Research Article

Decisions From Experience and the Effect of Rare Events in Risky Choice

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ABSTRACT—***When people have access to information sources such as newspaper weather forecasts, drug-package inserts, and mutual-fund brochures, all of which provide convenient descriptions of risky prospects, they can make* decisions from description. *When people must decide whether to back up their computer's hard drive, cross a busy street, or go out on a date, however, they typically do not have any summary description of the possible outcomes or their likelihoods. For such decisions, people can call only on their own encounters with such prospects, making* decisions from experience. *Decisions from experience and decisions from description can lead to dramatically different choice behavior. In the case of decisions from description, people make choices as if they overweight the probability of rare events, as described by prospect theory. We found that in the case of decisions from experience, in contrast, people make choices as if they underweight the probability of rare events, and we explored the impact of two possible causes of this underweighting—reliance on relatively small samples of information and overweighting of recently sampled information. We conclude with a call for two different theories of risky choice.***

Why are doctors and patients often at odds with one another? Rushed office visits, poor interpersonal skills on the part of doctors, and intransigence on the part of patients may all contribute to disagreement and misunderstandings. Here we focus on another factor that can strain the relationship: Patients' and doctors' decisions are often based on information that, though equivalent in content, comes from different sources. Consider, for example, the decision whether to vaccinate a child against diphtheria, tetanus, and pertussis (DTaP). Parents who research the side effects of the DTaP vaccine on the National Immunization Program Web site will find that up to 1 child out of 1,000 will develop high fever and about 1 child out of 14,000 will experience seizures as a result of immunization. Although doctors have these same statistics at their disposal, they also have access to information not easily available to parents—namely, personal experience, gathered across many patients, that vaccination rarely results in side effects; few doctors have encountered one of the unusual cases in which high fever or seizures follow vaccination. If the importance assigned to rare events differs as a function of how one learns about their likelihood, then doctors and patients might well disagree about whether vaccination is advised.

Does the impact of rare events on risky decisions depend on how knowledge about their likelihood was obtained? Before addressing this question—the focus of this article—we introduce the dominant decision-theoretic framework, according to which people evaluate possible outcomes of their decisions in terms of beliefs and values.

EXPECTATIONS: FROM PROBABILITIES TO DECISION WEIGHTS

The fundamental principles of probability were first formulated in the mid-1600s in an exchange of letters between the French mathematicians Blaise Pascal and Pierre Fermat. Dealing with various gambling problems, their epistolary discussion gave rise to the concept of mathematical expectation, which at the time was believed to capture the basis for rational choice. Choosing rationally meant choosing the option with the higher *expected value* (EV), which in modern notation is defined as

$$EV = \Sigma p_i x_i,$$

where p_i and x_i are the probability and the amount of money, respectively, associated with each possible outcome ($i = 1, \ldots, n$) of that option.

Despite its elegance, the definition of rational decision making as maximization of expected value ran into difficulty when Nicholas Bernoulli, a Swiss mathematician from Basel, posed the St. Petersburg paradox. The paradox is that, contrary to expected-value theory, people are willing to pay only relatively small amounts to take a gamble that is assumed to have an infinite expected value (but see Jorland's, 1987, analysis). To reconcile the theory with people's behavior, Nicholas's cousin Daniel Bernoulli proposed retaining the core of expected-value theory while replacing objective monetary outcomes with the notion of subjective utility. Specifically, he suggested that the

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utility of money increases nonlinearly with its amount, rising at a decreasing rate as absolute monetary value increases. In modern terms, Bernoulli's concept of *expected utility* (EU) is defined as

$$EU = \Sigma p_i u(x_i),$$

where $u(x_i)$ is a positive but decelerating function of the monetary amount x_i.

After von Neumann and Morgenstern (1947) put expected-utility theory on axiomatic grounds, it quickly became the most influential theory of individual choice behavior. Before long, however, experiments revealed systematic violations of the theory's axioms. Perhaps the most prominent violation is the Allais paradox (Allais, 1953), in which decision makers choosing between risky prospects do not conform to the *independence axiom*, according to which outcomes common to all prospects (and with known probabilities) should have no influence on the decision. In response to this and other anomalies, various modifications of the expected-utility framework have been proposed in recent decades. These modifications nevertheless retain the theory's key idea, namely, the Bernoullian multiplication. The most influential modification, *prospect theory*, assumes that the value (a form of utility) of each outcome is multiplied by a decision weight (Kahneman & Tversky, 1979).

