8.3 Prospect Theory

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Summary

Prospect theory is one of the most influential descriptive theories of risky choice. In this chapter, the core features of the theory are summarized and the theory is contrasted against theoretical standards of rationality as defined by expected utility theory. Developments of the theory, critical debates, and recent findings are presented. Empirical evidence overall supports prospect theory as a descriptive model of risky choice. The theory can qualitatively account for multiple deviations from theoretical rationality, and it predicts simple risky choices from given information better than heuristics and other competing models. Findings particularly concerning more complex risky choices and decisions from experiences, however, also show limitations of the theory. Prospect theory is mainly considered an as-if model that predicts choices only. Findings concerning the cognitive processes underlying risky choice are mixed and warrant further investigation.

1. Prospect Theory: A Descriptive Theory of Risky Choice

In everyday decisions, individuals often have to select between (more or less) risky options for which outcomes realize with particular probabilities. Here, "risk" refers to the fact that one of several possible states of the world can realize, but it is uncertain which. These states of the world lead to outcomes that differ concerning value or utility for the decision maker. Risky decision can in principle concern any kind of objects, and prospects can range from highly complex and important decisions, such as job selection or company investments, to consumer decisions for any kind of products (e.g., insurances, lottery tickets, health states, food).

According to typical standards of theoretical rationality as, for example, the economic approaches (Becker, 1976; von Neumann & Morgenstern, 1947), such decisions should only be influenced by the subjective utilities of outcomes and the probabilities of states of the world to realize (for details, see chapter 8.2 by Peterson, this handbook). Typical empirical investigations of risky decisions reduce complexity by focusing on exactly these factors. Research thus often abstracts from all further context factors and focuses on the selection between gambles with outcome and probability information provided. An example would be the choice between gambles *A* and *B* for which *A* pays €4 with certainty and *B* pays €10 with probability .50 and €0 otherwise. Prospect theory (Kahneman & Tversky, 1979; Tversky & Kahneman, 1992) is the most prominent descriptive theory for decisions between monetary gambles and also for risky choice outside the lab (Camerer, 2005; Kahneman, 2003; Rabin, 2003).

Of particular interest are regularities captured by prospect theory that deviate from the predictions of a strict interpretation of theoretical rationality as introduced above. In this chapter, I review prospect theory and recent findings and discuss relations between prospect theory and rationality.

2. Core Features of Prospect Theory and Important Findings

Prospect theory contains four core features: (i) reference dependence, (ii) diminishing sensitivity of outcomes relative to the reference point, (iii) loss aversion, and (iv) a nonlinear probability weighting function with overweighting of small probabilities and underweighting of large probabilities (figure 8.3.1; more detailed explanations for all four features below).

Specifically, the theory predicts (i) "that the carriers of value are changes in wealth or welfare, rather than final states" (Kahneman & Tversky, 1979, p. 277). This means that individuals perceive outcomes (or final wealth states) not in absolute terms but as changes relative to a reference point. The subjective utility of an option (which Kahneman and Tversky refer to as "value," *V*) is a function of the gains and losses relative to the reference points and their probabilities. The exact way in which outcomes are transformed into subjective

