

## BOUNDED RATIONALITY

### Two Interpretations from Psychology

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Perhaps more than anybody else in economic theory, Herbert A. Simon stressed that individual decision makers have no choice but to make decisions under the constraints of limited cognitive resources (e.g., Simon 1978). On the basis of this indisputable truth about the human cognitive system, he challenged classical economic theory, which in his view projected an omniscient rationality assuming unbounded knowledge, computational capacities, and time. He also targeted Milton Friedman's (1953) famous defense of classic economic theory, "The Methodology of Positive Economics." Responding to the criticism that economic theory rests on unrealistic assumptions, Friedman argued:

Complete "realism" is clearly unattainable, and the question whether a theory is realistic "enough" can be settled only by seeing whether it yields predictions that are good enough for the purpose in hand. (Friedman 1953, 41)

In Friedman's view, the purpose in hand is to account for aggregate behavior, that is, the behavior of firms, institutions, or, more generally, the market. Therefore, unrealistic assumptions and possible discrepancies between the predictions of the theories and individual choice behavior need not be detrimental to the fate of economic theory. Not without some smugness, Simon pointed out that "economists who are zealous in insisting that economic actors maximize [subsequently] turn around and become satisficers"—people satisfied with workable, if not optimal, solutions—"when the evaluation of their own theories is concerned," as in Friedman's good-enough criterion (Simon 1979, 495). Moreover, he argued that psychologically plausible theories of decision making, which assume realistic limits on the knowledge and computational abilities of the human agent, also lead to conclusions at the level of aggregate phenomena. Importantly, these conclusions are not always the same as those suggested by neoclassical theory, thus rendering possible crucial tests (Simon 1979). Simon's vision of a different rationality of economic behavior, *bounded rationality* (Simon 1956, 1990), has not only posed a challenge to economic theory but has also suggested a new research agenda revolving around the following key question: how rational are people, given their limited computational capabilities and their incomplete knowledge?

In psychology, two research programs have worked toward answering this question, and their answers are drastically different. One program is the heuristics and biases program instigated in the

early 1970s by Daniel Kahneman and Amos Tversky; the other is the program on fast and frugal heuristics initiated by Gerd Gigerenzer and colleagues (e.g., Gigerenzer and Goldstein 1996; Gigerenzer, Todd, and the ABC Research Group 1999). Economists have typically been exposed to only one of psychology's views on bounded rationality, namely, that of the heuristics and biases program (e.g., Rabin 1998). The goal of this chapter is to introduce economists to the view of bounded rationality as espoused by the fast and frugal heuristics program. Specifically, we describe how differently the two programs have portrayed decision making under the constraints of limited cognitive resources, how differently they have interpreted the role of classic standards of rationality, and how divergent their implications for economic theory are. We first turn to the heuristics and biases program.

### BOUNDED RATIONALITY AS IRRATIONALITY

The heuristics and biases program is undoubtedly the most influential psychological research program on human reasoning, judgment, and decision making over the past three decades. One key to this success is a brilliantly straightforward research strategy: first, participants in an experiment are presented with a reasoning problem to which there is, it is assumed, one unambiguous and normatively correct answer in terms of a rule from probability theory and statistics. Next, participants' responses are compared with the solution entailed by those norms, and the more-or-less inevitable (Hertwig and Todd 2000) systematic deviations that are found between the responses and the normative solutions are pronounced "biases," "fallacies," or "cognitive illusions." Finally, these biases are explained as the consequence of the use of some heuristic of reasoning.

Based on this strategy, the heuristics and biases program of Kahneman, Tversky, and others (e.g., Kahneman, Slovic, and Tversky 1982; Tversky and Kahneman 1974; Gilovich, Griffin, and Kahneman 2002) has produced two main results: (1) an extensive catalogue of norm violations such as the base-rate fallacy, the overconfidence bias, and the conjunction fallacy, and (2) explanations of these violations in terms of a small set of cognitive heuristics, of which the three most prominent are the availability, representativeness, and anchoring and adjustment heuristics. For illustration, consider base-rate neglect—from an economic perspective, a very significant error in probabilistic reasoning—and one of its explanations, the representativeness heuristic. When probabilities need to be updated to reflect new information, people are assumed to reason in a Bayesian way so as to maximize their benefit. In other words, people are assumed to be rational Bayesian expected utility maximizers. But are they really? Investigating people's reasoning in simple situations involving a binary predictor and criterion, Kahneman and Tversky concluded: "Man is apparently not a conservative Bayesian: he is not Bayesian at all" (1972, 450). They derived this conclusion from people's responses to reasoning problems such as the engineer-lawyer problem (Kahneman and Tversky 1973, 241). One group of participants read the following information:

A panel of psychologists have interviewed and administered personality tests to 30 engineers and 70 lawyers, all successful in their respective fields. On the basis of this information, thumbnail descriptions of the 30 engineers and 70 lawyers have been written. You will find on your forms five descriptions, chosen at random from the 100 available descriptions. For each description, please indicate the probability that the person described is an engineer, on a scale from 0 to 100.

A second group received the same instructions, except the base rates were inverted (i.e., 70 engineers and 30 lawyers). All participants received the same personality descriptions, of which one read as follows:

Jack is a 45-year-old man. He is married and has four children. He is generally conservative, careful, and ambitious. He shows no interest in political and social issues and spends most of his free time on his many hobbies, which include home carpentry, sailing, and mathematical puzzles. The probability that Jack is one of the 30 engineers in the sample of 100 is \_\_\_\_\_%.

Although the likelihoods— $p(\text{description}|\text{engineer})$  and  $p(\text{description}|\text{lawyer})$ —are not specified in this problem, it is still possible to use Bayes's theorem to compute the posterior probabilities by calculating the ratio of the odds in both groups, so that the likelihoods cancel out (see Kahneman and Tversky 1973). Bayes's theorem indicates that the posterior probabilities are different for the problems faced by the two groups of participants. In contrast to this norm, Kahneman and Tversky (1973) observed that the mean responses in the two groups, one receiving the base rate information 30 to 70, the other receiving 70 to 30, were for the most part the same. They concluded that "our subjects . . . failed to integrate prior probability with specific evidence. . . . The failure to appreciate the relevance of the prior probability in the presence of specific evidence is perhaps one of the most significant departures of intuition from the normative theory of prediction" (p. 243).

People's flawed intuition in the engineer-lawyer problem was explained by Kahneman and Tversky in terms of the *representativeness* heuristic. On this explanation, people determine the posterior probability by judging the similarity between the description of, say, Jack and the stereotype of an engineer. In other words, the degree to which the miniature bio is representative of (i.e., similar to) the stereotype shapes the probability assessment. In Kahneman and Tversky's view, reasoning abilities that reflect the laws of probability and logic are not part of the intuitive repertoire of the human mind. Instead, due to our limited cognitive capacities—the property of human information processing that Simon reminded economists about—adults need to rely on quick shortcuts, or heuristics such as representativeness, when we reason about unknown or uncertain aspects of real-world environments. But this use of heuristics leaves human reasoning prone to "severe and systematic errors" (Tversky and Kahneman 1974, 1124).

