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8 Decision-Making

Yuval Erez and Valerie F. Reyna

"*That the sun shines tomorrow is a judgement that is as true as the contrary judgement*"

– David Hume.

The history of the psychological study of decision-making has its roots in modern theory of probability in the seventeenth century. Here, we describe the historical evolution of ideas from a conception of decision-making as rational to one that is biased and emotional. The historical periods can be divided into two parts, roughly before and after the 1950s. Before the 1950s, decision-making in the mind was thought to reflect pure mathematics. After the 1950s, the weaknesses and inconsistencies of human decision-making became more and more obvious. Ultimately, the elegance of pure mathematics was rejected in favor of theories that captured the messy irrationality of the human mind. The most recent theory shows how biases and emotionality can be part and parcel of advanced decision processes that involve intuitive gist. Thus, modern theory has begun to move beyond Cartesian dualism to encompass cognition, emotion, personality, and social values to predict decision-making.

Background

In the movie *Next*, American actor Nicolas Cage plays a man with a unique ability – he can see a few minutes into his future. Thus, knowing what would be the ensuing outcomes of his own choices, within this time frame, he can easily pick the one that maximizes his well-being. Thus, a straightforward decision rule should dictate his choices – choose the best outcome. In the nonfiction world, however, people do not have certainty about future outcomes. They often choose between outcomes that vary in known (e.g., the spin of a roulette wheel) and unknown (e.g., the effectiveness of experimental medical treatments) probabilities.

Despite the uncertainty regarding future events, people still need to make plenty of choices, in various domains, every day. Some choices entail significant, long-term implications (e.g., deciding what to study, which house to buy, whether to start a business, who to marry). Other choices may sound less dramatic, yet they do carry the potential to either cause or prevent unwanted, and even disastrous, consequences (e.g., having unprotected sex, buying apartment insurance, or passing a vehicle on a two-way road), or to facilitate

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high-stakes benefits (e.g., purchasing a lottery ticket or investing in a risky but potentially high-return stock). Also, there are choices with mild to low impact over one's lifetime (e.g., carrying an umbrella on a cloudy day, purchasing a new toothpaste brand, or betting $20 on red in a roulette game).

The field of *judgment and decision-making* (JDM) classifies these sorts of choices, when outcomes are contingent upon whichever state of the world transpires, as *decision-making under uncertainty*. Importantly, it constitutes the heart of this field. It should be noted that uncertainty about future events can sometimes be measurable and sometimes immeasurable. That is, in some cases, we can accurately translate available information into numbers that indicate the likelihood to observe uncertain events. When rolling a (fair) die, for example, we cannot tell for sure which number will come up, but we do know for certain the *probability* to obtain the number six, an even number, or any other related event. In other cases, which apply to most real-life situations, the likelihood of uncertain events is incalculable. What is the probability of an economic crisis next year? To find a cure for cancer in the next decade? That the Los Angeles Lakers will win their next NBA game? In his 1921 book, *Risk, Uncertainty and Profit*, the economist Frank Knight made a formal distinction between the two types of uncertainty we have mentioned. He called the measurable one *risk* and the immeasurable one *true uncertainty*, which later has been termed in the literature as *Knightian uncertainty*. However, in order to keep things plain, in this chapter we will use both *risk* and *uncertainty* interchangeably to convey the same theoretical meaning.

There are multiple disciplines comprising the field of JDM (such as Psychology, Economics, Mathematics, and Philosophy), with a staggering number of works striving to account for the processes by which people make, or ought to make, choices in various circumstances. The purpose behind these efforts is not just to satisfy the whimsical curiosity of researchers in the field. In fact, the value of learning how people reason and make decisions stems from its real-life implications. Such knowledge enables policy-makers to design better policies and legislate laws to improve public welfare in different areas of life such as health, employment, transportation, insurance, pensions, and many more. It also allows executives in the private sector to devise suitable marketing and other business strategies. By learning the mechanisms of decision-making, we can avoid cognitive biases and "irrational" choices, which will be discussed later in this chapter.

In this chapter we explore how the topic of decision-making under uncertainty has intellectually evolved over time. However, before plunging into some of the main models and theories of this field, it is useful to discuss three fundamental types of analyses. Each study of decision-making can be classified as *normative*, *descriptive*, or *prescriptive*.[1] The normative approach is a "rational" one. It seeks to demonstrate how people ought to make choices in

[1] For a thorough discussion on this topic, see Bell, Raiffa, & Tversky (1988).

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a coherent, logical way. The key assumption underlying this approach is that the decision-maker is a logical, deliberative creature, who obeys some basic rules of sound-choice behavior formulated in what are called "axioms" (Von Neumann & Morgenstern, 1944). For example, an axiom called "transitivity" means that if a decision-maker prefers a red car to a blue car, and the blue car to a yellow one, she will prefer the red car to the yellow car. Similarly, the *Independence of Irrelevant Alternatives* (IIA) axiom posits that if an individual prefers a trip to Rome over Paris, she would not reverse her preference with the introduction of another alternative, say Barcelona (Rome should still be preferred to Paris, whether Barcelona was eventually chosen or not).[2] This ideal creature is further assumed to have the capacity to process all available and relevant information, and is fully capable of performing any level of calculation required in order to reach an optimal (best) decision.

Descriptive analysis focuses on how real, imperfect human beings make choices in practice, how they reason, and why they behave the way they do. In particular, it examines different patterns of behavior that systematically deviate from axioms of decision theory. Furthermore, unlike the normative approach, it is mostly based on empirical methods and statistical analysis conducted on observed choice behavior. For instance, in one of their experiments, Simonson and Tversky (1992) found that the proportion of subjects who, from a set of two different cameras, preferred to purchase the one that is more expensive grew larger when an even more expensive camera was introduced as a third alternative.[3] Clearly, this study falls under the descriptive category as it shows a situation in which the IIA axiom is violated using empirical data.

In short, normative theories draw upon philosophical standpoints about how the ideal decision-maker *ought to* choose, whereas descriptive analyses are the product of empirical findings showing how real people *do* make choices.

Finally, the prescriptive approach can be thought of as a mixture between normative and descriptive analyses. Its main goal is to help people make better and more coherent choices while taking into account that "human cognition is non-optimal, non-rational and non-probabilistic," as argued by Tversky and Kahneman (1983). To this end, prescriptive models typically provide people with decision-aiding tools in the form of specific rules and step-by-step guidelines to help navigate their choice behavior in a normative fashion (i.e., away from the human tendency to make inconsistent and illogical choices, or other cognitive biases, as shown in many situations). Assume, for example, a married couple (with the same set of preferences) who are looking to buy a new house and are considering two alternatives. In order to ensure their choice is indeed rational, at least from a normative perspective, they can apply various prescriptive models to aid their decision. One such model, for instance, can suggest the married couple to expand their set of alternatives to include more options, and if necessary adjust their choices to maintain consistent behavior. This

[2] IIA is sometimes referred to as the Chernoff condition or Sen's property alpha.
[3] This pattern of behavior is known in the literature as the *compromise effect*.

prescription will help them adhere to the IIA axiom. But how should these decision-makers handle choosing between options that differ in probability? The following section tackles that topic.

Expected Value and Expected Utility Theory

To think about how decision-makers cope with options that differ in probability, imagine that you have been given the opportunity to choose between two alternatives:

A. Win $5 for sure.
B. Roll a fair die four times. If it lands on six at least one time, you win $10, otherwise you win nothing.

Which option would you choose? Arguably, there is no universal right or wrong answer to this choice problem. Each of the two alternatives can be a good fit for different types of people, or even for the same type of people under different circumstances. Normally, the choice to this question is determined by factors such as an individual's skills or traits (e.g., numeracy skills or impulsiveness), values (e.g., gambling is bad), and beliefs (e.g., I am a winner) held by the decision-maker, as well as his or her financial state, experience, emotional and physical state (e.g., happy and tired), and attitude toward risk (e.g., I do not like taking chances, or *risk intolerance*). In addition, prevailing social norms, from which the decision-maker operates (e.g., taking chances is cool), and other environmental or external factors, can influence the decision.[4] But is there a more precise mathematical approach to this problem as well?

Evidently, a version of the abovementioned choice problem and other similar games of chance (which were quite popular during the seventeenth century) led to the emergence of modern probability theory as a branch of study. In the year 1654, Blaise Pascal and Pierre de Fermat, two of the most influential mathematicians of their time, sought to formulate a proper solution to a challenging, long-standing problem. The problem had arisen from a game of dice known as *The Points*, where two players contribute equally to a prize pot and then play several rounds against each other. The first to win a certain number of rounds is declared as the victor and gets to collect the entire pot. The problem was with concocting a *fair way* to divide the pot between the two contenders in the event that unexpected circumstances compelled them to end the game prematurely, before a victor could be properly declared. Hence, it was also called the problem of the *division of the stakes* (i.e., the pot). Pascal rose to the challenge and began discussing this problem with Fermat through a series of letters. Soon enough,

[4] Note that the factors mentioned here need not be independent of each other. In fact, there are situations in which one feeds the other (e.g., risk intolerance may trigger a feeling of stress when one is being posed with a risky choice; the sight of a rainbow may reinforce a feeling of optimism).