In the present context, the notion of decision weight is key. Prospect theory's decision weights are not assumed to reflect any explicit judgment of the subjective probability of outcomes that decision makers could be asked to provide. Instead, weights are inferred from choices and provide a measure of the impact that an outcome has on a decision. Prospect theory posits that people choose as if small-probability events receive more weight than they deserve according to their objective probabilities of occurrence and as if large-probability events receive less weight than they deserve. Prospect theory's decision-weight function plots weights (inferred from choices) that range from 0 to 1 against objective probabilities: Points above the 45° diagonal signal overweighting; that is, they represent weights that exceed the outcomes' objective probability of occurrence. Points below the 45° diagonal signal the opposite pattern. Prospect theory's overweighting of rare events has been crucial in accounting for many violations of expected-utility theory, including the classic Allais paradox (Camerer, 2000; Kahneman & Tversky, 1979; Tversky & Kahneman, 1992).

DECISIONS FROM DESCRIPTION AND DECISIONS FROM EXPERIENCE

In light of extensive empirical evidence consistent with prospect theory's weighting function, the results of several recent studies (Barkan, Zohar, & Erev, 1998; Barron & Erev, 2003; Erev, 1998; Weber, Shafir, & Blais, 2004) came as a surprise. Observed choices indicated not overweighting of small-probability outcomes (henceforth, *rare events*), but rather the opposite: People made choices as if they underweighted rare events; that is, rare events received less weight than their objective probability of occurrence warranted. What makes people choose as if they underweight rare events in some studies and as if they overweight them in other studies?[1]

We propose that the answer lies in how decision makers learn about the likelihood with which rare (and other) events can be expected to occur.[2] Research on risky choice typically provides respondents with a summary description of each option, for example:

A: Get $4 with probability .8, $0 otherwise.

or

B: Get $3 for sure.

The outcomes of each option and their probabilities are provided, and the information is conveyed visually (e.g., using a pie chart or frequency distribution) or numerically. Moreover, respondents are often required to make only one choice per problem and rarely receive feedback. We refer to such decisions as *decisions from description*. Studies of human risky choice almost exclusively examine decisions from description. In a recent meta-analysis of all studies involving decisions between a two-outcome risky prospect and a sure thing (with equal expected value), Weber et al. (2004) found that all 226 choice situations called for decisions from description.

Outside the laboratory, however, people often must make choices without a description of possible choice outcomes, let alone their probabilities. Because people can rely only on personal experience under such conditions, we refer to these as *decisions from experience*. Only a few studies have investigated decisions from experience in humans. In one (Barron & Erev, 2003), decision makers acquired information about outcomes and probabilities by making repeated choices (initially under ignorance) and receiving feedback about the outcomes of their choices. Specifically, decision makers were repeatedly asked to choose between two buttons projected on the computer screen. Each button selection initiated a random draw from the initially unknown payoff distribution associated with that button. Given the payoff distributions in the aforementioned example, selecting option A could lead to outcomes of $4 or $0. Selecting option B, in contrast, would always result in an outcome of $3. By choosing between the buttons (and associated payoff distributions) and experiencing the contingency between choices and outcomes over repeated trials, respondents in this *feedback* paradigm gradually acquired knowledge about the two payoff distributions. Across trials, 63% of respondents chose option A. In contrast, only 20% of respondents in Kahneman and Tversky's (1979) study, which provided a description of the two options, chose option A. The differences between the two studies are consistent with underweighting the rare event (the $0 outcome of option A) in decisions from experience and overweighting it in decisions from description: Underweighting the rare event increases the attractiveness of option A, whereas overweighting decreases A's attractiveness. What causes underweighting of rare events in decisions from experience?

UNDERWEIGHTING: THE RESULT OF DIRECT EXPERIENCE OR REPEATED DECISIONS?

In Kahneman and Tversky's (1979) study, respondents made a single choice in a problem that presented outcomes and probabilities. In

[1] Note that we refer to the weighting of events in the same *as if* sense as in prospect theory. Moreover, we assume that the weighting of outcomes with large probabilities is the mirror image of the weighting pattern for rare events.

