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# The Priority Heuristic: Making Choices Without Trade-Offs

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## Abstract

Bernoulli's framework of expected utility serves as a model for various psychological processes, including motivation, moral sense, attitudes, and decision making. To account for evidence at variance with expected utility, we generalize the framework of fast and frugal heuristics from inferences to preferences. The *priority heuristic* predicts (i) Allais' paradox, (ii) risk aversion for gains if probabilities are high, (iii) risk seeking for gains if probabilities are low (lottery tickets), (iv) risk aversion for losses if probabilities are low (buying insurance), (v) risk seeking for losses if probabilities are high, (vi) certainty effect, (vii) possibility effect, and (viii) intransitivities. We test how accurately the heuristic predicts people's choices, compared to previously proposed heuristics and three modifications of expected utility theory: security-potential/aspiration theory, transfer-of-attention-exchange model, and cumulative prospect theory.

Conventional wisdom tells us that making decisions becomes difficult whenever multiple priorities, appetites, goals, values, or simply the attributes of the alternative options are in conflict. Should one undergo a medical treatment that has some chance of curing a life-threatening illness but comes with the risk of debilitating side effects? Should one report a crime committed by a friend? Should one buy an expensive, high-quality camera or an inexpensive, low-quality camera? How do people resolve conflicts, ranging from the prosaic to the profound?

The common denominator of many theories of human behavior is the premise that conflicts are mastered by making trade-offs. Since the Enlightenment, it has been believed that weighting and summing are the processes by which such trade-offs can be made in a rational way. Numerous theories of human behavior—including expected value theory, expected utility theory, prospect theory, Benjamin Franklin's moral algebra, theories of moral sense such as utilitarianism and consequentionalism (Gigerenzer, 2004), theories of risk taking (e.g., Wigfield & Eccles, 1992), motivational theories of achievement (Atkinson, 1957) and work behavior (e.g., Vroom, 1964), theories of social learning (Rotter, 1954), theories of attitude formation (e.g., Fishbein & Ajzen, 1975), and theories of health behavior (e.g., Becker, 1974; for a review see Heckhausen, 1991)—rest on these two processes. Take how expected utility theory would account for the choice between two investment plans as an example. The reasons for choosing are often negatively correlated with one another. High returns go with low probabilities, and low returns go with high probabilities. According to a common argument, negative correlations between reasons cause people to experience conflict, leading them to make trade-offs (Shanteau & Thomas, 2000). In terms of expected

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utility, the trade-off between investment plans is performed by weighting the utility of the respective monetary outcomes by their probabilities and by summing across the weighted outcomes of each plan. The plan chosen is that with the higher expected utility.

Weighting and summing are processes that have been used to define not only rational choice but also rational inference (Gigerenzer & Kurz, 2001). In research on inference, weighting was the first to be challenged. In the 1970s and 1980s, evidence emerged that simple unit weights such as +1 and −1 often yield the same predictive accuracy—that is, the same ability to predict rather than simply “postdict” or fit—as the “optimal” weights in multiple regression (Dawes, 1979). According to these results, weighting does not seem to affect predictive accuracy as long as the weight has the right sign.

Next, summing was called into question. The 1990s brought evidence that the predictive accuracy of lexicographic heuristics can be as high as or higher than the accuracy of complex strategies that perform both weighting and summing. This was shown for both inferences (e.g., Gigerenzer & Goldstein, 1996; Gigerenzer, Todd, & the ABC Research Group, 1999) and preferences (e.g., Luce & Suppes, 1965; Payne, Bettman, & Johnson, 1993). The heuristics in question order attributes—which can be seen as a simple form of weighting—but do not sum them. Instead, they rely on the first attribute that allows for a decision. These results suggest that summing is not always necessary for good reasoning. In addition, some of the environmental structures under which weighting (ordering) without summing is ecologically rational have been identified (Hogarth & Karelaia, 2005; Martignon & Hoffrage, 2002; Payne et al., 1993).

Here is the question that concerns us. If, as the work just reviewed demonstrates, both summing without weighting and weighting without summing can be as accurate as weighting and summing, why should humans not use these simpler heuristics? Specifically, might human choice that systematically contradicts expected utility theory be a direct consequence of people's use of heuristics? The success of a long tradition of theories seems to speak against this possibility. Although deviations between the theory of expected utility and human behavior have long since been experimentally demonstrated, psychologists and economists have nevertheless retained the weighting and summing core of the theory, but adjusted the functions to create more complex models such as prospect theory and security-potential/aspiration theory. In this article, we demonstrate that a simple heuristic that forgoes summing and therefore does not make trade-offs can account for choices that are anomalies from the point of view of expected utility theory. In fact, it does so in the very gambling environments that were designed to demonstrate the empirical validity of theories of risky choice that assume both weighting and summing. By extension, we suggest that other areas of human decision making that involve conflicting goals, values, appetites, and motives may likewise be explicable in terms of simple heuristics that forego complex trade-offs.

## The Bernoulli Framework and its Modifications

Very few great ideas have an exact date of origin, but the theory of mathematical probability does. In the summer of 1654, the French mathematicians Blaise Pascal and Pierre Fermat exchanged letters on gambling problems posed by a notorious gambler and man-about-town, the Chevalier de Méré. This exchange resulted in the concept of mathematical expectation, which at the time was believed to capture the nature of rational choice. In modern notation, the principle of choosing the option with the highest *expected value* (EV) is defined as

$$EV = \Sigma p_i x_i \quad (1)$$

where $p_i$ and $x_i$ are the probability and the amount of money, respectively, of each outcome (i = 1, …, n) of a gamble. The expected value theory was a psychological theory of human reasoning, believed to describe the reasoning of the educated homme éclairé.

Despite its originality and elegance, the definition of a rational decision by EV soon ran into trouble when Nicholas Bernoulli, a professor of law in Basel, posed the perplexing St. Petersburg paradox. To solve the paradox, his cousin Daniel Bernoulli (1738/1954) retained the core of the expected value theory but suggested replacing objective money amounts with subjective utilities. In his view, the pleasure or utility of money did not increase linearly with the monetary amount; instead, the increases in utility declined. This phenomenon entered psychophysics a century later in the form of the Weber-Fechner function (Gigerenzer & Murray, 1987), and entered economics in the form of the concept of diminishing returns (Menger, 1871/1990). Daniel Bernoulli modeled the relation between objective and subjective value of money in terms of a logarithmic function. In modern terminology, the resulting expected utility (EU) is defined as

$$EU=\Sigma p_i u(x_i) \quad (2)$$

where $u(x_i)$ is a logarithmic function defined on objective money amounts $x_i$. At the time of Daniel Bernoulli, the maximization of EU was considered both a description and prescription of human reasoning —the present-day distinction between these two concepts, which seems so obvious to us, was not made, because the theory was identical with its application, human reasoning (Daston, 1988). However, the “rational man” of the Enlightenment was dismantled around 1840, when probability theory ceased to be generally considered a model of human reasoning (Gigerenzer et al., 1989). One of the reasons for the divorce between EU and human reasoning was apparent human irrationality, especially in the aftermath of the French Revolution. Following the demise of expected utility, psychological theories of thinking virtually ignored the concept of EU as well as the laws of probability until the 1950s. The revival of EU began with von Neumann and Morgenstern (1947), who based EU on axioms. After this landmark book appeared, followed by influential publications such as Edwards (1954, 1962) and Savage (1954) on subjective expected utility (SEU), theories of the mind once again started to model human reasoning and choice in terms of probabilities and the EU framework (e.g., Fishbein & Ajzen, 1975; Heckhausen, 1991).

However, it was not long until the first experiments were conducted to test whether people's choices actually follow the predictions of EU. Evidence emerged that people systematically violated EU theory (Allais, 1953; Ellsberg, 1961; MacCrimmon, 1968; Mosteller & Nogee, 1951, Preston & Baratta, 1948), and this evidence has accumulated in the subsequent decades (see Camerer, 1995; Edwards, 1968; Kahneman & Tversky, 2000). Although specific violations of EU, including their normative status, are still under debate (Allais, 1979; Hogarth & Reder, 1986), there is widespread consensus among experimental researchers that not all of the violations can be explained away.

This article is concerned with how to react to these empirical demonstrations that human behavior often contradicts EU theory. So far, two major reactions have surfaced. The first is to retain EU theory, by arguing that the contradictory evidence will not generalize from the laboratory to the real world. The arguments for this assertion include that in most of the experiments, participants were not paid contingent on their performance (see Hertwig & Ortmann, 2001), or not paid enough to motivate them to behave in accordance with EU, and that outside the laboratory, market pressures will largely eliminate behavior that violates EU theory (see Hogarth & Reder, 1986). This position is often reinforced by the argument that, even if one accepts the empirical demonstrations, no powerful theoretical alternative to EU exists, and given that all theories are false idealizations, a false theory is still better than no theory.

The second reaction has been to take the data seriously and, just as Bernoulli did, to modify the theory while retaining the original EU scaffolding. Examples include disappointment theory (Bell, 1985; Loomes & Sugden, 1986), regret theory (Bell, 1982; Loomes & Sugden, 1982), the transfer of attention exchange model (Birnbaum & Chavez, 1997), decision affect theory (Mellers, 2000), prospect theory (Kahneman & Tversky, 1979), and cumulative prospect theory (Tversky & Kahneman, 1992). These theories are noteworthy attempts to adjust Bernoulli's framework to the new empirical challenges by adding one or more adjustable parameters. They represent a "repair" program that introduces psychological variables such as emotions and reference points in order to rescue the Bernoullian framework (Selten, 2001).

Despite their differences, all of these modifications retain the assumption that human choice can or should be modeled in the same terms that Bernoulli used: that people behave as if they multiplied some function of probability and value, and then maximized. Because of the complex computations involved in some of these modifications, they have often been interpreted to be as-*if* models. That is, they describe and ideally predict choice outcomes but do not explain the underlying process. The originators of prospect theory, for instance, set themselves the goal "to assemble the minimal set of modifications of expected utility theory that would provide a descriptive account of … choices between simple monetary gambles" (Kahneman, 2000, p. x). Prospect theory deals with empirical violations of EU by introducing new functions that require new adjustable parameters. For instance, a nonlinear function $\pi$ was added to transform objective probabilities (assuming "regular prospects"):

$$V=\Sigma\pi(p_i)\,v(x_i) \quad (3)$$

where $\pi(p_i)$ are called decision weights and are obtained from the objective probabilities by a nonlinear, inverse S-shaped weighting function. Specifically, the weighting function $\pi$ overweights small probabilities and underweights moderate and large ones (inverse S-shape). The value function $v(x_i)$ is an S-shaped utility function. Just as Bernoulli introduced individual psychological factors (diminishing returns and a person's wealth) to save the expected value framework, Kahneman and Tversky (1979) postulated $\pi$ and $v$ to account for the old and new discrepancies. In the face of new empirical discrepancies and in order to extend prospect theory to gambles with more than three outcomes, Tversky and Kahneman (1992) further modified prospect theory into cumulative prospect theory (CPT).

The essential point is that the weighting function (defined by two adjustable parameters in CPT) and the value function (defined by three adjustable parameters) interpret people's choices that deviate from Bernoulli's framework within that very same framework. For example, the empirical shape of the weighting function is inferred by assuming a multiplication calculus. Overweighting small probabilities, for instance, is an interpretation of people's cognition within Bernoulli's framework—it is not the empirical phenomenon itself. The actual phenomenon is a systematic pattern of choices, which can be accounted for without reference to functions that overweight or underweight objective probabilities. We will demonstrate this in the alternative framework of heuristics. The aim of models of heuristics is to both describe the psychological process and predict the final choice.

## Heuristics in Risky Choice

In this article, we pursue a third way to react to the discrepancy between empirical data and EU theory: to explain choice as the direct consequence of the use of a heuristic. Unlike proponents of EU who dismiss the empirical data (e.g., de Finetti, 1979), we take the data seriously. In fact, we will test whether a sequential heuristic can predict classic violations of EU as well as four major bodies of choice data. Heuristics model both the choice outcome and the process, and there is substantial empirical evidence that people's cognitive processes and inferences can be predicted by models of heuristics (e.g., Bröder, 2000; Bröder & Schiffer, 2003; Dhami, 2003; Huber, 1982; Newell, Weston, & Shanks, 2003; Payne et al., 1993; Payne, Bettman, & Luce, 1996; Rieskamp & Hoffrage, 1999; Schkade & Johnson, 1989).

### Which Heuristic?

Two classes of heuristics are obvious candidates for two-alternative choice problems: lexicographic rules and tallying (Gigerenzer, 2004). Lexicographic rules order reasons—probabilities and outcomes—according to some criterion, search through $m \geq 1$ reasons, and ultimately base the decision on one reason only. The second class, tallying, assigns all reasons equal weights, searches through $m \geq 2$ reasons, and chooses the alternative that is supported by most reasons. For choices between gambles, the empirical evidence suggests that people do not treat the reasons equally, which speaks against the tallying family of heuristics (Brandstätter & Kühberger, 2005; Deane, 1969; Loewenstein, Weber, Hsee, & Welch, 2001; Sunstein, 2003). This result was confirmed in the empirical tests reported below. We are then left with a heuristic from the class of lexicographic rules and two questions. First, what are the reasons and in what order are they examined? Second, when is examination stopped? Based on the empirical evidence available, our first task is to derive a candidate heuristic from the set of all possible heuristics.

### Priority Rule: In What Order Are Reasons Examined?

First we consider simple monetary gambles of the type “a probability $p$ to win amount $x$; a probability (1 - $p$) to win amount $y$” ($x$, $p$; $y$). Here, the decision maker is given four reasons: the maximum gain, the minimum gain, and their respective probabilities (for losses, see below). All reasons are displayed simultaneously; they are available at no cost. Thus, unlike in tasks where information needs to be searched in memory (Gigerenzer & Goldstein, 1996), or in the environment (such as search in external information stores), all the relevant information is fully displayed in front of the participant. The resulting choices are thus “decisions from description” and not “decisions from experience” (Hertwig, Barron, Weber, & Erev, 2004). The *priority rule* refers to the order in which people go through the reasons after screening all of them once in order to make their decision.

