How to Address Uncertainty with Behavioral Economics: Expanding the Scope of Effective Nudges Postprint

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Abstract

This paper proposes five types of uncertainty in decision-making and their behavioral and psychological coping mechanisms: substituting simple heuristics for weighted summation to address information uncertainty, using intuition to address cognitive uncertainty, using values to predict choice preferences to address behavioral uncertainty, substituting the weights of decision reference points for probability to address outcome uncertainty, and employing time-for-time exchanges to reduce delay discounting and address future uncertainty. New behavioral economics should identify the psychological levers of behavioral nudging through a functional analysis of 'why' . Resolving uncertainty itself constitutes an effective form of behavioral nudging; simplifying the complex is the key to behavioral nudging.

Full Text

Preamble

Using Behavioral Economics to Cope with Uncertainty: Expanding the Scope of Effective Nudging

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Abstract

Within a framework of "libertarian paternalism," the idea of nudge promotes the use of behavioral interventions to reduce irrational decisions that may collectively lead to "behavioral market failures" (Thaler & Sunstein, 2008; Sunstein, 2014). This approach has been criticized, however, for its lack of transparency

in behavioral manipulations and for that nudging is not educating. In the current theory of nudging, whether a decision is judged as rational is largely based on a small number of neoclassic standards of expected utility theories under the assumption that all the expected consequences and their probabilities are available to the decision maker.

In this article, the author intends to expand the scope of effective nudging to include decisions under uncertainty where the probabilities associated with decision outcomes are unknown. The author explored behavioral strategies to reduce different types of uncertainty. From this perspective, reducing uncertainty is seen as an important way of behavioral nudging. A key for effective nudges is "less is more."

Based on an analysis of "Bertrand Russell' s Turkey," the author exemplified how probability-based calculations fail in a real world of uncertainty. Next, the author proposed a quintuple classification of uncertainty existing in the following stages of information processing in decision making, including uncertainty in the information source, information acquisition, cognitive evaluation, choice selection, and immediate and future outcomes. The author further examined behavioral and psychological mechanisms that help reduce each type of uncertainty: Reduce information uncertainty using simple heuristics and one-reason decision making, reduce cognitive uncertainty using intuition, reduce behavioral uncertainty by understanding values of decision makers, reduce outcome uncertainty by replacing probability estimates with prioritized decision reference points, and reduce future uncertainty using time-to-time exchanges to decrease delay discounting.

Many decision biases can be better understood in terms of the inconsistency between the modern market environment and the typical human evolutionary environment where behavioral adaptations evolved. Understanding functional reasons underlying decision biases will help improve the quality of human decision making. A new behavioral economics should ask questions of why in functional analysis to find psychological leverages for behavioral nudging.

Keywords: behavioral economics; behavioral decision making; uncertainty; the Turkey' s dilemma; choice preference

Classification Numbers: B849; C934; C935

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1. Current Behavioral Economics and Its Nudging Function

Behavioral economics rests on three fundamental assumptions about human nature: bounded rationality, bounded willpower, and bounded self-interest. In their book *Nudge*, Thaler and Sunstein (2008) argue that people often make decisions based on intuition, which systematically deviates from rational principles. The authors enumerate numerous "foolish mistakes" made by consumers and

advocate for nudge-based interventions in public policy and business management to reduce and correct such irrational decision-making. Nudging attempts to influence and change public behavior through non-coercive, psychologically-informed small measures, thereby curbing impulsivity and promoting rational consumption while conserving resources to the greatest extent possible. Thaler believes that applying nudging methods can enhance government efficiency in market regulation. Thus, nudging represents a non-coercive psychological intervention approach proposed by behavioral economists like Thaler to reduce irrational decision-making.