[2] There are different ways to define a rare event. Given that our study is one of the first attempts to systematically study decisions from experience, we somewhat arbitrarily defined rare events as those with a probability of .20 or less. Future studies may fine-tune or replace this definition with one according to which "the rarer the event, the greater the underweighting."

contrast, Barron and Erev's (2003) respondents made many choices and discovered outcomes and probabilities only from feedback. Both the information mode (symbolic description vs. direct experience) and the number of decisions (single vs. repeated) have been demonstrated to affect people's judgments and decisions. For example, repeated decisions (with outcome feedback) can eliminate preference reversals (Chu & Chu, 1990; see Hertwig & Ortmann, 2001), and direct experience of base rates can strongly improve Bayesian reasoning (Koehler, 1996; Hertwig & Ortmann, 2001). For instance, doctors use base rates acquired through personal experience in a normative fashion, but do not use numerically described base rates normatively (Weber, Böckenholt, Hilton, & Wallace, 1993).

Which properties of decisions from experience are thus responsible for the underweighting of rare events? To disentangle the two candidate properties—direct experience and repeated decisions—we exploited the fact that personal knowledge about risky prospects can be acquired in different ways. In the *sampling* paradigm of Weber et al. (2004), respondents experienced outcomes and their frequencies without making repeated consequential decisions (unlike in the feedback paradigm). If underweighting of rare events originates in repeated decisions, then the sampling paradigm should not produce underweighting of rare events. If underweighting of rare events originates in direct experience of the occurrence (or nonoccurrence) of rare events, however, then the sampling paradigm should result in underweighting.

METHOD

One hundred students at the Technion (Haifa, Israel) were presented with the six decision problems displayed in Table 1 (taken from Barron & Erev's, 2003, feedback design). All six problems present options that differ with respect to expected value; four of them offer positive and two offer negative prospects. Half the participants, the *description* group, saw the problems described (as in Table 1) on a computer screen. The other half, the *experience* group, saw two buttons on the computer screen and were told that each button was associated with a payoff distribution. In each group, 25 respondents were presented with three of the six problems, and the remaining 25 respondents were presented with the other three problems. Clicking on a given button elicited the sampling of an outcome (with replacement) from its distribution. Respondents could sample in whatever order they desired, and however often they wished; they were encouraged to sample until they felt confident enough to decide from which box to draw for a real payoff. Once they had stopped sampling and indicated their preferred option, they turned to the next problem. Finally, respondents played out the selected options and received real payoffs.

In both groups, participants received a $4.50 fee for showing up and 2¢ for each point won (e.g., outcome of 32 in Problem 6 was equivalent to 64¢).

RESULTS

Decisions from experience clearly differed from decisions from description. As shown in Table 1, the percentage of respondents who chose option H (i.e., the option with the higher expected value, as calculated by probability times monetary value) in each problem differed markedly between the two groups. For instance, in Problem 1, 88% of participants in the experience group selected option H, whereas only 36% of participants in the description group selected this option (these results are similar to Kahneman & Tversky's, 1979, finding of 20% H choices). Across all problems, the average (absolute) difference between the percentage of respondents choosing option H in the experience and description groups was 36 percentage points, and between-groups differences were statistically significant for all problems except Problem 2. Equally important, the direction of each difference was consistent with that predicted by the assumption that rare events are underweighted in decisions from experience (see Table 1). For example, fewer respondents in the experience group than in the description group were predicted to select option H in Problem 2, and the opposite prediction was made for Problem 4.

To summarize, respondents in the experience and description groups faced structurally identical problems. Yet their choices were

TABLE 1
Summary of the Decision Problems and Results

Decision problem	Options[a] H	Options[a] L	Expected value H	Expected value L	Percentage choosing H: Description group	Percentage choosing H: Experience group	Rare event	Prediction for H choices[b]	Difference between groups[c]
1	<u>4, .8</u>	3, 1.0	3.2	3	36	88	0, .2	Higher	+52 ($z = 3.79$, $p = .000$)
2	<u>4, .2</u>	3, .25	0.8	0.75	64	44	4, .2	Lower	−20 ($z = 1.42$, $p = .176$)
3	−3, 1.0	<u>−32, .1</u>	−3	−3.2	64	28	−32, .1	Lower	−36 ($z = 2.55$, $p = .005$)
4	−3, 1.0	<u>−4, .8</u>	−3	−3.2	28	56	0, .2	Higher	+28 ($z = 2.01$, $p = .022$)
5	<u>32, .1</u>	3, 1.0	3.2	3	48	20	32, .1	Lower	−28 ($z = 2.09$, $p = .018$)
6	<u>32, .025</u>	3, .25	0.8	0.75	64	12	32, .025	Lower	−52 ($z = 3.79$, $p = .000$)