This portrayal of flawed human decision making under the constraints of limited cognitive capacities has shaped the bleak image that many psychologists have of human reasoning. In a recent critical review of research in the tradition of the heuristics and biases program in social psychology, Krueger and Funder (2004) described how lopsided in their view the social-psychological portrayal of human reasoning has become: human reasoning in the view of many psychologists is "ludicrous," "indefensible," and "self-defeating." This negative view has also extended to the concepts of heuristics and bounded rationality. Kahneman and Tversky's treatment of the terms *heuristics* and *biases* as more or less two sides of the same coin has created a connotation of irrationality that differs sharply from earlier usage of the heuristic concept in psychology and beyond (see Hertwig and Todd 2002). Though in Kahneman and Tversky's articles one finds only scant explicit references to Simon, they see their program as being inspired by his concern, namely, the investigation of "strategies of simplification that reduce the complexity of judgment tasks, to make them tractable for the kind of mind that people happen to have" (Kahneman, Slovic, and Tversky 1982, xii). By identifying this common ground with Simon's concept of bounded rationality, they also suggested a new interpretation of bounded rationality in terms of errors, biases, cognitive illusions, and, ultimately, human irrationality. This interpretation is the one that was adopted by key players in the field of behavioral economics early on and has been explicitly promoted since then. In the words of Richard Thaler:

Research on judgment and decision making under uncertainty, especially by Tversky and Kahneman (1974; Kahneman and Tversky 1996), has shown that such mental illusions

should be considered the rule rather than the exception. Systematic, predictable differences between normative models of behavior and actual behavior occur because of what Herbert Simon (1957, p. 198) called "bounded rationality." (Thaler 2000, 270)

Indeed, much of today's behavioral economics and finance draws its inspiration and concepts from the heuristics and biases paradigm (e.g., Thaler 1993; Shiller 2000). There are excellent reasons for this attention, as systematic biases in individual decision making may have important economic implications that cannot or will not be remedied by the market. Camerer (1995, 594), for example, has conjectured that the well-documented high failure rate of small businesses may be due to overconfidence, one of the stock-in-trade examples of a cognitive illusion in the heuristics and biases program. Similarly, Odean and his collaborators have argued that overconfidence based on misinterpretation of random sequences of successes leads some (usually male) investors to trade too much (Barber and Odean 2000, 2001; Odean 1999). Shiller (2000) drew explicitly on the experimental findings of the heuristics and biases program to explain irrational exuberance in the stock market, and Hanson and Kysar (1999a, 1999b) argued that the reality of cognitive illusions has opened the door to systematic manipulation of consumer product markets. In what follows we analyze the notion of rationality endorsed by the heuristics and biases program and argue that the program's exclusive focus on human irrationality hinges critically on a narrow view of norms of sound reasoning.

### **Rationality Assumptions in the Heuristics and Biases Program**

Most researchers of reasoning and decision making today share a vision whose roots trace back to the Enlightenment (see Chase, Hertwig, and Gigerenzer 1998). The original classical view held that the laws of probability and logic stem from, and indeed are equivalent to, the laws of human inference. For French astronomer Pierre Laplace, for example, probability theory embodied human intuition: "The theory of probability is at bottom nothing more than good sense reduced to a calculus" (1814, 196). Nineteenth-century German philosopher Theodor Lipps wrote that logic "is nothing if not the physics of thought" (1880, 530). So fundamental was the belief that the mind worked by the rules of probability and logic that when human intuition was observed to deviate from the current set of rules, the rules themselves were revised (Daston 1988). In short, many pre-twentieth-century thinkers believed that the psychological defines the rational.

Variants of the classical view have flourished in twentieth-century psychology. Many researchers maintain the belief that the laws of probability theory and logic at least approximately describe human inference. In the view of Cameron Peterson and Lee Beach, for example, "probability theory and statistics can be used as the basis for psychological models that integrate and account for human performance in a wide range of inferential tasks" (1967, 29). According to Jean Piaget, cognitive development culminates in a set of logico-mathematical abilities that essentially reflect the laws of probability and logic. More recently, psychologist Lance Rips (1994) has argued for the existence of "mental logic." Unlike their Enlightenment predecessors, however, these modern researchers see classical logical models as norms against which human reasoning can be evaluated rather than as codifications of that reasoning: when the two diverge, it is now concluded that there is something wrong with the reasoning, not with the norms.

The research program that perhaps most strongly emphasizes the divergence between laws of reasoning and laws of probability theory is the heuristics and biases program. The proponents of this program share with proponents of the neo-Enlightenment view, such as Peterson and Beach (1967),

the conviction that rationality requires reasoning in accordance with the rules of probability theory. The problem is that people often fail to reason rationally in this way due to their limited resources. Indeed, in this view reasoning is error-prone to the extent that it is powered by quick-and-dirty cognitive heuristics. This premise is markedly different from Simon's view. Simon believed that investigations of bounded rationality would ultimately bring about new norms of rational decision making that, unlike the classical norms, rest on realistic assumptions about the human cognitive machine (Simon 1979, 499).

By pitting human behavior against classic norms of rationality, the heuristics and biases program has made good use of a simple and prolific research strategy. However, the research program relies on the premise that rationality requires reasoning in accordance with the rules of probability theory, statistics, and logic. This means that the broad conclusion that people do not behave rationally hinges on the assumption that these rules are the appropriate norms of rationality in the context of the tasks studied. As we next discuss, this assumption founders on the fact that there is often more than one applicable norm, and moreover, each norm may allow multiple solutions.

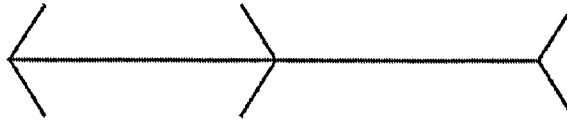
### **The Pretense of Unequivocal Norms**

Violations of probability theory as documented by the heuristics and biases program have been called "cognitive illusions" (Tversky and Kahneman 1974). By using the illusion metaphor, an analogy is drawn between inference and perception or, more precisely, between errors in reasoning and errors in visual perception. This analogy is indeed supported by the similar research strategy in both fields: just as vision researchers construct situations in which the functioning of the visual system leads to incorrect inferences about the world (e.g., about line lengths in the Müller-Lyer illusion; see Figure 11.1), researchers in the heuristics and biases program select problems in which reasoning by cognitive heuristics leads to violations of probability theory (Lopes 1991). However, the conclusions the latter researchers draw from such designs often differ sharply from those drawn by researchers of perception. Vision scientists do not conclude from the robustness of the Müller-Lyer illusion, for instance, that people are generally poor at inferring object length. In contrast, many advocates of the heuristics and biases program conclude from the cognitive illusions found in laboratory tasks that human judgment is subject to severe and systematic biases, that these biases are the rule rather than the exception (Thaler 2000), and that they compromise the mind's general functioning (e.g., Piattelli-Palmarini 1994).

These forlorn conclusions are even more surprising given that the benchmarks for determining the accuracy of mental inferences are much more controversial than benchmarks for perceptual inferences. In research on visual illusions, the perceiver's judgment is compared to the physical dimensions of the object. For instance, in the Müller-Lyer illusion one can establish the correct judgment by measuring the lengths of the two horizontal lines. In contrast, in research on cognitive illusions, the reasoner's judgment will be compared to the rules of probability theory such as Bayes's rule. While there is in all likelihood little disagreement over the length of two lines (once they are measured in an agreed-upon way), there is substantive disagreement over how to use a normative inference standard such as Bayes's rule.

For one thing, no single conception of probability is shared by all statisticians and philosophers. Champions of different conceptions disagree on the applicability of the rules of probability theory to unique events, with some contending that they apply to unique events and others arguing that they apply only to classes of events (see Gigerenzer et al. 1989). For someone who interprets probability in the latter, strictly frequentistic sense, these rules are irrelevant to the

Figure 11.1 Müller-Lyer Illusion



The line between the two arrows on the left is perceived as being shorter than the line between the two arrows at the right, although they are of identical length. Researchers in the heuristics and biases program have often drawn the analogy between illusions in perceptions and biases in reasoning. However, researchers in perception do not interpret the illusion as a demonstration of people's generally poor perception abilities.