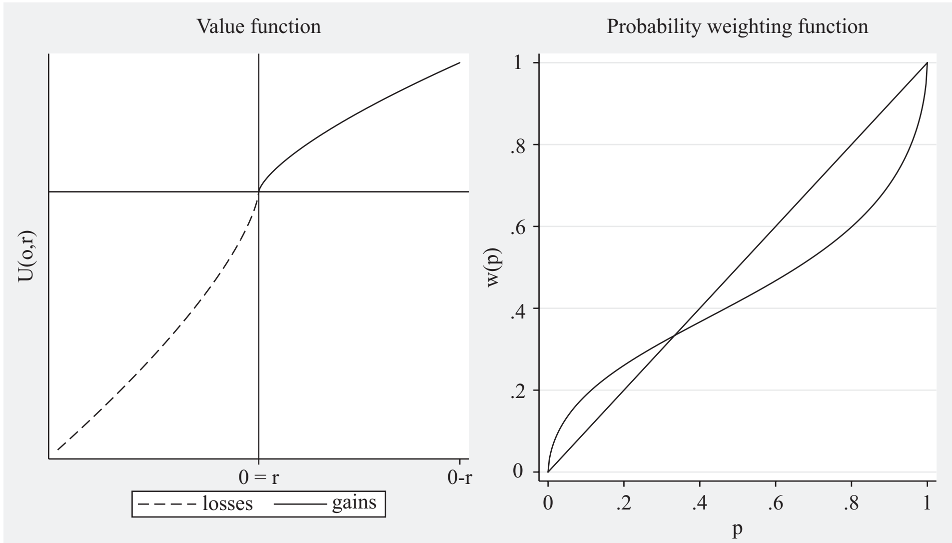

Figure 8.3.1
Prospect theory functions (examples) for transforming outcomes *o* into utilities *U*(*o*,*r*), taking into account a reference point *r* (left), and probabilities *p* into decision weights *w*(*p*) (right).

utilities is described by a value function with a kink at the reference point (figure 8.3.1, left). It is assumed that outcomes are considered and transformed in isolation, instead of being integrated with other outcomes or probabilities first.

Prospect theory assumes (ii) a concave value function in the gains and a convex value function in the losses, reflecting the principle of diminishing sensitivity of differences from the reference point (figure 8.3.1, left). From this functional form, it follows that individuals should be risk averse in the gain domain and risk seeking in the loss domain.[1]

The theory predicts (iii) that people are loss averse, which means that they are more averse to *losses* relative to their reference level than they are attracted to same-sized gains. This is reflected by the steeper value function in the losses as compared to the gains in figure 8.3.1 (left).

Finally, prospect theory predicts that (iv) outcomes are not weighted by their objective probabilities but by decision weights, which (according to more recent versions of the theory) follow an inverse S-shaped function (i.e., decision weights regress to the mean for extreme probabilities: figure 8.3.1, right; Tversky & Kahneman, 1992). Outcomes with low probabilities receive increased weight (i.e., decision weights are higher than the respective probabilities), whereas outcomes with high probabilities receive reduced weight (i.e., decision weights are lower than the respective probabilities).[2]

Prospect theory can account for a multitude of findings concerning risky choices in the field (for a review, see Camerer, 2005) and also in the lab. Overweighting of small probabilities, for example, can explain why people buy insurances and lottery tickets although their price is higher than their expected value and/or expected utility. Loss aversion can explain why stock returns are too high relative to bond returns (equity premium) and why people demand higher prices for selling a product they own as compared to their willingness to pay for the same product (endowment effects). Diminishing sensitivity can explain why people sell winning stocks too early (risk aversion in the gain domain) and hold losing stocks for too long (risk seeking in the loss domain) and why they shift to long shots in horse betting at the end of the day.

One of the most influential demonstrations of deviations from rationality predicted by prospect theory are framing effects (Tversky & Kahneman, 1981). In typical framing studies, choice problems are presented in different contexts (frames), while holding the normatively relevant factors (probabilities and outcomes) of the options constant. In the classic Asian disease study, for example, substantial shifts in preferences resulted from presenting two programs to cure an Asian disease either in a loss frame (by mentioning the persons who would be killed) or in a gain frame (by mentioning the remaining persons who would survive). In the loss frame, most people were risk seeking and preferred the risky program, a program in which all people could be killed with some probability. In the gain frame, in contrast, individuals were risk averse and preferred the safe program that assured the survival of some people (Tversky

& Kahneman, 1981). The very robust finding (e.g., Klein et al., 2014) that a mere reframing of what were objectively the same options influences choice, constitutes a violation of invariance that "cannot be defended as normative" (Kahneman, 2003, p. 163).

3. Normative Theories of Risky Choice and Prospect Theory

Descriptive theories of decision making, such as prospect theory, aim to describe and predict how people make decisions. Normative theories, in contrast, describe how decisions *should* be made and define a standard of rationality against which such descriptive models are typically evaluated. Normative theories have to be defined with respect to the goals that a decision maker aims to achieve. Not taking all goals of a person into account can thus lead to wrong standards (cf. chapter 9.4 by Dhami & al-Nowaihi, this handbook).

