An Affective Probability Weighting Function for Risky Choice with Nonmonetary Outcomes

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Abstract

The assumption of an inverse S-shaped probability weighting function allows cumulative prospect theory to explain several well-established regularities in risky choice between monetary lotteries. Empirical evidence indicates that in choices between options with *nonmonetary* outcomes, the shape of the weighting function is strongly influenced by the negative emotions often associated with these outcomes. In its current form, however, cumulative prospect theory is silent with respect to how to formally integrate the influence of affective processes on the shape of the weighting function. Here, we propose an affective probability weighting function in which the two main features of the weighting function, probability sensitivity and elevation, gradually change with the affective value of the nonmonetary outcomes. We test our proposition in a model competition with three data sets. The results show that the affective probability weighting function improves the ability of (cumulative) prospect theory to predict choices between options with nonmonetary outcomes. We observed approximately linear probability weighting for the least affective nonmonetary outcomes and probability neglect for the worst or multiple outcomes. These findings demonstrate that integrating the effect of affective processes in formal decision models is crucial for advancing the understanding of choices between nonmonetary risky options—and thus ensuring the generalizability of the models beyond choices between monetary lotteries.

Keywords: probability weighting function; prospect theory; affect; nonmonetary outcomes

Introduction

The consequences of many everyday decisions cannot be predicted with certainty. People deciding whether to get vaccinated, to buy travel insurance, or to gamble on a sporting event may have information (or a hunch) about the probability of a specific outcome—but they can never be sure. In recent decades, many formal models have been proposed to describe how people make such decisions under risk. One important line of development has focused on the notion of probability weighting, which accounts for violations of expected utility theory by assuming that the weight that a risky outcome receives results from a nonlinear transformation of its probability (Wu et al., 2004). One of the most influential models of this kind is (cumulative) prospect theory (Kahneman & Tversky, 1979; Tversky & Kahneman, 1992).

In cumulative prospect theory, probability weighting is formalized in terms of an inverse S-shaped probability weighting function, which overweights low-probability events and underweights high-probability events. The inverse S-shape allows the model to account for empirical phenomena such as the fourfold pattern of risk attitudes and the common-ratio effect (Tversky & Fox, 1995). The studies feeding into the development of (cumulative) prospect theory have involved choices with *monetary* outcomes, such as lotteries. However, many everyday decisions involve *nonmonetary* outcomes, such as the potential side effects of medical treatments. Several investigations have demonstrated that nonmonetary outcomes are often associated with higher affect than are their monetary equivalents (Pachur et al., 2014, 2017; Suter et al., 2016, 2015). Yet cumulative prospect theory does not account for the influence of emotions on people's decisions.

There are clear indications that affect influences decision making under risk. In a seminal study, Rottenstreich and Hsee (2001) found evidence that sensitivity to probability differences is lower when the outcomes are relatively affect-rich than when they are relatively affect-poor. There is also strong empirical support that probability weighting differs as a function of the amount of affect associated with the outcomes. However, the influences of affect on risky choice have not yet been systematically integrated into formal models. Few formal models include the emotions caused by choice option attributes (Bell, 1985; Loomes & Sugden, 1982; Mellers et al., 1997; Juvina et al., 2018; Marinier III et al., 2009; Marsella & Gratch, 2009), but none of these models explain how affect may influence probability weighting. Here we aim to close this gap by proposing and testing a formal account of how affect may influence the shape of the probability weighting function.

Next, we briefly describe cumulative prospect theory and review empirical evidence showing that probability weighting is sensitive to affect. We then propose an *affective probability weighting function* and test it in a rigorous model comparison that draws on three data sets involving choices between nonmonetary risky options.

Cumulative Prospect Theory

The simplified version of cumulative prospect theory described here applies to risky options with outcomes of the same sign—that is, where all outcomes are either gains or losses. Consider a risky option A with N negative outcomes $x_N < ... < x_1 < 0$ and corresponding probabilities $p_N, ..., p_1$. For illustration, assume that option A is a medication and that its outcomes are averse side effects. According to cumulative

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prospect theory, the overall subjective valuation of A, denoted $V(A)$, is determined as follows:

$$V(A) = \sum_{i=1}^{N} v(x_i)\pi(p_i), \qquad (1)$$

where $v(x_i)$ is the subjective value of outcome x_i, determined by the function value $v()$ and $\pi(p_i)$ is the decision weight of outcome x_i.