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they both came up with a similar mathematical solution that accounted for the chances that each player had to win the pot if they had continued playing from the stopping point. Essentially, their reasoning for a fair solution to the problem introduced a new and fundamental principle in probability theory, which was later referred to as *expected value*.

The expected value (EV) of a random variable calculates the average across all possible outcomes weighted by their probabilities. Formally, if X is a random variable with n possible outcomes, $x_1, x_2, \ldots, x_n$, and p_i denotes the probability to obtain x_i for every $i = 1, \ldots, n$, then

$$EV(X) = \sum_1^n p_i x_i.$$

Imagine, for example, a lemonade stand whose daily revenue from selling lemonade depends on the weather. On a sunny day, total revenue sums up to \$400; when it is cloudy and gray outside, the revenue drops to \$100; and when it rains, people prefer to stay home and the lemonade stand winds up selling nothing (no revenue). Assume now that, according to the weather forecast for tomorrow, there is a 50 percent chance of pure sunshine, 30 percent chance of clouds, and 20 percent chance of heavy rain. While future weather is uncertain, it is still possible to calculate the EV of the revenue the lemonade venture will experience (if open tomorrow):

$$EV = 0.5 \times \$400 + 0.3 \times \$100 + 0.2 \times \$0 = \$230.$$

Furthermore, based on the principle of the *law of large numbers*, EV represents the value to which the average outcome of the random variable converges when the choice is made repeatedly. That is, if you roll a six-sided die a thousand times, for example, and average across the observed outcomes, you will almost surely get a number very close to 3.5, which is indeed the expected value obtained from a given roll of a standard die.

With its ability to accurately predict the average outcome of uncertain events, EV soon was recognized as a prominent criterion for guiding rational-choice behavior (mostly, but not exclusively, for financial choices). Basically, the theory of expected value argues that rational decision-makers should choose the alternative that maximizes their expected value. Thus, when facing a decision problem such as: win \$3 for sure, or flip a coin and win \$8 if it comes up heads or \$0 otherwise, an *expected value maximizer* would pick the coin flip over the sure prize. In other words, $\$3 \times 1.0 = \$3$ and $\$8 \times .5 = \$4$; the maximizer would choose the coin flip because it has a higher EV (\$4) than the sure thing (\$3). In a similar fashion, we can now employ the EV theory to reexamine the choice problem posed at the beginning of this section – take \$5 for sure, or roll the die four times and win \$10 if a six comes up at least once (nothing otherwise). A simple calculation shows that the expected value of the risky option (i.e., rolling the die) is just under \$5.2. This means that, on average, the return from rolling the die is higher than that of the safe alternative, thus making it a better option for rational EV maximizers.

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But as much as this theory may seem plausible from a rational standpoint, people in the real world do not seem to apply the EV principle so avidly in their risky-choice behavior. A high proportion of American households, for example, refrain from investing their money in financially risky assets despite being an actuarially favorable gamble (i.e., the stock market provides high average return). This phenomenon is known as the "*stock market participation puzzle*" (Haliassos & Bartaut, 1995). Other evident examples for risky behavior that deviates from the EV maximization rule are: gambling at a casino, where the odds are always tilted in favor of the house; purchasing lottery tickets; and even getting cell-phone insurance. What is common to these examples – and many others like them – is that in the long run people will most likely lose money (or earn less) by not following the EV rule.

Occasionally, however, the long-run averages themselves are, at least prima facie, immaterial to the decision – particularly when facing a single, nonrepeated choice problem. Assume that the daily costs of running the lemonade stand from the earlier example are \$150 and recall that, based on tomorrow's weather forecast, a revenue of \$230 is expected on average. Clearly, an EV maximizer would choose to take a risk and open the stand the next day since the expected value of the revenue is higher than the costs (\$230 > \$150). But note that \$230 is merely the result of a theoretical concept and not an attainable outcome. That is, by repeating the same day, with the same weather forecast over and over again, the revenue will ultimately approach \$230, yet the actual choice to open the stand concerns only the next day, in which \$230 is not a feasible outcome. Why, then, should a choice be driven by the EV principle – even from a normative perspective? Scholars soon criticized the EV principle for this and other reasons.

The first formal challenge to the EV paradigm arose in 1738 when Daniel Bernoulli, a Swiss mathematician and physicist, published a paper in the *Commentaries of the Imperial Academy of Science of Saint Petersburg* (see Bernoulli, 1954). In his paper, Bernoulli proposed a resolution to a problem – known today as the *St. Petersburg Paradox* – which questioned the EV principle as a rational decision rule. The paradox is illustrated by a game of chance that was discovered by Daniel's cousin, Nicolas Bernoulli, in 1713. The game is played as follows: A fair coin is flipped repeatedly until the first time it comes up tails; then the game stops (so there is a 50 percent chance the game will end after just one toss). The player gets \$2 after the first toss, and then the prize is doubled with every coin flip until the game ends. Thus, if the game ends after one toss ("tails"), the player wins \$2; if it ends after two coin tosses ("heads," "tails"), the prize is \$4; with three tosses ("heads," "heads," "tails"), the prize grows exponentially to \$8, and so on. What is, then, the maximal price a rational individual would pay to enter this game? Would you pay \$100? How about \$100,000?

A decision-maker who obeys the EV maximization rule should enter the game for any price lower than the expected payoffs. But apparently, the mathematical expectation of this game is unbounded; namely, the game's long run average win is an infinite number of dollars! Thus, no matter how high the entry price is, a rational EV maximizer will readily pay it. Clearly, however, no rational human being will enter the St. Petersburg game at any cost, and hence the paradox. In fact, as Ian Hacking (1980) argues, the majority of people would not take part in this game even for as little as $25.

Bernoulli's solution to this problem distinguishes between the numerical value of the prize (i.e., number of dollars) and the level of satisfaction, or utility, obtained by the amount of money received. A rational decision-maker, then, is said to make choices based on satisfaction gained by the payoffs rather than their monetary value. Furthermore, Bernoulli argued that the level of utility goes up with money but in a nonlinear fashion, particularly as a concave function, such that every additional dollar increases the overall utility by less than the dollar before. Roughly speaking, $10 added to an initial prize of $100 seems more satisfying than the same $10 when added to a $10,000 prize.[5] Bernoulli proposed a logarithmic function to mathematically represent people's utility (log-utility function), which solves the St. Petersburg problem. A rational individual with a log-utility function characterizing his or her level of satisfaction from wealth will likely pay no more than $4 (the expected utility of the gamble using log-utility function) to participate in the St. Petersburg game.

The pioneering work of Bernoulli was the first to provide a formal explication of the notion of utility and diminishing marginal utility – bringing it to the forefront of decision-making research. His solution to the St. Petersburg paradox shifted the focus from expected value to expected utility as the key principle that underlies rational choice behavior, which inspired generations of researchers who embraced this principle in their work.

However, it took over two hundred years for the idea of expected utility to evolve into a full-blown theory. In 1944, John von Neumann and Oskar Morgenstern provided a set of four axioms of rational-choice behavior that are necessary and sufficient to be able to represent preferences over risky outcomes (gambles) using the expected utility model. We have discussed two of these axioms already: *independence* and *transitivity*. Transitivity is an axiom that entails consistency, as our earlier example with three cars suggests. It states that if an alternative A is preferred to B, and B preferred to C, then A must also be preferred to C. Another axiom, known as *completeness*, states that for every two alternatives, A and B, a decision-maker should either prefer A to B, B to A, or be indifferent between A and B. That is, inability to compare any two alternatives is not a viable possibility for a rational decision-maker. (The fourth axiom of *continuity* is beyond the scope of this chapter, but see von Neumann & Morgenstern, 1944.) Von Neumann and Morgenstern proved mathematically that decision-makers whose preferences obeyed these basic rules of consistency – the axioms – would maximize their utilities. Following von Neumann and Morgenstern's formulation, the expected utility (EU) theory has become the

[5] This has become a key property in the field of economics known as the *law of diminishing marginal utility*.

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dominant, most influential economic theory for analyzing choices under uncertainty.

Rational models of decision-making, such as EV and EU theory, rest on the premise that when making choices people are well informed regarding the available alternatives relevant to their decision, as well as every possible outcome for each of these alternatives. Furthermore, it is assumed that their preferences over the set of choice elements are well defined and coherent (e.g., complete and transitive) and that they are endowed with high enough cognitive capacity to allow them to solve the problem of value maximization through which they could pick the best alternative available. However, it is quite doubtful that a rational individual of this sort has ever existed. The question whether, and to what extent, people behave as rational decision-makers was mostly left to psychologists to explore and to suggest alternative models of choice behavior.