3.1 Standard Rational Models: Expected Value and Expected Utility Theory

If the decision maker's only goal is to maximize the average (or sum) of payoffs over an infinite number of decisions, then she should choose the option that maximizes expected value (*EV*). Here, *EV* is defined as the sum of lottery outcomes (payoffs) o_i multiplied by their probabilities p_i for all possible outcomes i: $EV = \Sigma_i p_i o_i$. In the above example, according to *EV*, the risky gamble $B\,(EV = 0.5 \times €10 = €5)$ should be chosen over the safe gamble A ($EV = €4$).

This picture has to be qualified for at least three reasons: utility might not be linearly related to monetary outcomes, individuals may have further or different goals than maximizing the average of payoffs, and decisions are not infinitely repeated. All three issues have been (or at least can be) taken into account in expected utility (EU) theory to develop a normative model for risky choice that goes beyond *EV*.

According to one common implementation of EU theory for monetary gambles, individuals choose the option that maximizes $EU = \sum_i p_i o_i^{\alpha}$, with p_i being the probability of outcome o_i to realize and $0 < \alpha < 1$. In the gamble example introduced above, for a person with a reasonable sensitivity to outcomes (often also referred to as "risk aversion") of $\alpha = 0.7$, choosing the safe gamble A ($EU = 2.64$) over the risky gamble B ($EU = 2.51$) in a one-time decision is rational according to this implementation of EU theory. The form of this *EU* value function is concave, which was originally suggested by Bernoulli (1738/1954) to account for the St. Petersburg paradox.[3] The *EU* value function considered here is equivalent to the value function of prospect theory when considering the gain domain only (figure 8.3.1, left, upper-right sector). Hence, EU theory assumes a diminishing marginal utility of money. That is, raising the wealth level of an individual by a particular amount (e.g., €1,000) leads to a larger change in utility than adding the same amount once again (e.g., adding another €1,000).

Importantly, in contrast to prospect theory, EU theory does not assume that utility is reference-dependent. Outcomes are assessed relative to a wealth level of zero. As a consequence, according to EU theory, there is no qualitative differentiation between gains and losses, and they should be treated the same (i.e., no reflection of the utility curve at the reference point and therefore no risk seeking in the losses; no loss aversion). Finally, EU theory assumes that probabilities are used without any transformation in weights. The core difference between EV and EU theory is that the latter assumes a value function that transforms outcomes into utilities (in this case by raising them to the power of α).

Individuals often not only want to maximize the sum of outcomes over a long or infinite number of gambles but also have further goals. In some situations, for example, it can be rational to be short-sighted and to think about the current situation in isolation, not taking into account potentially higher future outcomes. It will be reasonable for individuals to avoid falling below a minimum wealth level in order to keep a decent life, and short-sightedness might be extremely rational for an individual to ensure survival. More complex further goals are possible too. Individuals want to maximize joint outcomes, maximize the difference in wealth compared to others (Van Lange, 1999), or avoid sticking out from the crowd. These further goals can, in principle, be accounted for in EU theory by incorporating them (e.g., as further preferences) in individuals' utility functions (see chapter 9.4 by Dhami & al-Nowaihi, this handbook).

3.2 Prospect Theory and Rationality

Tversky and Kahneman (1981) used EU theory as a normative (rational) standard for risky choice by stating, "When faced with a choice, a rational decision-maker will prefer the prospect that offers the highest expected utility" (p. 453). They then demonstrated that behavior systematically deviates from these standards. Prospect theory, a descriptive decision theory, aims to account for individuals' actual choice behavior, which often follows, but in some cases systematically deviates from, these rational standards. The theory does not aim at providing new standards of rationality; quite the contrary, the description and prediction of deviations from these standards lie at the heart of the theory.