To quantify the nonmonetary outcome (i.e., side effect), we use an *affect rating* denoted a as a proxy and assume no further transformation of this value:

$$v(x) = a. \qquad (2)$$

In cumulative prospect theory, the decision weight π in Equation 1 is (sign- and) rank-dependent and is calculated using the probability weighting function, based on cumulative probabilities. However, Camerer and Ho (1994) tested what they called "separable" prospect theory (i.e., without cumulative weights) against the cumulative version in eight data sets and found no evidence in favor of the latter model. Recently, Bernheim and Sprenger (2020) likewise found no support for the assumption of probability weighting based on cumulative probabilities. Finally, results of a large-scale study show that separable prospect theory outperforms the cumulative model (Peterson et al., 2021). Hence, we assume that the decision weight π in Equation 1 is a function of an outcome's noncumulative probability. The probability is transformed by a probability weighting function.

Here, we use a two-parameter version of the weighting function, originally proposed by Goldstein and Einhorn (1987). It separates the curvature of the function from its elevation (Gonzalez & Wu, 1999):

$$\pi(p) = \frac{\delta p^{\gamma}}{\delta p^{\gamma} + (1-p)^{\gamma}}, \qquad (3)$$

where the parameter $\gamma \in [0,1]$ controls the curvature of the weighting function and is interpreted as indicating the decision maker's sensitivity to differences in probability, with higher values indicating higher sensitivity. The parameter $\delta > 0$ controls the function's elevation, with higher values resulting in more elevated functions, and thus higher overall decision weights. The elevation is often interpreted as indicating the decision maker's optimism/pessimism (Wakker, 2001). Figure 1 presents examples of the probability weighting function, showing shapes typically observed for monetary losses and for relatively affect-rich nonmonetary outcomes.

Finally, in the context of binary choices, the subjective valuations of two risky options A an B are entered into a stochastic choice rule to derive a predicted probability of choosing A over B. To this end, we use a logistic choice rule (also known as softmax):

$$P(A|\{A,B\}) = \frac{1}{1+e^{-\phi(V(A)-V(B))}}, \qquad (4)$$

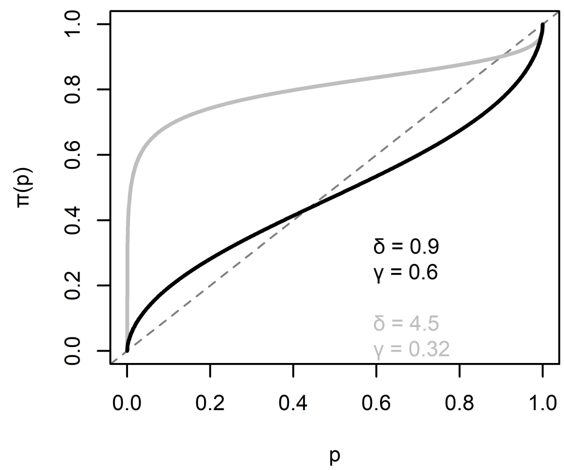

Figure 1: Example shapes of the probability weighting function. The black (gray) curve shows the weighting function usually observed in studies with monetary losses (affect-rich nonmonetary risky options).

where the parameter $\phi > 0$ is a choice sensitivity parameter that represents the degree to which the difference between the subjective valuations map onto the probability of choosing the option A. With $\phi = 0$, choices are random.

The Impact of Affect on Probability Weighting

Several lines of research have observed that probability weighting—that is, how risky outcomes are weighted as a nonlinear function of their probability—is modulated by emotion. In an analysis of US price market data, Kliger and Levy (2008) demonstrated that investors' probability sensitivity was lower in periods of the year associated with more negative mood (i.e., with less daylight time) than in periods associated with more positive mood. This effect was especially pronounced in the loss domain. Fehr-Duda et al. (2011) observed that when choosing between options with positive outcomes women in a neutral or "worse than usual" mood had slightly lower probability sensitivity and less elevated weighting functions—resulting in a more distorted weighting function—than women in a "better than usual" mood. When choosing between options with negative outcomes, women in "worse than usual" mood exhibited substantially more elevated weighting functions. Traczyk and Fulawka (2016) found that a carry-over effect of negative affect from an unrelated task led to a slight decrease in probability sensitivity in an insurance pricing task.

