Models of affective decision-making: how do feelings predict choice?

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Abstract

Intuitively, how we feel about potential outcomes will determine our decisions. Indeed, one of the most influential theories in psychology, Prospect Theory, implicitly assumes that feelings govern choice. Surprisingly, however, we know very little about the rules by which feelings are transformed into decisions. Here, we characterize a computational model that uses feelings to predict choice. Not only does the model perform better than existing value-based models, it also redefines some of their core assumptions. We reveal in three independent samples that, contrary to conventional wisdom, losses do not have a larger impact on explicit feelings than gains. Rather, loss feelings are weighted more when making a decision. It are these relative weights that explain individual differences in decision-making. The results provide new insights into how feelings are utilized to reach a decision.

Keywords: decision-making, feelings, subjective well-being, value, utility, Prospect Theory
Introduction

How would you feel if you received international recognition for outstanding professional achievement? How would you feel if your marriage broke apart? Intuitively, answers to these questions are important, as they should predict your actions. If the prospect of losing your spouse does not fill you with negative feelings you may not attempt to keep the unit intact.

But how exactly do feelings associated with possible outcomes relate to actual choices? What are the computational rules by which feelings are transformed into decisions? While an expanding body of literature has been dedicated to answering the reverse question, namely how decision outcomes affect feelings (Carter & McBride, 2013; Kassam, Morewedge, Gilbert, & Wilson, 2011; Kermer, Driver-Linn, Wilson, & Gilbert, 2006; McGraw, Larsen, Kahneman, & Schkade, 2010; Mellers, Schwartz, Ho, & Ritov, 1997; Rutledge, Skandali, Dayan, & Dolan, 2014; Yechiam, Telpaz, & Hochman, 2014), little is known of how feelings drive decisions about potential outcomes.

Here, we examine whether feelings predict choice and built a computational model that characterizes this relationship. We turn to Prospect Theory (Fox & Poldrack, 2014; Kahneman & Tversky, 1979; Tversky & Kahneman, 1986, 1992) as a starting point in this research. Prospect Theory was not derived by eliciting people’s feelings to predict choice, but rather by observing people’s choices in order to estimate the subjective value associated with possible outcomes. An implicit assumption of the theory, however, is that subjective value (utility) is a proxy for feelings, which in turn govern choice; “humans described by Prospect Theory are guided by the immediate emotional impact of gains and losses” (Kahneman, 2011). This suggests that if we measure a person’s feelings associated with different outcomes, we should be able to generate that person’s utility function and use it to predict their choices. While Prospect Theory is one of the most influential theories in economics and psychology, this implicit assumption has never been empirically tested. Thus, we do not know if and how feelings guide choice.

To address this question, in three separate studies (see Supplemental Material for replication studies), participants reported how they felt, or expected to feel, after winning or losing different amounts of money. We used those self-reported feelings to form a “feeling function”; a function that best relates feelings (expected and/or experienced) to objective value. Next, we used this function to predict participants’ choices in a different decision-making task. Our findings were replicated in all three studies.
An intriguing question is what such a “feeling function” would look like. One possibility is that it resembles Prospect Theory’s value function, which relates the subjective value estimated from choice data to objective value. First, for most people, the value function is steeper for losses in comparison to gains. This results in loss aversion, such that the absolute subjective value of losing a dollar is greater than that of winning a dollar. Yet, while losses appear to “loom larger than gains” (Kahneman & Tversky, 1979), we do not know whether the impact of a loss on our feelings is greater than the impact of an equivalent gain. Alternatively, it is possible that the impact of gains and losses on feelings is similar, but that the weight given to those feelings differs when making a choice. Second, Prospect Theory’s value function is convex in the loss domain while concave in the gain domain (resembling an “S-shape”). The curvature of the function in both domains represents the notion of diminishing sensitivity to changes in value as gains and losses increase. In other words, the subjective value of gaining (or losing) ten dollars is smaller than twice that of gaining (or losing) five dollars. This diminishing sensitivity results in risk aversion in the gain domain and risk seeking in the loss domain, with individuals tending to choose a small sure gain over a high but risky gain, but a high risky loss over a small sure loss. We examined whether our “feeling function” was also concave for gains and convex for losses, implying that similar to value, feelings associated with gains and losses are less sensitive to outcome value as gains and losses increase. That is, the impact of winning (or losing) ten dollars on feelings is less than twice the impact of winning (or losing) five dollars.

Once feelings were modeled using this “feeling function” we asked whether they can predict choice. Understanding how explicit feelings relate to behavior has important real-world implications for domains ranging from policy to industry.

Methods

Subjects. Fifty-nine healthy volunteers (24 males, mean age 23.94y, age range 19-35y) were recruited to take part in the experiment via the UCL Subject Pool. Sample size was determined using a power analysis (G*power version 3.1.9.2; Faul, Erdfelder, Lang, & Buchner, 2007). Based on previous studies that have investigated the link between decision outcomes and self-report feelings using within-subjects designs, effect sizes (Cohen’s d,) ranged from .245 to .798, with a mean at .401 (Harinck, Van Dijk, Van Beest, & Mersmann,
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2007; Kermer et al., 2006; Yechiam et al., 2014). A sample size of 59 subjects was therefore required to achieve 85% power of detecting an effect size of .401 with an alpha of 0.05. Data collection was therefore stopped after 59 subjects. Three subjects were excluded: one who showed no variation at all in their feelings ratings, one whose data from the gambling task were lost, and one who missed more than 50% of the trials in the gambling task. Final analyses were run on 56 subjects (22 males, mean age 23.91y, age range 19-35y). With 56 subjects included, our post-hoc power to detect a .401 effect size was still 83.8%. All participants gave written informed consent and were paid for their participation. The study was approved by the departmental ethics committee at University College London.

**Behavioral tasks.** Participants completed two tasks, the order of which was counterbalanced.

1. Feelings Task. In the feelings task, subjects completed 4 blocks of 40 to 48 trials each, in which they reported either expected (Fig. 1A) or experienced (Fig. 1B) feelings associated with a range of wins and losses (between £0.2 and £12), or no change in monetary amount (£0). At the beginning of each trial participants were told how much was at stake and whether it was a win trial (e.g., if you choose the “good” picture, you will win £10) or a loss trial (e.g., if you choose the “bad” picture, you will lose £10). Their task was then to make a simple arbitrary choice between two geometrical shapes, associated with a 50% chance of winning versus not winning (on win trials) or of losing versus not losing (on loss trials). On each trial participants were told that one novel stimulus was randomly associated with a gain or loss (between £0.2 and £12) and the other novel stimulus with no gain and no loss (£0). Each stimulus was presented once so learning was not possible. There was no way for the participants to know which abstract stimulus was associated with a better outcome. In fact, the probability of sampling each amount was controlled to ensure that each gain and each loss from the range was sampled twice in each block: on one instance this amount was experienced as the outcome (win/loss) and on the other one the outcome was £0 (no win/no loss). Participants reported their feelings by answering the questions “How do you feel now?” (experienced feelings, after a choice) or “How will you feel if you win/lose/don’t win/don’t lose?” (expected feelings, before a choice), using a subjective rating scale ranging from “Extremely unhappy” to “Extremely happy”. In 2 of the 4 blocks (counterbalanced order) they reported their expected feelings (Fig. 1A), and in the other 2 blocks, they reported their experienced feelings (Fig 1B). Expected and experienced feelings were collected in different blocks to avoid subjects simply remembering and repeating the same rating. The choice
between the two geometrical shapes was simply instrumental and implemented in order to have subjects actively involved with the outcomes.

A. Feelings task – Expected feelings block – 1 example trial

B. Feelings task – Experienced feelings block – 1 example trial

C. Gambling task – 6 example trials

**Fig. 1. Experimental design.** Participants completed two tasks in a counterbalanced order (A,B): a feelings task where they reported (in different blocks) expected (A) or experienced (B) feelings associated with winning, losing, not winning or not losing a range of monetary amounts; and (C) a gambling task where they selected between a sure option and a gamble involving the same amounts as those used in the feelings task. Feelings were modeled as a function of value and this resulting feelings function F was used to predict choice in the gambling task. For each trial, feelings associated with the sure option, the risky gain, and the risky loss were extracted and entered in a cross-trials within-subject logistic regression model.

2. Gambling Task. Participants completed a probabilistic choice task (Fig. 1C) in which they made 288-322 choices between a risky 50/50 gamble and a sure option. Importantly, all the amounts used in the gambling task were the same as those used in the feelings task (between £0.2 and £12), such that feelings associated with these outcomes could be combined to predict gamble choice. There were 3 gamble types: mixed (subjects had to choose between a gamble with 50% chance of a gain and 50% of a loss, or sure option of £0), gain-only (subjects had to choose between a gamble with 50% chance of a high gain and 50% chance of £0, or a sure, smaller, gain) and loss-only (subjects had to choose between a gamble with
50% chance of a high loss and 50% chance of £0, or a sure, smaller, loss). In Prospect Theory, these 3 types of choices are essential to estimate loss aversion, risk preference for gains, and risk preference for losses, respectively.