4. Theory Development and Versions of Prospect Theory

The original version of prospect theory (Kahneman & Tversky, 1979) contained two phases. In the "editing phase," a preliminary analysis of the offered prospects is conducted. The editing often yields a simpler representation of the prospects, for example, by discarding shared outcomes, combining probabilities of equal outcomes, or coding outcomes as gains and losses. In the subsequent "evaluation phase," the edited prospects are evaluated, and the option with the highest utility is chosen. The original version did not contain a formal description of the probability weighting function. Cumulative prospect theory, which was introduced in 1992, included fully specified functions for outcomes and probability weighting, as depicted in figure 8.3.1 (Tversky & Kahneman, 1992). Furthermore, the specification of the probability weighting function included a specification of outcome-rank-dependent probability weights and a cumulation principle to ensure that probability weights add up to 1. Therefore, probability weights are influenced by the size of the outcome they are attached to relative to the other outcomes.[4] Hence, cumulative prospect theory predicts not only nonlinear probability weighting but also that the same outcome with the same probability receives different weights, depending on the size of the other outcomes, which is in conflict with normative models such as EU theory. In the version suggested in 1992, cumulative prospect theory contains five parameters:

- α: the sensitivity to outcomes in the gains (it determines the curvature of the value function in the gains; figure 8.3.1, left, upper-right sector),
- β: sensitivity to outcomes in the losses (it determines the curvature of the value function in the losses, which is additionally scaled by λ; figure 8.3.1, left, lower-left sector),
- λ: loss aversion (it captures the relative increase in sensitivity to losses, that is, the factor by which losses loom larger than equal gains, when assuming $\alpha = \beta$),
- γ: probability weighting in gains (it determines the shape of the probability weighting function for gains, that is, the sensitivity to probabilities in gains),
- δ: probability weighting in losses (it determines the shape of the probability weighting function for losses, that is, the sensitivity to probabilities in losses).

Since the exact formalization of cumulative prospect theory is not of particular interest for the current chapter, it is not provided here, and I refer the reader to Tversky and Kahneman (1992) for a description of the full formalization of the theory.

Further extensions concerned, for example, modifications to the probability weighting function (for an overview, see Stott, 2006); the introduction of a two-stage model of prospect theory, taking into account in a first step probability estimation in decisions under uncertainty (i.e., without explicit probability information available) based on support theory (Fox & Tversky, 1998); and an extension that allows reference points to be uncertain too (i.e., lotteries as reference points; Schmidt, Starmer, & Sugden, 2008). Overall, prospect theory inspired several extensions and theoretical developments, but the core features generally remained (for an excellent overview, see Wakker, 2010).

5. Empirical Findings

The capability of prospect theory to account for risky choice behavior has been critically investigated using various methodological approaches. A full review would be beyond the scope of this chapter. I will exemplify some of the methodologies, debates, and crucial findings.

5.1 Predictive Ability

In the original paper, Kahneman and Tversky (1979) presented results for 12 selected decision problems in which the majority of participants chose the option that was predicted by prospect theory and contrary to EU theory. However, these problems were explicitly constructed to disprove EU theory. It remained unclear whether prospect theory is indeed a good theory for predicting choices also in a less selective set of decision problems. Furthermore, it has been argued that cumulative prospect theory (due to its free parameters) might only be able to fit data post hoc but that simpler models, such as the priority heuristic,[5] might be better at predicting choice, due to the overfitting of prospect theory (Brandstätter, Gigerenzer, & Hertwig, 2006).

We put this question to a direct test in an adversarial collaboration with a proponent of the heuristic perspective (Glöckner & Pachur, 2012). Participants made incentivized decisions in a large and diverse set of gamble problems at two points in time. Importantly, the set of gamble problems was intensely discussed a priori to avoid giving any model a strategic advantage. The competing models included various versions of prospect theory, EU theory, EV theory, and all existing simple heuristics that we were aware of. All models were fit to the data at time 1 to predict choices at time 2. The results showed that neither priority heuristic nor any of the other heuristics—or their adaptive use as specified in some models—could predict choices nearly as well as even a simple EV theory. EV theory in turn predicted significantly worse than EU theory. The best predictions by far were achieved by cumulative prospect theory. Among different versions, the model without any free parameters using Kahneman and Tversky's parameter values from 1992 did fairly well, but individual-level fitting improved predictive ability further and close to the maximum level possible given limited reliability in choices.