In addition to these effects of incidental affect (i.e., affect that is unrelated to the stimuli but present in the decision maker) on probability weighting, there is also evidence for an effect of integral affect (i.e., affect that is directly associated with the outcomes). Several studies contrasting choices between affect-rich options with choices between relatively affect-poor options with negative outcomes have shown substantially lower probability sensitivity and more elevated weighting functions in choices between affect-rich options (Pachur et al., 2014, 2017; Suter et al., 2016). A neuroimaging study demonstrated that brain areas associated with affective processes and autobiographical memory had higher activation when people chose between affect-rich options than when they chose between affect-poor (i.e., monetary) options (Suter et al., 2015). Integral affect also impacts probability weighting in decisions from experience (Lejarraga et al., 2016).

Whereas there is robust evidence for an effect of negative affect on probability weighting, the evidence for an effect of positive affect is scant and mixed. Pachur et al. (2014) observed more elevated weighting functions for choices with positive nonmonetary outcomes than for lotteries with positive monetary outcomes; there were no differences with respect to probability sensitivity. Petrova et al. (2014) found slightly higher elevation and lower probability sensitivity in an insurance pricing task for a camera that was a present from a grandparent (i.e., an affect-rich outcome) than for a camera that had been ordered from a website (i.e., an affect-poor outcome).

An Affective Probability Weighting Function

How can the observed effects of affect on probability weighting be integrated in a formal model? Previous analyses have mainly documented differences in probability weighting between situations with relatively high versus low affect. We propose a formalization that allows probability weighting in a given choice problem to be determined directly based on measures of affect in that specific choice problem. Our approach thus assumes a continuous influence of affect on probability weighting—rather than distinguishing categorically between affect-rich and affect-poor options.

Let us assume a nonmonetary outcome x (e.g., a side effect) that triggers an affective response a, and that the outcome occurs with probability p. Here we propose that the *affective probability sensitivity* γ_x for this particular outcome is given by:

$$\gamma_x = \gamma^{\frac{|a|}{\max|a|}}, \qquad (5)$$

where γ is a baseline probability sensitivity level and $\max|a|$ is a scaling factor that equals the maximum possible value on the affect rating scale. Equation 5 assures that the resulting exponent ranges between 0 and 1; as a result, for all combinations of the baseline level γ and the affective value a_i of the respective outcome, the resulting parameter γ_x will be in the 0–1 range. Importantly, for any fixed value of γ, the affective probability sensitivity increases as the affective value a of the nonmonetary outcome decreases.

For the *affective elevation* parameter δ_x, we propose a simple linear form:

$$\delta_x = \delta \times |a|, \qquad (6)$$

where δ is the baseline level of the function's elevation. Hence, the affective elevation parameter δ_x increases with the affective value a of the respective outcome. To obtain a decision weight based on affective probability sensitivity or affective elevation, one simply needs to substitute the γ and δ parameters in Equation 3 with γ_x and δ_x, respectively. The probability weighting function with both affect-specific probability sensitivity and elevation constitutes the *affective probability weighting function*. Note that in cases of risky options with multiple outcomes, the decision weight of each outcome is determined based on its own specific values of γ_x and δ_x.

We tested the affective probability weighting function by conducting a model comparison between four models: (1) standard prospect theory (PT), (2) prospect theory with affective elevation (PT_{ae}), (3) prospect theory with affective probability sensitivity (PT_{aps}), and (4) prospect theory with affective probability weighting (i.e., with both affective elevation and affective probability sensitivity; PT_{apse}). We drew on two data sets from previous studies examining choices between options with nonmonetary outcomes—specifically, medical drugs, each of which had one possible side effect (Pachur et al., 2017; Suter et al., 2016). In these data sets, the probabilities of the side effects ranged between zero and one, with the most frequent probability values being near zero and one. However, an analysis of the actual distribution of the probabilities of side effects (Kuhn et al., 2016) indicated a distribution with a right skew, with more than 90% of the side effects having probabilities lower than 10%. Additionally, a drug usually has several side effects. Thus, the choice problems in these single-outcome data sets have limited ecological validity. To address these issues, we also included an unpublished data set of choices between drugs with two side effects and with a probability distribution designed to match that observed in the Kuhn et al. (2016) data. Including this data set allowed us to measure the probability weighting function in the context of choices between risky options with multiple nonmonetary outcomes and to contrast the results with those emerging for the simpler choice problems used in previous studies.