Subjects started the experiment with an initial endowment of £12 and were paid according to their choices on two randomly chosen trials (across both tasks) at the end of the experiment.

**Feelings function models.** The impact of outcome on feelings was calculated relative to three different baselines: difference from the mid-point of the rating scale, difference from rating reported on the previous trial (for experienced feelings only), difference from corresponding zero outcome. These were calculated for each win and loss amount, for expected and experienced feelings separately. For each subject, for each of the above methods, feelings function models were then fit (ten for expected feelings and ten for experienced feelings) to explain how feelings best relate to value outcomes:

Feeling Model 1:

\[ F(x) = \beta x \]

Feeling Model 2:

\[
F(x) = \begin{cases} 
\beta_{\text{gain}}^x, & x > 0 \\
\beta_{\text{loss}}^x, & x < 0 
\end{cases}
\]

Feeling Model 3:

\[
F(x) = \begin{cases} 
\beta (|x|)^\rho, & x > 0 \\
-\beta (|x|)^\rho, & x < 0 
\end{cases}
\]

Feeling Model 4:

\[
F(x) = \begin{cases} 
\beta_{\text{gain}}^{|x|}^\rho, & x > 0 \\
-\beta_{\text{loss}}^{|x|}^\rho, & x < 0 
\end{cases}
\]

Feeling Model 5:

\[
F(x) = \begin{cases} 
\beta (|x|)^\rho_{\text{gain}}, & x > 0 \\
-\beta (|x|)^\rho_{\text{loss}}, & x < 0 
\end{cases}
\]

Feeling Model 6:

\[
F(x) = \begin{cases} 
\beta_{\text{gain}}^{|x|}^\rho_{\text{gain}}, & x > 0 \\
-\beta_{\text{loss}}^{|x|}^\rho_{\text{loss}}, & x < 0 
\end{cases}
\]

Feeling Model 7:

\[
F(x) = \begin{cases} 
\beta x + \varepsilon, & x > 0 \\
\beta x - \varepsilon, & x < 0 
\end{cases}
\]

Feeling Model 8:

\[
F(x) = \begin{cases} 
\beta_{\text{gain}}^x + \varepsilon, & x > 0 \\
\beta_{\text{loss}}^x - \varepsilon, & x < 0 
\end{cases}
\]

Feeling Model 9:

\[
F(x) = \begin{cases} 
\beta x + \varepsilon_{\text{gain}}, & x > 0 \\
\beta x - \varepsilon_{\text{loss}}, & x < 0 
\end{cases}
\]
Feeling Model 10:

\[ F(x) = \begin{cases} 
\beta_{gain} x + \varepsilon_{gain}, & x > 0 \\
\beta_{loss} x - \varepsilon_{loss}, & x < 0 
\end{cases} \]

In all these models, \( x \) represents the value (from -12 to -0.2 for losses and from 0.2 to 12 for gains) and \( F \) the associated feeling. The slope between feelings and values is represented by the parameter \( \beta \) estimated as a single parameter in all odd-numbered models, or separately for losses and gains in all even-numbered models. If loss aversion is reflected in feelings, \( \beta_{loss} \) should be significantly greater than \( \beta_{gain} \) and even-numbered models should perform better overall. Similar to the curvature parameter of Prospect Theory value function, \( \rho \) reflects the curvature of the feeling function, i.e. the fact that feelings become more or less sensitive to changes in value as absolute value increases (Feeling Models 3 to 6). In Feeling Models 5 and 6, the curvature is estimated separately in the gain and loss domains. If the feeling function is S-shaped (function concave for gains and convex for losses) \( \rho \) values should be significantly smaller than 1. To ensure that a function with curvature fit the feelings data better than a simple linear function with an intercept, Feeling Models 7 to 10 were defined (as respective comparisons for Feeling Models 3 to 6), where \( \varepsilon \) represents the intercept, or the offset (positive for gains, negative for losses) where feelings start for values close to £0. All these models were estimated in Matlab (www.mathworks.com) using a maximum-likelihood estimation procedure (Myung, 2003). Bayesian Information Criterion (BIC) scores were calculated for each subject and model, and then summed across subjects (see Supplemental Material for details). Lower sum of BICs for a given model compared to another indicates better model fit.

**Prediction of gambling choice.** Feelings values from Feeling Model 3 (found to be the most parsimonious model overall) were then used to predict choices in the gambling task. Specifically, for each participant, the feeling associated with each amount was calculated using Feeling Model 3 with that participant’s estimated parameters (\( \beta \) and \( \rho \)). Thus, for each trial of the gambling task, a feelings value was obtained for the sure option, the gain and the loss presented on that trial. A feelings value of 0 was used when the amount in the gamble trial was £0. The probability of choosing the gamble on each trial, coded as 1 if the gamble was chosen and 0 if the sure option was chosen, was then entered as the dependent variable of a logistic regression (Choice Model), with feelings associated with the sure option (\( S \), coded negatively in order to obtain a positive weight), the gain (\( G \), multiplied by its probability 0.5), and the loss (\( L \), multiplied by its probability 0.5) entered as the 3 predictor variables:
Logistic regressions were run on Matlab using the glmfit function, using either expected feelings (Choice Model 1) or experienced feelings (Choice Model 2). To determine whether those modeled feelings predicted choice better than value-based models, 5 other comparisons models were used to predict choice from values (Choice Models 3 to 7; see Supplemental Material for details).

In order to be compared across conditions and subjects, weight values $\omega$ were standardized using the following equation (Menard, 2004; Schielzeth, 2010):

$$\omega'_x = \omega_x \frac{s_x}{s_y}$$

where $\omega'_x$ is the standardized weight value, $\omega_x$ the original weight for predictor variable $x$ obtained from the regression, $s_x$ the standard deviation of variable $x$, and $s_y$ the standard deviation of the dependent variable $y$, here the binary choice values. Standardized weight values were extracted from each regression and compared using repeated-measures ANOVA and paired t-tests.

**Replication and extension studies.** Two separate studies were conducted to replicate the findings and extend them to cases where the impact of a loss and a gain on feelings is evaluated (i) within the same trial (Replication and extension study 1) and (ii) on the same unipolar rating scale (Replication and extension study 2). These studies suggest that the results are robust and not driven by these specific factors. See Supplemental Material for details and results.

**Results**

Our analysis followed two main steps. First we used participants’ reported feelings associated with different monetary outcomes to build a “feeling function”. Specifically, we found the best fitting computational model to characterize how feelings associated with different amounts of gains and losses relate to the objective value of these amounts. Second, we tested whether that model of feelings predicted participants’ choices on a separate task. Results of
the main study are reported below and results of the replication studies in the Supplemental Material.

**Characterizing a “feeling function”**

Feelings associated with losses and gains were elicited using one of two different scales and the impact of losses and gains on feelings were computed using three different methods (see Supplemental Material for details): as the change from the mid-point of the rating scale, as the change from the previous rating, and as the change from the rating associated with zero outcome (i.e., the rating associated with not winning or not losing the equivalent amount). For all the models described below the latter baseline resulted in the best fit (Table S1). Thus we report results using this baseline; however, the results are the same when using the other two methods of calculating feelings (see Supplemental Materials for details).

We aimed to characterize a model that best fit feelings to outcome value. To that end, for each subject ten models (see Methods for equations and details) were run to fit data of expected feelings to outcome value and ten equivalent models to fit experienced feelings to outcome value. The models differed from each other in two ways: with respects to their slope parameter ($\beta$) and to their curvature parameter ($\rho$). If models with one $\beta$ parameter fit better than models with one for gains ($\beta_{gain}$) and one for losses ($\beta_{loss}$), that would indicate that gains and losses affect feelings to different extents; if not that would indicate a symmetrical no difference in the magnitude of influence. If models with a curvature ($\rho$) fit better than linear models with an intercept ($\epsilon$) that would suggest that feelings do not increase linearly as a function of outcome value, but that their sensitivity varies as outcomes increase, such that the feeling of winning/losing £10 is more or less intense than twice the feeling of winning/losing £5. Models were estimated using a maximum-likelihood estimation procedure (see Methods for details). Bayesian Information Criterion (BIC), which penalises for additional parameters, showed that the best fitting model (i.e. the lowest BIC value) for both expected (Fig. 2A) and experienced (Fig. 2B) feelings was Feeling Model 3 (see Table S2 for BIC and $R^2$ values), which has one $\rho$ and one $\beta$:

\[
F(x) = \begin{cases} 
\beta(|x|)^\rho, & x > 0 \\
-\beta(|x|)^\rho, & x < 0 
\end{cases}
\]

(1)

where $x$ is the gain/loss amount (positive for gains and negative for losses) and $F$ the corresponding feeling.

This suggests that:
(i) feelings’ sensitivity to outcomes gradually decreased as outcomes increase. Similar to Prospect Theory’s value function, $\rho$ was significantly smaller than 1 (expected feelings: $\rho = .512 \pm .26$, $t(55) = -14.05$, $P < .001$, Cohen’s $d = 1.88$, 95% CI = [0.418; 0.558]; experienced feelings: $\rho = .425 \pm .23$, $t(55) = -18.52$, $P < .001$, Cohen’s $d = 2.5$, 95% CI = [0.513; 0.637]), indicating that the feeling function was concave in the gain domain and convex in the loss domain. Graphically, we can observe in Fig. 3 that the magnitude of feelings associated with £10 for example was less than twice the magnitude of feelings associated with £5.