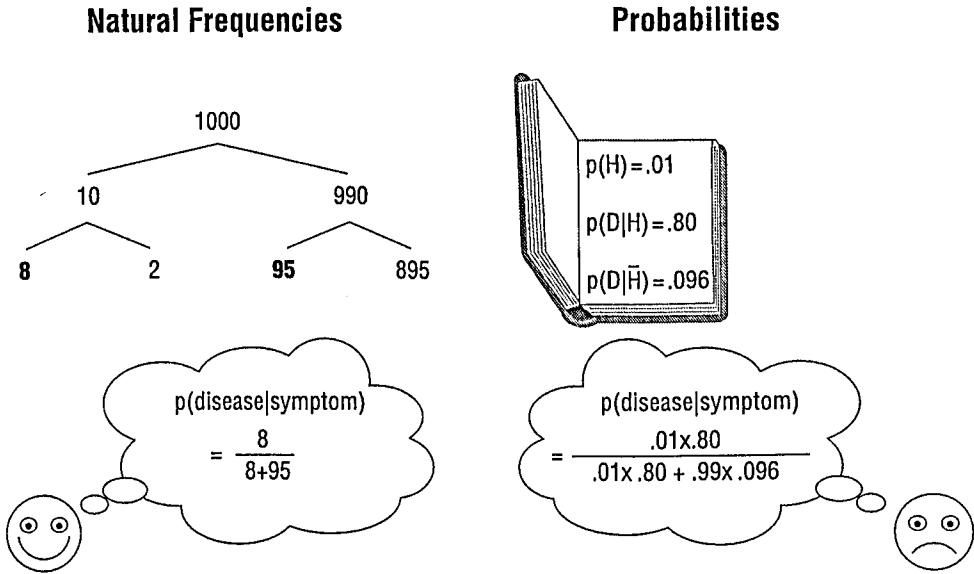
many tasks involving unique events studied in the heuristics and biases program (such as the probability that Jack is an engineer). Because of these existing different conceptions of probability, Gigerenzer (1991, 1994) has argued that wherever a norm's applicability depends on the interpretation of probability, it seems unjustified to treat it as an unequivocal norm of sound reasoning (for a recent debate on this point, see Kahneman and Tversky 1996; Gigerenzer 1996; Vranas 2000; Gigerenzer 2001).

This debate is not merely of philosophical relevance. In many experimental tasks people are asked to make probability judgments, and their judgments are compared with solutions derived from probability theory. But different norms also imply different ways of describing decision tasks, and this has implications for how to help people reason more clearly. Specifically, many of the acclaimed reasoning errors can be reduced or even made to disappear when people are given frequency information (e.g., "908 of 1,000") rather than probabilities (e.g., "90.8%") and asked for frequency judgments instead of probability judgments. For example, the prominent "overconfidence bias" refers to the finding that people's average probability judgment is often higher than their percentage of correct answers. Gigerenzer (1994) and Gigerenzer, Hoffrage, and Kleinböling (1991) showed that the overconfidence bias disappears when participants estimate the number of correct answers instead of the probability that a particular answer is correct (see also Juslin, Olsson, and Winman 1998). Koehler, Gibbs, and Hogarth (1994) reported that the "illusion of control," referring to people's greater confidence in their predictive ability when being personally involved in a judgment (Langer 1975), is reduced when the single-event format is replaced by a frequency format, that is, when participants judge a series of events rather than a single event. Hertwig and Gigerenzer (1999) showed that the "conjunction fallacy," which refers to erroneously judging the conjunction of two statements as more probable compared to one of the statements alone, is markedly reduced and sometimes completely eliminated when information is presented in frequencies instead of single-event probabilities (but see Mellers, Hertwig, and Kahneman 2001).

Finally, Bayesian reasoning, that is, judging conditional probabilities, improves in lay people (Cosmides and Tooby 1996; Gigerenzer and Hoffrage 1995) and experts (Hoffrage and Gigerenzer 1998; Hoffrage et al. 2000; Hertwig and Hoffrage 2002) when Bayesian problems are presented in natural frequencies (i.e., absolute frequencies obtained by natural sampling) rather than in a single-event probability format (see Figure 11.2). Natural frequencies have also proven very effective in training people to make conjoint and conditional probability judgments and Bayesian inferences (Kurzenhäuser and Hoffrage 2002; Sedlmeier and Gigerenzer 2001).

People's apparent violations of norms of rationality have also been reported frequently for their preferences among gambles. However, finding gold standards for evaluating preferences is at least as controversial as finding norms for people's probability judgments. Due to the subject-

Figure 11.2 Illustration of a Bayesian Reasoning Problem



In a Bayesian reasoning problem involving symptoms and disease, conditional probability must be determined in order to assess the likelihood that someone with a particular symptom suffers from a given disease. The problem can be represented in either of two information formats: a single-event probability format or natural frequencies. The latter improves Bayesian reasoning.

tive character of people’s preferences, it is common to evaluate those preferences by referring to consistency principles, including transitivity and procedural invariances such as preference reversals. Grether and Plott (1979) showed that when people are presented with two bets, one with a high probability of a low payoff (P-bet) and one with a low probability of a high payoff (\$-bet), people prefer the P-bet when choosing between them, but when asked to provide a buying price for the two, they provide a higher price for the \$-bet. Thus, the two procedures for eliciting preferences lead to a reversal of those preferences. One reason for these inconsistencies could be that people use different strategies for making choices compared to making price estimates (Billings and Marcus 1983). For instance, when choosing between gambles, strategies that compare the different aspects of the gamble step by step with each other might be applied. In contrast, when making price estimates, strategies might be used that evaluate the gambles independently of each other. These strategies can be rather efficient for making preference decisions, fulfilling a norm of adaptive behavior, but may sometimes violate the norm of preference consistency, again raising the question of which norms should be applied.

**The Pretense of Unequivocal Solutions**

As pointed out earlier, the research strategy of the heuristics and biases program is ingeniously simple: people are presented with word problems designed such that reasoning according to a normative principle (e.g., from probability theory or statistics) leads to the “correct” response. Reasoning according to other principles (e.g., using the representativeness heuristic) in these problems results in a qualitatively different and thus “incorrect” response. In this research strat-

egy, the content of the word problems (e.g., the engineer-lawyer problem, the Linda problem, the cab problem) is largely irrelevant, because the content-blind normative principles are assumed to apply irrespective of the particular subject matter of the problems. The function of the content is merely decorative, to deliver the values or pieces of information that are to be mechanically plugged into the normative equation. In contrast to this mechanistic use of content-free norms, any realistic psychological modeling of rational judgment requires considering how people decide on which numbers (e.g., prior probabilities, likelihoods) should enter the equations, or on the particular information in a word problem that is relevant for the required judgment.

Take Birnbaum's (1983) thoughtful explication of a rational response to the cab problem, which, like the engineer-lawyer problem, was used to demonstrate that people are not updating probabilities according to Bayes's rule. It features a cab that is involved in a hit-and-run accident at night. The text provides the information that a witness identified the cab as being blue, along with information about the eyewitness's ability to discriminate blue and green cabs, and the base rate of blue and green cabs in the city. Rather than coming up with a normative solution by mechanically plugging these values into Bayes's formula, as is typically done in the heuristics and biases program, Birnbaum started with the content of the problem and made assumptions about various psychological processes witnesses may use. In terms of a signal detection model, for instance, witnesses may try to minimize some error function: if witnesses are concerned about being accused of incorrect testimony, then they may adjust their criterion so as to maximize the probability of a correct identification. If instead witnesses are concerned about being accused of other types of errors, then they can adjust their criterion so as to minimize those specific errors. Obviously, different goals will lead to different posterior probabilities (see Gigerenzer 1998 and Mueser, Cowan, and Mueser 1999 for the detailed arguments).