Although many economists realized that rational models had some unrealistic assumptions about human information processing, these were considered trivial for most practical purposes. But psychologists became fascinated with the powerful EU model: Ward Edwards, the son of an economist, introduced the model to psychologists in 1954, asking whether people actually behave as economists had assumed, balancing the desirability of an outcome against its chance of occurring. Meanwhile, psychologists were identifying substantial limitations in human information processing, notably, George A. Miller in his influential 1956 paper, "The magical number seven, plus or minus two: Some limits on our capacity for processing information." The central idea of this paper – still believed by most psychologists today – is that people cannot think about alternatives exhaustively. Instead, decision-makers can remember and think about only a few chunks of information (seven according to Miller, four according to some recent theorists) at a time, which limits or bounds their ability to make decisions. Miller influenced his friend Herbert Simon, who then assumed people were limited but still "rational" in a scaled-down way: they did not pick the best option possible (maximizing), but, rather, chose options that were good enough, called "satisficing," as we will discuss later (Simon, 1957).

Challenging Rationality

Trying to acquire the relevant knowledge to make a rational decision as already outlined, including all available alternatives, probabilities, and outcomes, and then using that information to solve an optimization problem is both time consuming and mentally taxing. Generally, we even lack the cognitive capacity to execute the level of computation required by rational-choice models. Thus, in a world where people make numerous choices every day, it is actually inefficient to be entirely rational. Instead, it is essential for us to reduce the vast amount of available information and to be able to rely on some mental shortcuts and more practical decision rules – known as *heuristics* (or rules of thumb) – in order to reach a decision within a reasonable time frame.

Bounded Rationality and Satisficing

Among the earliest scholars who recognized the fact that people's rationality is limited, and thus cannot be represented by the ideal decision-maker as portrayed in standard models of rational choice, was Herbert Simon, the 1978 Nobel laureate. He referred to this principle as *bounded rationality* (Simon, 1957) and argued that in general it results in people settling for a cognitive heuristic, labeled *satisficing*, which significantly simplifies the decision-making process. That is, instead of maximizing across all available alternatives, using all the information they can gather, decision-makers aim at satisficing by setting aspiration levels, or "good enough" criteria, and then choosing the first alternative whose attributes, or value, exceed the minimum threshold set by these criteria. The chosen alternative is, thus, satisfactory by design but need not be the optimal one.

Consider a situation in which you are looking to buy a birthday present for your seven-year-old nephew. Clearly, the number of alternatives you can choose from is enormous and the amount of relevant information to consider is exponentially higher: Would you buy a board game, a book, tickets to a circus show, or maybe a pet? What color? How much money to spend on the gift? Those are just a few of the questions you can ask yourself. If you try to pick the ultimate gift by solving an optimization problem, you will probably miss your nephew's birthday altogether (maybe his eighth birthday too…). Satisficing, then, is a common course of action in these situations. You can decide to focus on items relevant to your nephew's favorite movie, for example, and set a range of prices you are willing to consider. This will reduce the complexity of the problem, allowing you to buy a satisfying gift in time for his birthday.

"Errors" in Probabilistic Reasoning

Probabilities are one of the key building blocks of rational models of risky choice (e.g., EV and EU). It is assumed, therefore, that the decision-maker is capable of judging the precise likelihood that each possible outcome will occur. But how good are we really at translating given information about events into the exact probabilities that those events will actually occur?

The Monty Hall Problem

To exemplify this point, consider the following game: There are three doors, A, B, and C, from which you have to choose one. Behind one of the doors lies a prize of $1 million, nothing lies behind the other two doors. The host of this game, who knows exactly where the prize is, asks you to make your choice. Suppose that you pick door A. At this point, your chance of winning the prize is 1/3. Before revealing what awaits you behind door A, the host opens another door and shows you that nothing is there, say door B (remember that he knows where the prize is). He, then, gives you the option to change your initial choice

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and switch to door C. Would you keep door A or would you choose door C now? Most people believe that there is a 50–50 chance now to find the prize behind either one of the two doors, and they typically stick with their initial choice. Surprisingly, though, they are wrong. By moving from door A to C, you actually double your chances to win the prize from 1/3 to 2/3. Thus, counter-intuitively, switching doors is an advantageous strategy. Note that changing the initial choice is equivalent to choosing where the prize is *not*, since effectively you are moving your choice to include both of the remaining two doors (and hence the 2/3 chance to win) – one of which is opened by the host and the other door is the one you moved your choice to. In contrast, by sticking with the original choice you have no control over which two doors will eventually be opened.

This game is known as the *Monty Hall problem*. It is based on a television game show from the early 1960s whose host's name was Monty Hall. In one experiment with this problem, for example, only 12 percent of all participants chose to switch (Granberg & Brown, 1995). This game, thus, provides a convincing evidence of our difficulty to derive intuition for probabilities from given information.

Conservatism Bias

Starting in the early 1960s, Ward Edwards introduced the idea of Bayesian probability inference into the field of psychology. A statistical formula, known as *Bayes theorem* (or *Bayes rule*) lies at the heart of this idea. This statistical tool allows us to accurately update prior belief regarding the probability of some random event when being presented with new evidence. Edwards, along with his colleagues, had conducted a number of experiments to assess whether people were indeed Bayesian in their probability judgment behavior. That is, how well do people revise their prior beliefs when new information is presented?

Here is a typical Edwards's experiment: There are two book bags, each with 1,000 poker chips. One has 700 red chips and 300 blue chips and the other one has 700 blue chips and 300 red chips. A subject is asked to pick one of the bags, sample a few chips one by one (with replacement) at random, and then estimate the likelihood that he picked the book bag that contains mostly red chips. Suppose that a sample of 12 chips has been drawn, 8 of which were red. What is, then, the likelihood this is the bag with the 700 red chips? The majority of subjects believed it is somewhere around 70 percent chance. However, the correct answer, using Bayes rule, is in fact closer to 97 percent.

It seems, then, that people do update their prior beliefs in the right direction (from 50–50 chance for each bag to around a likelihood of 70 percent to have the mostly-red-chips bag), but they do so insufficiently when compared to properly applied Bayesian inference. Given his findings, Edwards concluded that people tend to overestimate the prior and underestimate new evidence, or, in his own words, they are "conservative processors of fallible information" (Edwards, 1968). This effect is known as the *conservatism bias*.

Base-Rate Neglect

We just discussed how people can be prone to processing new information in a conservative way, giving too much weight to prior belief. However, interestingly, people can also exhibit the exact opposite bias, this time underweighting the prior. This bias is known as the *base-rate neglect* (or *base-rate fallacy*). The base rate of a certain event is defined as its prior likelihood, or unconditional prevalence. People are susceptible to this bias when they shift their attention away from the base-rate information and focus mainly on some newly acquired data.

A classic example that demonstrates this bias was originally introduced in 1973 by the two celebrated psychologists Amos Tversky and Daniel Kahneman.[6] Tversky was a student of Edwards, and was joined at the University of Michigan by Kahneman. They were intrigued by the exceptions to EV and EU theory. Here is a slightly modified version of that base-rate problem:

> A taxi-cab was involved in a hit-and-run accident one night. Of the taxi-cabs in the city, 85 percent belonged to the Green company and 15 percent to the Blue company. an eyewitness had identified the cab as Blue. The court tested the reliability of the witness under the same circumstances that existed on the night of the accident and concluded that the witness was able to make correct identifications 80 percent of the time (failing to identify only 20 percent of the time). What is the probability that the taxi-cab involved in the accident was Blue rather than Green?

The answers given by the vast majority of respondents ranged between 0.5 to 0.8 probability that a Blue cab was involved in the accident, with 0.8 being the most typical answer to this question. This answer coincides perfectly with the data regarding the witness's credibility, while neglecting the base-rate information about the relative frequencies of the two taxi-cab companies. The correct probability obtained by using Bayes rule is actually 0.41. It is very likely, then, that the witness was wrong, despite having good observation skills, which may seem counterintuitive. Importantly, the potential consequences of neglecting the base rate can be quite perturbing. Kahneman and Tversky (1973) expressed their concern regarding the taxi-cab problem as follows: "Much as we would like to, we have no reason to believe that the typical juror does not evaluate evidence in this fashion."

Other practical implications of the base-rate bias on decision-making can also be found in the field of medical diagnosis. As Eddy (1982) and others have noted, it is not at all uncommon for physicians, for example, to overly rely on specific test results and disregard the prevalence rate of the actual disease they are trying to diagnose (e.g., Gigerenzer et al., 2007; Gigerenzer, Hoffrage, & Ebert, 1998; Reyna, 2004). To counteract this bias, medical students are sometimes told, when you hear hoof beats (symptoms), think horses not zebras (common not rare diseases).

[6] See also: Lyon & Slovic (1976) and Bar-Hillel (1980).

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(In)consistent Choice Behavior

Normative models of decision-making are typically founded upon axioms of rational choice, such as completeness, transitivity, and so on. These axioms are designed to ensure consistency of the decision-maker's preferences and, at least from a philosophical standpoint, they are arguably sound. For example, it would be considered illogical for a person to strictly prefer some alternative A over B but then, in a similar situation, having no additional relevant information, choose B over A. Normally, the axioms will prevent this form of inconsistency.

But to what extent do real people exhibit coherent choice behavior as predicted by the rational models (such as EU theory)? We highlight here cases in which consistency seems to be violated.