(ii) neither sensitivity ($\beta$) nor curvature ($\rho$) differed for gains than losses. Equal sensitivity suggests that when feelings associated with losses and gains are evaluated separately their impact is symmetrical, such that losses are not experienced more intensely than gains. On the surface, these findings contradict the notion of “loss aversion” as proposed by Prospect Theory (Kahneman & Tversky, 1979; Tversky & Kahneman, 1986, 1992). However, what we will show later is that while losses do not necessarily impact feelings more than gains they are weighted to a greater extent when making a choice (see Results section on pg 16). With regards to curvature, a single $\rho$ was more parsimonious than two separate ones for gains and losses, suggesting that the extent of concavity for gains was equivalent to the extent of convexity for losses.

Further support for point (i) came from the fact that all models with a curvature parameter $\rho$ (Feeling Models 3-6) were better fits, as indicated by lower BIC values, than corresponding linear models with an intercept (Feeling Models 7-10). This was true both when comparing BICs for models fitting expected feelings (BIC difference < -112) and experienced feelings (BIC difference < -37) (Table S2). Further support for point (ii) came from the fact that Feeling Model 3 had lower BICs than other curved functions with additional parameters that fit gains and losses with separate parameters (Feeling Models 4-6, see Table S3) for both expected and experienced feelings. In addition, the absolute impact of losses and gains on ratings of feelings relative to a zero outcome revealed no difference ($F(1,55) = 0.01$, $P = 0.92$, $\eta^2_p = 0.00018$).

**Impact bias increases with the amount at stake**

Interestingly, comparing the functions for experienced and expected feelings revealed an “impact bias” that increased with amounts lost/gained. The “impact bias” is the tendency to expect losses/gains to impact our feelings more than they actually do (Gilbert, Pinel, Wilson, Blumberg, & Wheatley, 1998). Specifically, the curvature ($\rho$) was smaller for experienced feeling function relative to expected feeling function (paired t-test: $t(55) = 3.31$, $P = 0.002$, $\eta^2_p = 0.068$).
Cohen’s $d_z = .442$, 95% CI=[.034;.138]), while there was no difference in sensitivity values ($\beta$) ($t(55)=0.65$, $P=0.52$, Cohen’s $d_z = .087$, 95% CI=[-.079;.155]). Thus, although both expected and experienced feelings became less sensitive to outcomes as absolute values of loss/gain increased, this diminished sensitivity was more pronounced in experience than in expectation. As a result, for small amounts of money gained/lost people’s expectations of how they will feel were more likely to align with their experience. However, as amounts gained/lost increased, people were more likely to overestimate the effect of outcomes on their feelings, expecting to be affected more by gains and losses than they actually were (i.e., the impact bias (Gilbert et al., 1998)). Graphically, we can observe the growth of the impact bias in Fig. 3 as the increase in separation between the blue line (experienced feelings) and the more extreme orange line (expected feelings).

### A. Expected Feeling Models

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<th>Parameters in model</th>
<th>Better fit (lower BIC)</th>
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<tr>
<td>1</td>
<td>$\beta$</td>
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<td>2</td>
<td>$\beta_{\text{gain}}, \beta_{\text{loss}}$</td>
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<td>3</td>
<td>$\beta$, $\rho$</td>
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<td>$\beta_{\text{gain}}, \beta_{\text{loss}}, \rho$</td>
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<td>$\beta$, $\rho_{\text{gain}}, \rho_{\text{loss}}$</td>
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<td>7</td>
<td>$\beta$, $\varepsilon$</td>
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### B. Experienced Feeling Models

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**Fig. 2. Feeling Models.** BIC values, summed across all subjects, are plotted for ten models fitting feelings to outcome value (see Methods for equations), separately for (A) Expected feelings ratings and (B) Experienced feelings ratings. Feeling Model 3 was the most parsimonious model, as indicated by lower BIC values for both expected and experienced feelings.

![Feeling Models](image)

**Fig. 3. “Feeling function”.** Plotted are expected and experienced feelings ratings averaged across participants for each outcome value, as well as best fitting Feeling Model 3. Average beta ($\beta$) across participants, which represents the slope of the function, was 0.857 ± SD 0.36 for expected feelings and 0.819 ± SD 0.37 for experienced feelings (paired t-test revealed no significant difference between them: t(55)=0.65, $P=0.52$, Cohen’s $d_c=0.87$, 95% CI=[-0.079;1.55]). Average rho ($\rho$), which represents the curvature of the function, was 0.512 ± SD 0.26 for expected feelings and 0.425 ± SD 0.23 for experienced feelings. Both $\rho$ values were significantly smaller than 1 (t(55)>14, $P<0.001$, Cohen’s $d_c=1.87$), consistent with an S-shaped function and indicating diminishing sensitivity of feelings to increasing outcome values. $\rho$ was also significantly smaller for experienced relative to expected feelings (paired t-test: t(55)=3.31, $P=0.002$, Cohen’s $d_c=0.442$, 95% CI=[0.034;1.38]), suggesting that the “impact bias” grows with increasing outcomes. Error bars represent SEM.

**Feeling function predicts choice better than value-based models**
Once we established a function that fit feelings to outcome value, we turned to the question of how well those feelings predict choices, in particular how they are combined and weighted to make a decision.

To answer this question we used the Feeling Model built above from the data recorded in the first task to predict decisions made in a separate gambling task. To do so we conducted two logistic regressions for each participant (one using expected feelings – Choice Model 1 – and one using experienced feelings – Choice Model 2), where choice on the gambling task was entered as the dependent variable (either 1 if the subject selected the gamble or 0 if the subject selected the sure option) and feelings (predicted by Feeling Model 3) associated with the options were entered as the independent variable. Specifically, using the participant’s $\beta$ and $\rho$ from Feeling Model 3 we computed the feelings associated with each available option multiplied by their probability. For example, if a participant was offered a mixed gamble trial where s/he could either choose a gamble that offered a 50% chance of gaining £10 and a 50% chance of losing £6 or a sure option of £0, we estimated the feelings associated with these three elements multiplied by their probability: the feeling associated with gaining £10 $[F(\£10) = \beta \times 10^\rho \times 0.5]$; the feeling associated with losing £6 $[F(\£-6) = \beta \times (-6)^\rho \times 0.5]$ and the feeling associated with getting £0: $[F(\£0) = 0 \times 1 = 0]$. These were entered in the logistic regression to predict choice (Choice Model). Each logistic regression thus resulted in three weight parameters $\omega$, which reflected the weight assigned to feelings when making a choice; one for gains ($\omega_G$), one for losses ($\omega_L$) and one for sure options ($\omega_S$).

Importantly, choice models using feelings as predictors (Choice Models 1 and 2) were compared to five other regression models which predicted choice using: objective values (Choice Model 3), log of objective values (consistent with standard economics models to account for the curvature of utility – Choice Model 4), as well as three models derived from Prospect Theory, where value was weighted for each subject with their loss aversion parameter (Choice Model 5), risk aversion parameter (Choice Model 6), or both (Choice Model 7) (see Supplemental Material for more details). To avoid circularity and ensure all Choice Models were run on the same set of choice data, loss and risk aversion parameters were estimated using half the choice data; then, all seven Choice Models, including those in which we used extracted feelings rather than values, were run on the exact same test data, made of the other half of the choice data.
Feelings, extracted either from the expected or experienced feeling function (Choice Models 1 and 2) predicted choice better than all value-based comparison models (Choice Models 3-7), as indicated by lower BIC scores (Fig. 4A), and higher $R^2$ values (Table S4). Mean $R^2$ values were indeed higher for both models predicting choice from feelings ($R^2$=0.31 for both Choice Models 1 and 2) than for comparison models ($0.26<R^2<0.30$ for Choice Models 3-7), thus consistent with the BIC comparison result. Running the split-half analysis 100 times, with a different way to split the data on every simulation, revealed that models using feelings predicted choice better than all 5 comparison models in 99 simulations out of 100, thus confirming the reliability of this finding.

### A. Choice Models

![Choice Models](image)

**Fig. 4. Choice Models.** Seven logistic regressions (or Choice Models) were run to predict choices on the gambling task, using either feelings derived from the “feeling function” build using expected (Choice Model 1) or experienced (Choice Model 2) feelings as predictors, or using value-based comparison models (Choice Models 3-7). (A) BIC scores summed across subjects (smaller BIC scores indicate a better fit) show that derived feelings (both expected and experienced) predict choice significantly better than all other value-based models. (B) The resulting standardized parameters show that the weight of feelings associated with losses is largest, followed by the weight of feelings associated with gains, with the weight of
feelings associated with sure options smallest. This suggests that feelings associated with losses are weighted more than feelings associated with gains. Error bars represent SEM. Two-tailed paired t-tests: * $P<0.05$.