Note. Underlining indicates the options including rare events. H = option with the higher expected value; L = option with the lower expected value. [a]For each option, only one outcome is given, followed by its probability; the second outcome, which is not stated, was 0 and occurred with a probability complementary to the stated one. For instance, the outcomes of the H option in Problem 2 were 4 with a probability of .2 and 0 with a probability of .8; the outcomes of the L option in Problem 2 were 3 with a probability of .25 and 0 with a probability of .75. [b]The entries in this column indicate whether the percentage of respondents choosing the H option was expected to be higher or lower in the experience group than in the description group, assuming underweighting of the rare event in the experience group. [c]This column shows the percentage of H choices in the experience group minus the percentage of H choices in the description group, along with the z statistic testing whether the difference between the two sample proportions (relative frequencies) is significantly different from zero.

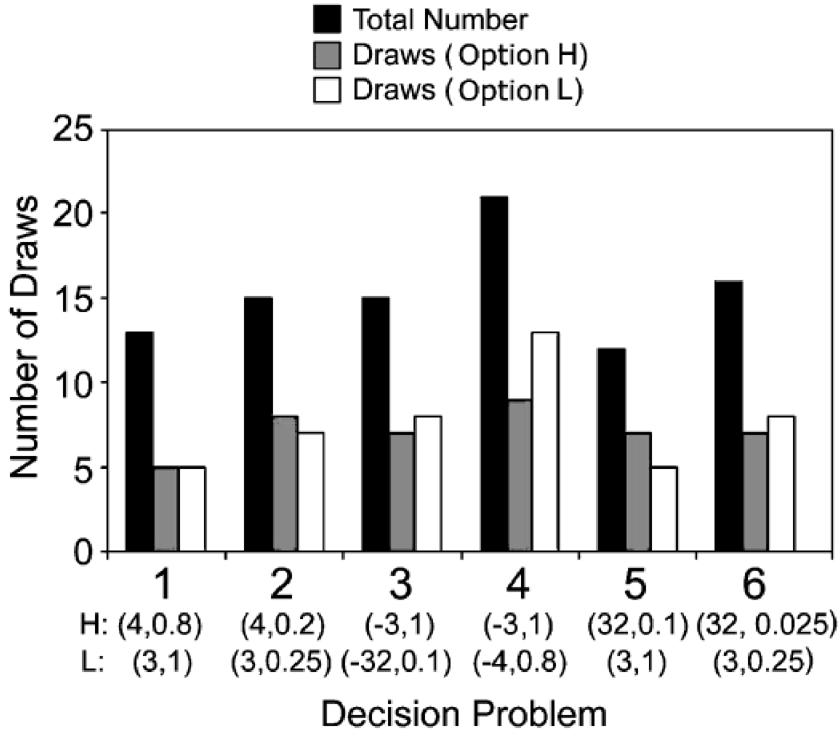

Fig. 1. Median number of draws in the experience group for each of the six decision problems (see Table 1). Results are shown separately for the total number of draws and for draws of the options with the higher (H) and lower (L) expected values (i.e., probability times monetary value). For each option, only one outcome is given, followed by its probability; the second outcome, which is not stated, was 0 and occurred with a probability complementary to the stated one. The standard deviations for the total number of draws per problem were 4.1, 21.4, 37.8, 20.1, 10.4, and 14.9 for Problems 1 through 6, respectively.

dramatically different. Differences in choices were consistent with the assumption that in decisions from experience, rare events had less impact than they deserved on the basis of objective probability (and in decisions from description, rare events had more impact than they deserved). Moreover, the underweighting of rare events in decisions from experience appears to be robust across experimental paradigms: The choice percentages in the experience group in the present study were close to the percentages Barron and Erev (2003) observed previously ($r = .93$, $p < .01$). The similar pattern of results suggests that it is indeed direct experience of outcomes and their likelihoods—and not repeated choices—that accounts for the underweighting of rare events in decisions from experience. But how does direct experience lead to underweighting?