The lesson from Birnbaum's analysis is that "the normative solution to the cab problem requires the assumption of the theory of the witness, whether by the subject or the experimenter" (1983, 93). More generally, for many word problems there is often not one single "correct" solution (e.g., Hertwig and Gigerenzer 1999; Hertwig and Todd 2000). People make different assumptions about the pragmatically or semantically ambiguous information available in a given setting, and different assumptions may favor different solutions. Thus, depending on the content of problems and how this interacts with psychological processes, multiple "correct" responses may exist. The failure to recognize these interactions can lead reasonable responses to be misclassified as cognitive illusions (Kahneman and Tversky 1996; Gigerenzer 1996; Mellers, Hertwig, and Kahneman 2001).

Beyond the fact that the solution to a reasoning problem requires additional assumptions (e.g., a theory of the witness), there are other problems where we cannot practically determine the solutions. Consider the game of chess. It has long been known that there exists an optimal strategy for the game, but the strategy itself is unknown, and thus not surprisingly, chess masters may not move the pieces in accordance with it. But does that make them irrational? That would be an absurd position—after all, chess masters tend to outperform most other players. The imposition of norms of rationality on decision making is even more difficult outside of the clearly defined context of a board game: life seldom equips us with a strategy space as clearly defined as in chess. Instead we are typically faced with highly uncertain consequences of our decisions, and no possibility of finding an optimal solution. Therefore the only thing that humans can hope to achieve in such situations is to reach a good—not optimal—solution, just as Simon's satisficing approach proposed.

We now turn to the second view of bounded rationality that has emerged from research in psychology: the research program on fast and frugal heuristics initiated by Gigerenzer and colleagues (e.g., Gigerenzer and Goldstein 1996; Gigerenzer, Todd, and the ABC Research Group



1999). Unlike the heuristics and biases program, this view sees heuristics not as a problem but as *the* solution to decision making under conditions of limited time, limited knowledge, and limited computational capacities. The findings from this program suggest that boundedly rational heuristics can yield surprisingly adaptive decisions, choices, and judgments.

## **BOUNDED RATIONALITY AS ECOLOGICAL RATIONALITY**

The research program on fast and frugal heuristics advocates a different interpretation of bounded rationality from that of heuristics and biases research—one that does not uncritically accept the normative standard of logic, statistics, and probability theory. In this view, psychological mechanisms such as heuristics are adapted to particular task environments, and this match between particular environment structures and heuristics can enable the reasoner to behave adaptively, that is, in a computationally fast, information-frugal, and comparatively accurate way in the face of environmental challenges. These real-world requirements fulfilled by the match between environment and cognition lead to a new conception of what proper reasoning is: ecological rationality. In other words, a heuristic is not just rational or irrational. Instead, it can be judged as rational only with respect to the environment in which it is used.

The notion of ecological rationality, that is, the tandem of cognition and environment, is highlighted in Simon's analogy between bounded rationality and a pair of scissors: "Human rational behavior . . . is shaped by a scissors whose two blades are the structure of task environments and the computational capabilities of the actor" (Simon 1990, 7). Just as one cannot understand the function of scissors by looking at a single blade, one cannot understand humans' cognition by studying either the environment or cognition alone.

### **Rationality Assumptions in the Program on Fast and Frugal Heuristics**

The steps in the research rationale of the fast and frugal heuristics program are different from those in the heuristics and biases program. The latter selects a normative rule from probability theory, for instance, and then investigates whether human cognition deviates from it, thus moving from the abstract canon of rationality to the psychological. In contrast, the former program begins by analyzing the structure of a specific task environment people face, and then—based on the analysis—derives attributes of the cognitive models of reasoning that could fare well within the environment. This program thus moves from the environmental structures to the psychological structures, or in terms of Simon's metaphor from the environmental blade to the cognitive blade.

As an illustration, imagine an investment environment in which a resource has to be allocated repeatedly to different financial assets. The assets' returns may depend on the investments in the other assets, for instance, due to economy of scale effects. Thus, searching for the optimal allocation that produces the maximum payoff is not a trivial task. When the search space reflecting the underlying return function has a single peak, simple search strategies such as hill climbing will lead to the optimal allocation. But in an allocation environment with several peaks in the distribution of returns, a more systematic search strategy is required to find the global maximum and avoid local maxima (Rieskamp, Busemeyer, and Laine 2003). The point is that to understand which reasoning processes people might follow, and when and why these processes work well, one needs to explore the characteristics of the environment. This point was made over sixty years ago by Egon Brunswik (1943) and has been made by various psychologists since (e.g., Anderson 1991; Gibson 1979; Shepard 1990).

The cognitive blade of Simon's scissors analogy implies that models of people's reasoning

should be psychologically plausible. That is, the cognitive processes proposed need to be realistic insofar as people need to be able to execute them given their computational capabilities. Simon (1956, 1990) repeatedly insisted that the cognitive constraints under which people make judgments and decisions have to be taken into account when modeling human behavior. Due to cognitive limitations, people cannot help but use “approximate methods to handle most tasks” (Simon 1990, 6). The strategy of taking both environmental structures and cognitive constraints into account winnows down the set of possible cognitive models that describe human decision making. Fast and frugal heuristics are suggested as one of the candidates for how humans actually make decisions. In this regard, Gigerenzer and colleagues’ (1999) research program does not differ from the heuristics and biases tradition; the differences come in how each construes and assesses the heuristics they propose.

Owing to the focus on the task environment and the match between cognition and environment, the fast and frugal heuristics program does not compare people’s judgments to mathematically defined norms of rationality with the explicit purpose of abstracting away from particular content domains and thus holding across a wide range of environments. Instead, it conceptualizes and measures human rationality in terms of performance criteria in the real world. Successful performance includes making accurate decisions in a minimal amount of time and using a minimal amount of information. In other words, this program of heuristics replaces the multiple coherence criteria (i.e., measures that evaluate the logical and mathematical consistency of decisions, stemming from the laws of probability theory and logic) with multiple correspondence criteria (i.e., measures that relate decision-making strategies to the external world and to success therein; Hammond 1996).

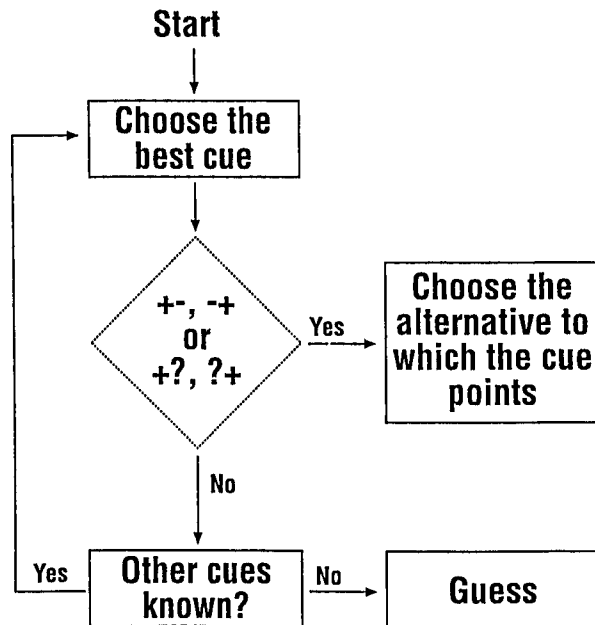
In what follows, we first illustrate the building blocks of ecologically rational heuristics and then describe one specific instance, the Take The Best heuristic, and show how it performs successfully while violating commandments that are often taken as characteristic of rational judgments.

### **Fast and Frugal Heuristics: How They Are Built and How Well They Perform**

In stark contrast to the vague specifications of heuristics such as “availability,” Gigerenzer and colleagues (1999) define heuristics as precise computational models that specify the steps of information gathering and processing involved in generating a decision. A heuristic consists of a search rule, a stopping rule, and a decision rule. Search rules specify how decision options are generated and how information about available options is gathered. Stopping rules define when the process of searching for options or information is terminated. These stopping principles themselves need to be simple (owing to the computational limitations of the human mind), such as the aspiration levels in Simon’s notion of satisficing (Simon 1956, 1990). Finally, decision rules specify how decisions are made based on the information obtained. They, in turn, must also be simple and computationally bounded. For instance, a decision could be made based on only one reason or cue, regardless of the total number of cues retrieved during the information search.