Feelings associated with losses are weighted more than feelings associated with gains when making a decision

Are feelings about potential losses and gains given equal weights when we deliberate on a decision? Our feeling function indicated that the impact of a loss on our feelings was equal to the impact of an equivalent gain. Yet, while losses and gains may impact explicit feelings similarly, we find that these feelings are weighted differently when making a choice.

Specifically, $\omega$ parameters from our choice models, which predicted choices from feelings, revealed a greater weight for feelings associated with losses ($\omega_L$) relative to gains ($\omega_G$) in predicting choice (for expected feelings: $t(55)=3.04$, $P=.004$, Cohen’s $d_e=.406$, 95% CI=[.684;3.33]; for experienced feelings: $t(55)=2.93$, $P=.005$, Cohen’s $d_e=.392$, 95% CI=[.599;3.19]; Fig. 4B). Models that allowed different weights for losses and gains performed significantly better than models that did not (Table S5).

Follow-up analysis revealed that this was true only in mixed-gamble trials, where losses and gains are weighted simultaneously, but not when comparing gain-only and loss-only trials, in which gains and losses are evaluated at different time points (different trials). Specifically, we ran logistic regressions to predict choice from feelings separately for each trial type, and then entered weight of feelings parameters into a two (trial type: mixed/non-mixed) by two (outcome: loss/gain) repeated-measures ANOVA. This revealed a significant interaction (expected feelings: $F(1,55)=6.54$, $P=.013$, $\eta_p^2=.106$; experienced feelings: $F(1,55)=7.46$, $P=.008$, $\eta_p^2=.119$; Fig. S1), driven by a greater weight put on feelings associated with losses relative to gains during mixed-gamble choices (expected feelings: $t(55)=3.66$, $P=.001$, Cohen’s $d_e=.489$, 95% CI=[1.67;5.71]; experienced feelings: $t(55)=2.45$, $P=.018$, Cohen’s $d_e=.327$, 95% CI=[.91;9.10]) but not during loss- versus gain-only trials (expected feelings: $t(55)=.82$, $P=.42$, Cohen’s $d_e=.109$, 95% CI=[-.3.25;7.71]; experienced feelings: $t(55)=.79$, $P=.43$, Cohen’s $d_e=.105$, 95% CI=[-2.75;6.32]). In other words, only when potential losses and gains are evaluated simultaneously (i.e. in the same gamble) are feelings about losses weighted more strongly during choice than feelings about gains. Results of our first replication and extension study supported this claim by showing that even when gains and
losses are evaluated in the same trial during the feelings task, their impact on feelings does not differ, but their weight on gamble choice does (see Supplemental Material for details).

To further tease apart the asymmetrical use of feelings associated with gains and losses in shaping choice from the use of value alone, we ran another logistic regression (Choice Model 8, run on all trials regardless of gamble type) in which raw feelings (i.e. reported feelings relative to baseline rather than those derived from the feeling function) were added as predictors of choice in the same logistic regression as objective values themselves. This was done to reveal the weight assigned to feelings in making a choice over and beyond the effect of value per se, when the two compete. The results showed no difference in the weight assigned to the value of losses and gains per se (t(55)<1.2, P>.23, Cohen’s d<.17), only to the weight assigned to the associated feelings (expected feelings: t(55)=3.59, P=.001, Cohen’s d=.479, 95% CI=[1.29;4.55]; experienced feelings: t(55)=2.28, P=.027, Cohen’s d=.307, 95% CI=[.197;2.89]). Again, this was only true for mixed gamble choices, not for gain-only or loss-only trials where neither feelings nor values were weighted differently between losses and gains (Table S6). This suggests that losses are not weighed differently from gains; rather feelings associated with losses are weighed differently from feelings associated with gains, emphasizing the importance of feelings in decision making.

This last conclusion raises the possibility that individual differences in decision-making could be explained by how people weigh feelings when making a choice. Indeed, using the weights from the above Choice Model 8 we show that individual differences in both loss aversion and the propensity to choose gambles were directly correlated with the extent to which feelings associated with losses were overweighed compared to gains while controlling for value (correlation between loss aversion and loss-gain weight difference for expected feelings: r(56)=0.56, P<0.001; for experienced feelings: r(56)=0.34, P=0.012; correlation between propensity to gamble and loss-gain weight difference for expected feelings: r(56)=−0.61, P<0.001; for experienced feelings: r(56)=−0.46, P<0.001; Fig. 5, see Supplementary Information for loss aversion modeling). Specifically, subjects who weighed feelings associated with losses more than gains were more loss averse and less likely to gamble.

This set of results suggests that the asymmetric influence of gains and losses on decision-making, as suggested by Prospect Theory, is neither reflected in expected nor experienced feelings, nor in different weights assigned to value per se, but rather in the extent to which feelings associated with losses and gains are taken into account when making a decision.
Fig. 5. Individual differences in choice are driven by the relative weights of feelings.

Raw feelings (i.e. reported feelings relative to baseline) and objective values were combined in the same regression model (Choice Model 8) to examine the extent to which feelings predict choice while controlling for value. Each regression used either Expected (A,C) or Experienced (B,D) raw feelings together with objective values of each of the 3 decision options (Gain, Loss, Sure option), leading to 6 weight parameters in each regression ($\omega^g_{feeling}$, $\omega^l_{feeling}$, $\omega^g_{value}$, $\omega^l_{value}$). The difference between the weight of feelings about losses ($\omega^l_{feeling}$) and the weight of feelings about gains ($\omega^g_{feeling}$) was then calculated for each individual and each regression and plotted against ln Loss Aversion (A,B) (parameter estimated for each individual from the choice data) and proportion of chosen gambles (C,D). These correlations indicate that the greater weight a participant puts on feelings associated with a loss relative to a gain when making a decision, the more loss averse (and less likely to gamble) they are. Note that loss aversion and propensity to gamble are highly correlated, therefore correlations in C and D are not independent from A and B, respectively, and are displayed for illustrations purposes.
Discussion

The relationship between human feelings and the choices they make has occupied scientists, policymakers and philosophers for decades. Indeed, in recent years numerous studies have investigated how decisions and outcomes impact people’s feelings (Carter & McBride, 2013; Kassam et al., 2011; Kermer et al., 2006; McGraw et al., 2010; Mellers et al., 1997; Rutledge et al., 2014; Yechiam et al., 2014) and life satisfaction (Boyce, Wood, Banks, Clark, & Brown, 2013; De Neve et al., 2015). Yet, the equally critical question of how people’s explicit feelings impact their decisions has been relatively neglected. In this study, we addressed this important question in a controlled laboratory setting and modeled how feelings are integrated into decisions. We demonstrated that feelings drive the decisions people make. However, the rules by which they do so differ from previously assumed.

Feelings were first modeled in a “feeling function” (Feeling Model), which was then used to predict choices (Choice Model). Our Feeling Model predicted choice better than objective values, and a unique contribution of feelings in the decision process was demonstrated. The “feeling function” that best related feelings to value was revealed to be concave for gains and convex for losses, similar to Prospect Theory value function (Kahneman & Tversky, 1979; Tversky & Kahneman, 1992) and other non-linear utility functions (Bernoulli, 1954; Fox & Poldrack, 2014; Stauffer, Lak, & Schultz, 2014; Von Neumann & Morgenstern, 1947). This curvature suggests that explicit feelings, similar to subjective value or utility, show diminishing sensitivity to outcomes as the value of these outcomes increases (Carter & McBride, 2013). In other words, the impact of winning or losing ten dollars on feelings is less than twice that of winning or losing five dollars.

Our Feeling Model also revealed no asymmetry between gains and losses, suggesting that the impact of a loss on feelings is not necessarily greater than the impact of an equivalent gain. This was replicated in two separate studies extending the symmetrical impact of gains and losses on feelings to cases where a gain and a loss were evaluated at the same time and when the associated feelings about gains and losses are reported using the same unipolar scale (McGraw et al., 2010). Nevertheless, loss aversion was still present in choice (see Supplemental Material for estimates of loss aversion), consistent with Prospect Theory. Importantly, when making a decision a greater weight was put on feelings associated with
losses relative to gains. This finding suggests that losses may not impact feelings more strongly than gains as previously implied, but rather that feelings about losses are weighted more when making a choice than feelings about gains. Moreover, the amount by which feelings associated with losses are over-weighted relative to gains in making a decision relates to individual differences in loss aversion and propensity to gamble.

This finding resolves a long-standing puzzle by which loss aversion is often observed in choice, but not necessary in explicit feelings (Harinck et al., 2007; Kermer et al., 2006; McGraw et al., 2010; Mellers et al., 1997). We suggest that the asymmetric influence of gains and losses on decision making, as suggested by Prospect Theory, is not reflected in expected or experienced feelings directly, neither in different weights assigned to value per se, but in the extent to which feelings about losses and gains are taken into account when making a decision. Our result is consistent with the interpretation of an increased attention to losses (Yechiam & Hochman, 2013). When losses and gains are presented separately they are experienced in a symmetrical way. However, when they compete for attention, as is the case in the mixed gambles, people may allocate more attention to the feelings they would derive from the loss than from the gain, leading them to choose in a loss averse manner. Another possibility is that people implicitly experience losses to a greater extent than gains (Hochman & Yechiam, 2011; Sokol-Hessner et al., 2009), but this difference is not exhibited in explicit reports. We also note that the monetary amounts used in the present study were relatively small, raising the possibility that a loss/gain asymmetry in feelings would emerge for higher amounts, as suggested previously (Harinck et al., 2007; McGraw et al., 2010).