DECISIONS FROM EXPERIENCE: LIMITED INFORMATION SEARCH

Because decisions from experience depend on the sampled information, any account of how such decisions are made ought to consider how people search for information and how the results of the search affect subsequent decisions (see also Fiedler, 2000; Kareev, 2000). Figure 1 displays the median number of draws per problem in the experience group. For our purposes, the most important observation is that the total number of draws per problem was relatively small, with a median of 15—a result close to the median of 17 draws observed by Weber et al. (2004). Across problems, the number of draws for option H was roughly equal to the number of draws for option L.

Although one may speculate about the reasons for people's limited search effort,[3] it exacts an obvious price: The smaller the number of draws from a payoff distribution, the larger the probability that the respondent will not come across the rare event and, consequently, will remain ignorant of its existence. For illustration consider Problem 5, in which the median respondent sampled seven cards from the payoff distribution that offered "32" with a probability of .1 (and "0" otherwise). Therefore, most respondents (18 out of 25) never encountered "32." In addition to increasing the chance of not encountering the rare event at all, small samples cause the rare event to be encountered less frequently than expected (given its objective likelihood). This is because the binomial distribution for the number of times a particular outcome will be observed in n independent trials when p is small (i.e., the event is rare) and n is small (i.e., few draws) is skewed. In such skewed distributions, one is more likely to encounter the rare event in small samples less frequently than expected (i.e., np) than to encounter it more frequently than expected. For example, let us assume that each of 1,000 people draws 20 times from a distribution in which

[3]One explanation involves short-term memory limits that provide a natural stopping rule for information search (Kareev, 2000). More than half of respondents sampled one choice option exclusively before they switched to the other one, and the median number of draws from each option was around seven—a number often associated with the capacity of short-term memory.

TABLE 2

Percentage of Respondents in the Experience Group Who Selected the Option Involving the Rare Event as a Function of How Often the Rare Event Was Encountered During Sampling

Decision problem	Options[a] H	Options[a] L	Rare event	Percentage choosing option with rare event[b]: Encountered less frequently than expected	Percentage choosing option with rare event[b]: Encountered as frequently as or more frequently than expected
1	4, .8	3, 1.0	0, .2 Negative	88 (21/24)	— (1/1)
2	4, .2	3, .25	4, .2 Positive	33 (6/18)	71 (5/7)
3	−3, 1.0	−32, .1	−32, .1 Negative	100 (12/12)	46 (6/13)
4	−3, 1.0	−4, .8	0, .2 Positive	44 (11/25)	— (0/0)
5	32, .1	3, 1.0	32, .1 Positive	5 (1/19)	67 (4/6)
6	32, .025	3, .25	32, .025 Positive	5 (1/19)	33 (2/6)

Note. Underlining indicates the options including rare events. H = option with the higher expected value; L = option with the lower expected value. [a]For each option, only one outcome is given, followed by its probability; the second outcome, which is not stated, was 0 and occurred with a probability complementary to the stated one. For instance, the outcomes of the H option in Problem 2 were 4 with a probability of .2 and 0 with a probability of .8; the outcomes of the L option in Problem 2 were 3 with a probability of .25 and 0 with a probability of .75. [b]Relative frequencies are given in parentheses.

the critical event occurs with a probability of .1. Of the 1,000 people, 285 will sample the critical event 2 times and thus could estimate its probability accurately, if asked explicitly. Another 323 of them will encounter the event 3, 4, 5, . . . , or 20 times and thus would most likely overestimate its probability. But 392 people—almost two fifths of the total—will not sample the event at all or will sample it only 1 time, and thus would most likely underestimate p.

The outcomes of sampling in the present study were consistent with the skewed binomial distribution for small samples. Averaging across all problems in the experience group showed that 78% of respondents sampled the critical rare event less frequently than expected (np), whereas 22% sampled it as frequently as expected or more frequently than expected. Moreover, the experienced frequency of the critical event had a clear impact on choices. Across all problems, when the rare event represented a positive event (e.g., "32" in Problem 5) and was encountered less frequently than its expected number of occurrences, people selected the option involving that event 23% of the time. When it was encountered as frequently as expected or more frequently than expected, people selected the option involving the rare, positive event 58% of the time. Similarly, when the rare event represented a negative event (e.g., "0" in Problem 1), it was selected 92% of the time when it was encountered less frequently than its expected number occurrences, and only 50% of the time when it was encountered as frequently as or more frequently than expected. Table 2 shows that the pattern is similar for the individual problems. (Note that the pattern cannot be tested in Problems 1 and 4, as everybody or almost everybody encountered the rare event in these problems less frequently than expected.)

