain intact.

For a serious tradeoff study analyst who is focused on finishing the broad structure of the tradeoff study, this aspect of the law of small numbers could result in the mistake of overestimating the significance of small sample sizes that go toward establishing the input values of some criteria, especially if these input values turn out to have the highest sensitivity.

Strength and Weight

In cognitive psychology, "strength and weight" refers to the magnitude of a measure and the measure of its confidence (e.g., sample size, reliability, uncertainty, or variance). Traditional tradeoff studies do not incorporate measures of confidence in the data. Because tradeoff studies usually focus on the strength of the evidence (criteria values or weights of importance, e.g.) they usually lack a critical component of psychological thought, namely, that of a measure of confidence of each value.

> Statistical theory and the calculus of chance prescribe rules for combining strength and weight. For example, probability theory specifies how sample proportion and sample size combine to determine posterior probability. . . . [Usually] people focus on the strength of the evidence . . . and then make some adjustment in response to its weight. [24]

This usual focus on strength or magnitude in tradeoff studies could thus be beneficial, if the analyst prefers to streamline her decision-making thoughts, or detrimental, if the analyst would prefer to have a strong association between strength and weight in the tradeoff study.

Elimination by Aspects; Killer Trades

In tradeoff studies, it is acceptable to narrow down the number of alternatives with a preliminary round of killer trades. Alternatives are eliminated by choosing an important aspect, or criterion, and eliminating all the alternatives that do not satisfy the criterion, or aspect. The focused-on criterion or aspect should obviously be very important.

This strategy does not consider the effect of criteria that are present in all alternatives, and could mistakenly eliminate a superior alternative by focusing on unimportant criteria; however, the attractiveness of this strategy lies in that it may be easily employed to eliminate a large number of alternatives, and can quickly reduce the complexity of a computational ranking decision. Humans usually shy away from computation, because their innate computational facilities are quite limited [41].

Tversky [45] stated,

> People are reluctant to accept the principle that (even very important) decisions should depend on computations based on subjective estimates of likelihoods or values in which the decision maker himself has only limited confidence. When faced with an important decision, people appear to search for an analysis of the situation and a compelling principle of choice that will resolve the decision problem by offering a clear-cut choice without relying on estimation of relative weights, or on numerical computations. From a normative standpoint, the major flaw in the principle of elimination by aspects lies in its failure to ensure that the alternatives retained are, in fact, superior to those that are eliminated. In general, therefore, the strategy of elimination by aspects cannot be defended as a rational procedure of choice. On the other hand, there may be many contexts in which it provides a good approximation to much more complicated compensatory models and could thus serve as a useful simplification procedure.

Cognitive Dissonance

People do not like sustained cognitive dissonance, the holding of competing alternatives within their minds. They like to make a decision and "forget about it." During man's evolutionary trajectory, at least until his settling down to an agricultural life approximately 10,000 years ago, man was not in a position to practice computational decision making. For a strong (over)emphasis on the evolutionary adaptive value of simple heuristics, see Gigerenzer et al. [22].

Experimenter's Regress

It is possible for a feedback loop to form detrimentally between theory and evidence. In science, theories are confirmed by evidence, but evidence is also judged according to theories. If cognitive biases or errors affect input data in

tradeoff studies, an alternative can improperly gain or lose perceived strength, leading to an erroneous conclusion—either in the tradeoff study itself or later in studies based on a previous one.

Theories of Randomness

Early in the history of the judgment and decision-making field, theories held that subjective values were determined by rules involving randomness [44]. Luce [30] held that a random element was involved in decision rules. Obviously, some randomness will always be present in decision studies, either because some randomness will be present in input data, or because the workings of the human brain involve some random components. In the presence of randomness in data, some people will say, "What is the use of doing detailed calculations on inexact data? I would rather just make a decision with which I feel comfortable."

The Case for Nonobjectivity

Philosophy has noted a number of reasons why people cannot reason objectively with probabilities.

1. An existence of n probabilities can immediately lead to a necessary consideration of 2^n conditional probabilities. For $n = 300$, there are 2^{300} conditional probabilities, which is a number larger than the Eddington number, 2^{258}, the estimated number of particles in the known universe.
2. Probability is an idealization from frequencies. "Probabilities" are often derived from limited samples, from populations whose extent is often unknown.
3. Philosophically speaking, there are no ultimate definitions for anything, only rules for how we reason about things. It is easy to be caught up in the "objective" and exact consideration of "probabilities," but there is in fact no permanent and fixed definition of such.