To illustrate the application of a heuristic, consider the inference problem of choosing between two potential oil fields, one of them having a larger quantity of oil (Dieckmann and Rieskamp 2006). For this inference, different tests could be carried out: chemical analysis could determine the content of the organic matter in the bedrock, groundwater could be analyzed, or a seismic analysis could be done. Each test can have either a positive result, indicating a large quantity of oil, or a negative result, indicating a small quantity of oil. Each test has a specific validity, defined as the probability of an oil field with a positive result actually having a larger quantity of oil compared to a second oil field with a negative test result. But how should the test results be used

Figure 11.3 Flow Diagram of the Take The Best Heuristic



The Take The Best heuristic is used to infer which of two alternatives—each described by several cues—has a higher criterion value. The decision to stop or to continue to search for more cues (center diamond) is made based on the pair of values for the current cue (each of which can be - [negative], + [positive], or ? [unknown]).

to make an inference? Gigerenzer and Goldstein (1996) suggested a simple heuristic called Take The Best for solving the inference problem of choosing between two alternatives, each described by several cues—the one with the higher criterion value (see Figure 11.3). According to its search rule, Take The Best searches sequentially through cues in the order of their validity, defined as the conditional probability of making a correct inference given that the cue discriminates (i.e., one alternative has a positive and the other a negative cue value). According to its stopping rule, search is stopped as soon as one cue is found that discriminates between alternatives. Finally, Take The Best selects the alternative with the positive cue value, ignoring all other cues. (If no cue discriminates, Take The Best makes a random choice.)

At first glance, the Take The Best heuristic appears rather naive when compared with more sophisticated statistical techniques. For one thing, it is reasonable to expect that a heuristic that relies on only a small amount of information will be outperformed by a strategy taking more information into account. For another, many researchers adopt a cost-benefit perspective on strategy evaluation, assuming that a strategy's performance is positively correlated with its complexity. In this view, if an individual is aiming for high accuracy and is willing to invest high cognitive effort, she will select a more complex strategy rather than something as simple as Take The Best (Camerer and Hogarth 1999; Payne, Bettman, and Johnson 1988, 1993; Smith and Walker 1993). However, as we show next, the assumed correlation between a strategy's information use or complexity and its performance may be less pronounced than is often believed.

In many settings, Gigerenzer and colleagues have found that the one-reason decision-making

approach of heuristics such as Take The Best performs surprisingly well when compared to more complex strategies that integrate available information. For instance, when the heuristic was applied to all pair comparisons of German cities with a population size of above 100,000 (e.g., is Braunschweig bigger than Bremen?), Take The Best achieved 74 percent correct decisions, thus matching the percentage correct made by a linear regression model that integrated all available information and took the correlations between cues into account (Gigerenzer and Goldstein 1996). Thus, a more complex mechanism did not guarantee better performance. At the same time, Take The Best achieved its good performance checking only a third of the cues that regression used before finding a discriminating cue and stopping its search; thus, the myth that more information is always better also falls (see also Hertwig and Todd 2003). This unexpectedly high performance of Take The Best was demonstrated across numerous environments, including inferring high house prices, car accidents, and automobile fuel consumption (see Czerlinski, Gigerenzer, and Goldstein 1999). For other tasks, such as estimating quantities, other simple heuristics have been proposed, and their good performance has been demonstrated (e.g., Hertwig, Hoffrage, and Martignon 1999).

What is the relationship between such successful heuristics and traditional normative principles of rationality? When considering the inference problem of choosing between two potential oil fields from a normative perspective, one could consider running a regression analysis that combines the three test results in a linear model to make a prediction, or one could consider building a Bayesian model that determines the posterior probability, given the three tests, that one oil field has a larger quantity of oil compared to the second oil field. However, these models do not represent psychological models of people's inferences, and they do not take the computational limits under which people make inferences into account. But what happens when we do apply a psychologically plausible mechanism such as Take The Best to making this inference about the oil fields?

Consider the three oil fields represented in Table 11.1, for which the test results are either positive, negative, or unknown. When comparing oil field A with oil field B, Take The Best first considers the highest-validity chemical analysis test. Since for oil field A the test is negative and for oil field B the test result is unknown, the second most valid test, groundwater analysis, is considered next, and that speaks for oil field A, which is therefore selected. When comparing oil fields B and C, the inference process leads to the selection of oil field B. Finally, when comparing oil fields A and C, Take The Best will lead to the selection of oil field C. Thus, the application of this fast and frugal heuristic leads to intransitive inferences ( $A > B$ ,  $B > C$ , but  $C > A$ ; see also Gigerenzer and Goldstein 1996). When evaluating it from a normative perspective, one would call the heuristic "irrational," because its inferences lead to violations of transitivity, and transitivity is often regarded as a cornerstone of rationality (Binmore 1994; Luce 2000). However, when considering Take The Best's performance in real-world environments, and thereby evaluating Take The Best by its ecological rationality (as done in the studies reported above), it does not appear less successful than other, more complex models such as linear regression. This does not mean that a heuristic always produces good solutions, and being intransitive can, in the long run, lead to severe losses. However, whether these losses actually occur will depend on the decision situation. For instance, one could build a money pump (see Cubitt and Sugden 2001; Davidson, McKinsey, and Suppes 1955) to exploit a person's intransitive choices. While we do not run into money pumps very often, if we did, we would probably learn to avoid them: experimental results show that building a successful money pump is not easy, because people typically recognize their losses and quickly change their behavior (Chu and Chu 1990). Thus, the argument that someone who makes intransitive choices by using an "irrational" simple heuristic can be exploited by a money pump holds little weight,

Table 11.1

**Choosing Between Oil Fields the One with the Larger Quantity of Oil**

Cue (validity)	Oil fields		
	A	B	C
Chemical analysis (0.80)	Negative	Unknown	Positive
Groundwater analysis (0.70)	Positive	Negative	Negative
Seismic analysis (0.60)	Positive	Positive	Negative

considering that the person will learn to change his or her behavior upon getting feedback that the intransitive choices led to large losses.

The study of heuristics is not limited to inference problems but has also been extended to preference and choice problems, such as choosing between apartments, cameras, or lottery tickets. Thorngate (1980) examined choices between gambles and demonstrated the good performance of heuristics that (partly) ignore the probability of outcomes. He concluded that “a wide variety of decision heuristics will usually produce optimal, or close to optimal, choices.” Furthermore, people “may ignore or misuse probability information because the time or effort required to use it properly may be more costly than any decrease in payoffs associated with their occasional suboptimal choices” (Thorngate 1980, 223–24). In a similar vein, Payne, Bettman, and Johnson (1988, 1993) showed how well heuristics approximate the predictions of the expected value model.

Brandstätter, Gigerenzer, and Hertwig (2006) proposed a sequential heuristic, the “priority heuristic,” to model the cognitive processes underlying choices between gambles. The heuristic first compares the gambles’ minimum outcomes. If these outcomes differ by a substantial amount (10 percent of the maximum monetary amount offered in the gambles), the gamble with the larger minimum outcome is chosen; otherwise the probabilities of obtaining the minimum outcome are compared. If the probabilities differ by more than 10 percentage points, then the gamble with the lower chance of obtaining the minimum outcome is selected; otherwise the gamble’s maximum outcomes are considered and the gamble with the larger maximum outcome is selected. Brandstätter and colleagues showed that the priority heuristic can predict violations of expected utility theory such as the Allais paradox, the certainty effect, and intransitive choices. They also showed that the heuristic predicted people’s choices across a set of more than 250 gambles better than did, for instance, cumulative prospect theory.