Our findings also provide the first demonstration of an increasing impact bias with value. Specifically, we found evidence for a general impact bias in feelings (also called affective forecasting error), where people expect the emotional impact of an event to be greater than their actual experience (Gilbert et al., 1998; Kermer et al., 2006; Kwong, Wong, & Tang, 2013; Levine, Lench, Kaplan, & Safer, 2013; Morewedge & Buechel, 2013; Wilson & Gilbert, 2013). Interestingly, this impact bias was not constant, but increased with value. This was due to a stronger curvature of experienced feelings relative to expected feelings. In other words, as absolute value increases, sensitivity to value diminished more quickly for experienced relative to expected feelings. This suggests that as people win or lose more money, they are more and more biased towards overestimating the emotional impact of these outcomes.
Our modeling approach provides novel insight into how explicit feelings relate to choice. Such understanding is both of theoretical importance and has practical implications for policy-makers, economists and clinicians who often measure explicit feelings to predict choice (Benjamin, Heffetz, Kimball, & Rees-Jones, 2012, 2014).

Authors’ contributions
C.J. Charpentier, J-E. De Neve, and T. Sharot developed the study concept and design. C.J. Charpentier and X. Li performed data collection and analysis. C.J. Charpentier and T. Sharot drafted the manuscript. All authors discussed data analysis and interpretation, provided critical revisions, and approved the final version of the manuscript for submission.

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References


Models of affective decision-making


Models of affective decision-making


Models of affective decision-making: how do feelings predict choice?

SI Methods and Results

Study groups

Participants were recruited in two different groups that were then collapsed in the analyses. A group of 29 participants (20 females, mean age=23.2y) were tested on a first version of the task, where each of the four blocks had 48 trials with different amounts (£0.2, £0.4, £0.6, £0.8, £1, £1.2, £2, £4, £8, £10, £12) that could be won, lost, not won or not lost. For expected feelings participants were asked “how will you feel if you win/lose?”; and for experienced feelings “how do you feel now?”. The rating scale ranged from 1 (extremely unhappy) to 10 (extremely happy) and participants had to press a key (1 to 9 for ratings 1 to 9 and 0 for rating 10) to indicate their feelings. A second group of 30 participants (15 females, mean age=24.5y) completed a slightly shorter version of the feelings task that had 40 trials per block (10 amounts instead of 12: £0.2, £0.5, £0.7, £1, £1.2, £2, £5, £7, £10, £12) and indicated their ratings by moving a cursor on a symmetrical rating scale, in which 0 was used as a reference point. Specifically, for expected feelings they were asked “if 0 is how you feel now, how will you feel if you win/lose?”; and for experienced feelings “if 0 is how you felt just before the choice, how do you feel now?”. Ratings ranged from -5 (extremely less happy) to +5 (extremely more happy). The first group of participants completed the feelings task first, while the second group completed the gambling task first. The data (parameters and model fits from the feelings function models, and from the regression models to predict choice) did not differ between the two study groups, indicating that those features of the design that varied between the two groups were not a significant factor. Data were therefore collapsed for all the analyses reported in the main text, and study group was controlled for by adding a dummy variable as a between-subject factor in all the analyses.

Agency manipulation in the feelings task
The instrumental choice present in the feelings task (i.e. the arbitrary selection between the two abstract stimuli) allowed us to manipulate agency: on 2 of the blocks (1 with expected feelings and 1 with experienced feelings) the participant made the choice between the two stimuli, and in the other 2 the computer made the choice for the participant who had to indicate the computer choice with a button press after it was made. There were no differences in the data between own choice and computer choice blocks, therefore data was collapsed. Even when making their own choices subjects had no control over the outcome, thus it may not be surprising that feelings did not differ between own choice and computer choice. Note, that the above relates only to the task in which we elicited feelings associated with outcomes and not, obviously, to the gambling task.

Estimation of Feeling Models

All ten Feeling Models were estimated using a maximum-likelihood estimation procedure in Matlab. Given a Feeling Model $f(x, \theta)$ with $\theta$ the set of parameters, $x$ the range of outcome values, and $y$ the feelings data to be modeled, the residuals from the model can be written as:

$$\mathcal{E} = y - f(x, \theta)$$  
(Eq. S1)

Assuming an appropriate normal distribution for the residuals, the likelihood of a given residual $\mathcal{E}_i$ is:

$$\mathcal{L}(\mathcal{E}_i | \theta, \sigma) = \frac{-\mathcal{E}_i}{\sqrt{2\pi\sigma^2}}$$  
(Eq. S2)

where $\sigma$ represents the standard deviation of the residuals (an additional parameter to be estimated). Then the fmincon function was used to find the optimal set of parameters $(\theta, \sigma)$ that minimizes the negative log likelihood (thereby maximizing the likelihood):

$$-\log \mathcal{L} = -\log[\mathcal{L}(\mathcal{E} | \theta, \sigma)] = \sum_i \left[ \frac{\mathcal{E}_i^2}{2\sigma^2} + 0.5 \log(2\pi\sigma^2) \right]$$  
(Eq. S3)

BIC scores were then calculated for each subject using the following equation that penalizes additional parameters in the model:

$$BIC = -2 \log \hat{\mathcal{L}} + k \log(n)$$  
(Eq. S4)
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where \( \log \mathcal{L} \) represents the maximum of loglikelihood \( \mathcal{L} \) (estimated using equation S3 above), \( k \) the number of parameters in the model (including \( \sigma \) as an extra parameter), and \( n \) the number of data points (trials) that were fitted.

Loss and risk aversion modelling

In order to assess loss and risk aversion, three models were estimated for each subject using choice data from the gambling task and based on Prospect Theory equations (Fox & Poldrack, 2014; Kahneman & Tversky, 1979; Sokol-Hessner et al., 2009). The model was estimated in Matlab using a maximum likelihood estimation procedure. For each trial, the utility (\( u \)) of each gamble was estimated using one of the three following equations:

\[
\begin{align*}
    u_{\text{gamble}} &= 0.5 \times \text{gain} + 0.5 \times \lambda \times \text{loss} \quad \text{(Eq. S5 - to estimate loss aversion only)} \\
    u_{\text{gamble}} &= 0.5 \times \text{gain}^\gamma + 0.5 \times \text{loss}^\gamma \quad \text{(Eq. S6 - to estimate risk aversion only)} \\
    u_{\text{gamble}} &= 0.5 \times \text{gain}^\gamma + 0.5 \times \lambda \times \text{loss}^\gamma \quad \text{(Eq. S7 – loss and risk aversion together)}
\end{align*}
\]

where \( \lambda \) is the “loss aversion” parameter: a \( \lambda \) value higher than 1 indicates an overweighing of gains relative to losses during decision-making and a \( \lambda \) value lower than 1 the converse; and \( \gamma \) is the “risk aversion” parameter: a \( \gamma \) value lower than 1 indicates diminishing sensitivity to changes in value and results in risk aversion, while a \( \gamma \) value higher than 1 indicates risk-seeking.

These utility values were used in a softmax function to estimate the probability of accepting each gamble (coded as 0 or 1 for each rejected or accepted gamble, respectively):

\[
P_{\text{gamble}} = \frac{1}{1 + e^{-\mu \times u_{\text{gamble}}}} \quad \text{(Eq. S8)}
\]

where \( \mu \) is the logit sensitivity or “inverse temperature” parameter, an index of choice consistency for repeated identical gambles, equivalent to the maximal slope of a logistic regression curve: higher \( \mu \) values indicate more consistent choices.

The three models were used to estimate risk and loss aversion on half the choice data, in order to predict choice from subjective utility on the other half of choice data (see “Comparison models to predict choice” paragraph below).
To predict individual differences in loss aversion from feelings, $\lambda$ values were extracted for each subject on the entire set of gambling choices using equation S5. They were then correlated across subjects with the difference in how feelings about losses and feelings about gains are weighted during choice (Fig. 5A-B). Across all participants, the average loss aversion ($\lambda$) was 2.38 (±SD=2.19), significantly greater than 1 ($t(55)=4.72$, $P<0.001$, Cohen’s $d_z=0.631$, 95% CI=[1.797;2.97]). This indicates that loss aversion was present in choice.