Preference Reversals

In 1971, the psychologists Sarah Lichtenstein and Paul Slovic (also students at the University of Michigan) documented a pattern of human choice behavior that challenged the supposition that human preferences are consistent. The researchers designed an experiment in which the stimuli consisted of a number of paired binary gambles. Each pair had roughly the same monetary expected value with one gamble structured as a high-probability, low-stakes payoff (the so-called P-bet), while the other gamble offered low probability to win a relatively large payoff (the so-called $-bet). Subjects were asked to choose one bet from every pair of gambles. Generally, the P-bet was chosen more frequently than the $-bet indicating a preference for the lower-risk gambles. However, when asked to state their bidding price for every gamble, the subjects typically placed a higher value on the $-bet, which reflects a reversal in their preference order – a phenomenon known as *preference reversal*.

This pattern of "inconsistent" behavior has been replicated many times since (e.g., Grether & Plott, 1979; Lichtenstein & Slovic, 1973; Tversky, Slovic, & Kahneman, 1990). One common explanation found in the literature for preference reversals is that different types of preference-elicitation methods tap into different attributes of the gamble. This is known as *scale compatibility* (Tversky et al., 1990). That is, when bidding their prices, subjects weighted the gamble's monetary payoffs more heavily than they did when directly choosing between the gambles. This clearly poses a violation to a fundamental principle of rational decision-making, which states that preferences should be invariant to the elicitation mode.

The Certainty Effect

During the 1970s, Kahneman and Tversky continued to search for behaviors that systematically deviated from core principles of rational-choice models (e.g., EU theory). In one of their experiments, ninety-five respondents were asked to give their choices for each of the following binary decision problems:[7]

Problem 1: Choose between

A: £3,000 for certain
B: £4,000 with probability of 0.8 (£0 otherwise)

Problem 2: Choose between

C: £3,000 with probability 0.25 (£0 otherwise)
D: £4,000 with probability of 0.2 (£0 otherwise)

Note that if you multiply the probabilities of both options A and B by 25 percent, you get options C and D respectively, so that choice problem 2 is merely a 25 percent version of problem 1. Nevertheless, in the first problem, the majority of respondents (80 percent) opted for the riskless option, the £3,000 for certain (option A) – although the gamble offers a higher EV, while in problem 2 a reversed pattern was observed, where this time the riskier option of £4,000 with probability 0.2 (option D) was chosen more frequently (65 percent). According to Kahneman and Tversky (1979), a significant reduction in the desirability of a prospect occurs when a riskless positive outcome is altered to a probable one. Thus, this bias is referred to as the *certainty effect*.

The Reflection Effect

As part of the same experiment, the ninety-five respondents were given another decision problem, this time with negative prospects (i.e., losses), in which they needed to choose between two options:

Problem 1': Choose between

A': –£3,000 for certain
B': –£4,000 with probability of 0.8 (£0 otherwise)

Note that problem 1' is a precise reflection of problem 1 in the previous section, only in the negative domain. It is a reflection in the same way an image is reflected in a mirror – everything is the same, except in the opposite direction. However, while in problem 1 the majority chose the safe option (option A), this time 92 percent of all respondents chose the risky option (option B'). Essentially, they accepted the risk of losing more money (i.e., £4,000) over a sure loss of £3,000. The incongruent behavior obtained from problems 1 and 1' follows a consistent pattern in which people exhibit risk aversion with gains and risk-seeking behavior with losses. Kahneman and Tversky (1979) labelled this pattern the *reflection effect*.

[7] These pairs of gambles are based on a problem constructed by the French physicist and economist Maurice Allais (1953), which was the first major challenge to EU theory (calling into question the independence axiom). It is known today as the *Allais paradox*.

To further test this effect, they also presented the following two decision problems:

Problem 3: In addition to whatever you own, you have been given £1,000. You are now asked to choose between

A: £1,000 with probability of 0.5 (£0 otherwise)
B: £500 for certain

Problem 4: In addition to whatever you own, you have been given £2,000. You are now asked to choose between

C: –£1,000 with probability of 0.5 (£0 otherwise)
D: –£500 for certain

In accordance with the reflection effect, the riskless option B was chosen by the majority (84 percent) in problem 3, yet most respondents (69 percent) chose to take a risk with option C in problem 4. That is, people (again) showed a tendency to avoid risk with positive payoffs but were willing to accept it with negative prospects. Importantly, note that by combining the bonus in each problem with the prospects (i.e., the options), problems 3 and 4 are collapsed into the same choice problem with the same final consequences (£1,500 for certain versus 50–50 chance for either £1,000 or £2,000). However, the disparate choice behavior between the two problems is strikingly evident, which puts a big question mark on rationality as defined by standard models of decision-making.

The Framing Effect

The notion of a *framing effect* is possibly the most striking demonstration of incoherent risky-choice behavior. A framing effect is being referred to when a shift in preferences is caused by the way outcomes of a prospect are described (i.e., *framed*). The popularity of this concept goes back to 1981 when Tversky and Kahneman published the results of an experiment they had run, which illustrated the effect of variations in framing. In one example, the researchers presented the following two problems to two groups of roughly 150 respondents each, such that every group received one problem:

Problem 1: Imagine that the United States is preparing for the outbreak of an unusual disease, which is expected to kill six hundred people. Two alternative programs to combat the disease have been proposed. Assume that the exact scientific estimates of the consequences of the programs are as follows:

- If Program A is adopted, two hundred people will be saved.
- If Program B is adopted, there is a 1/3 probability that six hundred people will be saved and a 2/3 probability that no people will be saved.

Which of the two programs would you favor?

While both programs have the same expected value of lives saved, the majority of respondents (72 percent) chose the riskless option, that is to save

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two hundred people for certain (Program A). The outcomes in problem 1 were framed as gains (lives saved). Problem 2, on the other hand, was described in terms of lives lost (loss frame) as follows:

Problem 2:

- If Program C is adopted, four hundred people will die.
- If Program D is adopted, there is a 1/3 probability that nobody will die and a 2/3 probability that six hundred people will die.

Which of the two programs would you favor?

Note that the (probabilistic) results from both Programs C and D are identical to those presented in Programs A and B (respectively) in terms of the number of people who will live and die. However, the majority of respondents (78 percent) presented with problem 2 chose the risky option (Program B). This is a clear evidence for the effect of framing. Particularly, it shows that people tend to be *risk averse* with prospects when outcomes are framed as gains and *risk seeking* when framed as losses.

The framing effect bias, which has been replicated many times, seems to be driven by context and, thus, poses a real challenge to the proponents of rational-choice models since it demonstrates a serious violation of the invariance axiom. In addition, its effect on people's decision-making has real-life implications in many different areas (e.g., law, politics, medicine, marketing, etc.). By framing a situation as either the half-full or the half-empty part of the glass, one can manipulate our choice behavior. When we react differently to a cash discount and a credit-card surcharge that amount to the same thing, we are demonstrating framing effects.[8]

Loss Aversion and the Endowment Effect

The shift in preferences illustrated by the example of the "dread disease" problem is a testament to the idea that people react differently to losses than they do to gains. In particular, the negative psychological effect experienced from losing a sum of money outweighs the positive one obtained from gaining the same amount. Hence, people will usually find a gamble that offers a 50–50 chance of losing $10 or winning $11 unattractive, despite the positive expected payoff. In other words, "losses loom larger than corresponding gains" (Tversky & Kahneman, 1991), which best describes the notion of *loss aversion*.

Loss aversion is one of the most widely used constructs in descriptive decision research. It was first introduced as a feature of risky-choice behavior in *prospect theory* – a model of decision-making under uncertainty formulated by Kahneman and Tversky in their seminal paper from 1979 in order to characterize the asymmetry between the level of aggravation and pleasure obtained by losses

[8] For more practical examples of the effect of framing on choices, see Thaler (1980, 1985), a winner of the Nobel Prize in 2017 for his work confirming that people are irrational.

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and gains of the same magnitude. Note that since gains and losses carry changes to some absolute value (e.g., overall wealth) they have to be defined relative to a *reference point* (e.g., the status quo), which makes it an integral part of every decision-making model that wishes to incorporate loss aversion. Any changes in the reference point may cause a shift in preferences and, accordingly, alter the observed choices (similar to the pattern we saw in the framing example).

In addition to accounting for the specific pattern of risky-choice behavior with mixed prospects, that contain both gains and losses, there is also a riskless manifestation of loss aversion, in which people often demand more to part with a valued object in their possession than they would be willing to pay in order to acquire it. The 2017 Nobel laureate, Richard Thaler (1980), called this phenomenon the *endowment effect*, which highlights the idea that out-of-pocket costs are weighted more heavily than forgone gains of the same magnitude. A number of examples were given by Thaler (1980) to illustrate this effect. According to one such example: "Mr. H mows his own lawn. His neighbor's son would mow it for $8. He wouldn't mow his neighbor's same-sized lawn for $20."