Overall, this and many further investigations, including analyses in applied settings (Camerer, 2005), show that prospect theory is a model well suited for describing risky choice behavior. Given this excellent performance as a descriptive theory, prospect theory seems particularly relevant as a starting point for reflecting about extended standards of practical rationality. Prominent alternative models seem less relevant for deriving such extended standards, considering their typically worse performance as descriptive models. For example, given that no single heuristic (simplified decision strategy) and no model of adaptive strategy usage exists that can predict behavior in the most basic gambling paradigm nearly as well as prospect theory (Glöckner & Pachur, 2012), such models might be less useful for deriving extended standards of rationality (but see Gigerenzer & Brighton, 2009, for a different position).

As a limitation, however, it remains unclear whether this superiority of cumulative prospect theory in predicting simple choices between two lotteries with two outcomes each and explicitly provided probabilities generalizes to more complex risky choice tasks, for which heuristics might be more prevalent (see below).

5.2 Critical Property Testing

A second approach to test cumulative prospect theory against alternative models is to investigate critical properties of the theory that are predicted under any set of parameters. Birnbaum conducted intense empirical investigations following this approach, particularly taking into account more complex lotteries with three outcomes. He demonstrated multiple critical choice anomalies that prospect theory could not account for but alternatively suggested models such as the transfer of attention exchange model (Birnbaum, 2006, 2008). Birnbaum showed that splitting the most (least) attractive branches of a gamble makes them more (less) attractive and can lead to preference reversals that prospect theory cannot account for. For example, most individuals prefer gamble *A*: .85 to win \$100 and .15 to win \$50, over gamble *B*: .95 to win \$100 and .05 to win \$7 (Birnbaum, 2008, Table 1). This (majority) preference, however, reverses if the less attractive outcome is split for gamble *A* (.85, \$100; .10, \$50; .05, \$50) and the more attractive outcome is split for gamble *B* (.85, \$100; .10, \$100; .05, \$7), although the games remain substantially equivalent.

Similarly, it was shown that in gambles with multiple winning and losing outcomes, choices are more in line with a p-win heuristic (i.e., choose the option that maximizes the overall probability of winning outcomes) and could not be accounted for well by prospect theory (Payne, 2005). These investigations show limitations of prospect theory concerning its ability to account for more complex decision tasks (i.e., ones with more than two outcomes). Given the higher task complexity, it is psychologically plausible that behavior is less in line with prospect theory in more complex tasks due to limitations of deliberate cognitive capacity. Further investigations are needed to test whether the average predictive ability of prospect theory in a broad set of more complex tasks falls below the performance of competing theories.

5.3 Decisions from Experience

The standard paradigm for investigating prospect theory relies on decisions from descriptions, that is, decisions between gambles with explicitly provided probabilities (see examples above). Many everyday decisions, however, involve decisions from experience, in which probabilities are not explicitly provided but have to be inferred. This has led to a large literature on ambiguity (unknown probabilities) in the economic literature (Ellsberg, 1961), surveyed by Trautmann and van de Kuilen (2015) and Wakker (2010). I will focus on another stream of literature, initiated by Erev, Hertwig, and colleagues (Barron & Erev, 2003; Hertwig, Barron, Weber, & Erev, 2004). These authors showed substantial differences between decisions from experience and decisions from description, the so-called description–experience gap. In typical studies on decisions from experience (Hertwig et al., 2004), individuals are allowed to sample outcomes as long as they wish, before making a consequential choice.[6] For example, an individual might sample five outcomes from gamble *A* (€4, €0, €4, €4, €4) and five outcomes from gamble *B* (€3, €3, €3, €3, €3) and then decide to stop search and select gamble *A*. Hertwig et al. (2004) showed, for example, that for a choice between gamble *A*: .8, €4; .2, €0, and gamble *B*: €3, 1.0 (i.e., with certainty), most individuals choose gamble *B* in decisions from descriptions but gamble *A* in decisions from experience.