Thaler' s 2017 Nobel Prize in Economics brought renewed attention to behavioral economics from scholars and the public alike. However, not all nudging strategies are effective or produce lasting effects. The author argues that the primary mechanisms enabling small interventions to produce large effects are twofold: first, simplifying complexity, and second, using psychology as leverage. Only after simplifying complexity can uncertainty be effectively reduced, enabling cognitive ease. Using psychological regulation to drive behavior can resolve the crudeness and rigidity of administrative management. This article focuses on exploring behavioral nudging mechanisms that simplify complexity and reduce uncertainty through behavioral and psychological interventions.

Two types of criticism have persistently targeted behavioral economics, particularly the Thaler-Sunstein school. The first criticism contends that the nudging philosophy erroneously promotes government intervention in individual behavior, violating core American values of personal freedom (Goodwin, 2012; Pykett et al., 2011; Wallace-Wells, 2010). In response, Sunstein addressed these critiques in his book *Why Nudge?* (Sunstein, 2014). He argues that while traditional economics posits free markets as optimal because individuals rationally make optimal choices, people frequently make erroneous decisions that lead to "behavioral market failures." Under such circumstances, Sunstein contends that government should intervene and remedy these failures appropriately. Such interventions should be grounded in decision psychology' s understanding of the factors and mechanisms underlying irrational behavior. Sunstein terms the philosophy behind such interventions "libertarian paternalism" and defines nudging as a form of "soft intervention" or "soft paternalism." According to Thaler and Sunstein' s nudging theory, because human rationality and willpower are limited, the outcomes of free choice are often suboptimal or inefficient, requiring correction. Since government' s fundamental function is management and intervention, lacking understanding of market behavior would only render such interventions more arbitrary and inefficient.

The second criticism of behavioral economics and nudging strategies stems from different understandings of decision-making rationality. The standards used by behavioral economics to evaluate rationality may themselves be unreasonable (Gigerenzer, 2015; Mols, Haslam, Jetten, & Steffens, 2015). From the perspective of evolutionary adaptation and ecological rationality, human decision-making rationality is limited not only by cognitive constraints but also

by decision environments. However, decision-makers are not passive; they can make effective adaptive decisions through understanding their own cognitive limitations and grasping environmental regularities (Gigerenzer & Selten, 2001; Simon, 1956, 1990; Wang, 1996, 2008). Consequently, ecological rationality models abandon the latter two assumptions of behavioral economics' three basic assumptions (bounded willpower and bounded self-interest) and revise the first assumption (bounded rationality). From this viewpoint, simple behavioral nudging only affects surface behavior without addressing its essence. Nudging is not educating, and therefore cannot truly change human behavior (Gigerenzer, 2015). After temporarily suppressing certain behaviors, nudging may even lead to behavioral rebound (Mols et al., 2015). Thaler-style nudging may invisibly influence people's extrinsic incentives but fails to shape their values and intrinsic motivations.

Most decision theories and models based on utility analysis and probability calculation, including behavioral economics models, do not consider the functionality and adaptability of behavior. Instead, they attempt to exhaust all relevant factors and rely on weighting, probability, and rational logic principles for decision-making. These rational principles emphasize not the ecological validity of decision cues but logical "consistency." For instance, according to the transitivity principle, if an individual' s preference ordering for options A, B, and C is A > B and B > C, then they must necessarily prefer A > C. The most commonly used principle in utility calculation is "weighted summation," which requires assigning probabilities to all possible outcomes and considering all relevant factors and cues. This non-functional analysis has rendered decision models in economics and finance increasingly complex. This complexity does not stem from convoluted fundamental ideas but from the inability of probability-based decision models to adequately handle uncertainty events that cannot be described probabilistically.

In summary, current behavioral economics and its nudging theory still employ traditional economic rationality principles to measure decision-making behavior. However, decision biases and irrationality may result from the mismatch between human evolutionary adaptation mechanisms and modern market environments. Therefore, truly understanding human decision-making requires appreciating its functionality and adaptability. Another limitation of current behavioral economics models is their reliance on probability models to evaluate decision-making behavior while lacking consideration for uncertainty. Through the following "Turkey Story," this article reveals how probability models cannot effectively address uncertainty and proposes methods for dealing with five types of uncertainty. The author argues that resolving uncertainty itself constitutes an effective behavioral nudge and provides direction for further expanding the scope of current behavioral economics and its nudging strategies.