The endowment effect was successfully tested in a series of experiments conducted on college students by Kahneman, Knetsch, and Thaler (1990). In one such experiment, half of the students in a classroom received decorated Cornell coffee mugs (with a price tag of $6), and were assigned to be *sellers*, while the other half were *buyers*. Then, the experimenters elicited the minimum price each seller was willing to accept (WTA) in exchange for the mug and the maximum price each buyer was willing to pay (WTP) to acquire the mug. The results of the experiment showed a significant discrepancy between WTA and WTP in the hypothesized direction. The WTA median was approximately twice the size of the WTP median. That is, the students who randomly received the mug valued it twice as much as those who did not. The endowment effect was also found in a successive experiment, in which the experimenters used ballpoint pens instead of mugs.

The Fourfold Pattern of Risk Attitudes

As demonstrated by the reflection effect, for example, a person can be both risk averse and risk seeking at the same time. That is, risk attitudes constitute another aspect of inconsistent human behavior. It is not uncommon, then, to see people buy an insurance policy (risk aversion) while also purchasing a lottery ticket (risk seeking). Tversky and Kahneman (1992) generalized this pattern of behavior by organizing the different types of attitudes toward risks according to four distinct domains, which they refer to as the *fourfold pattern of risk attitudes*. Particularly, they noticed that people are risk averse for gains with moderate-to-high probability and losses with low probability, and risk seeking for gains with low probability and losses with moderate-to-high probability. The fourfold pattern is illustrated in Table 8.1, using an example adapted from Tversky and Kahneman (1992).

Table 8.1 *The Fourfold Pattern of Risk Attitudes*

	Gains (amounts in $)	Losses (amounts in $)
Low probability	A: 5 for sure B: 100 with probability .05 *Risk seeking*: B is chosen over A	A: –5 for sure B: –100 with probability .05 *Risk aversion*: A is chosen over B
High probability	A: 95 for sure B: 100 with probability .95 *Risk aversion*: A is chosen over B	A: –95 for sure B: –100 with probability .95 *Risk seeking*: B is chosen over A

Prospect Theory

After conducting a countless number of experiments to study human choice behavior and derive preferences among various risky prospects, Kahneman and Tversky decided to put forth an alternative model to standard theories of rational choice (particularly the EU theory), intended to account for their many "irrational" observations. The model was referred to as *prospect theory* (Kahneman and Tversky, 1979), and it has become the most widely used behavioral model of human risky choice – rapidly expanding across the multiple disciplines of JDM research.

Prospect theory was built around the many biases and "errors" that characterize both probability judgment and choices, some of which were discussed earlier in this chapter. The model consists of two functions designed to capture the underlying psychological process of human decision-making: (a) a value function that encodes the level of satisfaction (or dissatisfaction) associated with the possible payoffs; and (b) a probability weighting function that assigns decision weights (psychological interpretations of the size of the probability) to the different consequences based on the objective probabilities of occurrence. According to the model, preferences over prospects are determined by their overall valuation – calculated as the sum of all values obtained by multiplying the possible payoffs by their respective decision weights.

Three fundamental features distinguish the value function from a standard utility function (see Figure 8.1): (1) *Reference dependence*: whereas standard utility function represents the satisfaction obtained by the *final* amount of wealth, the values in prospect theory are a function of *changes* in wealth – gains and losses relative to a natural reference point – positive for gains and negative for losses. (2) *Loss aversion*: the value function is steeper for losses than it is for equivalent gains. This feature captures the idea discussed earlier that losses loom larger than corresponding gains. (3) *Diminishing sensitivity*: the higher the size of a given gain or loss, the smaller the marginal change to the value function. This feature generates an S-shape, where the positive domain of the value function is concave and the negative one is convex. The S-shape implies risk aversion for gains and risk seeking for losses due to its mathematical properties (which can account for the reflection effect, for example).

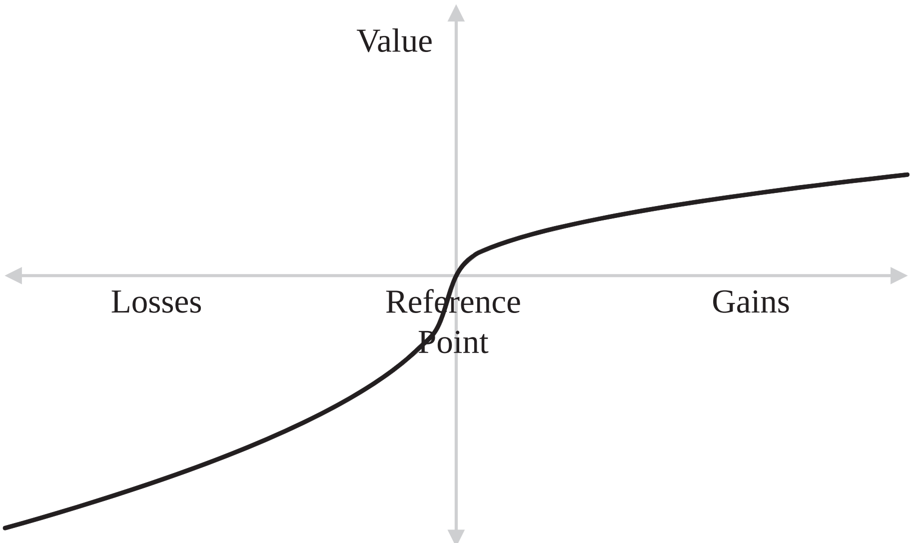

Figure 8.1 *The prospect theory value function.*

The other major component of prospect theory is the probability weighting function, which reflects the idea that probabilities are often distorted in a predicted way (see Figure 8.2). Thus, by converting the probabilities into decision weights, it generally captures the psychological impact of probabilities on the desirability of the prospect. For example, people tend to overestimate a 2 perccent chance to win $10,000, and might buy such a lottery ticket; they assign a higher decision weight to this consequence (say 3 percent), relative to its actual likelihood. The two main characteristics of the probability weighting function are overweighting of low probabilities (but greater than zero) and underweighting high probabilities (but less than one).[9]

In 1992, Kahneman and Tversky extended their theory in order to allow for more flexibility in predicting choice behavior with risky prospects, and to address some other technical issues that were prevalent in the original prospect theory (specifically in the probability weighting function). The updated model was referred to as *cumulative prospect theory* (CPT; Tversky & Kahneman, 1992). In particular, they modified the probability weighting function, while retaining the psychological aspects of the original one (see Figure 8.3).[10] The new function has an inverse S-shape form, which suggests that people tend to be more sensitive to changes in probabilities near the end points (i.e., zero and one) than in the midrange.[11]

[9] Decision weights are assumed to coincide with probabilities for the edge values of zero and one.
[10] The new functional form of the probability weighting function eliminates some possible violations of a central property of rational decision-making known as *first order stochastic dominance*.
[11] See, for example, Camerer & Ho (1994), Gonzalez & Wu (1999), and Wu & Gonzalez (1996).