Methods of computing feelings

The impact of losses and gains on feelings were computed using three different methods: as the change from the mid-point of the rating scale, as the change from the previous rating, and as the change from the rating associated with zero outcome (i.e., the rating associated with not winning or not losing the equivalent amount). For all ten Feelings Models the latter baseline resulted in the best fit (Table S1), which is why we report results using this baseline in the main text. However, we note that results were the same when using the other two methods of calculating feelings. First, when we estimated Choice Models to predict gambling choice from these feelings functions varying in their reference point, we replicated our finding that these feelings predicted choice better than the five other value-based Choice Models (Choice Model using expected feelings from scale mid-point: BIC=8884, $R^2=0.30$; Choice Model using experienced feelings from scale mid-point: BIC=8915, $R^2=0.30$; Choice Model using experienced feelings from previous trial feeling: BIC=8924, $R^2=0.30$; value-based Choice Models: BIC>9025, $R^2<0.29$). Second, we also find that feelings about losses are weighted more than feelings about gains in predicting choice, independent of the baseline used to calculate feelings (expected feelings from scale mid-point: t(55)=3.38, $P=0.001$; experienced feelings from scale mid-point: t(55)=3.33, $P=0.002$; experienced feelings from previous trial feeling: t(55)=3.20, $P=0.002$). This suggest that our findings do not depend on the method of calculating feelings.

Comparison models to predict choice

Choices were predicted from feelings using the previously built feelings function (Choice Models 1 and 2). In order to examine whether this feelings function does a better job at predicting choice than objective value, or choice-derived subjective utility, five other models were tested (Choice Models 3 to 7).
First a simple “Value” model (Choice Model 3) tries to predict choice simply by entering the amounts available multiplied by probability, regardless of associated feelings parameters $\beta$ and $\rho$ or subjective utility parameters such as loss and risk aversion. For example, if the choice is a mixed gamble between winning £10 and losing £6, the three predictors will be £0*1 (sure option), £10*0.5 (gain), and -£6*0.5 (loss).

The second comparison model included log(Value) as predictors (Choice Model 4). Most standard economic models account for the curvature of utility by taking the logarithm of linear values. In this model and with the example above, the three predictors would be computed as: 0 (sure option), log(10)*0.5 (gain), and -log(6)*0.5 (loss).

The three additional models predicted choice from Prospect Theory-derived subjective utility. To do so, risk and loss aversion parameters were estimated on half the choice data using the model described above (equations S5 to S8) for each subject. One model included value weighted with the loss aversion parameter $\lambda$ (£0×1, £10×0.5, $-\lambda$×£6×0.5; Choice Model 5); one included value parameterized with the risk aversion parameter $\gamma$ (£0×1, (£10)$\gamma$×0.5, $-(\gamma 6)^\gamma$×0.5; Choice Model 6); and the last model included both loss and risk aversion to compute subjective values (£0×1, (£10)$\gamma$×0.5, $-\lambda$×(£6)$\gamma$×0.5; Choice Model 7).

All seven logistic regression choice models were run on the other half of the choice data, in order to be comparable and to avoid circularity for the utility-based models. The gambling task was designed such that each gamble was repeated twice; therefore, one occurrence of each gamble was present in each half of the data. In addition, in order to ensure the reliability of this split-half analysis, 100 simulations were run with a different data splitting on every simulation. The loglikelihood of each model was extracted from the logistic regression and BIC scores were calculated for each subject using equation S4. The sum of BIC scores across subjects was then calculated for each model and each simulation, therefore allowing us to report the number of simulations where the two feelings model performed better than the five comparison models.

**Replication and extension study 1**

*Rationale.* Because the feelings task reported in the main text elicits feeling ratings about gains and about losses on separate trials, this design does not rule out the possibility that losses and gains may impact feelings differently when they are evaluated at the same time.
Methods. Thus, a follow-up study was run using exactly the same procedure as before, except that on each trial of the feelings task (Fig. S2), the outcomes at stake included a gain, a loss, and £0 (rather than gain versus £0 on some trials, and loss versus £0 on different trials).

Twenty participants were recruited and tested on this paradigm (12 males, 8 females, mean age = 23.8 years, age range = 19-33). Ten participants completed the feelings task first, and the remaining completed the gambling task first. Block order within the feelings task was also counterbalanced across subjects. The range of amounts and rating scale used were the same as in the second study group of the main study (see “Study groups” paragraph above).

Participants were told that each picture from the pair was associated with a certain probability to win, lose, or get £0, and that these probabilities were different for each picture and not shown to them. Therefore participants had to rate their feelings on every trial knowing that each picture chosen could result in a gain, a loss, or a null outcome (£0). To maintain consistency with the previous design, participants were only asked to rate their expected feelings about 2 of the 3 potential outcomes on each trial. These were determined such that each amount from £0.2 to £12 (win or lose) had at least one expected feeling rating associated with it; then the other rating was selected randomly from the other two options. The order of the two ratings was randomized. The impact of losses and gains on feelings were computed using three different baselines as in the main experiment. For all ten feelings models, using the change from the mid-point of the rating scale resulted in best fit of both expected and experienced feelings data as indicated by higher $R^2$ values and lower BIC values, and was therefore used for all the analyses below. Note that in contrast with the main experiment the zero baseline did not result in the best fit of feelings data. This is because in the replication study the zero outcome was always associated with two possible outcomes instead of one. Thus, the zero baseline was calculated differently – for each amount (for example £2), the ratings associated with £0 were averaged across all trials where that specific amount (£2) was at stake, regardless of third amount presented (which could be for example -£1, or -£10) – this conceptually and mathematically different approach resulted in different model fits.

Results

Feeling Models. Feelings were fit with the ten Feeling Models described in the main Methods to determine which function best relates feelings to value. If gains and losses impact feelings differently when evaluated at the same time, then a Feeling Model with different parameters (for example, a different slope $\beta$) for gains and losses, such as Feeling Model 4 or 6, should fit the feelings data better. However, this was not the case; instead we replicated our previous
finding showing that Feeling Model 3, with a single slope ($\beta$) and single curvature ($\rho$) parameter for gains and losses, was the most parsimonious function that explains how feelings relate to value (Fig. S3). This result replicates our previous finding that gains and losses impact feelings similarly and extends to cases where the loss and the gain are evaluated together.

**Choice Models.** To examine whether and how these feelings are weighed to predict choice, feelings extracted from best fitting Feelings Model 3 were entered in a logistic regression to predict choice on the gambling task. The same seven Choice Models were run as in the main data, again replicating our finding that feelings predicted choice better than value-based models (as indicated by lower BIC scores and higher $R^2$ values for Choice Models 1 and 2; Fig. S4A). Importantly, during choice, participants also weighed their feelings about losses more than their feelings about gains (expected feelings: $t(19)=2.41$, $P=0.027$; experienced feelings: $t(19)=2.32$, $P=0.032$; Fig. S4B). Finally, the extent to which feelings about losses were weighed more than feelings about gains (in a separate Choice Model controlling for the effect of value) was positively associated with individual estimates of behavioral loss aversion (expected feelings: $r(20)=0.54$, $P=0.014$; experienced feelings: $r(20)=0.44$, $P=0.052$; Fig. S4C).

**Replication and extension study 2**

**Rationale.** A recent study (McGraw et al., 2010) has reported that measuring feelings on a bipolar scale, like we do in our main experiment, resulted in no gain/loss asymmetry in feelings, consistent with our findings, while using a unipolar scale (which represents the magnitude of feelings only) does result in an asymmetry. The suggestion is that a unipolar scale allows positive and negative feelings to be directly scaled relative to one another. We thus reran our experiment using a unipolar scale.

**Methods.** We collected data on an independent group of 30 participants (15 males, 15 females, mean age = 24 years, age range = 18-35). The procedure was the same as in the main study, except that a unipolar rating scale was used in the feelings task. A power analysis indicated that a sample size of 30 would give us 99% power to detect an effect size similar to the one observed in McGraw et al ($d=0.76$ for the difference between feelings for gains and losses using the unipolar scale) at a threshold of $p<0.05$. Even if the actual effect size is lower ($d=0.5$), achieved power would be 85%.

On experienced feelings trials the question was “How is this outcome affecting your feelings now?” On expected feelings gain trials subjects were asked “How would winning £X affect
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845 your feelings?” and “How would not winning £X affect your feelings?”, and on expected
846 feelings loss trials “How would losing £X affect your feelings?” and “How would not losing
847 £X affect your feelings?”. Participants responded by moving a cursor on a scale ranging from
848 0 (“No effect”) to 5 (“Very large effect”).
849 For analysis, ratings associated with losing and with not winning were coded negatively.
850 Analysis then proceeded exactly as in the main experiment.