Method

Data Sets

Our study involved two types of data sets: First, we drew on data sets where each option had a single outcome, using two published studies that relied on the same method (Pachur et al., 2017; Suter et al., 2016), with 80 participants each. Participants were asked to imagine that they were suffering from an unspecified illness and that two equally effective medical drugs were available to treat the condition. Each drug could result in one side effect with a specific probability. Participants made 44 such choices and after the choice task provided negative affect ratings for the side effects on a 10-point Likert scale.

Second, we used data from an experiment where each option had two outcomes; here, 92 participants attended two identical sessions held at least two weeks apart. In each session, participants first provided negative affect ratings for 20 side effects on a 10-point Likert scale. Next, they made 100 hypothetical choices between two drugs with two possible side effects each, in the same way as in the Pachur et al. (2017) and Suter et al. (2016) studies. Order of presentation and information layouts were randomized within each participant. The distribution of probabilities ranged from 0.003 to 0.096 and was right-skewed to roughly match that in the Kuhn et al. (2016) data.

Henceforth, we will refer to the single-outcome data sets Pachur et al. (2017) and Suter et al. (2016) as Pa17 and Su16, respectively. The data from the first and the second session of the two-outcome experiment will be referred to as To1 and To2, respectively.

Modeling Approach and Model Comparison

All models were implemented in a hierarchical Bayesian approach, allowing for a simultaneous estimation of individual- and group-level parameters (e.g., Scheibehenne & Pachur, 2015). We used uninformed priors and parameter ranges that were consistent with previous findings. Samples from the posterior distribution were drawn using Gibbs sampling via the JAGS 4.3.0 software (Plummer, 2003), called from R 4.1.1. For each model, we used eight parallel chains and recorded 3,000 samples from each chain. To reduce autocorrelations in the recorded chains, only every 20th sample was saved. The burn-in period consisted of 11,000 samples, including 1,000 samples for adaptation. Convergence was assessed using the Gelman–Rubin statistic and visual inspection of the chains.

To compare the performance of the models, we used approximate leave-one-out cross-validation (Vehtari, Gelman, & Gabry, 2017). For each model, expected log pointwise predictive density (elpd) was approximated with the R package loo (Vehtari et al., 2020). A higher elpd indicates better out-of-sample predictive accuracy, taking into account model complexity. Two models were considered to differ reliably in their performance if the 95% confidence interval of the difference in elpd excluded zero. To provide an intuitive measure of overall model performance, we also report pseudo-R^2 (Nagelkerke, 1991) calculated with the elpd values.

Results

Overall, the tested models showed a better performance on the To2 data than on the other data sets (Fig. 2a). Regarding the single-outcome data sets, all models performed much better on the Pa17 data than on the Su16 data (Fig. 2a). This finding is consistent with the proportions of participants classified as guessing in the respective articles (which was considerably higher for the Su16 data). The better performance of the models in the To2 than in the To1 data might suggest that the affect ratings were more internally consistent in the second session than in the first.

The PT_{apse} model—which relies on both affective probability sensitivity and affective elevation—outperformed the other models on all the data sets except Pa17, as indicated by positive values of the elpd differences and 95% confidence intervals excluding zero (Figure 2b). In the Pa17 data