2. The Turkey Story—The Dilemma of Probabilistic Decision Models

British philosopher Bertrand Russell told a story in his book *The Problems of Philosophy* (1957): On a farm, there lived a clever turkey capable of inductive reasoning. A farmer appeared in its life, and the turkey worried the farmer would kill it. Instead, the farmer fed it. For the first few days, the turkey remained vigilant, still fearing harm. Yet day after day, the farmer arrived promptly at 9 AM to feed it. The turkey accumulated observations about feeding and continuously updated its probability predictions. According to the turkey' s collected data across numerous observations, the probability that the farmer would feed rather than kill it grew daily. If an event has occurred n times previously, the probability of it occurring again is (n + 1)/(n + 2). Thus, after the first day, the probability the farmer would feed it on the second day was 2/3. After the second day, the probability increased to 3/4, and so on, with feeding probability rising each day while the probability of being killed diminished. The clever turkey could also conduct Bayesian probability analysis. Regardless of the statistical method employed, by the 100th day, the turkey was nearly 100% certain the farmer would not kill it but would come to feed it again. Yet the harsh reality was that this day was Christmas Eve; that very morning, the farmer grabbed the turkey, took it to the kitchen, and chopped off its head.

This story illustrates that the turkey failed to distinguish between an uncertain world and a world where risks are predictable probabilistically. Confusing uncertainty with known risk is known as the "Turkey Dilemma" (Gigerenzer, 2014). "Risk" is not equivalent to "uncertainty" (Knight, 1921). We cannot predict the future and therefore cannot precisely quantify probabilities. While risk can be quantified, uncertainty cannot. Statistical analysis of possible outcomes can only be based on existing data, but the past often fails to reveal what the future holds.

In an uncertain world, when an event concludes and a decision produces an outcome, uncertainty naturally transforms into certainty. Decision-makers then face new uncertainty. This process continuously oscillates between the two ends of the probability scale without clear intermediate values. Both individual and organizational decisions involve a cyclical process from uncertainty to certainty. What has occurred is certain; what lies ahead is uncertain. What resides in memory represents former uncertainty; what we face is uncertainty requiring resolution. A crucial function of human cognition is reducing uncertainty.

The Turkey Dilemma has long persisted. Various expected-weighted risk decision theories developed under neoclassical economics consistently assume that individuals' estimates of decision outcomes and their probabilities are reliable, and that people can rationally select optimal options by calculating utility values (the sum of the product of possible outcomes' valence and their probability) according to utility maximization principles. Over the past century, most decision-theoretic models developed on the foundation of modern statistics have

required assigning specific probability values to various hypothetical outcomes. These models have formed the basis of modern macroeconomics, finance, decision support systems, business management research, and risk management. However, in the real world, events often occur without precise probabilities or conformity to statistical inductive inference.

Therefore, we need to further analyze the implications of the Turkey Dilemma. We might ask: besides divine intervention, what could have helped this reasoning turkey? What cognitive mechanisms could have enabled better future prediction? Statistics are not useless here. What is useless and harmful is focusing solely on outcome probabilities while neglecting the farmer' s motivations and the turkey' s function for the farmer. For the turkey, sophisticated Bayesian probability updating became utterly meaningless by the 100th day because such statistical analysis was not only unhelpful for survival but actively harmful. However, during its 100-day life, the turkey might have had the fortune to live among other turkeys. As a social animal, it could have obtained information about motivation and function. For instance, how many turkeys had been taken away? Among those taken, how many never returned? At what age were they typically taken? It might have discovered that all taken turkeys never returned, and they were generally captured around 100 days of age. Armed with this information, the turkey could have made survival judgments different from classical Bayesian probability and consequently made different decisions.