From a large enough perspective, reasoning is not deductive, but only practically useful and always defensible, that is, subject to annulment when the limits of its logic are found. With a built-in feeling of the infinite, humans often convince themselves that reasoning is of limited value.

Obviating Expert Opinion

Often, lay people or the lesser trained can converse with an expert—say a decision expert—and conclude that the expert is no better at making decisions than they are. Specific and preponderant evidence of the expert's skill is often needed. Why is this?

1. Although in some cases an expert may come to a very quick, almost instantaneous, assessment of a situation in the "blink" of an eye [23], usually a period of preliminary perception and assessment is necessary, as in the

case of chess players evaluating a chess game position they have never seen before [11]. During this stage, a chess expert may be quieter than a player who truly does not know the game, as a decision analyst may only be laying the groundwork for a decision.

2. In tasks only slightly unassociated with the tasks in which a person is an expert, an expert may fare no better than the average person may. For example, when simply counting the total number of chess pieces on a chess board, irrespective of type or position, experts fared no better than other subjects; however, in detecting critical patterns, experts performed much better [37].

3. All humans store about seven units or "chunks" of information at a time [31], in short-term memory, irrespective of skill level. However, the chess master's chunks are larger and richer in information than amateurs' chunks [5]. A novice cannot see the forest for the trees. In tasks other than the field of study, an expert may seem no smarter than the average person.

The above effects may combine and construe to convince an evaluator that an expert has nothing to offer, and that any person with no training will make a good decision.

Feeling Invincible

Many bad decisions can be attributed to the decision-maker's sense of invincibility. Teen-age boys are notorious for thinking, "I will not get caught; I cannot get hurt; I will avoid car accidents." Many other people think, "Nobody is going to steal my identity; I will be able to quit any time I want to; I do not need sun screen, I will not get skin cancer; I do not have to back up my hard drive, my computer will not crash." The Spanish Armada was thought to be invincible in 1588. The Japanese thought they were invincible at Pearl Harbor in 1941. The German military thought it was invincible as it stormed across Europe at the beginning of World War II. And of course, in 1912, the White Star line said that the Titanic was "unsinkable." The invincibility bias will affect the risk analysis and therefore the problem statement of a tradeoff study.

Summary

People rarely do formal tradeoff studies, because the factors listed in this section come together to hinder the implementation of tradeoff studies in settings other than when a sponsor directly orders a tradeoff study to be conducted, makes her ongoing interest in getting the study done clear, and provides significant funding and time for the effort.

5 Discussion

Humans usually consider alternatives in series [50], and are often moved to choose hastily one alternative after having their attention drawn, or fixated, to only one or a few criteria. Also, humans tend to form conclusions based on their favorite theories, not from a complete set of alternatives and then a shrinking set of hypotheses brought about by conclusions based on experimentation, empirical data, and data analysis.

In order to make good rational choices among alternatives the decision maker should be an expert in the relevant subject matter, and also be aware of cognitive biases and fallacies. Limited awareness can precipitate poor judgment. Decision makers should also have a complete understanding of the mathematical methods that allow the parallelization of human decision processes through tradeoff studies, and be able to apply them without error.

Despite the difficulties, the needed rationality and rigor to make good decisions is available. Employing a team approach, with the long-term horizon necessary to conduct iterations and public reviews, brings sobriety to the decision process.

Decision aids such as tradeoff studies bring rationality to decision making. Brown [4] notes that good decision-making aids (1) emulate or replicate the performance of some more competent decider, (2) replace the decider's current thinking and analyze decisions from scratch, and (3) enhance or improve on the decider's logical thinking.

On the level of an individual tradeoff study analyst, the actual mechanics of using knowledge of cognitive biases for improving a tradeoff study would involve the analyst stopping periodically and recognizing biases in his own cognitive processes. Such cognitive self-examination would have to be continually motivated, either by the analyst or by a supervisor. A formal mathematical or statistical examination process for cognitive biases, perhaps on a departmental level, has not been documented, and would probably be expensive.

Complex impersonal decisions involving alternatives should not be attempted holistically—at the least, nonexperts should wholly avoid making important decisions with a holistic, mental, feeling-based approach. In order to establish rationality, the components of the decision must be made clear. This is possible by focusing on each element individually. The higher-level decision then becomes a calculation based on a broad base of rationally considered components.

Consider the difference between an optimization search and a tradeoff study. As an example, let us consider the updated Pinewood tradeoff study, which has 201 parameters. Assuming that each parameter has only two settings, the number of possible combinations is 2^{201}, which is close to Eddington's number of particles in the known universe, 2^{258} [13]. From a combinatorial optimization standpoint, the Pinewood problem is an incalculable, time-impossible problem. Yet, after rationality is brought to bear on each

component individually, a preference order of alternatives can be calculated in a fraction of a second with a common computer and spreadsheet.