Four reasons result in 24 possible orderings. However, there are logical and empirical constraints. First, in two-outcome gambles, the two probabilities are complementary, which reduces the number of reasons to three. This in turn reduces the number of possible orders from 24 to 6. The number can be further constrained by empirical evidence. What is perceived as more important, outcomes or probabilities?

The primacy of outcome over probability had already been noted in Arnauld and Nicole's Enlightenment classic on the art of thinking (1662/1996). As an example, lottery buyers tend to focus on big gains rather than their tiny probabilities, which is historically grounded in the fact that winning the lottery was one of the very few ways to move upwards socially in traditional European societies (Daston, 1988). Similarly, empirical research indicates that emotional outcomes tend to override the impact of probabilities (Sunstein, 2003). Loewenstein et al. (2001) suggest that, in the extreme, people neglect probabilities altogether, and instead base their choices on the immediate feelings elicited by the gravity or benefit of future events. Similarly, Deane (1969) reported that anxiety (as measured by cardiac activity) concerning a future electric shock was largely influenced by the intensity of the shock, not by the probability of its occurrence. A series of choice experiments supports the hypothesis that outcome matters more than probability (Brandstätter & Kühberger, 2005).[1]

From these studies, we assume that the first reason is one of the two outcomes, not the probability. This reduces the number of orders once again, from 6 to 4. But which outcome is considered first, the minimum or the maximum outcome? The empirical evidence seems to favor the minimum outcome. The frequent observation that people tend to be risk-averse in the gain domain (Edwards, 1954) is consistent with ranking the minimum outcome first. This is because the reason for focusing on the minimum outcome is to avoid the worst outcome. In contrast, ranking the maximum outcome first would imply that people are risk seeking with gains—an assumption for which little empirical evidence exists. Further empirical support is given by research documenting that people try to avoid disappointment (from ending up with the worst possible outcome of the chosen gamble) and regret (from obtaining an inferior outcome compared to the alternative not chosen). This motivation to avoid winning nothing (or the minimum amount) is incorporated in regret theory (Loomes & Sugden, 1982), disappointment theory (Bell, 1985), and in the motivation for avoidance of failure (Heckhausen, 1991).

We conclude that the empirical evidence favors the minimum gain. This reduces the number of possible orders of reasons from 4 to 2. To distinguish between the two remaining orders, we conducted an experiment in which the minimal outcome was held constant, and thus all decisions depended on maximum gains and the probabilities of the minimum gains. These two reasons always suggested opposite choices. Forty-one students from the University of Linz (22 females, 19 males; *M* = 23.2 years, *SD* = 5.3 years) were tested on four problems:

| | |
|---|---|
| (€500, .50) and (€2.500, .10) | [88%] |
| (€220, .90) and (€500, .40) | [80%] |
| (€5.000, .50) and (€25.000, .10) | [73%] |
| (€2.200, .90) and (€5.000, .40) | [83%] |

For instance, the first choice was between €500 with $p = .50$, nothing otherwise, and €2,500 with $p = .10$, nothing otherwise. Faced with this choice, 36 out of 41 participants (88%) selected the first gamble, which has the smaller probability of minimum gain, but the lower maximum gain. On average, 81% of the participants chose the gamble with the smaller probability of the minimal gain. This result suggests the probability of the minimum gain—rather than the maximum gain—as the second reason. The same conclusion is also suggested by another study in which the experimenters held the minimum outcomes constant across gambles (Slovic, Griffin, & Tversky, 1990; Study 5). Thus, we propose the following order in which the reasons are attended to.

> *Priority rule*: Consider reasons in the order: minimum gain, probability of minimum gain, maximum gain.

[1]The results depend on the specific set of gambles: When one of the reasons is not varied, it is not likely that people attend to this reason. For instance, in a "dublex gamble" (Payne & Braunstein, 1971; Slovic & Lichtenstein, 1968), one can win $\$x$ with probability $p_1$ (otherwise nothing), and lose $\$y$ with probability $p_2$ (otherwise nothing). Here, the minimum gain of the winning gamble and the minimum loss of the losing gamble are always zero, rendering the minimum outcomes uninformative. Similarly, Slovic, Griffin, and Tversky (1990) argued that probabilities were more important than outcomes, but here again all minimum outcomes were zero. Thus, it would be misleading to conclude from this research that people do not attend to the minimum outcomes.

### Stopping Rule What Is a Good-Enough Reason?

Heuristic examination is limited rather than exhaustive. Limited examination makes heuristics different from EU theory and its modifications, which have no stopping rules and integrate all pieces of information in the final choice. A stopping rule defines whether examination stops after the first, second, or third reason. Again, we consult the empirical evidence to generate a hypothesis about the stopping rule.

What difference in minimum gains is good enough ("satisficing") to stop examination and decide between the two gambles solely on the basis of this information? Just as in Simon's theory of satisficing (1983), where people stop when an alternative surpasses an aspiration level (see also Luce, 1956), our use of the term *aspiration level* refers to the amount that, if met or exceeded, stops examination of reasons. Empirical evidence suggests that the *aspiration level* is not fixed but increases with the maximum gain (Albers, 2001). For instance, consider a choice between winning $200 with probability .50, otherwise nothing ($200; .50), and winning $100 for sure ($100). The minimum gains are $0 and $100, respectively. Now consider the choice between ($1,000; .50) and ($100). The minimum gains still differ by the same amount, the probabilities are the same, but the maximum outcomes differ. People who select the gamble with the higher minimum gain in the first pair may not select it in the second. Thus, the difference between the minimum outcomes that is considered large enough to stop examination after the first reason should be dependent on the maximum gain.

A simple way to incorporate this dependency is to assume that people intuitively define it by their cultural number system, which is the base-10 system in the Western world (Albers, 2001). This leads to the following hypothesis for the stopping rule:

> *Stopping rule*: Stop examination if the minimum gains differ by 1/10 (or more) of the maximum gain.

The hypothesis is that 1/10 of the maximum gain, that is, one order of magnitude, is "good enough." Admittedly, this value of the aspiration level is a first, crude estimate, albeit empirically informed. The aspiration level is a fixed (not free) parameter. If there is an independent measure of individual aspiration levels in further research, the estimate can be updated, but in the absence of such an independent measure, we do not want to introduce a free parameter. We refer to this value as the *aspiration level*. For illustration, consider again the choice between winning $200 with probability .50, otherwise nothing ($200; .50), and winning $100 for sure ($100). Here, $20 is "good enough." The difference between the minimum outcomes exceeds this value ($100 > $20), and therefore examination is stopped. Information concerning probabilities is not used for the choice.

What if the maximum amount is not as simple as 200, but a number such as 190? Extensive empirical evidence suggests that people's numerical judgments are not fine-grained but follow prominent numbers, as summarized in Albers (2001). Prominent numbers are defined as powers of 10 (e.g., 1, 10, 100, …), including their halves and doubles. Hence, the numbers 1, 2, 5, 10, 20, 50, 100, 200, … are examples of prominent numbers. They approximate the Weber-Fechner function in a culturally defined system. We assume that people scale the maximum gain down by 1/10 and round this value to the closest prominent number. Thus, if the maximum gain were $190 rather than $200, the aspiration level would once again be $20 (because $19 is rounded to the next prominent number).

If the difference between minimum gains falls short of the aspiration level, the next reason is examined. Again, examination is stopped if the two probabilities of the minimum gains differ by a "large enough" amount. Probabilities, unlike gains, have upper limits, and therefore are not subject to the Weber-Fechner property of decreasing returns (Banks &

Coleman, 1981). Therefore, unlike for gains, the aspiration level need not be defined relative to the maximum value. We define the aspiration level as 1/10 of the probability scale, that is, one order of magnitude: The probabilities need to differ by at least 10 percentage points in order to stop examination.

*Stopping rule:* Stop examination if probabilities differ by 1/10 (or more) of the probability scale.

If the differences in the minimum outcomes and their probabilities do not stop examination, then finally the maximum outcome—whichever is higher—decides. No aspiration level is needed.

## The Priority Heuristic

The priority and stopping rules combine to the following process model for two-outcome gambles with nonnegative prospects (all outcomes are positive or zero). We refer to this process as the *priority heuristic* because it is motivated by first priorities, such as to avoid ending up with the worst of the two minimum outcomes. The heuristic consists of the following steps:

*Priority rule*: Go through reasons in the order: minimum gain, probability of minimum gain, maximum gain.

*Stopping rule:* Stop examination if the minimum gains differ by 1/10 (or more) of the maximum gain; otherwise, stop examination if probabilities differ by 1/10 (or more) of the probability scale.

*Decision rule:* Choose the gamble with the more attractive gain (probability).

The term "attractive" refers to the gamble with the higher (minimum or maximum) gain and the lower probability of the minimum gain. The priority heuristic models difficult decisions, not all decisions. It does not apply to pairs of gambles in which one gamble dominates the other one, and it also does not apply to "easy" problems in which the expected values are strikingly different (see General Discussion).

The heuristic combines features from three different sources: Its initial focus is on outcomes rather than on probabilities (Brandstätter & Kühberger, 2005; Deane, 1969; Loewenstein et al., 2001; Sunstein, 2003), and it is based on the sequential structure of the Take The Best heuristic (Gigerenzer & Goldstein, 1996), which is a heuristic for inferences, whereas the priority heuristic is a model of preferential choices. Finally, the priority heuristic incorporates aspiration levels into its choice algorithm (Luce, 1956; Simon, 1983). The generalization of the priority heuristic to nonpositive prospects (all outcomes are negative or zero) is straightforward. The heuristic is identical except that "gains" are replaced by "losses":

*Priority rule:* Go through reasons in the order: minimum loss, probability of minimum loss, maximum loss.

*Stopping rule:* Stop examination if the minimum losses differ by 1/10 (or more) of the maximum loss; otherwise, stop examination if probabilities differ by 1/10 (or more) of the probability scale.

*Decision rule:* Choose the gamble with the more attractive loss (probability).

The term *attractive* refers to the gamble with the lower (minimum or maximum) loss and the higher probability of the minimum loss.

Next, we generalize the heuristic to gambles with more than two outcomes (assuming nonnegative prospects):

*Priority rule*: Go through reasons in the order: minimum gain, probability of minimum gain, maximum gain, probability of maximum gain.

*Stopping rule*: Stop examination if the gains differ by 1/10 (or more) of the maximum gain; stop examination if probabilities differ by 1/10 (or more) of the probability scale.

*Decision rule*: Choose the gamble with the more attractive gain (probability).

This priority rule is identical with that for the two-outcome gambles, apart from the addition of a fourth reason. In gambles with more than two outcomes, the probability of the maximum outcome is informative because it is no longer the logical complement of the probability of the minimum outcome. The stopping rule is also identical, except for the fact that the maximum gain is no longer the last reason, and therefore the same aspiration levels apply to both minimum and maximum gains. The decision rule is identical with that for the two-outcome case. Finally, the algorithm is identical for gains and losses, except that "gains" are replaced by "losses."

The priority heuristic is simple in several respects. It typically consults only one or a few reasons; even if all are screened, it bases its choice on only one reason. Probabilities are treated as linear, and a 1/10 aspiration level is used for all reasons except the last, where the amount of difference is ignored. No parameters for overweighting small probabilities and underweighting large probabilities or for the value function are built in. Can this simple model account for people's choices as well as multiparameter outcome models can?

To answer this question, we test whether the priority heuristic

(1) can account for evidence at variance with EU theory, namely (i) the Allais paradox, (ii) risk aversion for gains if probabilities are high, (iii) risk seeking for gains if probabilities are low (e.g., lottery tickets), (iv) risk aversion for losses if probabilities are low (e.g., buying insurance), (v) risk seeking for losses if probabilities are high, (vi) the certainty effect, (vii) the possibility effect, and (viii) intransitivities; and

(2) can predict the empirical choices in four classes of gambles: (i) simple choice problems (no more than two nonzero outcomes; Kahneman & Tversky, 1979), (ii) multiple-outcome gambles (Lopes & Oden, 1999), (iii) gambles inferred from certainty equivalents (Tversky & Kahneman, 1992), and (iv) randomly sampled gambles (Erev et al., 2002).

## Can the Priority Heuristic Predict Violations of EU Theory?

### Allais Paradox

In the early 1950s, choice problems were proposed that challenged EU theory as a descriptive framework for risky choice (Allais, 1953, 1979). For instance, according to the independence axiom of EU, aspects that are common to both gambles should not influence choice behavior (von Neumann & Morgenstern, 1947; Savage, 1954). For any three alternatives $X$, $Y$, and $Z$ taken from a set of options $S$, the independence axiom can be written (Fishburn, 1979):

$$\text{If } pX+(1-p)Z>pY+(1-p)Z \text{ then } X>Y \quad (4)$$

The following choice problems produce violations of the axiom (Allais, 1953, p. 527).

| | | | |
|---|---|---|---|
| *A*: | 100 | million | $p = 1.00$ |
| *B*: | 500 | million | $p = .10$ |
| | 100 | million | $p = .89$ |
| | 0 | | $p = .01$ |

By eliminating a .89 probability to win 100 million from both gambles *A* and *B*, Allais obtained the following alternatives:

| | | | |
|---|---|---|---|
| *C*: | 100 | million | $p = .11$ |
| | 0 | | $p = .89$ |
| *D*: | 500 | million | $p = .10$ |
| | 0 | | $p = .90$ |

The majority of people chose gamble *A* over *B*, and *D* over *C* (MacCrimmon, 1968), which constitutes a violation of the axiom.

EU does not predict whether *A* or *B* will be chosen; it only makes predictions of the type "if *A* is chosen over *B*, then it follows that *C* is chosen over *D*." The priority heuristic, in contrast, makes stronger predictions: It predicts whether *A* or *B* is chosen, and whether *C* or *D* is chosen. Consider the choice between *A* and *B*. The maximum payoff is 500 million, and therefore the aspiration level is 50 million; 100 million and 0 represent the minimum gains. Because the difference (100 million) exceeds the aspiration level of 50 million, the minimum gain of 100 million is considered good enough, and people are predicted to select gamble *A*. That is, the heuristic predicts the majority choice correctly.