Importantly, obtaining answers to these questions is not difficult; it requires only obtaining several frequencies through simple natural sampling. For example, 12 out of 12 (12 turkeys taken, none returned) or 12 out of 10 (10 of 12 taken turkeys were captured around day 100). Thus, the probability of this turkey being captured around day 100 is high, and once captured, the probability of returning home is nearly zero. Therefore, a wise turkey might abandon Bayesian probability updating and instead adopt natural frequency analysis for motivational assessment, deciding to flee the farm before its hundred-day banquet.

This demonstrates that a major flaw in risk decision models applying probability analysis is their focus on correlation rather than causation. Probability relies on empirical induction, analyzing "what" questions rather than "why" questions. Only by understanding "why" can we find relatively stable and long-term predictive variables in the complex and rapidly changing uncertain world. If decision outcome probabilities are difficult to predict, we can take an alternative approach by analyzing people and human nature. New behavioral economics must first understand decision-makers' motivations and the values underlying them. The contribution of behavioral science and psychology to resolving uncertainty should be providing functional analysis of behavioral motivations. However, the principles by which current behavioral economics judges rationality, much like the statistical principles used by Russell' s turkey, focus only on correlation rather than causation, failing to explore ultimate reasons for behavior or ask "why" questions. Therefore, behavioral economics' definition of

decision rationality needs expansion to include ecological rationality and social rationality. Rationality is not a vacuum; principles measuring decision quality must first conform to human nature to be rational. The vacuum rational agent in neoclassical economics is an isolated individual without kinship, ethnicity, or social connections, possessing complete information and operating in a world without institutional constraints or transaction costs. Such vacuum rationality often proves inadequate when facing cognitive limitations or when economic value conflicts with social value (Wang & Lu, 2015).

Whether behavioral economics can help us cope with uncertainty and whether nudging can produce large effects with small efforts depends crucially on whether interventions can target key decision-making stages. This article classifies uncertainties that may arise at important stages of the decision process and proposes ways to apply behavioral economics methods to address these five types of uncertainty. The relationship among the five types of uncertainty is parallel—they may exist separately or simultaneously. These uncertainties occur at different nodes of the decision process: from information sourcing and acquisition to cognitive analysis and judgment, to behavioral and strategic choices, and finally to decision outcomes and cross-temporal effects.

3. Five Types of Uncertainty and Behavioral Strategies

3.1. Coping with Information Uncertainty—Replacing Weighted Summation with Simple Heuristics

In today' s information society, a major source of uncertainty is no longer information scarcity but information overload and difficulty distinguishing quality information. One method for coping with information uncertainty is Simon' s (1956, 1990) bounded rationality and satisficing principle. Bounded rationality requires decision-makers to process information within their cognitive limits while utilizing environmental characteristics to aid decision-making. In other words, one must know one' s cognitive capacity while leveraging environmental advantages. Due to cognitive and environmental constraints, decision-makers evaluating various information and options no longer employ optimization and maximization principles but rather a "satisficing" principle—Simon' s coinage combining "satisfactory" and "sufficing." In a changing environment, once a satisfactory and adequate option is found, one should stop deliberating and act immediately.

Gerd Gigerenzer and colleagues' simple heuristics offer another pathway for coping with information uncertainty. Simple heuristics simplify complexity, enabling judgments and decisions based on a single reason with high ecological validity. Choosing based on only the most valid indicator among many often proves no worse than making optimal choices by integrating various indicators. In high-uncertainty environments, single-reason decision-making often outperforms utility maximization or complex Bayesian models (Gigerenzer & Gaissmaier, 2011; Gigerenzer & Selten, 2001).