Returning to the issue of complex decisions made in an instant [23], it should be noted that experts capable of making such judgments have probably spent long periods of time in training, during which they have individually, sequentially and rationally examined the components of the decision. Any pre-conscious parallelization occurring in such an expert's brain is reproduced in the parallel structure of a tradeoff study, which is ultimately based on hard data analysis.

6 Conclusions

Humans usually consider alternatives in series, and are often moved to hastily choose one alternative after having their attention drawn, or fixated, to only one or a few criteria. Prospect theory describes an information-editing stage followed by the application of subjective probability and value functions. In order to choose rationally among alternatives the decision-maker's awareness of cognitive biases and fallacies must increase. Limited awareness and irrationality can limit the decision-maker's trust in the tradeoff study. The tradeoff study should be based on a broad base of rationally considered components, calculation methods, and assumptions. Decision makers should have a complete understanding of the mathematical methods that allow the parallelization of human decision processes through tradeoff studies. Despite the difficulties, tradeoff studies provide a reliable method of rational decision making.

Acknowledgments

References

1. A. T. Bahill. Risk analysis of a pinewood derby, `http://www.sie.arizona.edu/sysengr/slides/risk.ppt`. Last accessed January 2008.
2. A. T. Bahill. *Tradeoff Studies: A Systems Engineering Skills Course.* BAE Systems, San Diego, 2006.
3. L. R. Beach and T. Connolly. *The Psychology of Decision Making: People in Organizations.* Sage, Thousand Oaks, CA, 2005.
4. R. Brown. *Rational Choice and Judgment: Decision Analysis for the Decider.* John Wiley & Sons, Hoboken, NJ, 2005.
5. W. G. Chase and H. A. Simon. Perception in chess. *Cognitive Psychology,* 4:55–81, 1973.

6. D. Clausen and D. D. Frey. Improving system reliability by failure-mode avoidance including four concept design strategies. *Systems Engineering*, 8:245–261, 2005.

7. CMMI. Capability maturity model integration. Software Engineering Institute: `http://www.sei.cmu.edu/cmmi/`. Last accessed January 2008.

8. J. Daniels, P. W. Werner, and A. T. Bahill. Quantitative methods for tradeoff analyses. *Systems Engineering*, 4:190–212, 2001.

9. DAR. DAR basics: Applying decision analysis and resolution in the real world, 2004. Software Engineering Institute: `http://www.sei.cmu.edu/cmmi/presentations/sepg04.presentations/dar.pdf`. Last accessed January 2008.

10. J. H. Davis. Group decision and social interaction: A theory of social decision schemes. *Psychological Review*, 80:97–125, 1973.

11. A. D. De Groot. *Thought and Choice in Chess*. Mouton, The Hague, The Netherlands, 1965.

12. Doing tradeoff studies with multicriterion decision making techniques. `http://www.incose.org.uk/incose99/tutt05.htm`. Last accessed January 2008.

13. A. Eddington. *Mathematical Theory of Relativity*. Cambridge University Press, Cambridge, UK, 1923.

14. W. Edwards. An attempt to predict gambling decisions. In J. W. Dunlap, editor, *Mathematical Models of Human Behavior*, pages 12–32. Dunlap and Associates, Stamford, CT, 1955.

15. W. Edwards. Conservatism in human information processing. In B. Kleinmuntz, editor, *Formal Representation of Human Judgment*, pages 17–52. John Wiley & Sons, New York, 1968.

16. D. Ellsberg. Risk, ambiguity, and the Savage axioms. *The Quarterly Journal of Economics*, 75:643–669, 1961.

17. D. Ellsberg. *Risk, ambiguity, and decision*. PhD thesis, Harvard University, Cambridge, MA, 1962.

18. C. R. Fox and A. Tversky. Ambiguity aversion and comparative ignorance. *Quarterly Journal of Economics*, 110:585–603, 1995.

19. C. R. Fox and M. Weber. Ambiguity aversion, comparative ignorance, and decision context. *Organizational Behavior and Human Decision Processes*, 88:476–498, 2002.

20. G. Gigerenzer. How to make cognitive illusions disappear: Beyond heuristics and biases. *European Review of Social Psychology*, 2:83–115, 1991.

21. G. Gigerenzer and R. Selten, editors. *Bounded Rationality: The Adaptive Toolbox*. The MIT Press, Cambridge, MA, 1991.