**What Makes Heuristics Work Well?**

There are two main reasons why simple heuristics often perform so well in comparison with more complex strategies. First, many problems have “flat maxima,” meaning the best solution does not differ substantially from other (e.g., heuristic) solutions. Second, heuristics can outperform other strategies in terms of generalization, that is, when applied to new situations.

Dawes and Corrigan (1974; see also Lovie and Lovie 1986) showed that if one uses a linear model for predicting a criterion, many sets of weights will lead to predictions that are similar to those made by optimal weights. In other words, around the model with maximum performance there are many other solutions with near-maximum performance—an example of the flat maximum phenomena. Likewise, Dawes (1979) showed that simply choosing unit (i.e., equal) weights for a linear model can lead to an accuracy similar to that of “proper linear models,” which are models that use weights that optimally predict a criterion, such as a linear regression analysis. Flat maxima will

especially occur when predictor variables (cues) are positively correlated with each other, so that different weighting schemes will nonetheless lead to similar predictions. This situation can be exploited by fast and frugal heuristics that base their decisions only on a subset of available information. The most extreme form of this is when a heuristic uses a noncompensatory weighting schema, so that basically only one single cue is employed for making a prediction (Martignon and Hoffrage 2002); even in this case, flat maxima can enable a simple heuristic to perform well.

The second advantage of these heuristics is their ability to generalize well. In many situations, the weights of “proper linear models” (or parameters of other models) are estimated on the basis of a sample. For instance, a policy to diagnose patients’ diseases based on a number of symptoms could be developed by using a sample of past patients’ records. But the sample might not accurately represent the population of future patients. In principle, the data of a sample can be thought of as consisting of two components: *structure* and *noise*. Although the structure is of primary interest, a relatively complex model will also increase its fit by adapting to (and trying to predict) the sample’s noise. This leads to “overfitting,” namely the problem that a model fits the data well but does poorly at predicting new data (see Browne 2000). When a complex model increases its sample accuracy by fitting noise, its performance will be relatively poor when applied to new independent data. In contrast, a relatively parsimonious, less flexible model—such as a simple heuristic—might perform worse when fitting the data but will often outperform the more general model when making predictions for a new sample. Thus, contrary to the cost-benefit perspective of strategy evaluation described above, the greater the complexity of a strategy, the greater the risk that it might perform poorly when applied to a new problem.

In sum, the decision maker can gain important advantages by selecting a simple heuristic for solving a new problem. First, a heuristic requires only a small amount of information, which is processed easily. Second, due to the flat maximum phenomenon and heuristics’ robustness, heuristics can perform as well as, or even better than, more complex strategies, undermining the complexity–accuracy relationship that is usually assumed. Hence the belief that basing a decision on more information and computation will always lead to more accurate decisions—a belief that has dominated much research, including that in the heuristics and biases tradition (Gigerenzer and Murray 1987)—is a fiction.

### Do People Use Simple Heuristics?

Empirical evidence for the use of simple heuristics such as lexicographic strategies (i.e., strategies that—like Take The Best—consider cues sequentially and where more important cues dominate less important cues) has been reported in several recent studies (e.g., Bröder 2000, 2003; Brandstätter, Gigerenzer, and Hertwig 2006; Bröder and Schiffer 2003; Newell and Shanks 2003; Newell, Weston, and Shanks 2003). Rieskamp and Hoffrage (1999, 2005) showed that under great time pressure, a lexicographic heuristic reached the highest fit in predicting participants’ inferences. In a similar vein, Bröder (2000) showed that Take The Best predicted participants’ inferences best in the presence of relatively high explicit information acquisition costs. Take The Best also predicted individuals’ inferences well when the cue information had to be retrieved from memory (Bröder and Schiffer 2003). The use of simple heuristics also depends on the overall payoffs the heuristics produce, such that Take The Best is selected more frequently when it produces the highest payoff compared to other strategies (Bröder 2003). Newell and Shanks (2003) and Newell, Weston, and Shanks (2003) showed that the way people search for cues follows the search predicted by Take The Best under high information acquisition costs. Besides this recent work on inferential choice, there is a large body of research examin-

ing strategy selection for preferential choice, led by the contributions of Payne, Bettman, and Johnson (1988, 1993).

Can people learn to select strategies based on their fit to the structure of the current task environment? Rieskamp and Otto (2006) addressed the question of whether pure outcome feedback is sufficient for an adaptive selection of strategies. In their experiments, participants repeatedly had to choose the more creditworthy company from a pair on the basis of six cues. Participants received feedback on the correctness of their inferences. For one group of participants, an environment was presented in which a lexicographic heuristic reached the highest accuracy, whereas in another environment condition a strategy that integrates all available information reached the highest accuracy. The crucial question was whether participants would be able to intuitively adapt the selection of strategies to the feedback from the environments. This was the case: after some learning, the strategy that best predicted participant's choices in the particular condition was also the strategy that performed best in each environment. This result, along with those cited earlier, indicates that people not only use simple heuristics but also use them in the appropriate circumstances.

## CONCLUSION

This chapter has given an overview of the two main views of bounded rationality from psychology. These two views relate very differently to the classical view of rationality typically found in economics, which defines rational behavior according to adherence to a strict set of normative mathematical principles. The first view of bounded rationality—expressed in the heuristics and biases program—accepts the normative standards of classical rationality. However, it argues that people systematically deviate from the norms and therefore do not behave rationally. The second view of bounded rationality—expressed in the fast and frugal heuristics program—does not take these normative standards at face value. Instead, it argues that unequivocal norms often do not exist, and that humans under the constraints of limited computational capacity and information can only strive to reach environmentally adaptive decisions.

One important contribution of the heuristics and biases program consists in challenging the view in economics that people follow the classical norms of rational behavior. However, since the program accepts the normative standards of rationality, violations are interpreted as “biases” or “fallacies,” leading to a rather negative view of people's judgment and decision-making capacities. The implication is that to “help” people to overcome their “biases,” they must be taught to follow the norms. The question is how helpful this will be. When people apply strategies that are well adapted to an environment, they might violate certain norms of rationality. If taught to obey the norms, they will need to give up the strategies that in general perform quite well in solving a task.

The program on fast and frugal heuristics leads to a rather different view of bounded rationality. The simple heuristics people use are adapted to particular task environments and perform well in solving decision problems in those specific environments, but they do not necessarily obey classical norms of rationality. While the application of a simple heuristic might often also lead to behavior that is consistent with the predictions from standard economic theory, this research approach offers a significant advantage over the “as if” optimizing approach typically adopted in mainstream economics. Because these heuristics are formulated and studied as precise cognitive mechanisms, they do not only provide deeper insight into how people make their decisions, but also allow better predictions of the conditions in which deviations from standard economic models will occur. In this way, the program on fast and frugal heuristics allows economic theory to be bound more closely to the reality of humans' thought.