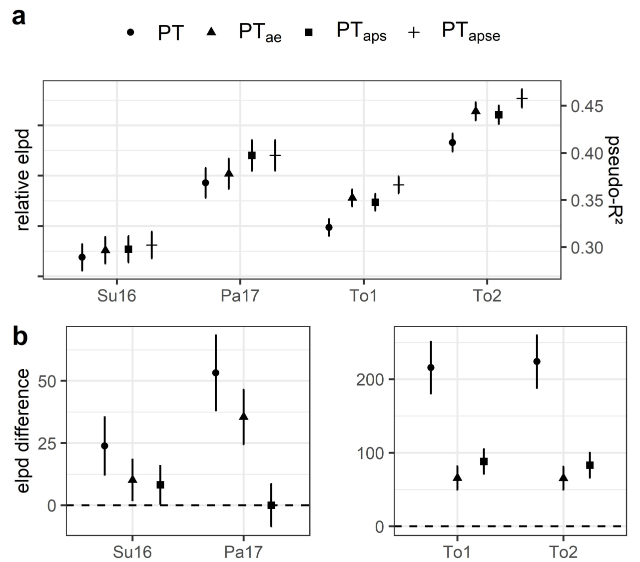

Figure 2: Model performance and model comparison results. **a:** Estimated log pointwise predictive densities (elpd) for each model, separately for each data set. The values were scaled with the log-likelihood of a guessing model, allowing model performance to be compared across data sets of different sizes. Vertical lines show elpd $+/-$ standard error. **b:** Elpd differences between the PT_{apse} model (which assumes affective probability weighting) and the remaining models, separately for each data set. Vertical lines show 95% confidence intervals of the difference.

set, the PT_{aps} model—which only relies on affective probability sensitivity—showed nearly the same performance as the PT_{apse} model. Overall, these results demonstrate that prospect theory's performance in accounting for choices between nonmonetary risky options can be improved without additional free parameters by assuming an affective probability weighting function.

A detailed investigation of the group-level parameter estimates revealed two regularities. First, the estimated probability sensitivity levels were much lower in the two-outcome than in the single-outcome data (Fig. 3); this indicates that differences between probabilities are even less important in more complex nonmonetary risky decisions. Second, with the PT_{apse} model and the PT_{ae} model—both of which rely on affective elevation—the range of the group-level posterior distribution of the δ parameter is greatly reduced in all data sets except for Su16. This suggests that the high initial uncertainty in the parameter estimate was caused by the fact that lower δ values were plausible for choice problems with less affective outcomes, and higher δ values were plausible for problems with more affective outcomes. Once the elevation was tied to the nonmonetary outcome's magnitude, the uncertainty in the parameter estimate was greatly reduced.

The shape of the group-level probability weighting function estimated for the Pa17 data reveals that the transforma-

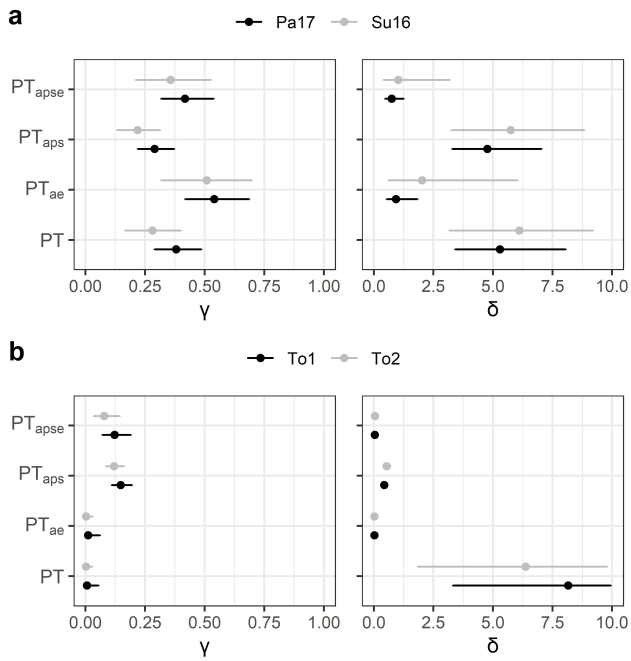

Figure 3: Group-level parameter estimates of the probability sensitivity (γ) and elevation (δ) parameters for all models tested, for the single-outcome (**a**) and two-outcome (**b**) data sets. Points represent the median of the posterior distribution and the horizontal lines are 95% credible intervals.