Single-reason decision-making enables rapid judgments and decisions when facing complex, urgent events. For instance, U.S. leaders responded quickly to the 9/11 terrorist attacks. On September 11, 2001, 19 terrorists hijacked four commercial airliners; two struck the Twin Towers of the World Trade Center in New York, causing both buildings to collapse within two hours and killing nearly 3,000 people in the buildings and all aboard the aircraft. A third hijacked plane crashed into the Pentagon near Washington, D.C. The fourth hijacked aircraft was heading toward Washington when Vice President Cheney, having lost contact with President Bush, rapidly decided to authorize the Air Force to shoot down the hijacked civilian airliner. Clearly, Vice President Cheney had no time for complex calculations and deliberation; the single reason for his decisive decision was national security considerations.

Using simple heuristics for judgment and decision-making can effectively reduce cognitive load while filtering out information noise resulting from inaccurate parameters in complex models. The "dog and frisbee" example effectively demonstrates how simple heuristics address information uncertainty. Catching a frisbee involves numerous physical and meteorological factors; wind speed, rotation rate, etc., all affect the outcome. If a physicist treated frisbee-catching as an optimal control problem, they would need to understand and apply Newton' s law of universal gravitation. Yet despite the complexity, successful catches are common—even an ordinary dog can accomplish this task, often better than humans. What is the secret to the dog' s success? Simple coping. Research shows that catching a frisbee can be achieved through the simplest rule of thumb, avoiding complex calculations: maintain a constant visual angle on the frisbee while running (see Gigerenzer, 2014).

Like catching a frisbee, applying simple heuristics can also effectively guard against economic crises. We often don' t know how sharp uncertainty' s blade is until it cuts us. The 2007 subprime mortgage crisis that triggered the global financial crisis serves as an example. One cause of this crisis was the failure of complex models used for risk control and regulation in the financial sector. The fundamental reason for the failure of financial models built on traditional decision theory and their role in causing the financial crisis lies in defining uncertainty using probabilities of risky events. The result is that each additional probability estimate adds noise to model calculations, while the associated price valuations often fail to reflect real utility changes. Utility differs from price and is often not linear, ordinal, or interval-based. For a large bank with numerous investment projects, calculating value at risk requires predicting thousands of parameters, and combining these predictions generates enormous errors, necessitating simplified calculation processes. The increasingly complex regulatory system developed over recent decades is not only costly and cumbersome but also fails to effectively control crises. In the volatile world of financial regulation, simpler may be better (Gigerenzer, 2014; Haldane, 2012).

3.2. Coping with Cognitive Uncertainty—Using Intuition to Aid Decision-Making

Uncertainty also has endogenous sources. People sometimes don' t truly know their own valuations and weights for different goals and possible outcomes, or which matters more. These valuations and weights are likely fluid before a decision is made. Thus, regarding personal values and preferences, we often don' t know until we choose. In other words, people frequently don' t know in order to choose but choose in order to know. This phenomenon offers behavioral economics an insight: a one-time choice regarding a descriptive problem may not reflect a decision-maker' s stable risk preferences. We need to examine whether differences exist between one-time decisions and repeated experience-based decisions. For example, when judging descriptive scenarios, people tend to overestimate the probability of uncommon events, whereas when judging through feedback from decision outcomes, they tend to overestimate the probability of recent events (Hertwig, Barron, Weber, & Erev, 2004).

The information society diversifies people' s choices, with numerous temptations and options overwhelming them. Each choice competes vigorously for consumers' limited attention, each with its legitimate cognitive justification, leaving decision-makers immersed in a labyrinth of deliberation, unable to decide. The dazzling array of options in the information society often causes consumers' different thoughts to clash. Sometimes only after making a choice can cognition update and upgrade. Only by choosing can one truly know where implicit preferences lie. More colloquially, only when seeing one' s mother and wife fall into water together does one know whom to rescue first; only when heartbroken does one know whom one truly loves; only under torture does one know whether one will become a traitor. Therefore, utility values calculated through statistics and weighting in decision theory are often unreliable.