22. G. Gigerenzer, P. M. Todd, and T. A. R. Group. *Simple Heuristics that Make us Smart*. Oxford University Press, New York, 1999.

23. M. Gladwell. *Blink: The Power of Thinking Without Thinking*. Little Brown, New York, 2005.

24. D. Griffin and A. Tversky. The weighting of evidence and the determinants of confidence. *Cognitive Psychology*, 24:411–435, 1992.

25. J. S. Hammond, R. L. Keeney, and H. Raiffa. Best of HBR: The hidden traps in decision making. *Harvard Business Review*, 84:118–126, 2006.

26. E. J. Johnson, J. Hershey, J. Meszaros, and H. Kunreuther. Framing, probability distortions, and insurance decisions. *Journal of Risk and Uncertainty*, 7:35–51, 1993.

27. D. Kahneman and A. Tversky. Prospect theory: An analysis of decision under risk. *Econometrica*, 47:263–291, 1979.

28. S. Lichtenstein, B. Fischhoff, and L. D. Phillips. Calibration of probabilities: The state of the art to 1980. In D. Kahneman, P. Slovic, and A. Tversky, editors, *Judgment Under Uncertainty: Heuristics and Biases*, pages 306–334. Cambridge University Press, Cambridge, UK, 1982.

29. List of cognitive biases. `http://en.wikipedia.org/wiki/Cognitive\_biases`. Last accessed January 2008.

30. R. D. Luce. *Individual Choice Behavior: A Theoretical Analysis*. Wiley, New York, 1959.

31. G. A. Miller. The magic number seven, plus or minus two: Some limits on our capacity for processing information. *Psychological Review*, 63:81–87, 1956.

32. M. Piattelli-Palmarini. *Inevitable Illusions: How Mistakes of Reason Rule our Minds*. John Wiley & Sons, New York, 1994.

33. M. Piattelli-Palmarini. Knowledge of probability. Graduate seminar on the foundations of judgment and decision making, The University of Arizona, Tucson, 2005.

34. Pinewood Derby tradeoff study. `http://www.sie.arizona.edu/MURI/software.html`. Last accessed January 2008.

35. S. Plous. The nuclear arms race: Prisoner's dilemma or perceptual dilemma? *Journal of Peace Research*, 30:163–179, 1993.

36. D. Prelec. The probability weighting function. *Econometrica*, 66:497–527, 1998.

37. P. Saariluoma. Chess players search for task relevant cues: Are chunks relevant? In D. Brogan, editor, *Visual Search*. Taylor & Francis, London, 1990.

38. L. J. Savage. *The Foundations of Statistics*. Wiley, New York, 1954.

39. N. Schwarz. Assessing frequency reports of mundane behaviors: Contributions of cognitive psychology to questionnaire construction. *Review of Personality and Social Psychology*, 11:98–119, 1990.

40. E. Shafir, editor. *Preferences, Belief and Similarity: Selected Writings*. The MIT Press, Cambridge, MA, 2004.

41. R. N. Shepard. On the subjective optimum selection among multiattribute alternatives. In M. W. Shelly and G. L. Bryan, editors, *Human Judgments and Optimality*. Wiley, New York, 1964.

42. R. A. Shweder. Likeness and likelihood in everyday thought: Magical thinking in judgments about personality. *Current Anthropology*, 18:637–648, 1977.

43. E. D. Smith. *Tradeoff studies and cognitive biases*. PhD thesis, Department of Systems and Industrial Engineering, The University of Arizona, Tucson, 2006.

44. L. L. Thurstone. *The Measurement of Values*. University of Chicago Press, Chicago, 1959.

45. A. Tversky. Elimination by aspects: A theory of choice. *Psychological Review*, 79:281–299, 1972.

46. A. Tversky and D. Kahneman. Belief in the law of small numbers. *Psychological Bulletin*, 76:105–110, 1971.

47. A. Tversky and D. Kahneman. Extensional vs. intuitive reasoning: The conjunction fallacy in probability judgment. *Psychological Review*, 90:293–315, 1983.

48. A. Tversky and D. Kahneman. Advances in prospect theory: Cumulative representation of uncertainty. *Journal of Risk and Uncertainty*, 26:297–323, 1992.

49. A. Tversky and E. Shafir. The disjunction effect in choice under uncertainty. *Psychological Science*, 3:305–309, 1992.

50. W. A. Wickelgren. *How to Solve Problems: Elements of a Theory of Problems and Problem Solving*. Freeman, San Francisco, 1974.

51. A. W. Wymore. *Model-based Systems Engineering*. CRC Press, Boca Raton, FL, 1993.