In the second choice problem, the minimum gains (0 and 0) do not differ. Hence, the probabilities of the minimum gains are attended to, $p = .89$ and .90, a difference that falls short of the aspiration level. The higher maximum gain (500 million versus 100 million) thus decides choice, and the prediction is that people will select gamble *D*. Again, this prediction is consistent with the choice of the majority. Together, the pair of predictions amount to the Allais paradox.

The priority heuristic captures the Allais paradox by using the heuristic building blocks of order, a stopping rule with a 1/10 aspiration level, a lexicographic decision rule, and the tendency to avoid the worst possible outcome.

## Reflection Effect

The reflection effect refers to the empirically observed phenomenon that preferences tend to reverse when the sign of the outcomes is changed (Fishburn & Kochenberger, 1979; Markowitz, 1952; Williams, 1966). Rachlinski's (1996) copyright litigation problem offers an illustration in the context of legal decision making. Here, the choice is between two gains or between two losses for the plaintiff and defendant, respectively:

> The plaintiff can either accept a $200,000 settlement [*] or face a trial with a .50 probability of winning $400,000, otherwise nothing.
>
> The defendant can either pay a $200,000 settlement to the plaintiff, or face a trial with a .50 probability of losing $400,000, otherwise nothing [*].




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The asterisks in brackets indicate which alternative the majority of law students chose, depending on whether they were cast in the role of the plaintiff or the defendant. Note that the two groups made opposite choices. Assuming that plaintiffs used the priority heuristic, they would have first considered the minimum gains, $200,000 and $0. Because the difference between the minimum gains is larger than the aspiration level ($40,000 rounded to the next prominent number, $50,000), plaintiffs would have stopped examination and chosen the option with the more attractive minimum gain, that is, the settlement. The plaintiff's gain is the defendant's loss: Assuming that defendants also used the priority heuristic, they would have first considered the minimum losses, which are $200,000 and $0. Again, because the difference between these outcomes exceeds the aspiration level, defendants would have stopped examination and chosen the option with the more attractive minimum loss, that is, the trial. In both cases, the heuristic predicts the majority choice.

How is it possible that the priority heuristic predicts the reflection effect without—as prospect theory does—introducing value functions that are concave for gains and convex for losses? In the gain domain, the minimum gains are considered first, thus implying risk aversion. In the loss domain, the minimum losses are considered first, thus implying risk seeking. Risk aversion for gains and risk seeking for losses together make up the reflection effect.

## Certainty Effect

According to Allais (1979, p. 441), the certainty effect captures people's “preference for security in the neighborhood of certainty.” A simple demonstration is the following (Kahneman & Tversky, 1979):

| | | |
|---|---|---|
| *A*: | 4,000 | with $p = .80$ |
| | 0 | with $p = .20$ |
| *B*: | 3,000 | with $p = 1.00$ |

A majority of people (80%) selected the certain alternative *B*.

| | | |
|---|---|---|
| *C*: | 4,000 | with $p = .20$ |
| | 0 | with $p = .80$ |
| *D*: | 3,000 | with $p = .25$ |
| | 0 | with $p = .75$ |

Now the majority of people (65%) selected gamble *C* over *D*. Note that the choice of *B* implies that $u(3{,}000)/u(4{,}000) > 4/5$, whereas the choice of *C* implies the reverse inequality.

The priority heuristic starts by comparing the minimum gains of the alternatives *A* (0) and *B* (3,000). The difference exceeds the aspiration level of 500 (400, rounded to the next prominent number), examination is stopped, and the model predicts that people prefer option *B*, which is in fact the majority choice. Between *C* and *D*, the minimum gains (0 and 0) do not differ; in the next step, the heuristic compares the probabilities of the minimum gains (.80 and .75). Because this difference does not reach 10 percentage points, the decision is with the higher maximum gain, that is, option *C* determines the decision.

As the example illustrates, it is not always the first reason (minimum gain) that determines choice; it can also be one of the others. The priority heuristic can predict the certainty effect without assuming a specific probability weighting function.

## The Possibility Effect

To demonstrate the possibility effect, participants received the following two choice problems (Kahneman & Tversky, 1979).

| | | |
|---|---|---|
| *A*: | 6,000 | with $p = .45$ |
| | 0 | with $p = .55$ |
| *B*: | 3,000 | with $p = .90$ |
| | 0 | with $p = .10$ |

The second choice problem is derived from the first by multiplying the probabilities of the nonzero gains with 1/450, making the probabilities of winning merely “possible”:

| | | |
|---|---|---|
| *C*: | 6,000 | with $p = .001$ |
| | 0 | with $p = .999$ |
| *D*: | 3,000 | with $p = .002$ |
| | 0 | with $p = .998$ |

While a majority of people (86%) selected gamble *B* in the first choice problem, most (73%) chose gamble *C* in the second. Note that in the certainty effect, “certain” probabilities are made “probable,” whereas in the possibility effect, “probable” probabilities are made “possible.” Can the priority heuristic predict this choice pattern?

In the first choice problem, the priority heuristic starts by comparing the minimum gains (0 and 0). Because there is no difference, the probabilities of the minimum gains (.55 and .10) are examined. This difference exceeds 10 percentage points and the priority heuristic, consistent with the majority choice, selects option *B*. Analogously, in the second choice problem, the minimum gains (0 and 0) are the same; the difference between the probabilities of the minimum gains (.999 and .998) does not exceed 10 percentage points. Hence, the priority heuristic correctly predicts the choice of gamble *C*, due to its higher maximum gain of 6,000.

## The Fourfold Pattern

The fourfold pattern refers to the phenomenon that people are generally risk-averse when the probability of winning is high but risk seeking when it is low (as when buying lotteries), and risk-averse when the probability of losing is low (as with buying insurances) but risk seeking when it is high. Table 1 exemplifies the fourfold pattern (Tversky & Fox, 1995).

Table 1 is based on certainty equivalents *C* (obtained from choices rather than pricing). Certainty equivalents represent that amount of money where a person is indifferent between taking the risky gamble or the sure amount *C*. For instance, consider the first cell: The median certainty equivalent of $14 exceeds the expected value of the gamble ($5). Hence, in this case people are risk seeking, because they prefer the risky gamble over the sure gain of $5. This logic applies in the same way to the other cells.




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The certainty equivalent information of Table 1 directly lends itself to the construction of simple choice problems. For instance, from the first cell we obtain the following choice problem:

| | | |
|---|---|---|
| *A*: | 100 | with $p = .05$ |
| | 0 | with $p = .95$ |
| *B*: | 5 | with $p = 1.00$ |

The priority heuristic starts by comparing the minimum gains (0 and 5). Because the sure gain of $5 falls short of the aspiration level of $10, probabilities are attended to. The probabilities of the minimum gain do not differ either (1.00 - .95 < .10); hence, people are predicted to choose the risky option *A*, due to its higher maximum gain. This is in accordance with the certainty equivalent of $14 (see Table 1), which implies risk seeking.

Similarly, if the probability of winning is high we obtain:

| | | |
|---|---|---|
| *A*: | 100 | with $p = .95$ |
| | 0 | with $p = .05$ |
| *B*: | 95 | with $p = 1.00$ |

Here, the sure gain of $95 surpasses the aspiration level ($10) and the priority heuristic predicts the selection of the sure gain *B*, which is in accordance with the risk-avoidant certainty equivalent in Table 1 ($78 < $95). The application to losses is straightforward:

| | | |
|---|---|---|
| *A*: | −100 | with $p = .05$ |
| | 0 | with $p = .95$ |
| *B*: | −5 | with $p = 1.00$ |

Because the minimum losses (0 and −5) do not differ, the probabilities of the minimum losses (.95 and 1.00) are attended to, which do not differ either. Consequently, people are predicted to choose the safe option *B*, due to its lower maximum loss (−5 vs. −100). This is in accordance with the risk-avoidant certainty equivalent in Table 1. Similarly, if the probability of losing is high we obtain:

| | | |
|---|---|---|
| *A*: | −100 | with $p = .95$ |
| | 0 | with $p = .05$ |
| *B*: | −95 | with $p = 1.00$ |

In this case, the minimum losses differ (0 - [−95] > 10) and the priority heuristic predicts the selection of the risky gamble *A*, which corresponds to the certainty equivalent of Table 1.

Note that in this last demonstration, probabilities are not attended to and one does not need to assume some nonlinear function of decision weights. As shown above, the priority heuristic correctly predicts the reflection effect and, consequently, the entire fourfold pattern in terms of one simple, coherent strategy.

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### Intransitivities

Intransitivities violate EU's fundamental *transitivity axiom*, which states that a rational decision maker who prefers $X$ to $Y$ and $Y$ to $Z$ must then prefer $X$ to $Z$ (von Neumann & Morgenstern, 1947). Consider the choice pattern in Table 2, which shows the percentages of choices in which the row gamble was chosen over the column gamble. For instance, in 65% of the choices, gamble A was chosen over gamble B. As shown therein, people prefer gambles $A > B$, $B > C$, $C > D$, and $D > E$. However, they violate transitivity by selecting gamble $E$ over $A$.

If one predicts the majority choices with the priority heuristic, one gets A > B because the minimum gains are the same, their probabilities do not differ, and the maximum outcome of $A$ is higher. Similarly, the heuristic can predict all 10 majority choices with the exception of the .51 figure (a close call) in Table 2. Note that the priority heuristic predicts $A > B$, $B > C$, $C > D$, $D > E$, and $E > A$, which results in the intransitive circle. In contrast, cumulative prospect theory, which reduces to prospect theory for these simple gambles, or the transfer of attention exchange model attach a fixed overall value $V$ to each gamble and therefore cannot predict this intransitivity.

## Can the Priority Heuristic Predict Choices in Diverse Sets of Choice Problems?

One objection to the previous demonstration is that the priority heuristic has only been tested on a small set of choice problems, one for each anomaly. How does it fare when tested against a larger set of problems? We tested the priority heuristic in four different sets of choice problems (Erev et al., 2002; Kahneman & Tversky, 1979; Lopes & Oden, 1999; Tversky & Kahneman, 1992). Two of these sets of problems were designed to test prospect theory and cumulative prospect theory, and one was designed to test security-potential/aspiration theory (Lopes & Oden, 1999); none, of course, were designed to test the priority heuristic. The contestants used were three modifications of expected utility theory: cumulative prospect theory, security-potential/aspiration theory, and the transfer of attention exchange model (Birnbaum & Chavez, 1997). In addition, we included the classic heuristics simulated by Thorngate (1980); two heuristics taken from Payne et al. (1993), that is, the lexicographic and the equal-weight heuristic (Dawes, 1979); and the tallying heuristic (Table 3). The criterion for each of the four sets of problems was to predict the majority choice. This allows a comparison between the various heuristics, as well as between heuristics, cumulative prospect theory, security-potential/aspiration theory, and the transfer of attention exchange model.

### The Contestants

The contesting heuristics can be separated into two categories: those that solely use outcome information and ignore probabilities altogether (outcome heuristics), and those that use at least rudimentary probabilities (dual heuristics).[2] These heuristics are defined in Table 3, where their algorithm is explained through the following choice problem:

| | |
|---|---|
| $A$: | 80% chance to win 4,000 |

[2]We did not consider three of the heuristics listed by Thorngate (1980). These are: low expected payoff elimination, minimax regret, and low payoff elimination. These strategies demand unrealistically high cognitive effort (even more than the better than average heuristic).

| | |
|---|---|
| | 20% chance to win 0 |
| *B*: | 3,000 for sure |

Cumulative prospect theory (Tversky & Kahneman, 1992) attaches decision weights to cumulated rather than single probabilities. The theory uses five adjustable parameters. Three parameters fit the shape of the value function; the other two fit the shape of the probability weighting function. The value function is:

$$v(x) = x^{\alpha} \qquad \text{if } x \geq 0 \quad (5)$$

$$v(x) = -\lambda(-x)^{\beta} \qquad \text{if } x < 0 \quad (6)$$

The α and β parameters modulate the curvature for the gain and loss domain, respectively; the λ parameter (λ > 1) models loss aversion. The weighting function is:

$$w^{+}(p) = p^{\gamma}/(p^{\gamma} + (1-p)^{\gamma})^{1/\gamma} \quad (7)$$

$$w^{-}(p) = p^{\delta}/\left(p^{\delta} + (1-p)^{\delta}\right)^{1/\delta} \quad (8)$$

where the γ and δ parameters catch the inverse S-shape of the weighing function for gains and losses, respectively.

Another theory that incorporates thresholds (i.e., aspiration levels) in a theory of choice is security-potential/aspiration theory (Lopes, 1987, 1995; for details, see Lopes & Oden, 1999). Security-potential/aspiration theory is a six-parameter theory, which integrates two logically and psychologically independent criteria. The security-potential criterion is based on a rank-dependent algorithm (Quiggin, 1982; Yaari, 1987) that combines outcomes and probabilities in a multiplicative way. The aspiration criterion is operationalized as the probability to obtain some previously specified outcome. Both criteria together enable security-potential/aspiration theory to model people's choice behavior.

The third modification of expected utility theory entering the contests is the transfer of attention exchange model (Birnbaum & Chavez, 1997), which was proposed as a response to problems encountered by prospect theory and cumulative prospect theory. This model has three adjustable parameters and is a special case of the more general configural weight model (Birnbaum, 2004). Like prospect theory, the transfer of attention exchange model emphasizes how choice problems are described and presented to people. Unlike prospect theory, it offers a formal theory to capture the effects of problem formulations on peoples' choice behavior.

In models with adjustable parameters, parameter estimates are usually fitted for a specific set of choice problems and individuals. Data fitting, however, comes with the risk of overfitting, that is, fitting noise (Roberts & Pashler, 2000). To avoid this problem, we used the fitted parameter estimates from one set of choice problems to predict the choices in a different one. For cumulative prospect theory, we used three sets of parameter estimates derived from Erev et al. (2002), Lopes and Oden (1999), and Tversky and Kahneman (1992). For the choice problems by Kahneman and Tversky (1979), no such parameter estimates exist. The three sets of parameter estimates are shown in Table 4. As one can see, they cover a broad range of value. Thus, we could test the predictive power of cumulative prospect theory with three independent sets of parameter estimates for the Kahneman and Tversky (1979) choice problems, and with two independent sets of parameter estimates for each of the other three sets of problems. In addition, for testing security-potential/aspiration theory, we used the parameter estimates from Lopes and Oden (1999); for testing the transfer of attention exchange model, we used its prior parameters (see Birnbaum, in press), which were estimated from Tversky and Kahneman (1992), to predict choices for the other three sets of choice problems.