In a world where risk can be estimated, statistical thinking suffices; but when facing a world full of variables, we also need heuristics—rules of thumb—and good intuition. Heuristics address information uncertainty, while intuition better suits cognitive uncertainty. A major difference between heuristic decision-making and intuitive decision-making is that heuristics are decision tools with clear cognitive steps and procedures, whereas intuitive decision-making requires decision-makers to rely on integrated feelings when lacking clear cognitive judgment. Intuition does not emerge from a vacuum but originates from human evolution and personal experience. In situations with high uncertainty, lacking precedent, and time pressure—where no optimal reason or cue may be available—intuition rather than rational analysis is needed. Psychologist John Bargh (2017) cites many examples of solving problems through unconscious intuition in his new book. For instance, when tasting and evaluating different strawberry jams, people' s rapid judgments based on feeling are often more accurate and effective than those made after careful analysis.

People' s common assessments of whether something is "reliable" or "unreli-

able" represent judgments made through intuition. For proposals in uncertain environments, despite lacking any probability information, people still make judgments. For example, people often intuitively characterize a proposal as "reliable," "unreliable," "promising," or "dubious." In high-uncertainty situations, intuition combined with crisis awareness (bottom-line thinking) enables effective decision-making. Intuition containing crisis awareness itself incorporates cues with high ecological validity. So-called reliability is using intuition to resolve uncertainty and can be viewed as a heuristic that transforms uncertainty into risk. If an expected outcome sounds reliable, its likelihood is perceived as high; if it sounds unreliable, its likelihood is perceived as low. Through intuitive qualitative assessment of a proposal' s "reliability" or "unreliability," uncertainty begins transforming into risk.

Like values, intuition helps break deadlocks. If intuition can be further transformed into insight, it can discover keys to problem-solving and find priority reasons for effective decision-making.

3.3. Coping with Behavioral Uncertainty—Using Values to Predict Choice Preferences

New behavioral economics needs to focus on decision-makers' motivations to grasp and anticipate behavioral preferences. Understanding decision-makers' values greatly benefits behavioral prediction. Values differ from value. Valuation of an option is influenced by various factors including supply-demand relationships and expected probabilities. However, despite myriad changes, the "constant factor" is values. Here, values refer to the ranking of what matters more or less in decision-making (e.g., wealth, fame, status, health, etc.). Because values are relatively stable, understanding an individual' s or group' s values helps predict their goals, bottom lines, behavioral preferences, and tendencies, thereby reducing predicted behavioral uncertainty through analysis of decision-makers' values. When facing trade-offs and choices, decision-makers need to understand what is most important, important, relatively important, nice-to-have, regrettable to abandon, dispensable, unimportant, and insignificant to "me, us, him, her, them." Values form the basis of trade-offs and have long-term effects on decision tendencies. Understanding both parties' values helps infer motives and intentions in an uncertain world.

Values determine what matters more or less, but this "weight" does not have a linear relationship with monetary value, demonstrating that money is not omnipotent. When value touches bottom lines, understanding values helps solve thorny problems. The 1979 Egypt-Israel Peace Treaty ending war between the two nations exemplifies this principle.

From the perspective of national values, for Egypt, which lost territory (the Sinai Peninsula) in the 1967 Six-Day War, the most important priority was national territorial integrity. For Israel, the primary concern was gaining recognition of its national legitimacy. One side valued recovering lost territory above

recognizing Israel' s status; the other valued national legitimacy above territory acquired through war. Through lengthy negotiations, the two nations finally reached a peace agreement through "land for peace," achieving long-term stability in their relationship. The success of Egypt-Israel negotiations lay in finding interchangeable dimensions at the values level. Decision theories based on price (value) analysis could not have found solutions. People have win-win possibilities precisely because their values differ. Understanding the ranking of each party' s value dimensions makes it possible to exchange 各自的"次优"换来"更优" (each side' s "suboptimal" for "better"). If values were identical, win-win would be impossible. Two people competing for fame or two competing for profit often fight incessantly. However, a person who values wealth over fame and another who values fame over wealth can achieve mutual benefit. In summary, analysis at the values level helps people more effectively integrate economic, social, political, and cultural factors, find foundations for win-win outcomes, and improve decision quality.