One important factor that contributes to this difference in choice behaviors are sampling biases. Of particular importance here is the bias that results from the fact that rare events are more likely to be underrepresented in small samples due to the skewness of the binomial distribution. That is, small samples have a higher likelihood of containing too *few* rare events than of containing too many.[7]

It has been controversially debated whether a new theory has to be developed for decisions from experience (Hertwig & Erev, 2009) or whether choices can be explained by sampling biases plus prospect theory (Fox & Hadar, 2006). While the former perspective assumes that cognitive processes might be entirely different in decisions from experience, proponents of the latter perspective assume that individuals merely sample outcomes to estimate probabilities. These estimates are, however, influenced by sampling biases, which in turn lead to different choices in experience-based decisions.

A large-scale prediction competition (Erev et al., 2010) showed that a psychologically not very plausible "ensemble" (mixture) of models predicted choices in experience-based decision making best. Several further process models were developed and tested (Barron & Erev, 2003; Gonzalez & Dutt, 2011; Lejarraga, Dutt, & Gonzalez, 2012). A more recent model comparison, taking into account the data from the Erev prediction competition and additional data (Glöckner, Hilbig, Henninger, & Fiedler, 2016), provided support for prospect theory as a model for decisions from experience too. It was found that a two-stage model (cf. Fox & Hadar, 2006; Fox & Tversky, 1998), assuming (i) probability estimations that are influenced by sampling biases and (ii) an application of prospect theory based on these probability estimations, could explain choice behavior very well and better than important alternative process models (Gonzalez & Dutt, 2011; Lejarraga et al., 2012).

Furthermore, it was shown that the initially assumed direction of the description–experience gap, a qualitative difference in that rare events are overweighted in description but underweighted in experience, does not hold universally (Glöckner et al., 2016; Kellen, Pachur, & Hertwig, 2016). The assumed gap is highly problem dependent, as confirmed by a large-scale meta-analysis (Wulff, Mergenthaler-Canseco, & Hertwig, 2018). Specifically, after accounting for sampling bias[8] and when taking into account a more representative sample of tasks, the description–experience gap reverses (Glöckner et al., 2016; Kellen et al., 2016). That is, when considering the outcomes that people have truly experienced by sampling, they overweight small probabilities even more strongly in decisions from experience than in decisions from description. This finding is in line with much research showing that smaller probabilities tend to be overestimated due to a universal regression-to-the-mean effect (K. Fiedler & Unkelbach, 2014).

Overall, this research highlights that sampling biases and also further (partially task-dependent) factors have to be taken into account in modeling decisions from experience. Given the complexity of the findings (for an excellent summary, see Wulff et al., 2018), it is up to further research whether adaptations to cumulative prospect theory are sufficient to account for decisions from experience or whether qualitatively different models have to be developed. In a first approximation, a model based on sampling bias and cumulative prospect theory does surprisingly well also in predicting decisions from experience (in the sampling paradigm).

One important distinction in experience-based decision making concerns the differentiation between the sampling paradigm (discussed so far) and a feedback paradigm. In the feedback paradigm, each sampled outcome from a gamble is paid, whereas in the sampling paradigm, only the outcome of the final choice is paid.

Considerable differences between the two paradigms, as well as between them and the standard decision-from-description paradigm, indicate that dependent on the requirements of the situation, people do not focus on the current choice task only. Instead, individuals seem to adapt—at least partially—to whether adopting a narrower or a broader perspective, by taking into account the outcomes of further decisions, is appropriate. This should be considered in future theoretical developments.

5.4 Process Measures

Aside from the analysis of choice behavior, further measures of, for example, information search and/or response time are used to test hypotheses concerning the underlying cognitive processes (Schulte-Mecklenbeck, Kühberger, & Johnson, 2019). Various such process measures have been applied to risky choice to determine whether and how prospect theory might be implemented computationally and whether it is a reasonable model at all. Similarly to the classic bounded rationality critique of EU theory (Simon, 1955), it is unreasonable to assume that individuals deliberately apply complex multiplication operations to implement prospect theory. Hence, prospect theory is usually considered an as-if model instead of a process model.