## Contest 1: Simple Choice Problems

The first test set consisted of monetary one-stage choice problems from Kahneman and Tversky (1979).[3] These 14 choice problems were based on gambles of equal or similar expected value and contained no more than two nonzero outcomes.

### Results

Figure 1 shows how well the heuristics, cumulative prospect theory, security-potential/aspiration theory, and the transfer of attention exchange model each predicted the majority response. The maximum number of correct predictions is 14. The white parts of the columns show correct predictions due to guessing. All heuristics, with the exceptions of the priority, equiprobable, and the lexicographic heuristic, had to guess in this set of problems.

The priority heuristic predicted all 14 choice problems correctly. In no instance did it need to guess. All other heuristics performed at or near chance level, except for the equiprobable and tallying heuristics: equiprobable correctly predicted 10 out of 14, whereas tallying predicted 4 out of 11 choices correctly.[4] It is interesting that among the ten heuristics investigated, those that used only outcome information performed slightly better than those also using probability information did.

For testing cumulative prospect theory, we used three different parameter sets. The first parameter set was taken from Lopes and Oden (1999) and resulted in 64% correct predictions. The second set was taken from Tversky and Kahneman (1992) and resulted in 71% correct predictions. The third was taken from Erev et al.'s (2002) randomly constructed gambles, which resulted in chance performance (50% correct).

On average, cumulative prospect theory correctly predicted 64% of the majority choices.[5] One might assume that each of the parameter sets failed in predicting the same choice problems. However, this was not the case; the failures to predict were distributed across ten problems. This suggests that choice problems correctly predicted by one parameter set were incorrectly predicted by another set and vice versa. Finally, security-potential/aspiration theory correctly predicted 5 out of 14 choice problems, which resulted in 36% correct predictions, and the transfer of attention exchange model correctly predicted 71% of the choice problems (i.e., 10 out of 14).

Why did the heuristics in Table 3 perform so dismally in predicting people's deviations from EU theory? Like the priority heuristic, these heuristics ignore information. However, the difference lies in how information is ignored.

---

[3]These are the choice problems 1, 2, 3, 4, 7, 8, 3′, 4′, 7′, 8′, 13, 13′, 14, 14′ in Kahneman and Tversky (1979).

[4]Note that tallying fails to predict choice behavior for problems with more than two outcomes. Whereas it is easy to compare the highest and the lowest outcomes of each gamble as well as their respective probabilities, it is unclear how to evaluate the probabilities of an intermediate outcome.

[5]As one can see from Table 4, the Erev et al. (2002) estimates of prospect theory's parameters only refer to gains. Therefore, only a subset of the problems in the Kahneman and Tversky (1979) set of problems could be predicted, which was accounted for by this and the following means.

For gains, the priority heuristic uses the same first reason that minimax does (Table 3). Unlike minimax, however, the priority heuristic does not always base its choice on the minimum outcomes, but only when the difference between the minimum outcomes exceeds the aspiration level. If not, then the second reason, the probability of the minimum outcome, is given priority. This reason captures the policy of the least likely heuristic (Table 3). Again, the priority heuristic uses an aspiration level to "judge" whether this policy is reasonable. If not, the maximum outcome will decide, which is the policy of the maximax heuristic (Table 3). The same argument holds for gambles with losses, except that the positions of minimax and maximax are switched. Thus, the sequential nature of the priority heuristic integrates several of the classic heuristics, brings them into a specific order, and uses aspiration levels to judge whether they apply.

In summary, the priority heuristic was able to predict the majority choice in all 14 choice problems in Kahneman and Tversky (1979). The other heuristics did not predict well, mostly at chance level, and cumulative prospect theory did best when its parameter values were estimated from Tversky and Kahneman (1992).

## Contest 2: Multiple-Outcome Gambles

The fact that the priority heuristic can predict the choices in two-outcome gambles does not imply that it can do the same for multiple-outcome gambles. These are a different story, as illustrated by prospect theory (unlike the revised cumulative version), which encountered problems when it was applied to gambles with more than two nonzero outcomes. Consider the choice between the multiple-outcome gamble *A* and the sure gain *B*:

| | | |
|---|---|---|
| *A*: | 0 | with $p = .05$ |
| | 10 | with $p = .05$ |
| | 20 | with $p = .05$ |
| | … | |
| | 190 | with $p = .05$ |
| *B*: | 95 | with $p = 1.00$ |

The expected values of *A* and *B* are 95. According to the probability weighting function in prospect theory, each monetary outcome in gamble *A* is overweighted, because $\pi$ (.05) > .05. For the common value functions, prospect theory predicts a higher subjective value for the risky gamble *A* than for the sure gain of 95. In contrast, 28 out of 30 participants opted for the sure gain *B* (Brandstätter, 2004).

The priority heuristic gives first priority to the minimum outcomes, which are 0 and 95. The difference between these two values is larger than the aspiration level (20, because 19 is rounded to 20), so no other reason is examined and the sure gain is chosen.

The second set of problems consists of 90 pairs of five-outcome lotteries taken from Lopes and Oden (1999). In this set, the expected values of each pair are always equal. The probability distributions over the five rank-ordered gains have six different shapes: Lotteries were (i) nonrisk (the lowest gain was larger than zero and occurred with the highest probability of winning), (ii) peaked (moderate gains occurred with the highest probability of winning), (iii) negatively skewed (the largest gain occurred with the highest probability of winning), (iv) rectangular (all five gains were tied to the same probability $p = .20$), (v) bimodal (extreme gains occurred with the highest probability of winning), and (vi)




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positively skewed (the largest gain occurred with the lowest probability of winning). An example is shown in Figure 2.

These six gambles yielded 15 different choice problems. From these, Lopes and Oden (1999) created two other choice sets by (a) adding $50 to each outcome and (b) multiplying each outcome by 1.145, making 3 * 15 = 45 choice problems. In addition, negative lotteries were created by appending a minus sign to the outcomes of the three positive sets, making 90 choice problems. This procedure yielded six different choice sets (standard, shifted, multiplied—separately for gains and losses), each one comprising all possible choices within a set (i.e., 15).

### Results

The priority heuristic yielded 87% correct predictions, as shown in Figure 3. All other heuristics performed around chance level or below. The result from the previous competition—that outcome heuristics are better predictors than the dual heuristics—did not generalize to multiple-outcome gambles.

The parameter values for the cumulative prospect theory were estimated from the two independent sets of problems. With the parameter estimates from the Tversky and Kahneman (1992) set of problems, cumulative prospect theory predicted 67% of the majority responses correctly. With the estimates from the Erev et al. (2002) set of problems, the proportion of correct predictions was 87%. With the second set of parameter estimates, cumulative prospect theory tied with the priority heuristic, whereas cumulative prospect theory's performance was lower with the first set. Its average predictive accuracy was 73%. The fact that it did not perform better than the heuristic did is somewhat surprising, given that cumulative prospect theory was specifically designed for multiple-outcome gambles. Finally, the transfer of attention exchange model correctly predicted 63% of the majority responses.

Lopes and Oden (1999) fitted cumulative prospect theory to their set of problems. We used these parameter estimates and “tested” cumulative prospect theory on the Lopes and Oden set of problems, which is known as data fitting. The resulting fitting power with five adjustable parameters was 87%. A slightly higher result emerged for security-potential/aspiration theory, where the fitting power with six parameters was 91%.

To sum up, the 90 five-outcome problems no longer allowed the priority heuristic to predict 100% correctly. Nevertheless, the consistent result in the first two contests was that the priority heuristic could predict the majority response as well as and better than the three modifications of expected utility theory or any of the other heuristics. We were surprised by the heuristic's good performance, given that it ignores all intermediate outcomes and their probabilities. It is no doubt possible that gambles can be deliberately constructed with intermediate outcomes that the priority heuristic does not predict as well. Yet in these six systematically varied sets of gambles, no other model outperformed the priority heuristic.

## Contest 3: Risky Choices Inferred From Certainty Equivalents

The previous analyses used the same kind of data, namely choices between explicitly stated gambles. The next contest introduces choices inferred from certainty equivalents. The certainty equivalent $C$ of a risky gamble is defined as the sure amount of money $C$, where a person has no preference between the gamble and the sure amount. Certainty equivalents can be translated into choices between a risky gamble and a sure payoff. Our third test set comprised 56 gambles studied by Tversky and Kahneman (1992). These risky gambles are not a random or representative set of gambles. They were designed for the purpose of




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demonstrating that cumulative prospect theory accounts for deviations from EU theory. Half of the gambles are in the gain domain ($\$x \geq 0$); for the other half, a minus sign was added. Each certainty equivalent was computed from observed choices (for a detailed description, see Brandstätter, Kühberger, & Schneider, 2002). Consider a typical example from this set of problems:

$$C(\$50, .10; \$100, .90) = \$83$$

Because this empirical certainty equivalent falls short of the expected value of the gamble ($95), people are called risk-averse. We can represent this information as a choice between the risky gamble and a sure gain of equal expected value:

| | |
|---|---|
| *A*: | 10% chance to win 50 |
| | 90% chance to win 100 |
| *B*: | 95 for sure. |

The priority heuristic predicts that the minimum outcomes, which are $50 and $95, are compared first. The difference between these two values is larger than the aspiration level ($10). No other reason is examined and the sure gain is chosen.

### Results

The priority heuristic made 89% correct predictions (Figure 4). The equiprobable heuristic was the second-best heuristic with 79%, followed by the better than average heuristic. All other heuristics performed at chance level or below, and tallying had to guess all the time (Table 3). The pattern obtained resembles that of the first competition; the outcome heuristics fared better than did those that also used probability information.

Cumulative prospect theory achieved 80% correct predictions with the parameter estimates from the Lopes and Oden (1999) set of problems, and 75% with those from the Erev et al. (2002) data set (Figure 4). Thus, the average predictive accuracy was 79%. Security-potential/aspiration theory fell slightly short of these numbers and yielded 73% correct forecasts. In contrast, when one “tests” cumulative prospect theory on the same data (Tversky & Kahneman, 1992) from which the five parameters were derived (i.e., data fitting rather than prediction), one can correctly “predict” 91% of the majority choices. The parameters of the transfer of attention exchange model were fitted by Birnbaum and Navarrete (1998) on the Tversky and Kahneman (1992) data; thus, we cannot test how well it predicts the data. In data fitting, it achieved 95% correct “predictions.”

## Contest 4: Randomly Drawn Two-Outcome Gambles

The final contest involved 100 pairs of two-outcome gambles that were randomly drawn (Erev et al., 2002). Almost all minimum outcomes were zero. This set of problems handicapped the priority heuristic, given that it could rarely make use of its top-ranked reason. An example from this set is the following (units are points that correspond to cents):

| | |
|---|---|
| *A*: | 49% chance to win 77 |
| | 51% chance to win 0 |

| | |
|---|---|
| *B*: | 17% chance to win 98 |
| | 83% chance to win 0 |

These pairs of lotteries were created by random sampling of the four relevant values $x_1$, $p_1$, $x_2$, $p_2$. Probabilities were randomly drawn from the uniform distribution (.00, .01, .02, … 1.00) and monetary gains from the uniform distribution (1, 2, 3, … 100). The constraint $(x_1 - x_2)(p_1 - p_2) < 0$ eliminated trivial choices, and the sampling procedures generated choices consisting of gambles with unequal expected value.

### Results

Although the priority heuristic could almost never use its top-ranked reason, it correctly predicted 85% of the majority choices reported by Erev et al. (2002). In this set, the outcome heuristics performed worse than those also using probability information did (Figure 5). As a further consequence, the performance of minimax was near chance level, because its only reason, the minimum gains, was rarely informative, and it thus had to guess frequently (exceptions were four choice problems, which included a sure gain). Cumulative prospect theory achieved 89% and 75% correct predictions, depending on the set of parameters, which resulted in an average of 82% correct predictions. The security-potential/aspiration theory correctly predicted 88%, and the transfer of exchange model achieved 74% correct forecasts. In the four contests, with a total of nine tests of cumulative prospect theory, three tests of security-potential/aspiration theory, and three tests of the transfer of attention exchange model, these 89% and 88% figures were the only instances where the two models could predict slightly better than the priority heuristic did (for a tie, see Figure 3).

Again, we checked the fitting power of cumulative prospect theory by using the Erev et al. (2002) set of problems. This resulted in a fitting power of 99%. As in the previous analyses, a substantial discrepancy between fitting and prediction emerged.

## The Priority Heuristic as a Process Model

Process models, unlike as-if models, can be tested on two levels: the choice and the process. In this article, we focus on how well the priority heuristic can predict choices, compared to competing theories. Yet we now want to illustrate how the heuristic lends itself to testable predictions concerning process. Recall that the priority heuristic assumes a sequential process of examining reasons that is stopped as soon as an aspiration level is met. Therefore, the heuristic predicts that the more reasons that people are required to examine, the more time they need for making a choice. Note all three modifications of expected utility theory tested here assume that all pieces of information are always used, and thus do not imply this process prediction.

To illustrate the prediction, consider the following choice:

| | | |
|---|---|---|
| *A*: | 2,500 | with $p = .05$ |
| | 550 | with $p = .95$ |
| *B*: | 2,000 | with $p = .10$ |
| | 500 | with $p = .90$ |

Given the choice between *A* and *B*, the priority heuristic predicts that people examine three reasons and therefore need more time than for the choice between *C* and *D*, which demands examining one reason only:

| | | |
|---|---|---|
| *C*: | 2,000 | with $p$ = .60 |
| | 500 | with $p$ = .40 |
| *D*: | 2,000 | with $p$ = .40 |
| | 1,000 | with $p$ = .60 |

In summary, the prediction is: If the priority heuristic implies that people examine more reasons (e.g., three as opposed to one), the measured time people need for responding will be longer. This prediction was tested in the following experiment for two-outcome gambles, for five-outcome gambles, for gains and losses, and for gambles of similar and dissimilar expected value.