3.4. Coping with Outcome Uncertainty—Using Decision Reference Point Weights Instead of Probabilities

Values determine people' s different goals and bottom lines. Using goals and bottom lines as decision reference points helps resolve outcome uncertainty. When the distribution of expected outcomes cannot be precisely calculated using probabilities, decision reference points can demarcate functional spaces of outcomes. Tri-Reference Point Theory (Wang & Johnson, 2012; Wang & Wang, 2013) uses bottom line, status quo, and goal as reference points to divide decision outcome space into four functional regions: failure, loss, gain, and success. Based on the psychological weight ordering of the three reference points—bottom line > goal > status quo—the theory predicts choice preferences for expected outcomes crossing different reference points. The fundamental task of reference point-based decision-making is to maximize the probability of achieving goals while minimizing the probability of bottom line violation. When facing different options, adaptive decisions are made by analyzing relationships between expected outcome distributions and the three reference points. While certain environmental variables (such as different stocks' market values after one year) often cannot be estimated precisely through probability, their range of variation can be predicted. For example, decision-makers may be unable to calculate expected values of different stocks through statistical methods but can predict expected ranges of stock prices. Under such outcome uncertainty, introducing decision task reference points (specific bottom line requirements and target values) can effectively guide choices without considering probabilities. That is, according to the principle that bottom line weight exceeds goal weight, choose stocks whose variation range will not touch the bottom line; on the premise of not violating the bottom line, choose stocks that may reach the goal.

Consider two uncertain investment options: A (-100, 600) and B (100, 400). Option A may yield a profit of 600 million or a loss of 100 million; Option B

may yield a profit of 100 million or 400 million. Which to choose? Suppose the decision-maker' s bottom line is at least 150 million profit, with a goal of 500 million profit. Option A' s lower value of -100 and Option B' s lower value of 100 both fail to meet the bottom line and can be considered essentially indistinguishable. At this point, only the upper values of 600 and 400 need comparison; Option A' s upper value of 600 can successfully reach the goal, whereas Option B' s upper value of 400 remains below the goal, so Option A is chosen.

If bottom line = 0 and goal = 300, the differences between upper values 400 and 600 can be ignored because both have reached the standard. Then only the bottom line differences between the two options need comparison. Because Option A may violate the bottom line while Option B' s lower value remains above it, Option B is chosen.

Bottom line violation is an important cause of economic crises. When economic conditions appear excellent, both enterprises and consumers easily neglect bottom line risks in investment and borrowing, leading to credit crises when expenses exceed income. Behavioral interventions can help guard against this by introducing decision reference points.

3.5. Coping with Future Uncertainty—Using Time-for-Time Exchanges to Reduce Delay Discounting

Time is another important source of uncertainty, yet statistics and probability are often powerless in forecasting future events. In fact, every innovation is unpredictable before it occurs; if it were predictable, it would not be an innovation. The outcome uncertainty analyzed above does not include changes brought by time. The unknowns brought by time include both all possible changes during waiting periods and the delay discount rate that varies with time between immediate and future outcomes (Frederick, Loewenstein, & O' Donoghue, 2002). If outcome uncertainty primarily affects people' s risk decisions, future uncertainty mainly affects intertemporal decisions (choices between smaller-sooner and larger-later outcomes) and self-control (such as whether to persist in controlling diet) (Ainslie, 2001).