851 Results
852 Feeling Models. As in the main experiment Feeling Model 3, with a single slope ($\beta$) and
853 single curvature ($\rho$) parameter for gains and losses, was the best model of the ten in
854 explaining how feelings relate to value (Fig. S5). This suggests that even when using the
855 same unipolar scale that allows scaling positive and negative feelings relative to each other
856 regardless of valence, gains and losses have a symmetrical impact on feelings.
857 Bayes Factor analysis. To corroborate the null effect of losses relative to gains on feelings a
858 Bayes Factor analysis was run on the feelings data using JASP (version 0.7.1; Love et al.,
859 2015; Morey & Rouder, 2015). A Bayesian repeated-measures ANOVA was conducted with
860 domain (gain/loss) and amount (the range of 10 amount values from £0.2 to £12) as within-
861 subject factors. The winning Bayesian ANOVA model included a main effect of amount, but
862 no effect of domain or domain*amount interaction, consistent with our Feeling Models result.
863 In particular, adding a main effect of domain made the model about 11 times worse
864 (BF[Amount Model over Amount & Domain Model]=10.87 for expected feelings and 10.62
865 for experienced feelings), indicating strong evidence for an absence of feelings asymmetry
866 between gains and losses (for correspondence between BF magnitude and strength of
868 Choice Models. As in the main experiment, feelings extracted from best fitting Feeling Model
869 3 predicted choice better than value-based models (as indicated by lower BIC scores and
870 higher $R^2$ values for Choice Models 1 and 2; Fig. S6A). During choice, we again find that
871 participants weighted their feelings about losses more than their feelings about gains
872 (expected feelings: $t(29)=2.29, P=0.030$; experienced feelings: $t(29)=2.08, P=0.047$; Fig.
873 S6B). Finally, we also replicate our finding that the extent to which participant overweight
874 their feelings about losses relative to gains (in an additional Choice Model where the effect of
875 value per se is accounted for) predict individual differences in behavioral loss aversion
876 (expected feelings: $r(30)=0.62, P<0.001$; experienced feelings: $r(30)=0.63, P<0.001$; Fig.
877 S6C).
With these additional studies, we replicate our findings in two further independent samples, thereby confirming and strengthening our interpretation that gains and losses do not impact feelings differently, but that when it comes to making a decision involving a potential loss and a potential gain, people give more weight to feelings associated with the loss than with the gain.

SI Figures and Tables

**Fig. S1.** Influence of gamble type on differential weighting of feelings associated with losses versus gains. Logistic regressions were run to predict choice from feelings separately for each trial type. Standardized parameter estimates representing the decision weight of feelings were analyzed in a two (trial type: mixed/non-mixed gambles) by two (outcome: loss/gain) repeated-measures ANOVA. Significant interactions for both expected (A) and experienced (B) feelings indicate that more weight is given to feelings about a loss relative to a gain only when the loss and the gain are evaluated simultaneously (i.e. in the same gamble). Error bars denote SEM. Paired t-tests: * P<0.05.
Fig. S2. Replication and extension study 1 – design of the feelings task. An additional study was run to replicate the finding and test whether gains and losses impact feelings differently when they are evaluated in the same trial. Task structure was similar to the main study (main text Fig. 1), except that on each trial of the feelings task, 3 potential outcomes were presented to the subject, always including a gain, a loss, and a null outcome (£0). The design of the gambling task (main text Fig. 1C) remained the same.
Fig. S3. Replication and extension study 1 – “Feeling function” and Feeling Model fits.
Feelings data collected on the replication and extension study were fit using the same procedure as the main study. (A) Expected and Experienced feelings ratings are plotted for each outcome value as the average rating across participant. Error bars represent SEM. The line representing best fitting Feeling Model 3 is also plotted. Average beta ($\beta$) across participants was $0.702 \pm 0.24$ for expected feelings and $0.669 \pm 0.25$ for experienced feelings. Average rho ($\rho$) was $0.474 \pm 0.17$ for expected feelings and $0.469 \pm 0.23$ for experienced feelings (both significantly smaller than 1, consistent with diminishing sensitivity of feelings to increasing outcome values: $t(19) > 10$, $P < 0.001$). BIC values, summed across all subjects, for each of ten Feeling Models are plotted separately for (B) Expected feelings ratings and (C) Experienced feelings ratings. This replicates the finding of the main study (main text Fig. 2 and Fig. 3) that Feeling Model 3 was the most parsimonious model, with no asymmetry in either the slope or curvature of the feeling function between the gain and the loss domain, while the impact of gains and losses on feelings is evaluated during the same trial.
A. Choice Models

<table>
<thead>
<tr>
<th>Model #</th>
<th>Predictor of choice</th>
<th>BIC (sum across subjects)</th>
<th>Better fit (lower BIC)</th>
<th>Better fit (higher R²)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Expected feelings</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>2</td>
<td>Experienced feelings</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>3</td>
<td>Log(Value)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>4</td>
<td>Value</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>5</td>
<td>Value &amp; Loss aversion</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>6</td>
<td>Value &amp; Risk aversion</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>7</td>
<td>Value, Loss &amp; Risk aversion</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Fig. S4. Replication and extension study 1 – Choice Models. Using the same procedure as in the main study (main text Fig. 4), choices on the gambling task were entered in logistic regression models with expected feelings, experienced feelings, or various value-based regressors as predictors. Replicating our findings, BIC scores indicated that derived feelings predicted choice better than all other value-based models (A), with feelings about losses weighted more during a decision than feelings about gains (B). When running an additional Choice Model where both raw feelings and values were added as predictor of choice (similar to main text Fig. 5), thereby allowing us to examine the predictive weight of feelings on choice while controlling for value, we replicated our finding that the extent to which participants overweigh their feelings about losses relative to gains during choice predict individual differences in loss aversion (C). Two-tailed paired t-tests: * P<0.05.
Fig. S5. Replication and extension study 2 – “Feeling function” and Feeling Model fits.
Feelings data collected on the second replication and extension study were fit using the same
procedure as the main study. The only difference from the main study was the use of a
unipolar rating scale to measure reported feelings. (A) Expected and Experienced feelings
ratings are plotted for each outcome value. Error bars represent SEM. The line representing
best fitting Feeling Model 3 is also plotted. Average beta ($\beta$) across participants was $1.339 \pm
SD 0.36$ for expected feelings and $1.509 \pm SD 0.34$ for experienced feelings. Average rho ($\rho$)
was $0.299 \pm SD 0.18$ for expected feelings and $0.215 \pm SD 0.16$ for experienced feelings
(both significantly smaller than 1, consistent with diminishing sensitivity of feelings to
increasing outcome values: $t(29)>20$, $P<0.001$). BIC values, summed across all subjects, for
each of ten Feeling Models are plotted separately for (B) Expected feelings ratings and (C)
Experienced feelings ratings. This replicates the finding of the main study (main text Fig. 2
and Fig. 3) that Feeling Model 3 was the most parsimonious model, with no asymmetry in
either the slope or curvature of the feeling function between the gain and the loss domain, and
extends the finding to cases where the impact of losses and gains on feelings is reported on a
unipolar rating scale.
A. Choice Models

Fig. S6. Replication and extension study 2 – Choice Models. Using the same procedure as in the main study (main text Fig. 4), choices on the gambling task were entered in logistic regression models with expected feelings, experienced feelings, or various value-based regressors as predictors. Replicating our findings, BIC scores indicated that derived feelings predicted choice better than all other value-based models (A), with feelings about losses weighted more during a decision than feelings about gains (B). When running an additional Choice Model where both raw feelings and values were added as predictor of choice (similar to main text Fig. 5), thereby allowing us to examine the predictive weight of feelings on choice while controlling for value, we replicated our finding that the extent to which participants overweigh their feelings about losses relative to gains during choice predict individual differences in loss aversion (C). Two-tailed paired t-tests: * P<0.05.
Models of affective decision-making

### Table S1. Mean R² values associated with each Feeling Model, separately for each method of calculating feelings

<table>
<thead>
<tr>
<th>Model #</th>
<th>Name of parameters</th>
<th>Expected feelings</th>
<th></th>
<th>Experienced feelings</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Sum of BICs</td>
<td>Mean R²</td>
<td>Sum of BICs</td>
<td>Mean R²</td>
<td></td>
</tr>
<tr>
<td>1</td>
<td>β</td>
<td>6625.7</td>
<td>0.720</td>
<td>6561.1</td>
<td>0.637</td>
</tr>
<tr>
<td>2</td>
<td>β_{gain}, β_{loss}</td>
<td>6731.5</td>
<td>0.731</td>
<td>6695.0</td>
<td>0.648</td>
</tr>
<tr>
<td>3</td>
<td>β, ρ</td>
<td><strong>5716.1</strong></td>
<td>0.804</td>
<td><strong>5594.0</strong></td>
<td>0.744</td>
</tr>
<tr>
<td>4</td>
<td>β_{gain}, β_{loss}, ρ</td>
<td>5792.2</td>
<td>0.814</td>
<td>5628.4</td>
<td>0.758</td>
</tr>
<tr>
<td>5</td>
<td>β, ρ_{gain}, ρ_{loss}</td>
<td>5793.4</td>
<td>0.814</td>
<td>5685.6</td>
<td>0.753</td>
</tr>
<tr>
<td>6</td>
<td>β_{gain}, β_{loss}, ρ_{gain}, ρ_{loss}</td>
<td>5938.8</td>
<td>0.819</td>
<td>5758.4</td>
<td>0.764</td>
</tr>
<tr>
<td>7</td>
<td>β, ε</td>
<td>5833.3</td>
<td>0.800</td>
<td>5674.7</td>
<td>0.742</td>
</tr>
<tr>
<td>8</td>
<td>β_{gain}, β_{loss}, ε</td>
<td>5905.1</td>
<td>0.811</td>
<td>5757.2</td>
<td>0.752</td>
</tr>
<tr>
<td>9</td>
<td>β, ε_{gain}, ε_{loss}</td>
<td>5947.7</td>
<td>0.808</td>
<td>5723.9</td>
<td>0.755</td>
</tr>
<tr>
<td>10</td>
<td>β_{gain}, β_{loss}, ε_{gain}, ε_{loss}</td>
<td>6069.4</td>
<td>0.814</td>
<td>5851.3</td>
<td>0.761</td>
</tr>
</tbody>
</table>