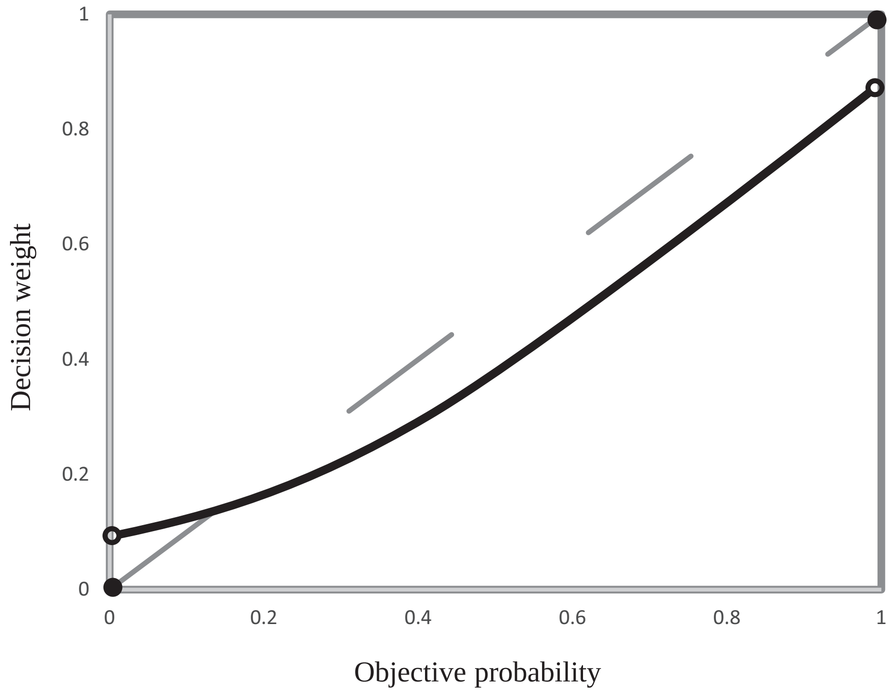

Figure 8.2 *The probability weighting function.*

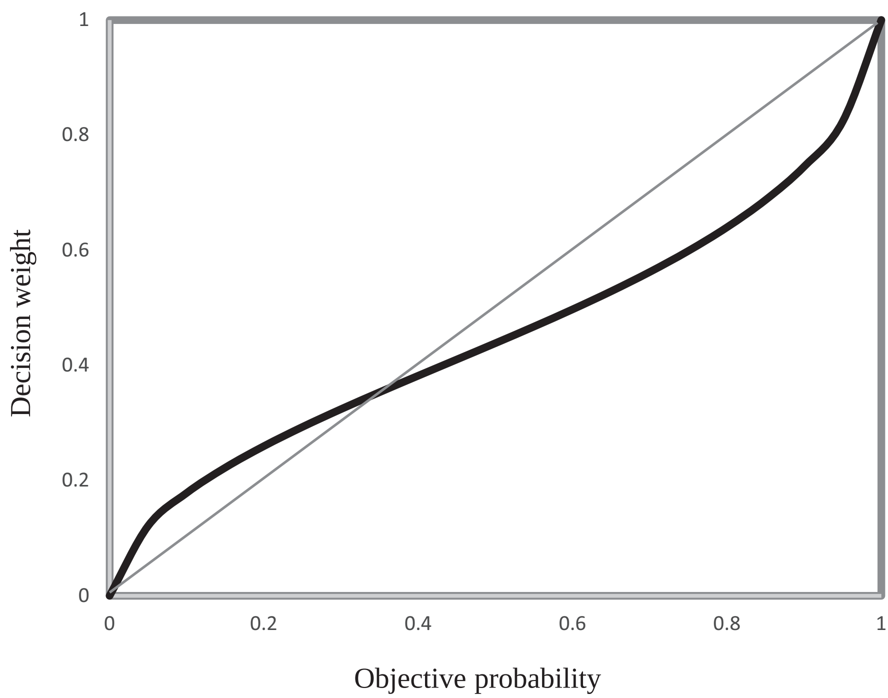

Figure 8.3 *Cumulative prospect theory's probability weighting function.*

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The predictive power of prospect theory is quite remarkable, especially in light of the tractability and rather simple structure that characterize the model. A combination of the features listed earlier can account for many of the risky decision-making patterns that deviate from the standard models of rational choice, including the certainty effect, reflection effect, framing effect, loss aversion, fourfold pattern, and so on. However, the predictions derived from prospect theory hinge on the idea of psychophysics and the perception of numbers (e.g., probabilities and payoffs), which as we see next, fail to actually predict some key findings, such as results of critical tests of framing effects and the Allais paradox.

Fuzzy-Trace Theory

The cognitive process behind the act of decision-making implicates memory and reasoning – namely, making sense of the available information and consequently reaching a conclusion that facilitates a choice between alternatives. Findings from psycholinguistics, JDM, and memory were integrated into the modern version of *fuzzy-trace theory* (FTT) in the 1990s (see Reyna, 2012, for an overview of the theory).

FTT is a model of memory, reasoning, judgment, and decision-making that was first proposed in 1991 by the two psychologists Valerie F. Reyna and Charles Brainerd in an attempt to provide an adequate account for the line of results, which challenged earlier, conventional approaches to cognition. The model distinguishes between two mental representations of informational inputs: *verbatim* and *gist*. Verbatim representation encodes the exact, surface details of a given problem or event, whereas gist representation is fuzzier in nature, extracting the patterns and meaning implied by the information. Furthermore, the verbatim and gist traces of information are encoded and stored in the brain simultaneously (rather than sequentially). For example, when presented with the following data: "Farmer Brown owns twelve cows, seven sheep, and three horses," one can encode and store verbatim traces, such as "twelve cows," or "three horses," concurrently with gist traces in the form of "cows are most," "more cows than sheep," and "horses are least" (Reyna & Brainerd, 2008).

When facing a choice problem, stored information fuels the decision-making process. According to FTT, relying on gist representations of the available information leads to a type of reasoning that is inherently different from reasoning based on verbatim representations. This can often lead to different conclusions and choices for the same decision problem. Consider, for example, a choice problem between \$50 for sure, and a 50 percent chance to receive \$100 and a 50 percent chance to receive nothing (\$0). The precise, surface details of this problem entail an equivalence between the EV of the riskless option and the EV of the gamble, whereas the bottom-line meaning of this problem yields a categorical distinction of the sort: "something" (the riskless option) versus "a chance of something and a chance of nothing" (the gamble). Thus, reliance on verbatim representations will generate indifference between the alternatives

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Table 8.2 *Verbatim and Gist Representations of the Dread Disease Problem*

	Verbatim information	Gist representation
Gain frame	A: 200 people will be saved.	A: Some people will be saved.
	B: 1/3 chance that 600 people will be saved and a 2/3 chance that no people will be saved.	B: Some people will be saved or no one will be saved.
Loss frame	C: 400 people will die.	C: Some people will die.
	D: 1/3 chance that nobody will die and a 2/3 chance that 600 people will die.	D: Some people will die or no one will die.

(equal expected value), while reliance on gist promotes risk aversion (i.e., picking the $50 because something is better than a chance of nothing). Note that the gist version of the options is not just any interpretation: the simplest interpretation of outcomes (here, as categorically something or nothing) is favored in decision-making, according to FTT.

Given its distinctive properties, FTT can provide an alternative explanation to the observed biases and other anomalies in risky-choice behaviors as discussed earlier in this chapter (e.g., framing effect, reflection effect, base-rate neglect, etc.). For instance, recall the dread disease example, which is expected to kill six hundred people. Table 8.2 presents word by word the two alternative programs proposed in each frame (the verbatim information) as well as the extracted gist representations.

Note that regardless of how the programs are framed, the expected value of the risky option is equal to the number of people who will be saved (or die) by applying the "riskless" program. However, reliance on the simplest gist (called a "fuzzy-processing preference" that most adults have) highlights the categorical distinction between the two programs instead of the exact details. Consequently, program A is favored in the gain frame (it is better to save some than risk saving no one), whereas in the loss frame the pattern is flipped and program D is the one chosen (accepting a chance that no person will die is preferred to the alternative, in which some people will surely die). Furthermore, choice behavior based on gist representations, with qualitative information only, can produce a nonnumerical framing effect. For example, in one experiment, Reyna and Brainerd (1991) presented a version of the dread disease problem to a group of participants, in which the numerical values were substituted with vague terms such as "some." Thus, the options in the gain frame, for example, became: "some people will be saved" versus "there is some probability that many people will be saved and a higher probability that no people will be saved." A similar alteration was made in the loss frame. Results from this experiment showed a strong framing effect (i.e., participants chose the safe option in the gain frame and the gamble in the loss frame). This shows that behavioral anomalies, such as the framing effect, need not be the product of psychophysics of presented numerical information. That is, numbers are *not necessary* to observe the classic effects.

In addition, FTT poses a major challenge to prospect theory and similar utility-based models by demonstrating that numerical values may *not be sufficient* to produce the framing effect. In particular, according to prospect theory consequences that generate no change relative to the reference point (e.g., "no one will be saved," "no one will die") are valued as zero and, therefore, carry no valuable information to the decision-maker. Thus, omitting the zero complement from a framing problem (e.g., the "2/3 chance that no one will be saved" is omitted from the presentation) should have no impact on the framing effect. In FTT, however, those zero outcomes contain qualitative information ("none"), which supports categorical reasoning and produces framing effects. A large number of experiments supported the FTT hypothesis by demonstrating that the framing effect disappears when the zero complement is omitted from the dread disease problem and other decision problems (e.g., Kühberger & Tanner, 2010).[12]

Similarly, FTT can explain the certainty effect (e.g., Allais paradox), in which a sure (positive) outcome is disproportionately more attractive than a probable outcome. Recall that most respondents preferred £3,000 for sure over an 80 percent chance to receive £4,000 (and nothing otherwise), but when the likelihood of each option was multiplied by 0.25, the choice pattern flipped, namely, a 20 percent chance to win £4,000 was chosen more frequently than £3,000 with 25 percent probability. This sort of inconsistent behavior poses one of the most fundamental challenges to the idea that people are rational. The certainty effect (that people prefer the sure option) is accounted for by the prospect theory, for example, by using a nonlinear probability distortion function (the inverse S-shaped probability function), which captures the idea of psychophysics of numerical information – people tend to overweight small probabilities and underweight large probabilities. Instead, FTT provides an underlying cognitive process that accounts for the reasoning that leads to this phenomenon.

In the first choice problem (comparing a sure £3,000 to an 80 percent chance to receive £4,000), reliance on the simplest gist representation contrasts "winning something" (£3,000 for sure) against "a chance of winning something and a chance of winning nothing" (£4,000 with an 80 percent chance), which renders the riskless option more attractive than the gamble, despite having a lower EV than the risky option ($3{,}000 < 0.8 \times 4000 = 3{,}200$); again, something is better than nothing. Using gist reasoning in the second choice problem leads to an impasse as both options (25 percent chance to win £3,000 or 20 percent chance to win £4,000) are probable with a bottom-line meaning of "a chance of winning something and a chance of winning nothing." Thus, in order to reach a decision, one needs to go higher on the gist–verbatim reasoning hierarchy and rely on increasingly precise comparisons, ultimately processing the exact numerical data presented. Consequently, based on verbatim reasoning, the riskier gamble (20 percent chance to win £4,000) is chosen as it has a higher

[12] This included problems with both monetary and nonmonetary outcomes.