People cannot accurately predict the future and therefore cannot accurately arrange their own and their families' futures. For example, how to implement savings and pension plans has long troubled policymakers, economists, corporate planners, and ordinary citizens. People exchange work time for compensation and invest part of that compensation in future retirement. We know what one dollar can provide us now, but no one can accurately grasp what that dollar can do for us in the future. If we save it, we cannot use it now, creating opportunity costs. In the future, it may appreciate or depreciate, or become worthless due to inflation. Therefore, future dollars are devalued in our assessment—what economics calls delay discounting or future discounting. Delay discounting becomes an important obstacle to retirement savings. Because future judgments cannot

be accurate, and because individuals differ in discount rates, it is difficult to have a universally accepted value. Lacking a valuation applicable to everyone or even just a group, we struggle to find an appropriate discount rate to guide investment and savings. That is, due to future uncertainty, the exchange between time and money becomes extremely difficult and variable. Under such circumstances, what behavioral economics methods can help us resolve the investment and savings dilemma caused by future uncertainty?

If money' s future value is difficult to judge, we can consider exchanging time for time. The concept and practice of time banking represent a promising solution. For example, through a pension program developed by the Swiss Federal Social Insurance Department, people can store the time spent caring for the elderly when young and use it later when they themselves are old, sick, or need care. Each person' s service hours are deposited into individual accounts in the social insurance system. Time banking can also enable mutual assistance among voluntarily participating community members. For instance, if I help you clean for 10 hours, when I need it, I can request 10 hours of work from you based on your skills. As China gradually enters an aging society, time banking can obviously reduce the burden on only children supporting their parents while expanding the function of retirement security from single families to community mutual assistance. These social and cultural functions of time banking derive from resolving future uncertainty. Although time banking is only a single case of resolving future uncertainty, its underlying mechanism can be applied to more decision problems. The core of this mechanism lies in exchanging time for time rather than money for time. This enables decision-makers to avoid complex calculations of delay discounting and the difficult equivalence exchange between time and money in intertemporal decisions.

Behavioral economists like Thaler and Sunstein attempt to influence and change decision-making behavior through non-coercive psychological interventions, thereby curbing impulsivity and promoting rational consumption. However, behavioral economics has consistently used probabilistic statistics and traditional economic rationality criteria to measure whether people' s decisions are rational. The author' s analysis of the Turkey Dilemma demonstrates that in an uncertain world, people cannot effectively use probability predictions to guide judgments and decisions. Statistical thinking and rational analysis prevalent in economics and behavioral science research focus on correlations between outcome variables and predictor variables while neglecting behavioral functions and causes and the motivations of decision-making parties. Behavioral economics models need to distinguish between decisions under risk and uncertainty. This article classifies uncertainties that may arise at important stages of the decision process—information acquisition, cognitive judgment, behavioral strategy selection, risk decision outcomes, and future effects of intertemporal decisions—and proposes behavioral economics approaches to address these five types of uncertainty.

Behavioral nudging for coping with uncertainty must target key decision-making

stages to succeed. Current nudging models promote invisible interventions in behavior without emphasizing education or shaping values and decision motivations. While simple behavioral nudging may invisibly change behavior, it cannot influence deeper mechanisms behind behavior. These deeper mechanisms formed through long-term human evolution. However, modern environmental changes often differ dramatically from humans' typical evolutionary environments. Decisions made based on evolved intuition in modern environments often violate rationality principles used by traditional and behavioral economics to measure decisions, because these rationality principles emphasize logical consistency rather than evolutionary adaptiveness. New behavioral economics needs to find psychological leverage points through functional analysis asking "why." These leverage points are often key determinants of values and features of evolutionary adaptation. If nudging targets appropriate points, it can achieve large effects with small efforts rather than small efforts gambling for large effects. Resolving uncertainty itself is an effective behavioral nudge; the common characteristic of the behavioral methods for reducing uncertainty described above is "less is more." Simplifying complexity is the key to behavioral nudging.

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Note: Figure translations are in progress. See original paper for figures.