## Method

One hundred and twenty-one students (61 females, 60 males, $M$ = 23.4 years, $SD$ = 3.8) from the University of Linz participated voluntarily in this experiment. The experimental design was a 2 (one reason or three reasons examined) by 2 (choice between two two-outcome gambles or choice between two five-outcome gambles) by 2 (gambles of similar or dissimilar expected value) by 2 (gains versus losses) mixed factorial design, with domain (gains versus losses) as a between participants factor, and the other three manipulations as within participants factors. The *dependent variable*, response time (in milliseconds), was measured from the first appearance of the decision problem until the moment when the participant indicated his or her choice by clicking either gamble *A* or *B*. Then the next choice problem appeared on the computer screen. Each participant responded to 40 choice problems, which appeared in random order within each kind of set (i.e., two-outcome and five-outcome set). The order was counterbalanced so that half of the participants received the five-outcome gambles before the two-outcome gambles, whereas this order was reversed for the other half of the participants. All 40 choice problems from the gain domain (gains were converted into losses by adding a minus sign) are listed in the appendix.

## Results and Discussion

The prediction was that the response time is shorter for those problems where the priority heuristic implies that people stop examining after one reason, and longer when they examine all three reasons. As shown in Figure 6, results confirmed this prediction.

This result held for both choices between two-outcome gambles (one reason: $Md$ = 9.3, $M$ = 10.9, $SE$ = 0.20; three reasons: $Md$ = 10.1, $M$ = 11.9, $SE$ = 0.21; $z$ = −3.8, $p$ = .001) and choices between five-outcome gambles (one reason: $Md$ = 10.3, $M$ = 12.6, $SE$ = 0.26; three reasons: $Md$ = 11.8, $M$ = 14.1, $SE$ = 0.41; $z$ = −2.9, $p$ = .004). Not surprisingly, five-outcome gambles need more reading time than two-outcome gambles, which may explain the higher response time for the former. We additionally analyzed response times between the number of reasons people examined (one or three) when the expected values were similar (one reason: $Md$ = 9.8, $M$ = 12.1, $SE$ = 0.24; three reasons: $Md$ = 11.1, $M$ = 13.2, $SE$ = 0.30; $z$ = −4.5, $p$ = .001) and when expected values were dissimilar (one reason: $Md$ = 9.7, $M$ = 11.5, $SE$ = 0.22; three reasons: $Md$ = 10.1, $M$ = 12.1, $SE$ = 0.26; $z$ = −1.7, $p$ = .085); when people decided between two gains (one reason: $Md$ = 9.3, $M$ = 11.5, $SE$ = 0.22; three reasons: $Md$ = 10.5, $M$ = 12.7, $SE$ = 0.27; $z$ = −4.2, $p$ = .001), or when they decided between two losses (one reason: $Md$ = 10.2, $M$ = 12.1, $SE$ = 0.25; three reasons: $Md$ = 10.5, $M$ =




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12.5, $SE = 0.29$; $z = -1.7$, $p = .086$). In addition to our predictions, we observed that the effects are stronger for gambles from the gain than from the loss domain, and when the expected values are similar rather than dissimilar.

The priority heuristic gives rise to process predictions that go beyond those investigated in this paper. One of them concerns the order in which people examine reasons. Specifically, the priority heuristic predicts that reasons are considered in the following order: minimum gain, probability of minimum gain, and maximum gain. This and related predictions can be examined with process tracing methodologies such as eye tracking and mouse lab. Using mouse lab, for instance, Schkade and Johnson (1989) report evidence for choice processes that are consistent with lexicographic strategies like the priority heuristic.

## Frugality

Predictive accuracy is one criterion for comparing models of choice between gambles; frugality is another. The latter has not been the focus of models of risky choice. For instance, expected utility theory and cumulative prospect theory take all pieces of information into account (exceptions to this are sequential search models such as heuristics and decision field theory; see Busemeyer & Townsend, 1993).

How to define frugality? All heuristics and modifications of expected utility theory assume a specific reading stage, in which all pieces of information are read and the relevant one (which varies from model to model) is identified. For instance, a person who relies on the minimax heuristic will read the text and determine what the minimal outcomes are. A person who relies on cumulative prospect theory will read the text and identify all relevant pieces of information from the point of view of this theory. This reading phase is common to all choice models and is not what we refer to in our definition of frugality. The frugality of a strategy refers to the processes that begin after the text is read.

We define frugality as the proportion of pieces of information that a model *ignores* when making a decision. Guessing, for instance, is the most frugal strategy; it ignores 100% of the information, and therefore its frugality is 100%. In a two-outcome gamble, the probabilities are complementary, which reduces the number of pieces of information from eight to six (the minimal outcomes, their probabilities, and the maximal outcomes). Minimax, for instance, ignores four out of these six pieces of information; thus its frugality is 67%. The modifications of expected utility theory do not ignore any information (regardless of whether one assumes six or eight pieces of information), and thus their frugality is 0%.

Unlike heuristics such as minimax, which always derive their decision from the same pieces of information, the frugality of the priority heuristic depends on the specific choice problem. For two-outcome gambles, the probabilities of the maximal outcomes are again complementary, reducing the number of pieces of information from eight to six. In making a choice, the priority heuristic then ignores either four pieces of information (the probabilities of the minimal outcomes and the maximal outcomes), two pieces (the maximal outcomes), or no information. This results in frugalities of 4/6, 2/6, and 0, respectively. However, for the stopping rule, the heuristic needs information about the maximum gain (or loss), which reduces the frugalities to 3/6, 1/6, and 0, respectively.[6]

[6]For two-outcome gambles, six instead of eight pieces of information yield a lower-bound estimate of the frugality advantage of the heuristics over parameter-based models such as cumulative prospect theory, which do not treat decision weights as complimentary. For $n$-outcome gambles, with $n > 2$, all $4n$ pieces of information were used in calculating frugalities. Similarly, in the case of ambiguity, we calculated a heuristic's frugality in a way to give this heuristic the best edge against the priority heuristic.

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For each of the four sets of choice problems, we calculated the priority heuristic's frugality score. In the first set of problems (Figure 1; Kahneman & Tversky, 1979), the priority heuristic ignored 22% of the information. For the five-outcome gambles in Figure 3, the heuristic ignored 78%. As mentioned before, one reason for this is that the heuristic solely takes note of the minimum and maximum outcomes and their respective probabilities, and ignores all other information. Cumulative prospect theory, in contrast, ignored 0%. In other words, for these gambles, the heuristic predicted people's choices (87%) as good as or better than CPT (87% and 67%; see Figure 3) with less information than CPT. In the Tversky and Kahneman (1992) set of problems, the priority heuristic frugality score was 31%; for the set of randomly chosen gambles, the heuristic ignored 15% of the information. This number is relatively low, because, as mentioned before, the information about the minimum gain was almost never informative. In summary, the priority heuristic predicted the majority choice on the basis of fewer pieces of information than multiparameter models did, and its frugality depended strongly on the type of gamble in question.

## Overall Performance

We now report the results for all 260 problems from the four contests. For each strategy, we calculated its mean frugality and the proportion of correct predictions (weighted by the number of choice problems per set of problems). As shown in Figure 7, there are three clusters of strategies: the modifications of expected utility and tallying, the classic choice heuristics, and the priority heuristic. The clusters have the following characteristics: The modifications of expected utility and tallying could predict choice fairly accurately, but required the maximum amount of information. The classic heuristics were fairly frugal, but performed dismally in predicting people's choices. The priority heuristic achieved the best predictive accuracy (87%) while being relatively frugal.

Security-potential/aspiration theory, cumulative prospect theory, and the transfer of attention exchange model correctly predicted 79%, 77%, and 69% of the majority choices, respectively. With the exception of the least likely heuristic (LL) and tallying (TALL), most classic heuristics did not predict better than chance. For instance, the performances of the minimax and lexicographic rules were 49% and 48%, respectively.

The four sets of problems allowed for 15 comparisons between the predictive accuracy of the priority heuristic and cumulative prospect theory, security-potential/aspiration theory, and the transfer of attention exchange model.[7] The priority heuristic achieved the highest predictive accuracy in 12 of the 15 comparisons (Figures 1, 3, 4, and 5), and cumulative prospect theory and security potential/aspiration theory in one case each (plus one tie).

## Discussion

The present model of sequential choice continues the works of Luce (1956), Simon (1957), Tversky (1969), and Selten (2001). Luce (1956) began to model choice with a semiorder rule, and Tversky (1969, 1972) extended this work and added heuristics such as “elimination by aspects.” In his later work with Kahneman, he switched to modeling choice by modifying EU theory. The present article pursues Tversky's original perspective, as well as the emphasis on sequential models by Luce, Selten, and Simon.

[7]For the first set of problems, there were three independent parameter sets for cumulative prospect theory, one for security-potential/ aspiration theory, and one for the transfer of attention exchange model, resulting in 5 comparisons. For the second set, these numbers were 2, 0 and 1; for the third set, 2, 1, and 0; and for the fourth set, 2, 1, and 1; resulting in 15 comparisons.

## Limits of the Model

Our goal was to derive from empirical evidence a psychological process model that predicts choice behavior. Like all models, the priority heuristic is a simplification of real world phenomena. In our view there are four major limitations: the existence of individual differences, low-stake (“peanuts”) gambles, widely discrepant expected values, and problem representation.

**Individual differences and low stakes—**The priority heuristic embodies risk aversion with gains and risk seeking with losses. Even if the majority of people are risk-averse in a particular situation, a minority will typically be risk seeking. Some of these risk lovers may focus on the maximum gain rather than on the minimum one as the first reason. Thus, the order of reasons is one potential source of individual differences; another one is the aspiration level that stops examination. We did not explore either of them in this article. Moreover, risk seeking can also be produced by the properties of the choice problem itself. For instance, low stakes can evoke risk seeking for gains. Thus, low stakes can lead to the same reversal of the order of reasons as postulated before for individual differences.

**Discrepant expected values—**Another limiting condition for the application of the priority heuristic is widely discrepant expected values. The set of random gambles by Erev et al. (2002) revealed this limitation. For instance, gamble *A* offers 88 with $p = .74$, nothing otherwise, and gamble *B* offers 19 with $p = .86$, nothing otherwise. The expected values of these gambles are 65.1 and 16.3, respectively. The priority heuristic predicts the choice of gamble *B*, whereas the majority of participants chose *A*.

To investigate the relation between the ratio of expected values and the predictive power of the priority heuristic, we analyzed a set of 450 problems with a large variability in expected values (Mellers, Chang, Birnbaum, & Ordóñez, 1992). In this set, all minimal outcomes are zero; thus the priority heuristic could not use its top-ranked reason. We also tested how well cumulative prospect theory, security-potential/aspiration theory, the transfer of attention exchange model, and expected value theory predict the majority choices.

Figure 8 shows the proportion of correct predictions as a function of the ratio between expected values.[8] As was suggested by our analysis of the Erev et al. (2002) set of problems, the priority heuristic's accuracy decreased as the ratio between expected values became large. For instance, in the fourth quartile, its performance was only slightly above 50%. In the first quartile, however, the priority heuristic outperformed all other contestants by a minimum of 16 percentage points (security-potential/aspiration theory) and a maximum of 40 percentage points (transfer of attention exchange model). In the second quartile, the priority heuristic still outperformed the other modifications of expected utility theory. These performed better than the priority heuristic when the ratio between expected values exceeded about two. Interestingly, however, expected value theory performed virtually as well as the best-performing modification for larger ratios. Tallying (not shown in Figure 8) performed identically to security-potential/aspiration theory in the first two quartiles and worse than any other model when the ratios between expected values were larger. Thus, the results suggest that when choices become difficult—due to similar expected values—a simple sequential heuristic performs best. When choices become easy—due to widely discrepant expected values—expected value theory predicts choices as well as or better than the parametrized models.

[8]For each problem we calculated the ratio between the larger and the smaller expected value. We then divided the ratios into four quartiles and calculated the mean ratios for each quartile, which were 1, 1.8, 2.6, and 5.8. We used the same parameter estimates as in the four contests. For cumulative prospect theory, Figure 8 shows the mean performance across the three analyses using the parameter estimates from Erev et al. (2002), Lopes and Oden (1999), and Tversky and Kahneman (1992).

Figure 8 suggests that people do not rely on the priority heuristic indiscriminately. How can we model when they rely on the heuristic and when they do not? One way would be to assume that people estimate the expected values, and if the ratio is smaller than two, they turn to the priority heuristic. But calculating expected values is not the only method. Alternatively, people may first look at the three (four) reasons, and if no difference is markedly larger than the others, they apply the priority heuristic. Screening the reasons for a large difference is akin to what Tversky, Sattath, and Slovic (1988) called looking for a decisive advantage.

**Problem representation—**A final potential limitation refers to the impact of different representations of the same decision problems on people's choices. For illustration, consider the following two problems reported by Birnbaum (2004, p. 28). In the first problem, participants faced the following scenario: "A marble will be drawn from an urn, and the color of the marble drawn blindly and randomly will determine your prize. You can choose the urn from which the marble will be drawn. In each choice, which urn would you choose?"

| | |
|---|---|
| Urn *A*: | 85 black marbles to win $100 |
| | 10 white marbles to win $50 |
| | 5 blue marbles to win $50 |
| Urn *B*: | 85 black marbles to win $100 |
| | 10 yellow marbles to win $100 |
| | 5 purple marbles to win $7 |

The same participants were also asked to choose between the following two urns:

| | |
|---|---|
| Urn $A'$: | 85 black marbles to win $100 |
| | 15 yellow marbles to win $50 |
| Urn $B'$: | 95 red marbles to win $100 |
| | 5 white marbles to win $7 |

The A versus B problem is the same as the $A'$ versus $B'$ problem, except that the latter adds up the probabilities of the same outcomes (e.g., 10 white marbles to win $50 and 5 blue marbles to win $50 in Urn $A$ are combined to 15 yellow marbles to win $50 in Urn $A'$). According to Birnbaum (2004), 63% of his participants chose $B$ over $A$ and only 20% chose $B'$ over $A'$. His transfer of attention exchange model predicts this and other new paradoxes of risky decision making (see also Loomes, Starmer, & Sugden, 1991). The priority heuristic, in contrast, does not predict that such reversals will occur. The heuristic predicts that people prefer Urn $A$ and $A'$, respectively (based on the minimum gains).