The impact of outcomes on feelings was computed using three different methods: as the change from the rating associated with zero outcome (i.e., the rating associated with not winning or not losing the equivalent amount – zero baseline), as the change from the midpoint of the rating scale, or as the change from the previous rating. All feeling models were then fit to these feelings data. For all feeling models the zero baseline resulted in the best fit. Note, feeling change compared to previous trial feeling could only be computed for experienced feelings, as actual feelings are not measured during expected feelings blocks. Bold indicates the best fitting model.
Table S2. Feeling Models

<table>
<thead>
<tr>
<th>Model #</th>
<th>Number of parameters</th>
<th>Name of parameters</th>
<th>Expected feelings</th>
<th>Experienced feelings</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td></td>
<td>Sum of BICs</td>
<td>Mean R²</td>
</tr>
<tr>
<td>1</td>
<td>1</td>
<td>β</td>
<td>6625.7</td>
<td>0.720</td>
</tr>
<tr>
<td>2</td>
<td>2</td>
<td>β&lt;sub&gt;gain&lt;/sub&gt;, β&lt;sub&gt;loss&lt;/sub&gt;</td>
<td>6731.5</td>
<td>0.731</td>
</tr>
<tr>
<td>3</td>
<td>2</td>
<td>β, ρ</td>
<td><strong>5716.1</strong></td>
<td>0.804</td>
</tr>
<tr>
<td>4</td>
<td>3</td>
<td>β&lt;sub&gt;gain&lt;/sub&gt;, β&lt;sub&gt;loss&lt;/sub&gt;, ρ</td>
<td>5792.2</td>
<td>0.814</td>
</tr>
<tr>
<td>5</td>
<td>3</td>
<td>β, ρ&lt;sub&gt;gain&lt;/sub&gt;, ρ&lt;sub&gt;loss&lt;/sub&gt;</td>
<td>5793.4</td>
<td>0.814</td>
</tr>
<tr>
<td>6</td>
<td>4</td>
<td>β&lt;sub&gt;gain&lt;/sub&gt;, β&lt;sub&gt;loss&lt;/sub&gt;, ρ&lt;sub&gt;gain&lt;/sub&gt;, ρ&lt;sub&gt;loss&lt;/sub&gt;</td>
<td>5938.8</td>
<td>0.819</td>
</tr>
<tr>
<td>7</td>
<td>2</td>
<td>β, ε</td>
<td>5833.3</td>
<td>0.800</td>
</tr>
<tr>
<td>8</td>
<td>3</td>
<td>β&lt;sub&gt;gain&lt;/sub&gt;, β&lt;sub&gt;loss&lt;/sub&gt;, ε</td>
<td>5905.1</td>
<td>0.811</td>
</tr>
<tr>
<td>9</td>
<td>3</td>
<td>β, ε&lt;sub&gt;gain&lt;/sub&gt;, ε&lt;sub&gt;loss&lt;/sub&gt;</td>
<td>5947.7</td>
<td>0.808</td>
</tr>
<tr>
<td>10</td>
<td>4</td>
<td>β&lt;sub&gt;gain&lt;/sub&gt;, β&lt;sub&gt;loss&lt;/sub&gt;, ε&lt;sub&gt;gain&lt;/sub&gt;, ε&lt;sub&gt;loss&lt;/sub&gt;</td>
<td>6069.4</td>
<td>0.814</td>
</tr>
</tbody>
</table>

Ten different models were fit to the feelings data in order to best explain its relationship to amount lost and gained (see Methods for exact equations). All models were run separately on expected and experienced feelings. Bayesian Information Criterion (BIC) scores were summed across subjects and R² values averaged across subjects. Smaller BIC values and higher R² values are indicative of better model fit. Note that BIC values cannot be directly compared between expected and experienced feelings models because the numerical values of the dependent variables are different. R² alone cannot be used to determine the best fitting model as it does not account for the number of parameters.

Table S3. Comparison between Feeling Model 3 and Feelings Models 4 to 6

<table>
<thead>
<tr>
<th>Expected feelings</th>
<th>Experienced feelings</th>
</tr>
</thead>
<tbody>
<tr>
<td>Number of subjects (/56)</td>
<td>BIC difference</td>
</tr>
<tr>
<td>Model 3 &gt; Model 4</td>
<td>46</td>
</tr>
<tr>
<td>Model 3 &gt; Model 5</td>
<td>46</td>
</tr>
<tr>
<td>Model 3 &gt; Model 6</td>
<td>50</td>
</tr>
</tbody>
</table>

Feeling Model 3 performed better than Feeling Models 4, 5, and 6 with additional parameters. The table shows the number of subjects for which Model 3 performed better than the compared model, as well as the statistics for the BIC difference between the two models (BIC<sub>model3</sub> – BIC<sub>comparison model</sub>). Negative values indicate that Feeling Model 3 was more parsimonious (had a lower BIC).
Models of affective decision-making

Table S4. Predictive value of Choice Models

<table>
<thead>
<tr>
<th>Model #</th>
<th>Predictor of choice</th>
<th>Pseudo $R^2$</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Expected feelings</td>
<td>0.31</td>
</tr>
<tr>
<td>2</td>
<td>Experienced feelings</td>
<td>0.31</td>
</tr>
<tr>
<td>3</td>
<td>Log(Value)</td>
<td>0.30</td>
</tr>
<tr>
<td>4</td>
<td>Value</td>
<td>0.26</td>
</tr>
<tr>
<td>5</td>
<td>Value &amp; Loss aversion</td>
<td>0.27</td>
</tr>
<tr>
<td>6</td>
<td>Value &amp; Risk aversion</td>
<td>0.27</td>
</tr>
<tr>
<td>7</td>
<td>Value, Loss &amp; Risk aversion</td>
<td>0.28</td>
</tr>
</tbody>
</table>

Choice Models using feelings derived from each subject’s feeling function predicted choice better than Choice Models using value or value-derived functions. Note that all Choice Models were run on the exact same half of the choice data and that feeling and value functions were extracted from separate, independent data. Therefore, these Choice Models are directly comparable. Given that all models have the same number of parameters ($\omega^G$, $\omega^L$, and $\omega^S$, representing the weights associated with gain, loss and sure option on choice, respectively), higher pseudo $R^2$ value indicate better model fit.

Table S5. Choice Models where losses and gains are weighted differently perform better

<table>
<thead>
<tr>
<th></th>
<th>Expected Feelings</th>
<th>Experienced Feelings</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>BIC</td>
<td>$R^2$</td>
</tr>
<tr>
<td>Losses and gains weighted differently ($\omega^S$, $\omega^G$, $\omega^GL$)</td>
<td>17092</td>
<td>0.30</td>
</tr>
<tr>
<td>Losses and gains weighted together ($\omega^S$, $\omega^GL$)</td>
<td>19594</td>
<td>0.18</td>
</tr>
</tbody>
</table>

Separate logistic regressions models were run on all choice trials to predict choice from feelings (either expected or experienced). Specifically, to demonstrate that feelings for losses and feelings for gains had a different weight on choice, choice models where losses and gains are weighed differently were compared to choice models where both losses and gains are given the same weight $\omega^GL$. This revealed that choices are predicted significantly better when feelings for losses and feelings for gains are assigned different weights.
### Table S6. Weight of feelings on choice, while controlling for value, separated by gamble type

<table>
<thead>
<tr>
<th></th>
<th>Expected feelings</th>
<th>Experienced feelings</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Mixed</td>
<td>Gain/Loss-only gambles</td>
</tr>
<tr>
<td>Weight of feelings about <strong>gains</strong> on choice, controlling for value (±SD)</td>
<td>-0.202 (±6.01)</td>
<td>1.976 (±5.92)</td>
</tr>
<tr>
<td>Weight of feelings about <strong>losses</strong> on choice, controlling for value (±SD)</td>
<td>4.017 (±8.11)</td>
<td>2.246 (±4.43)</td>
</tr>
<tr>
<td>T-test Loss vs Gain</td>
<td>t(53)= 2.843</td>
<td>0.302</td>
</tr>
<tr>
<td>P</td>
<td>0.006</td>
<td>0.763</td>
</tr>
</tbody>
</table>

Both raw feelings (i.e. reported feelings relative to baseline rather than those derived from the feeling function) and objective values were added as predictor of gambling choice in the same logistic regression, separately for each gamble type. The weights of feelings about gains and losses were extracted from each regression, averaged across subjects, and compared using a paired t-test. Data from two participants were excluded because the logistic regression models could not be fit and resulted in aberrant parameter values.