Classic studies on processes in risky choice (Payne, Bettman, & Johnson, 1988) used the computer-based information search paradigm Mouselab. In Mouselab, individuals can reveal pieces of information (outcomes and probabilities) concerning multiple complex lotteries by moving the mouse to the respective information boxes. Payne et al. (1988) have demonstrated that in complex risky choice paradigms (multiple options with multiple outcomes each), manipulations of the environmental structure and time pressure induce changes in information search. This indicates that individuals also change their decision strategies. Payne et al. show that these changes are adaptive to the structure of the environment, in that individuals tend to change to strategies that are more successful in the respective environments.

The findings by Payne et al. preclude that (all) individuals search for all pieces of information and use prospect theory to evaluate them. Results can be better explained by assuming that individuals are adaptive decision makers and switch, for example, from more complex to simpler and less effortful strategies (i.e., simple heuristics that ignore large parts of the information) dependent on task demands (Payne, Bettman, & Johnson, 1993). These results converge with the findings from critical property testing (see section 5.2) indicating that prospect theory's ability to account for choices in more complex tasks might be limited.

Eye-tracking studies provide further insights concerning the potential processes underlying risky choices in less complex tasks. In these studies (S. Fiedler & Glöckner, 2012; Franco-Watkins & Johnson, 2011; Glöckner & Herbold, 2011), it was repeatedly shown that individuals (i) look up all pieces of information, (ii) mainly search information *within* gambles (instead of comparing between gambles), and (iii) show choices that are in line with a compensatory integration of outcomes and probabilities. Thereby, (iv) response times are too short to allow for an integration of outcomes and probabilities by deliberate calculation. Also, (v) individuals look up information with short fixations, while deliberate calculations are accompanied by long fixations. These findings are hard to reconcile with the assumption that—even for simple risky choice tasks—weighted sums of (transformed) outcomes and probabilities are deliberately calculated. The processes might be better accounted for by evidence accumulation models (Busemeyer & Townsend, 1993; Usher & McClelland, 2004) or parallel constraint satisfaction models (Glöckner & Herbold, 2011; Holyoak & Simon, 1999), which allow approximating weighted integration of probabilities and outcomes by psychologically plausible processes.

6. Summary and Future Directions

Prospect theory is arguably the most influential descriptive model for risky choice. Prospect theory assumes (i) reference dependence, (ii) diminishing sensitivity of outcomes relative to the reference point, (iii) loss aversion, and (iv) a nonlinear probability weighting function with overweighting of small probabilities and underweighting of large probabilities. Prospect theory predicts multiple deviations from expected utility theory, the standard normative model of theoretical rationality. These predictions have received ample support in the lab, and the theory can explain deviations from theoretical rationality that are observed in the field.

As a descriptive model of choice, prospect theory does not aim to define new standards of rationality. Quite the contrary, Kahneman and Tversky developed the theory to (among other things) account for deviations from these standards, such as violations of the invariance principle as demonstrated by framing effects.

A review of recent findings and debates indicated that prospect theory is still one of the best models for predicting simple decisions from descriptions. For complex tasks, the evidence is more mixed. In risky choice between options with multiple outcomes, evidence from critical property testing and process tracing converges to show that individuals rely on different, potentially more heuristic processes. For decision from experience, sampling biases in probability estimation and subsequent application of prospect theory can account for choice behavior surprisingly well. Still, in both areas, more research is needed to clarify the issues and to develop and comparatively test improved models.

Process measures for simple decisions from descriptions indicate that individuals do *not* apply prospect theory by deliberately calculating weighted sums of (transformed) outcomes and probabilities—even if choices are in line with the theory's predictions. This highlights the status of prospect theory as an as-if model. To integrate (transformed) outcomes and probabilities, individuals seem to rely on qualitatively different processes, which also have to be explored in future research.

Notes

1. When taking into account the value function and the probability weighting function (described below) simultaneously, a more complex fourfold pattern of risk attitudes emerges (i.e., risk aversion for gains and risk seeking for losses of high probability, as well as risk seeking for gains and risk aversion for losses of low probability; Tversky & Kahneman, 1992).