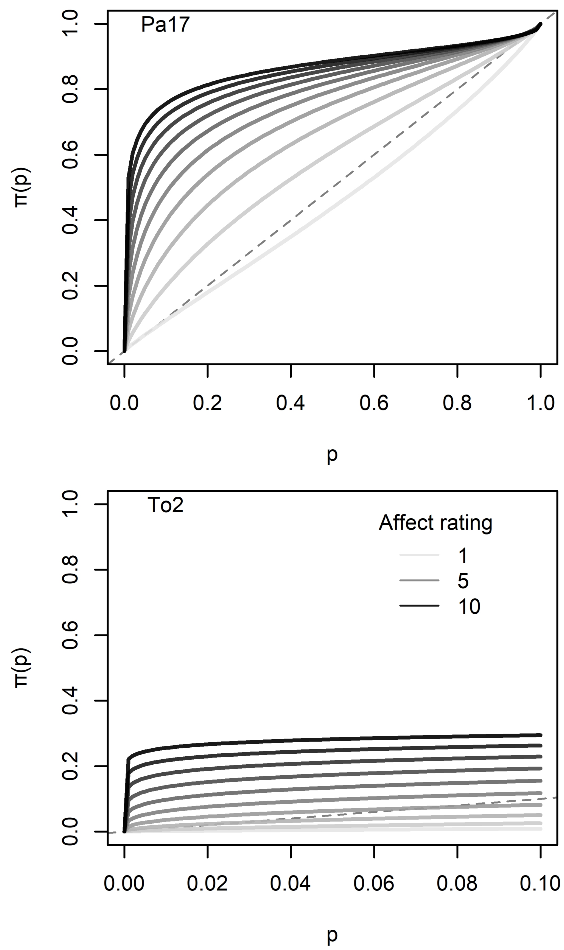

Figure 4: Estimated group-level affective probability weighting functions for choices between drugs with a single side effect (top) and with two side effects with small probabilities (bottom).

tion was nearly linear for the least affective outcomes (Fig. 4, top). An increase in the negative affect associated with an outcome results in the flattening and elevating of the curve; for the outcomes inducing the strongest negative affect, the function resembles the pattern associated with probability neglect.

For the two-outcome data with small probabilities, we observed different patterns of probability weighting. The probability weighting function (Fig. 4, bottom) was almost entirely flat over the range of probabilities used in the study. The function changes with an outcome's affective value mainly with respect to the elevation. This indicates that for more complex nonmonetary risky options with small probabilities, the decision weight may reflect the outcome's relative importance. In fact, the PT$_{ae}$ model outperformed the PT$_{aps}$ model in the two-outcome data sets, as indicated by a robust difference between elpds (for the To1 data: 22.2, 95% CI: [7.4, 37]; for the To2 data: 17.6, 95% CI: [1.67, 33.6]). In the single-outcome data sets, the PT$_{aps}$ model outperformed the PT$_{ae}$ model in the Pa17 data, (35.3, 95% CI: [22.1, 48.5]). In the Su16 data, the performance of two models did not differ (2.4, 95% CI: [-8.8, 13.6]).

Robustness Checks

Alternative Weighting Function. To test to what extent our results may depend on the choice of a specific probability weighting function and the assumption of separable weights, we conducted additional model comparisons. First, we tested another form of widely used two-parameter weighting function proposed by Prelec (1998):

$$\pi(p) = \exp(-\delta(-\ln(p))^{\gamma}). \tag{7}$$

The parameters $\gamma \in [0,1]$ and $\delta \in [0,1]$ control the curvature and the elevation of the function, respectively, as in Equation 3. One of the minor differences between the two functional forms is that the elevation of the function in Equation 7 *increases* as the value of the δ parameter *decreases*. To integrate affective probability weighting into Equation 7, we therefore set both parameters to change with affective values as in Equation 5 (i.e., the parameters γ_x and δ_x were forced to decrease with an increasing absolute affective value a of the corresponding side effect x). We modeled the Pa17 and To2 data with the candidate models, now equipped with the weighting function based on Equation 7. As in the previous analyses, the PT$_{apse}$ model outperformed the PT model in both studies (elpd difference in the single-outcome Pa17 data: 45.6, 95%CI: [38.2, 53]; in the two-outcome To2 data: 181.6, 95%CI: [152.2, 211]).