## REFERENCES

- Anderson, J.R. 1991. "Is Human Cognition Adaptive?" *Behavioral and Brain Sciences* 14: 471–517.
- Barber, B.M., and T. Odean. 2000. "Trading Is Hazardous to Your Wealth: The Common Stock Investment Performance of Individual Investors." *Journal of Finance* 55: 773–806.
- . 2001. "Boys Will Be Boys: Gender, Overconfidence, and Common Stock Investment." *Quarterly Journal of Economics* 116: 261–92.
- Billings, R.S., and S.A. Marcus. 1983. "Measures of Compensatory and Non-compensatory Models of Decision Behavior: Process Tracing Versus Policy Capturing." *Organizational Behavior and Human Performance* 31: 331–52.
- Binmore, K. 1994. *Game Theory and the Social Contract*. Vol. 1, *Playing Fair*. Cambridge, MA: MIT Press.
- Birnbaum, M.H. 1983. "Base Rates in Bayesian Inference: Signal Detection Analysis of the Cab Problem." *American Journal of Psychology* 96: 85–94.
- Brandstätter, E., G. Gigerenzer, and R. Hertwig. 2006. "The Priority Heuristic: Making Choices Without Trade-Offs." *Psychological Review* 113.
- Bröder, A. 2000. "Assessing the Empirical Validity of the 'Take-the-Best' Heuristic as a Model of Human Probabilistic Inference." *Journal of Experimental Psychology: Learning, Memory, and Cognition* 26: 1332–46.
- . 2003. "Decision Making with the 'Adaptive Toolbox': Influence of Environmental Structure, Intelligence, and Working Memory Load." *Journal of Experimental Psychology: Learning, Memory, and Cognition*, 29: 611–25.
- Bröder, A., and S. Schiffer. 2003. "Take the Best Versus Simultaneous Feature Matching: Probabilistic Inferences from Memory and Effects of Representation Format." *Journal of Experimental Psychology: General* 132: 277–93.
- Browne, M.W. 2000. "Cross-Validation Methods." *Journal of Mathematical Psychology* 44: 108–32.
- Brunswik, E. 1943. "Organismic Achievement and Environmental Probability." *Psychological Review* 50: 255–72.
- Camerer, C. 1995. "Individual Decision Making." In J.H. Kagel and A.E. Roth, eds., *The Handbook of Experimental Economics*, 587–703. Princeton, NJ: Princeton University Press.
- Camerer, C.F., and R.M. Hogarth. 1999. "The Effects of Financial Incentives in Experiments: A Review and Capital-Labor-Production Framework." *Journal of Risk and Uncertainty* 19: 7–42.
- Chase, V.M., R. Hertwig, and G. Gigerenzer. 1998. "Visions of Rationality." *Trends in Cognitive Sciences* 2: 206–14.
- Chu, Y.-P., and R.-L. Chu. 1990. "The Subsidence of Preference Reversals in Simplified and Marketlike Experimental Settings: A Note." *American Economic Review* 80: 902–11.
- Cosmides, L., and J. Tooby, 1996. "Are Humans Good Intuitive Statisticians After All? Rethinking Some Conclusions from the Literature on Judgment Under Uncertainty." *Cognition* 58: 1–73.
- Cubitt, R.P., and R. Sugden. 2001. "On Money Pumps." *Games and Economic Behavior* 37: 121–60.
- Czerlinski, J., G. Gigerenzer, and D.G. Goldstein. 1999. "How Good Are Simple Heuristics?" In G. Gigerenzer, P.M. Todd, and the ABC Research Group, *Simple Heuristics That Make Us Smart*, 97–118. New York: Oxford University Press.
- Daston, L. 1988. *Classical Probability in the Enlightenment*. Princeton, NJ: Princeton University Press.
- Davidson, D., J. McKinsey, and P. Suppes. 1955. "Outlines of a Formal Theory of Value." *Philosophy of Science* 22: 140–60.
- Dawes, R.M. 1979. "The Robust Beauty of Improper Linear Models in Decision Making." *American Psychologist* 34: 571–82.
- Dawes, R.M., and B. Corrigan. 1974. "Linear Models in Decision Making." *Psychological Bulletin* 81: 95–106.
- Dieckmann, A., and J. Rieskamp. 2006. "Information Redundancy Influencing Probabilistic Inferences." Manuscript submitted for publication.
- Friedman, M. 1953. *Essays in Positive Economics*. Chicago: University of Chicago.
- Gibson, J.J. 1979. *The Ecological Approach to Visual Perception*. Boston: Houghton Mifflin.
- Gigerenzer, G. 1991. "How to Make Cognitive Illusions Disappear: Beyond 'Heuristics and Biases.'" In W.S.M. Hewstone, ed., *European Review of Social Psychology* 2: 83–115. New York: Wiley.
- . 1994. "Why the Distinction Between Single-Event Probabilities and Frequencies Is Important for Psychology (and Vice Versa)." In G. Wright and P. Ayton, eds., *Subjective Probability*, 129–61. New York: Wiley.



- . 1996. "On Narrow Norms and Vague Heuristics: A Reply to Kahneman and Tversky." *Psychological Review* 103: 592–96.
- . 1998. "Ecological Intelligence: An Adaptation for Frequencies." In D.D. Cummins and C. Allen, eds., *The Evolution of Mind*, 9–29. New York: Oxford University Press.
- . 2001. "Content-Blind Norms, No Norms, or Good Norms? A Reply to Vranas." *Cognition* 81: 93–103.
- Gigerenzer, G., and D.G. Goldstein. 1996. "Reasoning the Fast and Frugal Way: Models of Bounded Rationality." *Psychological Review* 103: 650–69.
- Gigerenzer, G., and U. Hoffrage. 1995. "How to Improve Bayesian Reasoning Without Instruction: Frequency Formats." *Psychological Review* 102: 684–704.
- Gigerenzer, G., U. Hoffrage, and H. Kleinbölting. 1991. "Probabilistic Mental Models: A Brunswikian Theory of Confidence." *Psychological Review* 98: 506–28.
- Gigerenzer, G., and D.J. Murray. 1987. "Thinking: From Insight to Intuitive Statistics." In G. Gigerenzer and D.J. Murray, eds., *Cognition as Intuitive Statistics*, 137–81. Hillsdale, NJ: Erlbaum.
- Gigerenzer, G., Z.G. Swijtink, T.M. Porter, L. Daston, J. Beatty, and L. Krueger. 1989. *The Empire of Chance: How Probability Changed Science and Everyday Life*. Cambridge, MA: MIT Press.
- Gigerenzer, G., P.M. Todd, and the ABC Research Group. 1999. *Simple Heuristics That Make Us Smart*. New York: Oxford University Press.
- Gilovich, T., D. Griffin, and D. Kahneman, eds. 2002. *Heuristics and Biases: The Psychology of Intuitive Judgment*. New York: Cambridge University Press.
- Grether, D.M., and C.R. Plott. 1979. "Economic Theory of Choice and the Preference Reversal Phenomenon." *American Economic Review* 69: 623–38.
- Hammond, K.R. 1996. "Upon Reflection." *Thinking and Reasoning* 2: 239–49.
- Hanson, J.D., and D.A. Kysar. 1999a. "Taking Behavioralism Seriously: The Problem of Market Manipulation." *New York University Law Review* 74: 630–749.
- . 1999b. "Taking Behavioralism Seriously: Some Evidence of Market Manipulation." *Harvard Law Review* 112: 1420–572.
- Hertwig, R., and G. Gigerenzer. 1999. "The 'Conjunction Fallacy' Revisited: How Intelligent Inferences Look Like Reasoning Errors." *Journal of Behavioral Decision Making* 12: 275–305.
- Hertwig, R., and U. Hoffrage. 2002. "Technology Needs Psychology: How Natural Frequencies Foster Insight in Medical and Legal Experts." In P. Sedlmeier and T. Betsch, eds., *Etc. Frequency Processing and Cognition*, 285–302. New York: Oxford University Press.
- Hertwig, R., U. Hoffrage, and L. Martignon. 1999. "Quick Estimation: Letting the Environment do the Work." In G. Gigerenzer, P.M. Todd, and the ABC Research Group, *Simple Heuristics That Make Us Smart*, 209–34. New York: Oxford University Press.
- Hertwig, R., and P.M. Todd. 2000. "Biases to the Left, Fallacies to the Right: Stuck in the Middle with Null Hypothesis Significance Testing. Commentary on Krueger on Social Bias." *Psychology* 11(028). <http://www.cogsci.ecs.soton.ac.uk/cgi/psyc/newpsy?11.028>.
- . 2002. "Heuristics." In V.S. Ramachandran, ed., *Encyclopedia of the Human Brain*, 2:449–60. New York: Academic Press.
- . 2003. "More Is Not Always Better: The Benefits of Cognitive Limits." In D. Hardman and L. Macchi, eds., *Thinking: Psychological Perspectives on Reasoning, Judgment and Decision Making*, 213–31. Chichester, UK: Wiley.
- Hoffrage, U., and G. Gigerenzer. 1998. "Using Natural Frequencies to Improve Diagnostic Inferences." *Academic Medicine* 73: 538–40.
- Hoffrage, U., S. Lindsey, R. Hertwig, and G. Gigerenzer. 2000. "Communicating Statistical Information." *Science* 290: 2261–62.
- Juslin, P., H. Olsson, and A. Winman. 1998. "The Calibration Issue: Theoretical Comments on Suantak, Bolger, and Ferrell (1996)." *Organizational Behavior and Human Decision Processes* 73: 3–26.
- Kahneman, D., P. Slovic, and A. Tversky, eds. 1982. *Judgment Under Uncertainty: Heuristics and Biases*. Cambridge: Cambridge University Press.
- Kahneman, D., and A. Tversky. 1972. "Subjective Probability: A Judgment of Representativeness." *Cognitive Psychology* 3: 430–54.
- . 1973. "On the Psychology of Prediction." *Psychological Review* 80: 237–51.
- . 1996. "On the Reality of Cognitive Illusions." *Psychological Review* 103: 582–91.
- Koehler, J.J., B.J. Gibbs, and R.M. Hogarth. 1994. "Shattering the Illusion of Control: Multi-Shot Versus Single-Shot Gambles." *Journal of Behavioral Decision Making* 7: 183–91.