2. According to cumulative prospect theory (Tversky & Kahneman, 1992), decision weights are furthermore dependent on the rank of the outcome, and it is assured that they add up to 1 (details below and in note 4).

3. The paradox is that individuals are not willing to pay a particularly high amount of money for playing the following St. Petersburg game, which has an infinitely large *EV* (for a detailed discussion, see also chapter 8.2 by Peterson, this handbook): a coin is flipped repeatedly until heads appears. If, on the first coin flip, tails appears, the person receives €1 (otherwise zero). The payment amount doubles with each further coin flip landing on tails. When heads appears, the game ceases and the player receives the amount determined at the previous coin flip (i.e., only this one amount is paid). See also section 7.2 of chapter 8.2 by Peterson (this handbook).

4. This is realized by outcomes being sorted by magnitude separately for gains and losses. The decision weight for the highest outcome in the gains (and the lowest outcome in the losses) is directly determined according to the probability weighting function w (figure 8.3.1, right), whereas the weights of the subsequent outcomes are determined as differences in weights. For example, consider a gamble with three outcomes O_1: .20, €20; O_2: .40, €10; O_3:.40, €5. The probability weight of O_1 is the weight $w(p_1)$ with p_1 = .20 being transformed according to function w. The weight for O_2 is the difference between the weights for $w(p_1 + p_2)$ with $p_1 + p_2$ = .60 and $w(p_1)$. The weight for O_3 is the difference between weights $w(p_1 + p_2 + p_3)$ with $p_1 + p_2 + p_3 = 1$ and $w(p_1 + p_2)$. Note that in this example, the decision weight for O_2 will typically be lower than for O_3, although both outcomes have the same probability of .40.

5. According to the priority heuristic, individuals apply a stepwise noncompensatory comparison of specific attributes of gambles, namely, (i) worst outcomes, (ii) probabilities of worst outcomes, and (iii) best outcomes with particular difference thresholds.

6. This describes the sampling paradigm. In the also-often-used feedback paradigm, the outcome of each draw is paid (Barron & Erev, 2003). Differences are discussed at the end of this section.

7. In our example, the likelihood of the rare event from gamble *A* (.2, €0) to be underrepresented (i.e., experiencing €0 in *less* than 2 out of 10 samples) is .38, while the likelihood of it being overrepresented in the sample (i.e., experiencing €0 in *more* than 2 out of 10 samples) is .32, according to the binomial distribution.

8. Realized, in this case, by considering only the outcomes that people had indeed experienced and not the hypothetical probabilities of the gambles.

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This is a section of doi:10.7551/mitpress/11252.001.0001

The Handbook of Rationality

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Citation:

The Handbook of Rationality
Edited by: Markus Knauff, Wolfgang Spohn
DOI: 10.7551/mitpress/11252.001.0001
ISBN (electronic): 9780262366175
Publisher: The MIT Press
Published: 2021

Funding for the open access edition was provided by the MIT Libraries Open Monograph Fund.

The MIT Press

The MIT Press would like to thank the anonymous peer reviewers who provided comments on drafts of this book. The generous work of academic experts is essential for establishing the authority and quality of our publications. We acknowledge with gratitude the contributions of these otherwise uncredited readers.

This book was set in Stone Serif and Stone Sans by Westchester Publishing Services.

Library of Congress Cataloging-in-Publication Data

Names: Knauff, Markus, editor. | Spohn, Wolfgang, editor.
Title: The handbook of rationality / edited by Markus Knauff and Wolfgang Spohn.
Description: Cambridge : The MIT Press, 2021. | Includes bibliographical references and index.
Identifiers: LCCN 2020048455 | ISBN 9780262045070 (hardcover)
Subjects: LCSH: Reasoning (Psychology) | Reason. | Cognitive psychology. | Logic. | Philosophy of mind.
Classification: LCC BF442 .H36 2021 | DDC 153.4/3—dc23
LC record available at https://lccn.loc.gov/2020048455