Probability Weighting with Cumulative Probabilities. Second, we considered a model with cumulative weights. In cumulative prospect theory, decision weights W for a risky option with two negative outcomes $x_2 < x_1 < 0$ and corresponding probabilities p_2, p_1 are given as:

$$\begin{aligned} W(p_2,x_2) &= \pi(p_2), \\ W(p_1,x_1) &= \pi(p_1+p_2) - \pi(p_2), \end{aligned} \tag{8}$$

where π is a probability weighting function, which we set to the one used in the main analyses (i.e., Equation 3). When implementing affective probability weighting based on cumulative weights, it is important to note that $\pi(p_1 + p_2) \geq \pi(p_2)$ always has to be true, because the weights W cannot be negative. To ensure this, the affective parameters γ_x and δ_x should have the same values in $\pi(p_1 + p_2)$ and $\pi(p_2)$. We assumed that the worse side effect x_2 was more important than x_1 for the overall value of the drug and thus used the corresponding affective value a_2 to set the values of γ_x and δ_x to determine the weights *within the option*. This ensured that the weights W were always non-negative.

Comparison of the performance of cumulative prospect theory with standard versus affective weighting functions in the two-outcome data set again showed that the model equipped with our proposed affective weighting function outperformed the standard implementation of the model in both sessions (elpd difference in the To1 data: 58.2, 95%CI: [49.8, 66.6]; in the To2 data: 63.1, 95%CI: [52.9, 73.3]).[1] In conclusion, the robustness checks confirmed that assuming an affective probability weighting function improves the performance of both separable and cumulative prospect theory and that the success of our proposition does not depend on the form of the weighting function.

Discussion

Recent decades have seen important advances in integrating cognitive and affective processes in order to account for human behavior (Dukes et al., 2021). Building on these advances, we demonstrated that assuming affective probability weighting substantially improves the ability of prospect theory to predict choices between risky options with nonmonetary outcomes. In our proposed probability weighting function, probability sensitivity and elevation gradually change with the affective value of the nonmonetary outcome.

The affective probability weighting functions that we obtained for the different data sets are consistent with the framework of the affect heuristic (Slovic et al., 2007), according to which probability information influences decision making only when the associated outcomes do not carry much affective information. We observed nearly linear probability weighting functions for the least affective outcomes in the data sets with single outcomes, and an almost flat weighting function for the most affective ones (Fig. 4, top). This finding indicates that probability neglect in such simple contexts occurs only for the most affective outcomes and not for moderately affective outcomes; this highlights the importance of assuming affective probability sensitivity in this context.

Interestingly, in the data set comprising choices between drugs with two side effects and small probabilities (i.e., $p < .1$), we observed a very low level of probability sensitivity, which decreased only slightly with increasing affect (Fig. 4, bottom). This result is consistent with the proposal of Loewenstein et al. (2001) that people perceive small probabilities as subjectively indistinguishable and react only to the "possibility" of a dreadful event. At the same time, we observed an important role of affective elevation, with more affective outcomes having noticeably higher overall decision weights (Fig. 4, bottom). Thus, in the risky nonmonetary context with multiple outcomes, more affect-rich outcomes received higher weights and probabilities were largely ignored.

Johnson and Busemeyer (2016) demonstrated via formal analysis that the probability weighting function can constitute high-level representation of an attentional process in risky choice. In their model, the function's curvature represents the tendency for attention to dwell on the associated outcome. The authors predicted that the tendency to dwell would be stronger for more affect-rich outcomes, which would result in a flatter weighting function. However, recent empirical evidence links the curvature of the weighting function to the attention paid to probabilities rather than to outcomes (Pachur et al., 2018). Our results show that the affective value of a nonmonetary outcome is related to the function's curvature and elevation, which indicates that the outcome induced emotions influence probability weighting. Further research is required to understand how these results might be linked to attentional processes.

In conclusion, our results indicate that both the curvature and the elevation of the probability weighting function strongly hinge on the intensity of affect induced by nonmonetary risky outcomes. Thus, the exact levels of probability sensitivity and pessimism/optimism seem to be unique to the nonmonetary choice problem at hand. Even more importantly, we proposed a modeling approach that allows to integrate this effect seamlessly into the formal framework of prospect theory—without assuming additional estimated parameters. These results show that taking affective processes into account is crucial for advancing the understanding of choices between nonmonetary risky options.

Acknowledgments

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[1] Cumulative prospect theory reduces to separable prospect theory for risky options with one nonzero outcome; hence, this model comparison was not meaningful for the Su16 and Pa17 data sets.

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