Reliance on small samples of experience not only plays a key role in decisions from experience but also contributes to perception of the world as less variable than it actually is. In fact, underestimating the variance of a population is equivalent to underweighting a rare event. For instance, in Problem 6, about two thirds of the respondents encountered a uniform sequence of one "0" after another when drawing from the payoff distribution involving the rare event. If they had used sample variability, or the lack thereof, to estimate population variability (without correcting for sample size), then they would have underestimated the true variability in this payoff distribution. Kareev, Arnon, and Horwitz-Zeliger (2002) discovered that people indeed tend to misperceive variability and that using experience samples of limited size (with the size often being related to the capacity of working memory) appears to cause variability to be underestimated.

DECISIONS FROM EXPERIENCE: RECENCY EFFECTS

Although small samples have the result that decision makers explicitly and hence presumably also implicitly underestimate the probability of rare events, underweighting of rare events is likely to emerge in decisions from experience even if people can provide accurate explicit estimates of the probabilities. Here is why. In decisions from experience, respondents need to update their impression of the options' attractiveness by combining newly sampled outcomes with their knowledge from previous draws. Such updating can give rise to recency effects (e.g., Hogarth & Einhorn, 1992), that is, to judgments in which recently sampled outcomes receive greater weight than earlier sampled ones. Note that a recency effect would result in the underweighting of rare events even in large samples: Owing to their rarity, they are less likely than more common events to have occurred recently and thus less likely to affect the decision. By the same logic, common events will tend to be overweighted because they are more likely to have occurred recently.

To examine whether recency affected decisions in the experience group, we split the sequence of draws from each option into two halves for each problem and each respondent. Then we computed the options' average payoffs obtained for the first and second halves of the samples, predicted each person's choice on the basis of the payoffs, and analyzed how many of the actual choices coincided with the predicted choices (for the first and second halves of the samples, separately). The second half of samples clearly had greater predictive power than the first half. Whereas the first half predicted, on average, 59% of the final choices, the second half predicted 75% of the choices, $t(49) = -3.1$, $p = .003$, two-tailed. In other words, rare events have less impact than they deserve not only because decision makers have not encountered them, or have encountered them less frequently than expected, but also because they have not encountered them recently.

Elsewhere (Hertwig, Barron, Weber, & Erev, in press), we have proposed and tested a model that successfully captures the effects of both recency and sample size on risky choice by specifying how old and new information is integrated.

DECISIONS FROM EXPERIENCE IN HUMANS AND OTHER ANIMALS

Not only probabilities and outcomes but many kinds of information can be learned through experience or description. Base rates, distributional information, and degrees of causal strength are a few examples. Thus, one might expect the way in which information is learned to influence cognitive processes in many domains. Indeed, in research on Bayesian reasoning, for instance, there is evidence that performance depends on whether base rates are directly experienced or symbolically described (see, e.g., Koehler, 1996, and Weber et al., 1993).

Because animals do not share humans' ability to process symbolic representations of risky prospects, all their decisions (e.g., about where to forage) are decisions from experience. Weber et al. (2004) reported some striking similarities in the behavior of humans and lower animals when humans are placed in situations in which they, too, must make decisions from experience. Human decisions from description, however, differ markedly from human decisions from experience, provoking these authors—and us—to call for two different theories of risky choice. In a study of foraging decisions made by bees, Real (1991) observed that "bumblebees underperceive rare events and overperceive common events" (p. 985), when the events are instances of food. To explain why bees' "probability bias" diverges from that observed in humans, Real cited, among other factors, the fact that bees' samples from payoff distributions are truncated because of memory constraints. Although humans and bumblebees do not share a recent evolutionary history, our results suggest that there is no contradiction between the decisions of bumblebees and those of humans when humans must also rely on experience.

Acknowledgments—We are grateful to Eduard Brandstätter, Valerie Chase, Eric Johnson, Yaakov Kareev, Barbara Spellman, and Masanori Takezawa for helpful comments. We also thank Anita Todd for editing the manuscript, the German Research Foundation (Deutsche Forschungsgemeinschaft) for a grant to the first author (He 2768/6-1), and the Max Wertheimer Minerva Center for technical and financial support. Preparation of the manuscript was facilitated by a fellowship from the Institute for Advanced Study in Berlin to the third author.

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(Received 6/24/02; Revision accepted 11/20/03)