- Krueger, J.I., and I. Funder. 2004. "Towards a Balanced Social Psychology: Causes, Consequences and Cures for the Problem-Seeking Approach to Social Behavior and Cognition." *Behavioral and Brain Sciences* 27: 313–27.
- Kurzenhäuser, S., and U. Hoffrage. 2002. "Teaching Bayesian Reasoning: An Evaluation of a Classroom Tutorial for Medical Students." *Medical Teacher* 24: 516–21.
- Langer, E. 1975. "The Illusion of Control." *Journal of Personality and Social Psychology* 32: 311–28.
- Laplace, P.S. 1814. *A Philosophical Essay on Probabilities*. New York: Dover, 1951.
- Lipps, T. 1880. "Die Aufgabe der Erkenntnistheorie und die Wundt'sche Logik I." *Philosophische Monatshefte* 16: 529–39.
- Lopes, L.A. 1991. "The Rhetoric of Irrationality." *Theory and Psychology* 1: 65–82.
- Lovie, A.D., and P. Lovie. 1986. "The Flat Maximum Effect and Linear Scoring Models for Prediction." *Journal of Forecasting* 5: 159–68.
- Luce, R.D. 2000. *Utility of Gains and Losses*. Mahwah, NJ: Erlbaum.
- Martignon, L., and U. Hoffrage. 2002. "Fast, Frugal, and Fit: Simple Heuristics for Paired Comparison." *Theory and Decision* 52: 29–71.
- Mellers, B., R. Hertwig, and D. Kahneman. 2001. "Do Frequency Representations Eliminate Conjunction Effects? An Exercise in Adversarial Collaboration." *Psychological Science* 12: 269–75.
- Mueser, P.R., N. Cowan, and K.T. Mueser. 1999. "A Generalized Signal Detection Model to Predict Rational Variation in Base Rate Use." *Cognition* 69: 267–312.
- Newell, B.R., and D.R. Shanks. 2003. "Take the Best or Look at the Rest? Factors Influencing 'One-Reason' Decision Making." *Journal of Experimental Psychology: Learning, Memory, and Cognition* 29: 53–65.
- Newell, B.R., N. Weston, and D.R. Shanks. 2003. "Empirical Tests of a Fast and Frugal Heuristic: Not Everyone 'Takes-the-Best.'" *Organizational Behavior and Human Decision Processes* 91: 82–96.
- Odean, T. 1999. "Do Investors Trade Too Much?" *American Economic Review* 89: 1279–98.
- Payne, J.W., J.R. Bettman, and E.J. Johnson. 1988. "Adaptive Strategy Selection in Decision Making." *Journal of Experimental Psychology: Learning, Memory, and Cognition* 14: 534–52.
- . 1993. *The Adaptive Decision Maker*. New York: Cambridge University Press.
- Peterson, C.R., and L.R. Beach. 1967. "Man as an Intuitive Statistician." *Psychological Bulletin* 68: 29–46.
- Piattelli-Palmarini, M. 1994. *Inevitable Illusions: How Mistakes of Reason Rule Our Minds*. New York: Wiley.
- Rabin, M. 1998. "Psychology and Economics." *Journal of Economic Literature* 36: 11–46.
- Rieskamp, J., J.R. Busemeyer, and T. Laine. 2003. "How Do People Learn to Allocate Resources? Comparing Two Learning Theories." *Journal of Experimental Psychology: Learning, Memory, and Cognition* 29: 1066–81.
- Rieskamp, J., and U. Hoffrage. 1999. "When Do People Use Simple Heuristics, and How Can We Tell?" In G. Gigerenzer, P.M. Todd, and the ABC Research Group, *Simple Heuristics That Make Us Smart*, 141–67. New York: Oxford University Press.
- . 2006. "The Use of Simple Heuristics: Inferences and Preferences Under Time Pressure." *Journal of Experimental Psychology: General* 135.
- Rieskamp, J., and P.E. Otto. 2006. "SSL: A Theory of How People Learn to Select Strategies." Manuscript submitted for publication.
- Rips, L. 1994. *The Psychology of Proof: Deductive Reasoning in Human Thinking*. Cambridge, MA: MIT Press.
- Sedlmeier, P., and G. Gigerenzer. 2001. "Teaching Bayesian Reasoning in Less than Two Hours." *Journal of Experimental Psychology: General* 130: 380–400.
- Shepard, R.N. 1990. *Mind Sights: Original Visual Illusions, Ambiguities, and Other Anomalies, with a Commentary on the Play of Mind in Perception and Art*. New York: W.H. Freeman.
- Shiller, R.J. 2000. "Measuring Bubble Expectations and Investor Confidence." *Journal of Psychology and Financial Markets* 1: 49–60.
- Simon, H.A. 1956. "Rational Choice and the Structure of the Environment." *Psychological Review* 63: 129–38.
- . 1957. "A Behavioral Model of Rational Choice." In H.A. Simon, ed., *Models of Man: Social and Rational*, 241–60. New York: Wiley.
- . 1978. "Rationality as Process and as Product of Thought." *American Economic Review* 68: 1–16.
- . 1979. "Rational Decision Making in Business Organizations." *American Economic Review* 69: 493–513.

- . 1990. "Invariants of Human Behavior." *Annual Review of Psychology* 41: 1–19.
- Smith, V.L., and J.M. Walker. 1993. "Monetary Rewards and Decision Cost in Experimental Economics." *Economic Inquiry* 31: 245–61.
- Thaler, R.H., ed. 1993. *Advances in Behavioral Finance*. New York: Russell Sage Foundation.
- . 2000. "Toward a Positive Theory of Consumer Choice." In D. Kahneman and A. Tversky, eds., *Choices, Values, and Frames*, 269–87. New York: Cambridge University Press.
- Thorngate, W. 1980. "Efficient Decision Heuristics." *Behavioral Science* 25: 219–25.
- Tversky, A., and D. Kahneman. 1974. "Judgment Under Uncertainty: Heuristics and Biases." *Science* 185: 1124–31.
- Vranas, P.B.M. 2000. "Gigerenzer's Normative Critique of Kahneman and Tversky." *Cognition* 76: 179–93.