EV ($0.2 \times 4{,}000 = 800$) than the EV of the other gamble ($0.25 \times 3{,}000 = 750$) (for more details on FTT and the Allais paradox, see: Broniatowski & Reyna, 2017; Reyna & Brainerd, 1994, 2011).

Another aspect of FTT posits that decision-makers calibrate the specific mental representation – that is, whether to reason based on gist or verbatim – according to the demands of the task (e.g., Reyna, 2012). This can explain the preference reversal phenomenon discussed earlier, in which people respond differently when they are asked to make a choice between two options compared to how much they value (what they are willing to pay for) each option. For example, one may choose apartment A over apartment B but be willing to pay higher rent for apartment B than apartment A. We use the following example to show how FTT explains this mystery. People tend to prefer a 0.75 chance of winning $1.10 and a 0.25 chance of losing $0.10 (low-risk gamble) over a riskier gamble of a 0.25 chance of winning $9.20 and a 0.75 chance of losing $2 (high-risk gamble) with the same expected value ($0.80). While technically both gambles entail winning something and losing something, people often perceive the $0.10 as nothing (see Stone, Yates, & Parker, 1994), which renders a qualitative contrast between the two gambles. Hence, FTT predicts that, based on the simplest gist representation, winning something or nothing is better than winning something or losing something. However, when asked to separately assess the WTP for each gamble, people gave a higher dollar value to the high-risk gamble – exhibiting, thus, preference reversal. The elicitation procedure of the WTP task requires a more detailed, accurate representation (i.e., verbatim representation) of the given information in order to extract an exact number that represents the subjective value of the gamble. In short, the choice between the two gambles is driven by gist reasoning, which promotes risk avoidance and, thus, making the low gamble *more* attractive (due to the categorical contrast), whereas the assessment task is driven by verbatim representations – trading-off risks and benefits – making the low gamble relatively *less* attractive (Corbin et al., 2015).

Finally, a central characteristic of FTT can explain a counterintuitive phenomenon, in which behavioral biases, such as the framing effect, are more prevalent in adults than in children and adolescents, despite the fact that reasoning develops with age. This phenomenon is called *developmental reversal* and was initially predicted by FTT. According to FTT, while both verbatim and gist processes consistently improve from childhood to adulthood (e.g., Reyna & Brainerd, 2011), developmental reversal is the product of a shift from relying mainly on verbatim to relying mainly on gist, which increases with age and expertise (see Reyna, Chick et al., 2014; Reyna, Estrada et al., 2011).

A large number of studies have applied the constructs of FTT to test its predictions in various real-life situations that involve choice behavior under uncertainty, particularly in areas such as law, health (e.g., HIV prevention), and medical decision-making. In one such study, a group of researchers, led by Valerie F. Reyna and Valerie P. Hans, conducted an experiment in which 173 subjects were asked to each play the role of a juror and arrive at a dollar value to compensate the plaintiff for pain and suffering caused by a car accident (based on a scenario from a real trial; Reyna, Hans et al., 2015). The experimenters systematically varied the size, context, and meaningfulness of numerical comparisons or anchors (i.e., an initial piece of numerical information that need not be related to the subsequent judgment or decision-making) to manipulate the bottom-line meaning of the perceived award magnitude, which resulted in large and predicted differences in the size of award judgments across the subjects (for the same incurred damage). If people already have a precise idea of a number, they wouldn't be as affected by comparisons to other numbers. Instead, their judgments of damage awards should be driven by the severity of the damage caused to the plaintiff. Hence, this result provides another evidence for the tendency to rely on gist reasoning to drive the processes of judgment and decision-making ("fuzzy-processing preference"). That is, people seem to have vague ordinal judgments of damages (mentally represented as qualitative gists) that they map onto vague ordinal judgments of dollar amounts.

In association with the principle of *encoding specificity* (Tulving & Thomson, 1973) – stating that recollection of stored information is related to the conditions present while encoding that information (e.g., it is easier to remember a happy event when one is happy) – FTT predicts that the specificity of retrieval cues in questions can affect the types of representations (gist or verbatim) retrieved from memory. This idea was supported by several studies (e.g., Bigman, 2014; Brown & Morley, 2007; Brown et al., 2013; Mills, Reyna, & Estrada, 2008; Reyna, Estrada et al., 2011). One experiment, for example, used two methods to assess perceived risk of smoking among smokers and nonsmokers (Baghal, 2011) – one method cued retrieval of verbatim by asking participants to estimate the risk of smoking using a numerical (verbatim-like) scale, and another cued retrieval of gist representations using an ordinal (gistlike) measure. Findings from this experiment showed negative correlations between perceived risk and the likelihood of smoking for both methods (i.e., greater perceived risk was associated with a lower likelihood of smoking). However, a significantly stronger relationship was produced by the method that cued the retrieval of gist. Furthermore, predictions of current smoking status using the "gist" method were better among adults than adolescents, which supports the FTT's key principle of developmental reversal (see Blalock & Reyna, 2016).

FTT, as already mentioned, also predicts that gist-based reasoning will often be associated with risk avoidance for rewards (when there is the presence of a categorical distinction between some and none; something is better than nothing), and verbatim-based (or more precise) reasoning will be associated with risk taking (trading-off between risks and benefits may lead to risk taking). In other words, people often choose between smaller sure rewards and larger uncertain ones, the latter offering potentially no rewards or bad outcomes; gist promotes risk avoidance under these conditions. A number of studies focused on risky behaviors (i.e., adolescent sexuality, drinking, smoking, speeding) lent support for this prediction. In particular, both Mills et al. (2008) and Reyna, Estrada et al. (2011) found that measures designed to cue retrieval of gist representations relevant to adolescent sexuality were associated with greater risky sexual behavior avoidance, whereas measures designed to cue retrieval of verbatim representations were associated with greater risk taking. Similarly, Reyna, Croom et al. (2013) found that first-year college students who endorsed the categorical gist principle: "I have a responsibility to myself to wait until I am legal to drink" were less likely to drink and, as a result, be harmed (e.g., experience an injury). In addition, studies that examined issues involving patient decision-making found that gist reasoning is associated with improved decision-making and adoption of behaviors to reduce health risks (e.g., Hawley et al., 2008; Smith et al., 2014).

Because FTT provides insights into how choices under uncertainty are made, interventions can be developed that take advantage of these principles. Hence, the theory offers innovative approaches designed to facilitate gist-based reasoning in order to effectively reduce unhealthy risk behaviors (specifically for adolescents). For example, in a randomized experiment, Reyna and Mills (2014) created a "gist-enhanced" version of an existing sexual education program known as *Reducing the Risk* (RTR; Hubbard, Giese, & Rainey, 1998; Kirby et al., 1991). On top of the topics covered in the original RTR program, the "gist-enhanced" version (RTR+) emphasized framing sexual decisions in categorical ways (e.g., even small risks add up over time) in order to promote the extraction of bottom-line meaning (the gist) associated with each class activity. The experiment randomized 734 adolescents into one of three groups: RTR, RTR+, or unrelated control. Results from this study showed that the positive effect of RTR+ on self-reported measures such as sexual behavior, behavioral intentions, attitudes, self-efficacy, knowledge, and so on, was significantly greater than that achieved for both the RTR program and the control group. Importantly, at the end of the twelve-month follow-up period, 9.5 percent of participants in the RTR+ group reported having initiated sexual activity since baseline, compared to 18.9 percent and 15.9 percent in the control and RTR groups, respectively.

Emotions and Decision-Making

Traditionally, models of decision-making – both normative and descriptive – focused mainly on logic and cognition processes when modeling and accounting for human choice behavior. Deviations from rational decision-making (such as inconsistent choice behavior) were often attributed to humans' *bounded rationality* (the limited capacity of the brain to process information and perform complex calculations needed to maximize our well-being), and the use of mental shortcuts (cognitive heuristics) in order to reach a decision. The role of feelings and emotions was rarely recognized in these models as an underlying component of decision-making. The psychologist George Loewenstein (1996) described this oversight as follows: "With all its cleverness, however, decision theory is somewhat crippled emotionally, and thus detached from the emotional and visceral richness of life."

Over the past few decades, however, this trend has dramatically changed. The relation between emotions and choice behavior gained a lot of traction in the field of judgment and decision-making – mostly by psychologists who increasingly acknowledged its importance and have begun to incorporate the role of feelings and emotions in their theories of choice behavior.

In the early 1990s, Antonio Damasio proposed a theoretical account for the role of affect in decision-making, the so called *somatic marker hypothesis*. According to this theory, positive and negative feelings, which are acquired through a lifetime's experience of realized outcomes, are associated with different kinds of bodily signals (e.g., rapid heartbeat, muscle tone, etc.) – namely, *somatic markers*. These changes in body and brain states, which occur in response to some situational stimuli, help guide the decision-maker's behavior to quickly and efficiently reach a favorable choice (Damasio, 1994). Seeing a big spider, for example, may induce a physiological marker – a warning sign – associated with the feeling of anxiety, which can facilitate a quick responsive behavior. Damasio also showed in a laboratory experiment that emotionally impaired people (due to some brain damage, for example) were repeatedly choosing the riskier, less favorable financial option (at least in the long run) over a safer one, even to the point of bankruptcy.