In evaluating the validity of models of risky choice, it is important to keep in mind that it is always possible to design problems that elicit choices that a given model—be it the expected utility theory, prospect theory, cumulative prospect theory, the transfer of attention exchange model, or the priority heuristic—can and cannot explain. For this reason, we refrained from opportunistic sampling of problems. Instead, we tested the priority heuristic on a large set of existing problems that were initially designed to demonstrate the validity of several of its contestants.




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## Process Models

The priority heuristic is intended to model both choice and process: It not only predicts the outcome but also specifies the order of priority, a stopping rule, and a decision rule. As a consequence, it can be tested on two levels, on the level of choice and of process. For instance, if a heuristic predicts choices well, it may still fail in describing the process, thus falsifying it as a process model. Models of choice that are not intended to capture the psychological processes (i.e., as-if models), however, can only be tested at the level of choice. In discussions with colleagues, we learned that there is debate about what counts as a process model for choice. For instance, whereas many people assume that cumulative prospect theory is mute about the decision process, some think the theory can be understood in terms of processes. Lopes (1995) explicitly clarified that the equations in theories such as security-potential/aspiration theory are *not* meant to describe the process. She even showed that the outcomes of lexicographic processes—similar to those in the priority heuristic—can resemble those of modifications of SEU theories.

The priority heuristic can be seen as an explication of Rubinstein's (1988) similarity-based model (see also Leland, 1994; Mellers & Biagini, 1994). The notion of similarity in his model is here defined by the aspiration level, and the priority rule imposes a fixed order on the reasons. Unlike the algebra in EU theory and its modifications, which assume weighting, summing, and exhaustive use of information, the priority heuristic assumes cognitive processes that are characterized by order, aspiration levels, and stopping rules. In Rubinstein's (2003) words, "we need to open the black box of decision making, and come up with some completely new and fresh modeling devices" (p. 1215). We believe that process models of heuristics are key to opening this black box.

## Predicting Choices: Which Strategies Are Closest?

Which of the strategies make the same predictions and which make contradictory ones? Table 5 shows the percentage of identical predictions between each pair of strategies tested on the entire set of problems. The strategy that is most similar to the priority heuristic in terms of prediction (but not in terms of process) is not a heuristic, but rather cumulative prospect theory using the parameters from the Erev et al. (2002) set of problems. The least similar strategy in terms of prediction is the equal weight heuristic, which, unlike the priority heuristic, ignores probabilities and simply adds the outcomes.

A second striking result concerns models with adjustable parameters. The degree of overlap in prediction is not so much driven by their conceptual similarity or dissimilarity, but by whether or not they are fitted to the same set of problems. Consider first the cases where the parameters of different models are derived from the same set of problems. The transfer of attention exchange model (with parameter estimates from Tversky & Kahneman, 1992) most closely resembles cumulative prospect theory when its parameters are estimated from the same set of problems (96% identical predictions). Similarly, security-potential/aspiration theory (with parameter estimates from Lopes & Oden, 1999) most closely resembles cumulative prospect theory when its parameters are estimated from the same problem set (91% identical predictions). Consider now the cases where the parameters of the same model are derived from different sets of problems. There are three such cases for cumulative prospect theory, and the overlaps are 92%, 80%, and 60%. Thus, on average the overlap is higher (94%) when the same problem set is used rather when the same model is used (77%). This shows that the difference between problem sets has more impact than the difference between models does.

## Can the Priority Heuristic Predict Choices in Gambles Involving Gains and Losses?

In the four contests, we have shown that the priority heuristic predicts choices by avoiding trade-offs between probability and outcomes; we have not investigated trade-offs between gains and losses. The priority heuristic can be generalized to handle gain-loss trade-offs, without any change in its logic. This is illustrated by the following choice between two mixed gambles (Tversky & Kahneman, 1992):

| | |
|---|---|
| *A*: | 1/2 probability to lose 50 |
| | 1/2 probability to win 150 |
| *B*: | 1/2 probability to lose 125 |
| | 1/2 probability to win 225 |

The heuristic starts by comparing the minimum outcomes (−50 and −125). Because this difference exceeds the aspiration level of 20 (1/10 of the highest absolute gain or loss: 22.5 rounded to the next prominent number), examination is stopped, and no other reasons are examined. The priority heuristic selects gamble *A*, which is the majority choice (inferred from certainty equivalents as in Contest 3). Applied to all six choice problems with mixed gambles in the Tversky and Kahneman (1992) set of problems, the priority heuristic predicted the majority choice in each case. We crosschecked this result against the set of problems by Levy and Levy (2002) with six choices between mixed gambles with two, three, or four outcomes. Again, the priority heuristic predicted the majority choice in each case correctly. However, we did not test the proposed generalization of the priority heuristic against an extensive set of mixed gambles and thus cannot judge how appropriate this generalization is.

## Choice Proportions

The priority heuristic predicts majority choices but not choice proportions. However, a rank order of choice proportion can be predicted with the additional assumption that the earlier the examination stops, the more extreme the choice proportions will be. That is, when examination is stopped after the first reason, the resulting choice proportions will be more unequal (e.g., 80/20) than when stopping occurs after the second reason (e.g., 70/30), and so on. To test this hypothesis, we analyzed the problems in the two sets of problems (Kahneman & Tversky, 1979; Lopes & Oden, 1999) where the priority heuristic predicted stopping after the first, second, or third reason (this was not the case for the Erev et al. [2002] choice problems, where stopping after the first reason was not possible in almost all problems; the problems in the Tversky & Kahneman [1992] data set were derived from certainty equivalents and hence do not contain choice proportions). Thus, the hypothesis implies that the predicted choice proportions should be higher when fewer reasons are examined. The results show that if examination stopped after the first, second, and third reason, the respective mean choice proportions (*SD*) are .85 (.06; $n = 3$), .83 (.09; $n = 4$), and .72 (.09; $n = 7$) in the Kahneman and Tversky (1979) set of problems. Similarly, in the Lopes and Oden (1999) set of problems, these values are.75 (.10; $n = 30$), .66 (.11; $n = 48$), and .54 (.03; $n = 12$), which supports the heuristic's capacity to predict a rank order of choice proportions.

We suggest that the number of reasons examined offers one account for the process underlying the observed relationship between choice proportion and response time. Our analysis showed that when fewer reasons were examined, the choice proportions became more extreme and the response times decreased. This implies, everything else being equal, that more extreme choice proportions should be associated with faster response times. Some




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support for this implication is given in Mosteller and Nogee (1951) and Busemeyer and Townsend (1993).

## Occam's Razor

Models with smaller numbers of adjustable parameters, which embody Occam's razor, have a higher posterior probability in Bayesian model comparison (MacKay, 1995; Roberts & Pashler, 2000). Consider an empirically obtained result that is consistent with two models, one of which predicts that behavior will be located in a small range of the outcome space, and the other predicting a wider range. The empirical result gives more support (a higher Bayesian posterior probability) to the one that bets on the smaller range. Consequently, if several models predict the same empirical phenomenon equally well, the simplest receives more support (Simon, 1977). We provided evidence that the priority heuristic (i) is simpler and more frugal than SEU and its modifications; (ii) can predict choices equally well or better across four sets of gambles; (iii) predicts intransitivities, which some modifications of EU theory have difficulty predicting; and (iv) predicts process data such as response times.

Every model has parameters; the difference is whether they are free, adjustable within a range, or fixed. The parameters in modifications of EU theory are typically adjustable within a range, due to theoretical constraints. In contrast, most heuristics have fixed parameters. One can fix a parameter by (i) measuring it independently, (ii) deriving it from previous research, or (iii) deriving it theoretically. For modifications of EU theories, we used parameters measured on independent sets of problems. For the priority heuristic, we derived its order from previous research, and obtained the 1/10 aspiration level from our cultural base-10 number system. These ways of fixing parameters can help to make more precise predictions, thus increasing the empirical support for a model.

## Fast and Frugal Heuristics: From Inferences to Preferences

By means of the priority heuristic, we generalize the research program on fast and frugal heuristics (Gigerenzer et al., 1999) from inferences to preferences, thus linking it with another research program on cognitive heuristics, the *adaptive decision maker* program (Payne et al., 1993). This generalization is not trivial. In fact, according to a widespread intuition, preference judgments are not likely to be modelled in terms of noncompensatory strategies such as the priority heuristic. The reason is that preferential choice often occurs in environments in which reasons—for example, prices of products and their quality—correlate negatively. Some researchers have argued that negative correlations between reasons cause people to experience conflict, leading them to make trade-offs, and trade-offs in turn are not conducive to the use of noncompensatory heuristics (e.g., Shanteau & Thomas, 2000). The priority heuristic's success in predicting a large majority of the modal responses across 260 problems challenges this argument.

The study of fast and frugal heuristics for inferences has two goals. One is to derive descriptive models of cognitive heuristics that capture how real people actually make inferences. The second goal is prescriptive in nature: to determine in which environments a given heuristic is less accurate than, as accurate as, or even more accurate than informationally demanding and computationally expensive strategies. In the current analysis of a fast and frugal heuristic for preferences, we focused on the descriptive goal at the expense of the prescriptive one for the following reason: When analyzing preference judgments in prescriptive terms, one quickly enters muddy waters because, unlike in inference tasks, there is no *external* criterion of accuracy. Moreover, Thorngate (1980) and Payne et al. (1993) have already shown that in some environments, preference heuristics can be highly competitive—when measured, for instance, against the gold standard of a weighted additive model. Notwithstanding our focus on the descriptive accuracy of the priority heuristic, we showed that it performed well on two criteria that have also been used to evaluate the performance of fast and frugal inference strategies, namely, frugality and transparency.

Perhaps one of the most surprising outcomes of the contest between the priority heuristic, the neo-Bernouillian models (i.e., those assuming some type of weighing and summing of reasons), and previously proposed heuristics, respectively, is the dismal performance of the latter. Why does the priority heuristic so clearly outperform the other heuristics? The key difference is that the classic heuristics (with the exception of the lexicographic heuristic) always look at the same piece or several pieces of information. The priority heuristic, in contrast, relies on a flexible stopping rule. Like the classic heuristics, it is frugal, but unlike them, it is adapted to the specific properties of a problem and its frugality is hence not independent of the problem in question. The sequential nature of the priority heuristic is exactly the same as that assumed in heuristics such as Take The Best, Take The Last, and fast and frugal trees (Gigerenzer, 2004). These heuristics, equipped with flexible stopping rules, are "in between" the classic heuristics that always rely on the same reason(s) and the neo-Bernoulli models that use all reasons. We believe this new class of heuristics to be of great importance. Its heuristics combine some of the advantages of both classic trade-off models and heuristics, thus achieving great flexibility, which enables them to respond to the characteristics of individual problems.

## Conclusion

We have shown that a person who uses the priority heuristic generates (i) the Allais paradox, (ii) risk aversion for gains if probabilities are high, (iii) risk seeking for gains if probabilities are low (e.g., lottery tickets), (iv) risk aversion for losses if probabilities are low (e.g., buying insurance), (v) risk seeking for losses if probabilities are high, (vi) the certainty effect, and (vii) the possibility effect. Furthermore, the priority heuristic is capable of accounting for choices that conflict with (cumulative) prospect theory, such as systematic intransitivities that can cause preference reversals. We tested how well the heuristic predicts people's majority choices in four different types of gambles; three of these had been designed to test the power of prospect theory, cumulative prospect theory, and security-potential/aspiration theory, and the fourth was a set of random gambles. Nevertheless, despite this test in "hostile" environments, the priority heuristic predicted people's preference better than previously proposed heuristics as well as three modifications of expected utility theory did. We also identified an important boundary of the priority heuristic. Specifically the heuristic performed best when the ratio between expected values was about two or smaller. Finally, the heuristic specifies a process that leads to predictions about response time differences between choice problems, which we tested and confirmed.

We believe that the priority heuristic, which is based on the same building blocks as Take The Best, can serve as a new framework for models for a wide range of cognitive processes, such as attitude formation or expectancy-value theories of motivation. The heuristic provides an alternative to the assumption that cognitive processes always compute trade-offs in the sense of weighting and summing of information. We do not claim that people never make trade-offs in choices, judgments of facts, values, and morals. That would be as mistaken as assuming that they always do. Rather, the task ahead is to understand when people make trade-offs and when they do not.

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# Appendix

Choice Problems from the Gain Domain Used in Response Time Experiment

| **Two-outcome gambles** | | | |
|---|---|---|---|
| **One reason examined** | | **Three reasons examined** | |
| **EV similar** | **EV dissimilar** | **EV similar** | **EV dissimilar** |
| (2,000, .60; 500, .40) | (3,000, .60; 1,500, .40) | (2,000, .10; 500, .90) | (5,000, .10; 500, .90) |
| (2,000, .40; 1,000, .60) | (2,000, .40; 1,000, .60) | (2,500, .05; 550, .95) | (2,500, .05; 550, .95) |
| (5,000, .20; 2,000, .80) | (6,000, .20; 3,000, .80) | (4,000, .25; 3,000, .75) | (7,000, .25; 3,000, .75) |
| (4,000, .50; 1,200, .50) | (4,000, .50; 1,200, .50) | (5,000, .20; 2,800, .80) | (5,000, .20; 2,800, .80) |
| (4,000, .20; 2,000, .80) | (5,000, .20; 3,000, .80) | (6,000, .30; 2,500, .70) | (9,000, .30; 2,500, .70) |
| (3,000, .70; 1,000, .30) | (3,000, .70; 1,000, .30) | (8,200, .25; 2,000, .75) | (8,200, .25; 2,000, .75) |
| (900, .40; 500, .60) | (1,900, .40; 1,500, .60) | (3,000, .40; 2,000, .60) | (6,000, .40; 2,000, .60) |
| (2,500, .20; 200, .80) | (2,500, .20; 200, .80) | (3,600, .35; 1,750, .65) | (3,600, .35; 1,750, .65) |
| (1,000, .50; 0, .50) | (2,000, .50; 1,000, .50) | (2,500, .33; 0, .67) | (5,500, .33; 0, .67) |
| (500, 1.00) | (500, 1.00) | (2,400, .34; 0, .66) | (2,400, .34; 0, .66) |
| Five-outcome gambles | | | |
| One reason examined | | Three reasons examined | |
| EV similar | EV dissimilar | EV similar | EV dissimilar |
| (200, .04; 150, .21; 100, .50; 50, .21; 0, .04) | (200, .04; 150, .21; 100, .50; 50, .21; 0, .04) | (200, .04; 150, .21; 100, .50; 50, .21; 0, .04) | (250, .04; 200, .21; 150, .50; 100, .21; 0, .04) |
| (200, .04; 165, .11; 130, .19; 95, .28; 60, .38) | (250, .04; 215, .11; 180, .19; 145, .28; 110, .38) | (140, .38; 105, .28; 70, .19; 35, .11; 0, .04) | (140, .38; 105, .28; 70, .19; 35, .11; 0, .04) |
| (200, .04; 165, .11; 130, .19; 95, .28; 60, .38) | (250, .04; 215, .11; 180, .19; 145, .28; 110, .38) | (200, .20; 150, .20; 100, .20; 50, .20; 0, .20) | (250, .20; 200, .20; 150, .20; 100, .20; 0, .20) |
| (140, .38; 105, .28; 70, .19; 35, .11; 0, .04) | (140, .38; 105, .28; 70, .19; 35, .11; 0, .04) | (240, .15; 130, .30; 100, .10; 50, .30; 0, .15) | (200, .15; 150, .30; 100, .10; 50, .30; 0, .15) |
| (200, .20; 150, .20; 100, .20; 50, .20; 0, .20) | (200, .20; 150, .20; 100, .20; 50, .20; 0, .20) | (200, .32; 150, .16; 100, .04; 50, .16; 0, .32) | (250, .32; 200, .16; 150, .04; 100, .16; 0, .32) |
| (200, .04; 165, .11; 130, .19; 95, .28; 60, .38) | (250, .04; 215, .11; 180, .19; 145, .28; 110, .38) | (348, .04; 261, .11; 174, .19; 87, .28; 0, .38) | (348, .04; 261, .11; 174, .19; 87, .28; 0, .38) |
| (200, .04; 165, .11; 130, .19; 95, .28; 60, .38) | (250, .04; 215, .11; 180, .19; 145, .28; 110, .38) | (348, .04; 261, .11; 174, .19; 87, .28; 0, .38) | (398, .04; 311, .11; 224, .19; 137, .28; 0, .38) |
| (200, .32; 150, .16; 100, .04; 50, .16; 0, .32) | (200, .32; 150, .16; 100, .04; 50, .16; 0, .32) | (260, .15; 180, .15; 120, .15; 80, .20; 0, .35) | (260, .15; 180, .15; 120, .15; 80, .20; 0, .35) |
| (348, .04; 261, .11; 174, .19; 87, .28; 0, .38) | (348, .04; 261, .11; 174, .19; 87, .28; 0, .38) | (260, .15; 180, .15; 120, .15; 80, .20; 0, .35) | (310, .15; 230, .15; 170, .15; 130, .20; 0, .35) |
| (200, .04; 165, .11; 130, .19; 95, .28; 60, .38) | (250, .04; 215, .11; 180, .19; 145, .28; 110, .38) | (200, .32; 150, .16; 100, .04; 50, .16; 0, .32) | (200, .32; 150, .16; 100, .04; 50, .16; 0, .32) |




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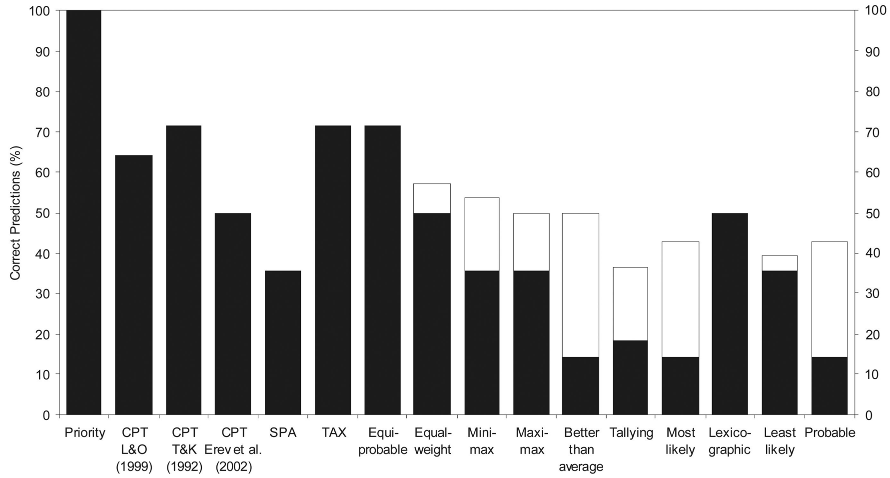


**Figure 1.**

Correct predictions of the majority responses for all monetary one-stage choice problems (14) in Kahneman and Tversky (1979). The black parts of the bars represent correct predictions without guessing, the union of the black and white parts represents correct predictions with guessing (counting as 0.5). Because the Erev et al. (2002) set of problems consists of positive gambles, its fitted parameters only allow for predicting the choice behavior for positive one-stage gambles (making eight problems). CPT (L&O, 1999), CPT (T&K, 1992), CPT (Erev et al., 2002): Parameters for cumulative prospect theory (CPT) were estimated from Lopes and Oden (1999), Tversky and Kahneman (1992), and Erev et al. (2002), respectively. SPA: Security-potential/aspiration theory; TAX: Transfer of attention exchange model.

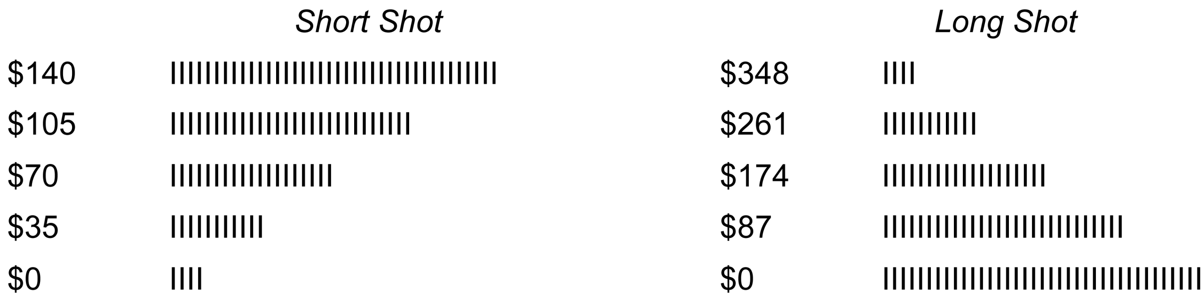


**Figure 2.**

A typical choice problem used in contest 2, taken from Lopes and Oden (1999). Each lottery has 100 tickets (represented by marks) and has an expected value of approximately $100. Values at the left represent gains or losses.

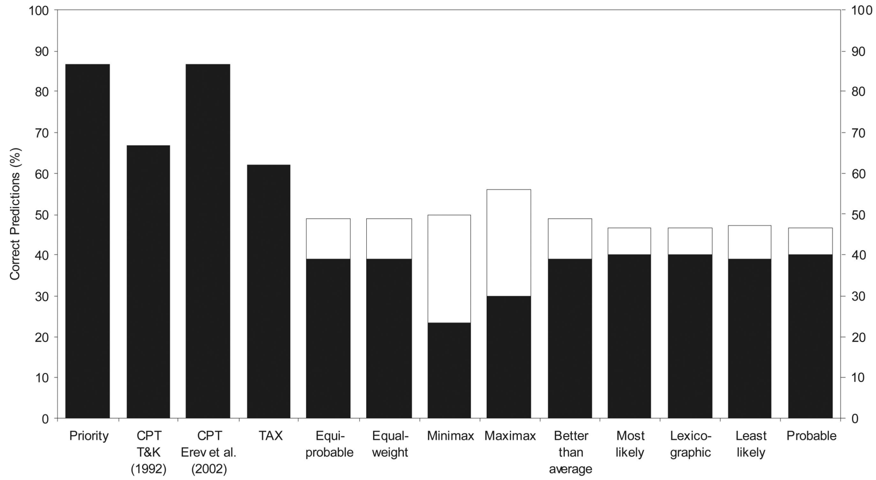


**Figure 3.**
Correct predictions of the majority responses for the 90 five outcome choice problems in Lopes and Oden (1999). The black parts of the bars represent correct predictions without guessing, the union of the black and white parts represents correct predictions with guessing (counting as 0.5). Tallying was not applicable (see footnote 4). The parameters taken from Erev et al. (2002) predict gains only. CPT (T&K, 1992), CPT (Erev et al., 2002): Parameters for cumulative prospect theory (CPT) are from Tversky and Kahneman (1992) and Erev et al. (2002), respectively. TAX: Transfer of attention exchange model.

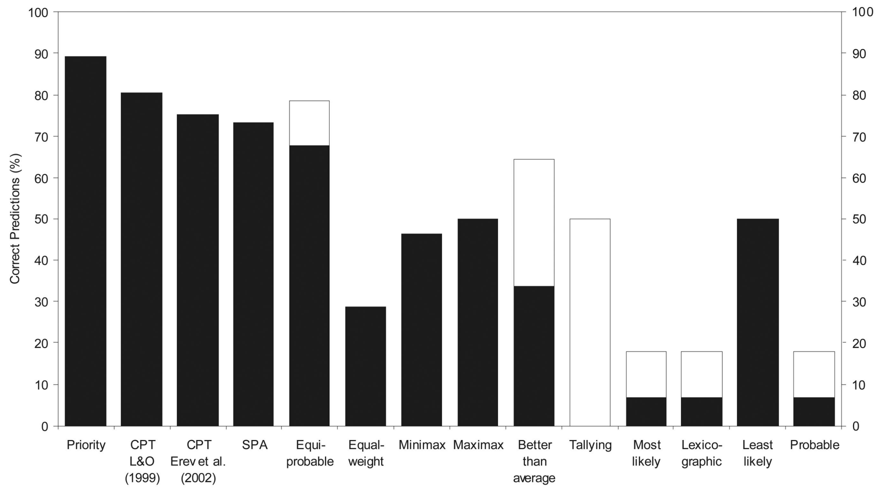


**Figure 4.**

Correct predictions of the majority responses for the 56 certainty equivalence problems in Tversky and Kahneman (1992). The black parts of the bars represent correct predictions without guessing, the union of the black and white parts represents correct predictions with guessing (counting as 0.5). The parameters taken from Erev et al. (2002) predict gains only. CPT (L&O, 1999), CPT (Erev et al., 2002): Parameters for cumulative prospect theory (CPT) are from Lopes and Oden (1999) and Erev et al. (2002), respectively. In the latter set of problems predictions refer to gains only. SPA: Security-potential/aspiration theory.




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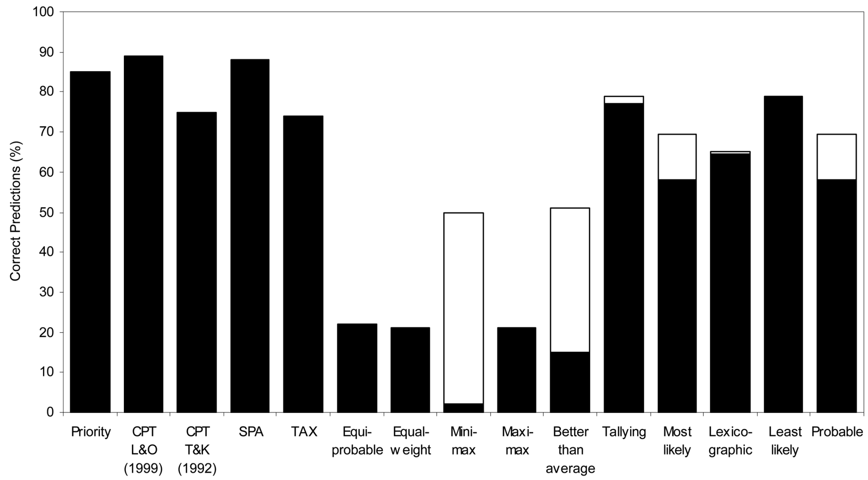


**Figure 5.**

Correct predictions of the majority responses for the 100 random choice problems in Erev et al. (2002). The black parts of the bars represent correct predictions without guessing, the union of the black and white parts represents correct predictions with guessing (counting as 0.5). CPT (L&O, 1999), CPT (T&K, 1992): Parameters for cumulative prospect theory (CPT) were taken from Lopes and Oden (1999) and Tversky and Kahneman (1992), respectively. SPA: Security-potential/aspiration theory; TAX: Transfer of attention exchange model.