Another theory that links emotions with decision-making was proposed by Paul Slovic and colleagues and is known as the *affect heuristic* (e.g., Finucane et al., 2000; Slovic et al., 2002). This hypothesis asserts that emotions can influence people's judgment and decision-making. Affect-based choices are quick positive or negative emotional responses to stimuli (rooted in past experience), which are easier and more efficient than those guided by deliberative judgments (hence, they are labeled as *heuristic*). They help people reach a quick and automatic decision, especially when facing complex problems. The affect heuristic theory explains, for example, a phenomenon by which people tend to inversely judge the benefits and risks (i.e., high benefit and low risk or vice versa) of different activities, medical treatments, and technologies (e.g., smoking, antibiotics, Xrays, nuclear power, etc.). That is, items that trigger negative/positive emotional responses (such as pesticides or cell phones, for example) are perceived as risky/safe with low/high benefit (e.g., Alhakami & Slovic, 1994; Fischhoff et al., 1978; Slovic et al., 2007). In contrast to this largely misconception, the risk and benefit of many of these items are in fact positively correlated (high risk/high benefit, or low risk/low benefit). Generally, "activities that are low in benefit are unlikely to be high in risk (if they were, they would be proscribed)" (Finucane et al., 2000). Naturally, the relationship between risks and benefits varies across domains of decision-making.

Other notable and closely related models that incorporate the effect of emotions are: the *risk-as-feeling* framework (Loewenstein et al., 2001), the *determinants and consequences of emotions* model (Loewenstein & Lerner, 2003), and the *affect integrated model of decision-making* (Lerner et al., 2015).

Emotions in these models are integrated into decision-making in two distinct ways, *expected emotions* and *immediate (current) emotions*. Expected emotions are the predicted feelings a decision-maker is thought to experience with each possible outcome of his or her choice. In this case, emotions influence decisions in a similar fashion to standard rational-choice models (e.g., EU). That is, decision-makers choose alternatives that maximize anticipated positive emotions and minimize anticipated negative emotions. The expected feelings of regret from an unsuccessful investment in the stock market, for example, may promote risk-avoidance behavior – seeking safer alternatives to invest one's money. Immediate emotions are feelings decision-makers experience at the time of decision. The models distinguish between two types of influences that constitute current emotions – *anticipatory influences* and *incidental influences*. Anticipatory influences capture the effect of anticipated emotional reactions, from the decision at hand, on immediate emotions. Reflecting on the possible outcomes (and the associated emotional reactions) of a risky choice, for example, can cause an immediate feeling of anxiety. Incidental influences are current feelings, completely unrelated to the decision at hand, that can influence choice behavior. This is an idea that falls outside the scope of traditional models of decision-making (although emotions have been integrated into FTT; Rivers, Reyna, & Mills, 2008). Such influences include people's mood, weather conditions, motivational factors (e.g., hunger, sexual arousal, etc.), and so on. Numerous experiments have been conducted to test the effect of expected and immediate emotions on decision-making. We list some of them here.

Several studies showed, for example, that people are reluctant to exchange lottery tickets (where each had the same probability to win a prize) – even when they are offered a small monetary incentive to do so – and that this reluctance is stronger the more aversive it would be if the exchanged ticket did in fact win (see Bar-Hillel & Neter, 1996; Risen & Gilovich, 2007). The authors generally concluded that regret plays a prominent role in this behavior. That is, the exchange aversion is driven by the desire to avoid the anticipated feeling of regret associated with the act of giving up on a possible winning ticket. (It is important for future research to measure regret to be sure about this interpretation of the results.)

Furthermore, Christopher K. Hsee and Yuval Rottenstreich examined the effect of *affect-rich* outcomes (such as kisses, vacations, music, etc.) versus *affect-poor* outcomes (e.g., money, tuition, etc.) on decision-making and its implications on people's sensitivity to changes in reward magnitudes and probabilities (see Rottenstreich & Hsee, 2001; Hsee & Rottenstreich, 2004). They found that for affect-rich stimuli people tend to exhibit a more inverse S-shaped probability weighting behavior (similar to the one proposed in cumulative prospect theory discussed earlier in this chapter). That is, high sensitivity to small and high probabilities (particularly for departure from certainty and impossibility), and relatively low sensitivity to intermediate probabilities. In addition to that, the researchers showed that people's subjective valuation of

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affect-rich outcomes is less sensitive to the scope of the stimulus (e.g., the reward magnitude) than that of affect-poor outcomes.

Similarly, the effects of incidental feelings on decisions were also thoroughly investigated. Lerner and Keltner (2000, 2001), for example, studied the effect of dispositional fear and anger (unrelated to the decision) on risky-choice behavior. They showed that while fear and anger are both negative feelings, they influence risk perceptions and decisions differently. Fearful people made pessimistic judgments and exhibited risk-averse choices, whereas angry people were more optimistic, taking more risks. Lerner, Small, and Loewenstein (2004) tested the impact of incidental sadness and disgust (induced in a laboratory experiment by showing the participants different emotional film clips prior to the task) on the endowment effect – where people value an object in their possession higher than their willingness to pay in order to acquire it. The researchers found that the feeling of disgust eliminated the endowment effect, whereas the feeling of sadness reversed it. That is, the willingness to pay for an object (a highlighter set) was actually higher than the price set by sellers who were endowed with this object.

Finally, there is abundant empirical evidence showing a substantial relation between different motivational drives (such as hunger, thirst, and sexual arousal) and decision-making. Ariely and Loewenstein (2006), for example, conducted an experiment to test the effect of sexual arousal on judgment and decision-making with sex-relevant choices. They found that subjects under the "hot" (aroused) state were willing to engage in a risky behavior more than those in the "cool" state. Furthermore, Levy, Thavikulwat, and Glimcher (2013) tested in a laboratory the effect of food and drink deprivation on risk attitude for gambles with monetary, food, and water outcomes. They found that, on average, subjects under the deprivation state exhibited more risk tolerance with all types of reward. That is, they were willing to take more risks than satiated subjects.

Summary

The emergence of decision-making as a formal field of study was intertwined with the birth of modern probability theory back in the seventeenth century and has evolved significantly ever since. The evolution of the field can be divided into two distinct time periods – before and after the 1950s. The dominant paradigm in decision-making during the first period was a normative one. That is, the focus was on how a rational individual *should* make choices. This approach began with the introduction of Pascal's EV theory in the middle of the seventeenth century and culminated with von Neumann and Morgenstern's EU theory in 1944, which has become the most widely used model of rational choice. However, it has become more and more apparent that people do not follow an optimization process when making decisions, as prescribed by these rational models.

Simon (1957) was one of the first scholars to build on the idea that human mental capacity is limited. He argued that people behave as "satisficers" instead

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of maximizers, choosing alternatives that are "good enough" for them, which he referred to as bounded rationality. This was the kickoff of the second period. The focus during that time period has shifted toward a descriptive analysis, namely how people *do* make choices. A very large number of studies have begun to explore the different ways in which people's behavior deviates from models of rational choice. As a result of the growing evidence of systematic cognitive biases, including errors in probability judgment (e.g., base-rate neglect) and inconsistent choice behavior (e.g., framing effect), descriptive theories have started to emerge in an attempt to account for such anomalous behaviors.

In 1979, Kahneman and Tversky introduced their prospect theory, which has become one of the most prominent descriptive models for human risky-choice behavior. Prospect theory can account for many of the observed cognitive biases by using a relatively simple mathematical formulation, which captures the idea that people often perceive values in a nonlinear way (e.g., they overweight small probabilities and underweight large probabilities).

Fuzzy-trace theory, proposed in 1991 by Reyna and Brainerd, is another model that accounts for prior effects, such as framing effects and the Allais paradox, as well as new effects by explaining the underlying cognitive reasoning that drives the decision-making process. The model posits that adults tend to rely on the simplest gist (bottom-line meaning) representations of the information (e.g., winning something; losing nothing) when making decisions, which promotes healthy behaviors, and that this tendency to rely on gist increases with age and expertise. FTT has lots of real-life implications in areas such as law, health, and medical decision-making. It integrates cognition, emotion, personality, and social values to predict decision-making (see Reyna, Wilhelms et al., 2015).

Another important landmark in the history of decision-making has transpired in the last few decades. Until the 1990s, the majority of the models of decision-making focused mainly on cognitive aspects to explain human behavior. However, an affect revolution that started in the early 1990s has shifted the focus away from solely cognitive reasoning to include emotional reactions. A growing number of theories began to recognize the role of emotions in decision-making, arguing that affective processes are quick and automatic and, thus, can guide choices efficiently with very little mental effort. Finally, numerous experiments have been conducted to test the effect of emotions on decision-making. Findings from these experiments showed that feelings such as anger, sadness, fear, and even hunger and sexual arousal have a systematic effect on choice behavior.

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