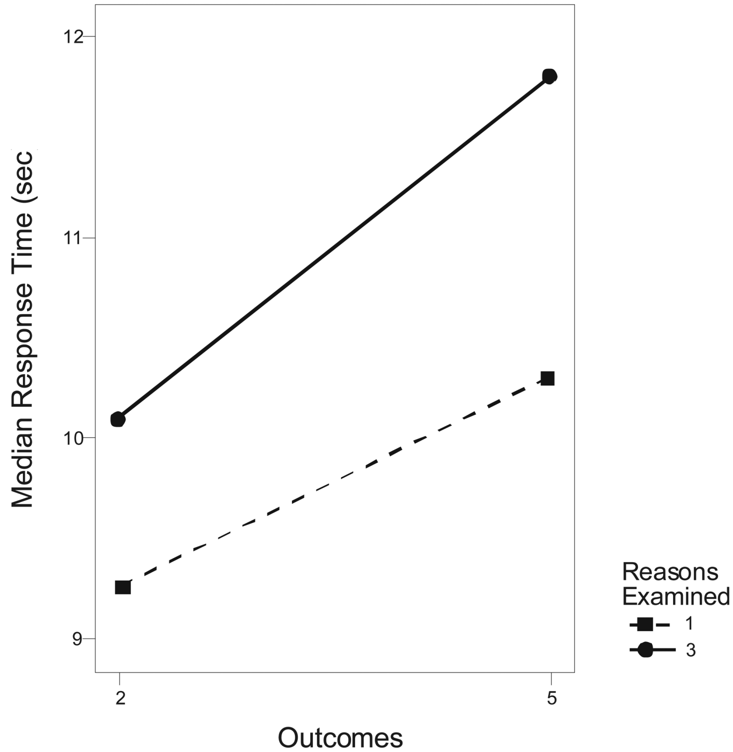


**Figure 6.**
Participants' median response time dependent on the number of outcomes and the number of reasons examined.


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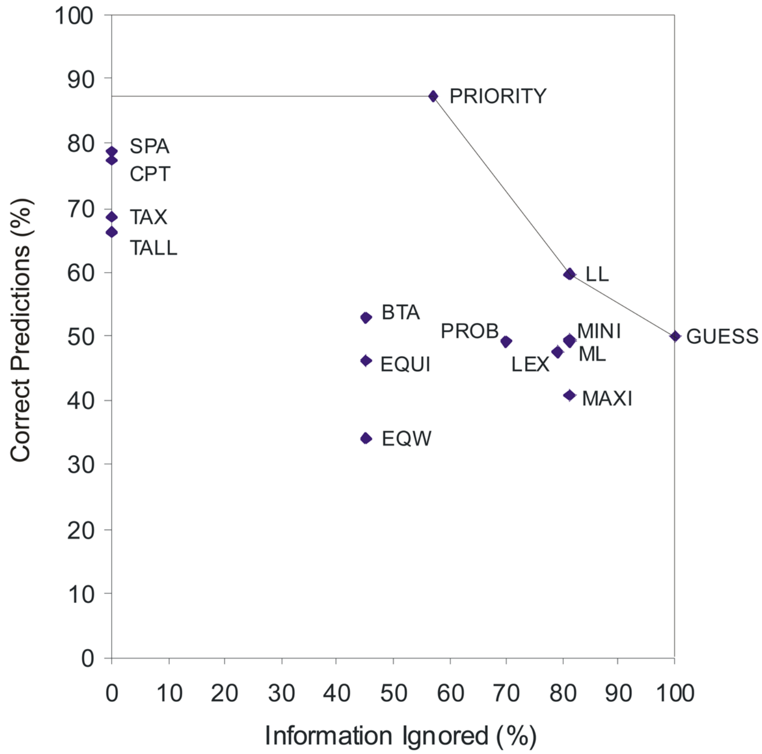


**Figure 7.**

Predictability/frugality trade-off, averaged over all four sets of problems. The percentage of correct predictions refers to majority choices (including guessing).

PRIORITY: Priority heuristic, CPT: Cumulative prospect theory, SPA: Security-potential/aspiration theory, TAX: Transfer of attention exchange model, TALL: Tallying, LEX: Lexicographic heuristic, EQW: Equal-weight heuristic, LL: Least likely heuristic, ML: Most likely heuristic, BTA: Better than average heuristic, EQUI: Equiprobable heuristic, PROB: Probable heuristic, GUESS: Pure guessing, MINI: Minimax heuristic, MAXI: Maximax heuristic. For a description of the heuristics, see Table 3.

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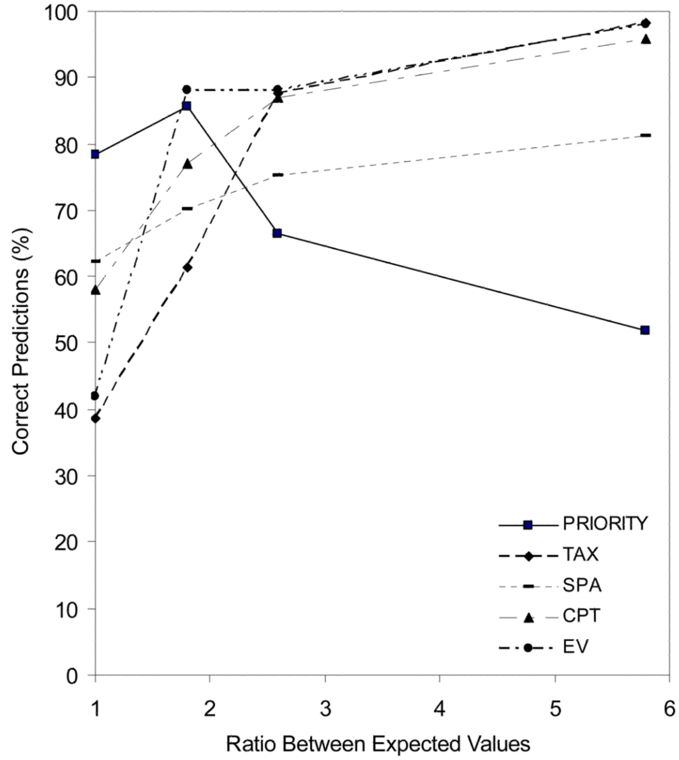


**Figure 8.**
Correct predictions dependent on the ratio between expected values for the set of problems in Mellers et al. (1992). PRIORITY: Priority heuristic, CPT: Cumulative prospect theory, SPA: Security-potential/aspiration theory, TAX: Transfer of attention exchange model, EV: Expected value model.

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## Table 1

The Fourfold Pattern

| Probability | Gain | Loss |
|---|---|---|
| low | $C(100, .05) = 14$ | $C(-100, .05) = -8$ |
| | Risk seeking | Risk aversion |
| high | $C(100, .95) = 78$ | $C(-100, .95) = -84$ |
| | Risk aversion | Risk seeking |

*Note*: $C(100, .05)$ represents the median certainty equivalent for the gamble to win $100 with probability $p = .05$, otherwise nothing (based on Tversky & Fox, 1995).

## Table 2

Violations of Transitivity:

| | B | C | D | E |
|---|---|---|---|---|
| *A* (5.00; .29) | **.65** | **.68** | .51 | **.37** |
| *B* (4.75; .33) | | **.73** | **.56** | **.45** |
| *C* (4.50, .38) | | | **.73** | **.65** |
| *D* (4.25; .42) | | | | **.75** |
| *E* (4.00; .46) | | | | - |

*Note*. Gamble *A*, (5.00; .29), for instance, offers a win of $5 with probability $p = .29$, otherwise nothing. Cell entries represent proportion of times that the row gamble was preferred to the column gamble, averaged over all participants from Tversky (1969). Bold numbers indicate majority choices correctly predicted by the priority heuristic.

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**Table 3**

Heuristics for Risky Choice

| ***Outcome Heuristics*** |
|---|
| *Equiprobable:* Calculate the arithmetic mean of all monetary outcomes within a gamble. Choose the gamble with the highest monetary average.<br>Equiprobable chooses gamble *B*, because *B* has a higher mean (3,000) than *A* (2,000). |
| *Equal-weight:* Calculate the sum of all monetary outcomes within a gamble. Choose the gamble with the highest monetary sum.<br>Equal-weight chooses gamble *A*, because *A* has a higher sum (4,000) than *B* (3,000). |
| *Minimax:* Select the gamble with highest minimum payoff.<br>Because gamble *A* has a lower minimum outcome (0) than *B* (3,000), minimax selects *B*. |
| *Maximax:* Choose the gamble with the highest monetary payoff.<br>Maximax chooses *A*, since its maximum payoff (4,000) is the highest outcome. |
| *Better than average*: Calculate the grand average of all outcomes from all gambles. For each gamble, count the number of outcomes equal to or above the grand average. Then select the gamble with the highest number of such outcomes.<br>The grand average equals 7,000 / 3 = 2,333. Because both gambles, *A* and *B*, have one outcome above this threshold, the better than average heuristic has to guess. |
| ***Dual Heuristics*** |
| *Tallying:* Give a tally mark to the gamble with (a) the higher minimum gain, (b) the higher maximum gain, (c) the lower probability of the minimum gain, and (d) the higher probability of the maximum gain. For losses, replace "gain" by "loss" and "higher" by "lower" (and vice versa). Select the gamble with the higher number of tally marks.<br>Tallying has to guess, because both the sure gain of 3,000 (one tally mark for the higher minimal outcome, one for the higher probability of the maximum outcome) and the risky gamble (one tally mark for the lower probability of the minimal outcome, one for the higher maximum outcome) receive two tally marks each. |
| *Most likely:* Determine the most likely outcome of each gamble and their respective payoffs. Then select the gamble with the highest, most likely payoff.<br>Most likely selects 4,000 as the most likely outcome for gamble *A*, and 3,000 as the most likely outcome for *B*. Because 4,000 exceeds 3,000, most likely chooses gamble *A*. |
| *Lexicographic:* Determine the most likely outcome of each gamble and their respective payoffs. Then select the gamble with the highest, most likely payoff. If both payoffs are equal, determine the second most likely outcome of each gamble, and select the gamble with the highest (second most likely) payoff. Proceed until a decision is reached.<br>Lexicographic selects 4,000 as the most likely outcome for gamble *A*, and 3,000 as the most likely outcome for *B*. Because 4,000 exceeds 3,000, lexicographic chooses gamble *A*. |
| *Least likely:* Identify each gamble's worst payoff. Then select the gamble with the lowest probability of the worst payoff.<br>Least likely selects 0 as the worst outcome for gamble *A*, and 3,000 as the worst outcome for *B*. Because 0 is less likely to occur (i.e., with $p = .20$) than 3,000 ($p = 1.00$), least likely chooses gamble *A*. |
| *Probable:* Categorize probabilities as probable (i.e., $p \geq .50$ for a two-outcome gamble, $p \geq .33$ for a three-outcome gamble, etc.) or improbable. Cancel improbable outcomes. Then calculate the arithmetic mean of the probable outcomes for each gamble. Finally, select the gamble with the highest average payoff.<br>Probable selects gamble *A*, because of its higher probable outcome (4,000) compared to *B* (3,000). |

*Note*. Heuristics are from Thorngate (1980) and Payne et al. (1993). The choice predicted by each heuristic is shown for the pair of gambles *A* (4,000; .80) and *B* (3,000).

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## Table 4

Parameter Estimates for Cumulative Prospect Theory

| | Parameter Estimates | | | | |
|---|---|---|---|---|---|
| **Set of problems** | **α** | **β** | **λ** | **γ** | **δ** |
| Lopes & Oden (1999) | 0.55 | 0.97 | 1.00 | 0.70 | 0.99 |
| Tversky & Kahneman (1992) | 0.88 | 0.88 | 2.25 | 0.61 | 0.69 |
| Erev et al. (2002) | 0.33 | | | 0.75 | |

*Note*. The parameters $\alpha$ and $\beta$ capture the shape of the value function for gains and losses, respectively; $\lambda$ captures loss aversion, $\gamma$ and $\delta$ capture the shape of the probability weighting function for gains and losses, respectively. See Equations 5 to 8. The Erev et al. (2002) set of problems is based on gains only.

**Table 5**

Percentage of Same Predictions of Each Pair of Strategies

| | PRIORITY | CPT L&O (1999) | CPT Erev et al. (2002) | CPT T&K (1992) | TAX | SPA | MAXI | MINI | TALL | ML | LL | BTA | EQUI | EQW | PROB |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| CPT L&O (1999) | 78 | | | | | | | | | | | | | | |
| CPT Erev et al. (2002) | 89 | 92 | | | | | | | | | | | | | |
| CPT T&K (1992) | 68 | 80 | 60 | | | | | | | | | | | | |
| TAX | 65 | 77 | 57 | *96* | | | | | | | | | | | |
| SPA | 72 | *91* | 81 | 77 | 76 | | | | | | | | | | |
| MAXI | 38 | 40 | 26 | 57 | 58 | 44 | | | | | | | | | |
| MINI | 51 | 49 | 75 | 59 | 60 | 47 | 39 | | | | | | | | |
| TALL | 70 | 62 | 56 | 52 | 51 | 63 | 20 | 49 | | | | | | | |
| ML | 51 | 57 | 48 | 42 | 41 | 62 | 39 | 43 | 60 | | | | | | |
| LL | 64 | 62 | 48 | 38 | 36 | 66 | 36 | 32 | 81 | 67 | | | | | |
| BTA | 49 | 57 | 46 | 70 | 72 | 57 | 67 | 53 | 43 | 32 | 39 | | | | |
| EQUI | 43 | 43 | 51 | 64 | 70 | 41 | 77 | 59 | 19 | 22 | 19 | 74 | | | |
| EQW | 31 | 27 | 32 | 62 | 65 | 27 | 77 | 58 | 19 | 32 | 19 | 69 | 84 | | |
| PROB | 51 | 57 | 48 | 42 | 41 | 62 | 39 | 43 | 60 | 89 | 67 | 32 | 22 | 32 | |
| LEX | 50 | 53 | 44 | 44 | 42 | 60 | 44 | 44 | 51 | 89 | 62 | 33 | 28 | 37 | 89 |

*Note*. The numbers specify the percentage of problems in which two strategies made the same predictions. For instance, the priority heuristic and minimax (MINI) made the same predictions in 51% of all problems and different predictions in 49% of them. PRIORITY: Priority heuristic. CPT (L&O, 1999), CPT (Erev et al., 2002), CPT (T&K, 1992): Parameters for cumulative prospect theory (CPT) were estimated from Lopes and Oden (1999), Erev et al. (2002), and Tversky and Kahneman (1992), respectively. TAX: Transfer of attention exchange model, SPA: Security-potential/aspiration theory, MAXI: Maximax heuristic, MINI: Minimax heuristic, TALL: Tallying, ML: Most likely heuristic, LL: Least likely heuristic, BTA: Better than average heuristic, EQUI: Equiprobable heuristic, EQW: Equal-weight heuristic, PROB: Probable heuristic, LEX: Lexicographic heuristic. For a description of the heuristics, see Table 3.