Supporting Information

Rutledge et al. 10.1073/pnas.1407535111

SI Methods

Laboratory-Based Experimental Tasks. Stimuli were presented in MATLAB (MathWorks, Inc.) using Cogent 2000 (Wellcome Trust Centre for Neuroimaging). Subjects made 150 choices in each task. During each trial of the functional MRI (fMRI) task, subjects chose between a certain option and a gamble, with equal probabilities of two outcomes (Fig. 1*A*). There were three trial types: mixed trials (a certain amount of £0 or a gamble with a gain and loss amount), gain trials (a certain gain or a gamble with £0 and a larger gain), and loss trials (a certain loss or a gamble with £0 and a larger loss). If subjects failed to respond within the 3-s time limit, they received the worst outcome. Unchosen options disappeared immediately following a choice. Certain choices remained on the screen for 7 s. Gamble choices remained for 6 s before the outcome was revealed for 1 s. Each trial was followed by a 3 to 11-s jittered intertrial interval. The intervals followed a gamma distribution with a shape parameter of 6 and a scale parameter of 1 with values exceeding the boundary values of 3 s and 11 s set to those values.

The 50 mixed trials consisted of a choice between a certain £0 and a gamble with equal probabilities of a monetary gain or loss. There were five gamble gain amounts in pence (30, 50, 80, 110, 150) and gamble loss amounts were determined by 10 multipliers on the gain amount (0.2, 0.3, 0.4, 0.52, 0.66, 0.82, 1, 1.2, 1.5, 2) chosen to accommodate a range of loss sensitivity. The 50 gain trials consisted of a choice between a certain gain and a gamble with equal probabilities of a larger gain or £0. There were five certain amounts (20, 30, 40, 50, 60) and the gamble gain amount was determined using 10 multipliers on the certain amount (1.68, 1.82, 2, 2.22, 2.48, 2.8, 3.16, 3.6, 4.2, 5). The 50 loss trials used the same monetary amounts as the gain trials with five certain amounts (−20, −30, −40, −50, −60) and the same 10 multipliers as used for gain trials. The maximum gamble gain or loss for a single trial was £3.

Subjects were presented with the question, "How happy are you at this moment?" after every two to three trials. After a 5-s-delay period, a rating line appeared and subjects had 4 s to move the cursor along the scale with button presses. The left end of the line was labeled "very unhappy" and the right end of the line was labeled "very happy." The cursor always started at the midpoint. Because the largest movements were required when reporting being very happy or very unhappy, there was no relationship between the amount of movement made and happiness ratings [$t(25) = 0.54$, $P = 0.59$]. Therefore, any neural activity correlated with happiness ratings is not explained by any trivial motor confound. Furthermore, there was no difference in the percentage of trials where the rating was greater than or less than 50 [50.8% versus 47.9%, $t(25) = 0.29$, $P = 0.78$; the remaining ratings were equal to 50] and no difference in the average movement from the midpoint for those ratings [14.0 versus 15.0, $t(25) = -0.57$, $P = 0.57$].

Each rating was followed by a 3 to 11-s jittered intertrial interval. Subjects completed 150 choice trials and answered the happiness question 63 times. Subjects rarely failed to respond and the median number of missed choice trials in both fMRI and behavioral experiments was 1 (range of 0 to 5 for both). Missed trials were excluded from further analysis. Trials were divided into three 50-trial blocks of ∼19 min each. Subjects were informed of their current task earnings after each block. Each block started and ended with a happiness question. We refer to the rating at the start of the first block as the "initial happiness" and at the end of the third block as the "final happiness." Model fits included all ratings that were preceded by trials (20 per block).

Twenty-one of 26 subjects participated in a behavioral experiment ("only some gamble outcomes shown"). This experiment was identical to the fMRI experiment except that, although all choices counted for real money, only some gamble outcomes were revealed, enabling us to dissociate expectation effects at choice and outcome. After gamble choices there was a 50% probability that the delay period would end with the text "outcome added to total" appearing alongside the chosen gamble for 1 s. The current task earnings were reported at the end of each block as before.

Twenty-two subjects participated in an additional behavioral experiment ("current earnings always shown") including 11 subjects from the fMRI experiment. The behavioral experiment was identical to the fMRI experiment except that the current task earnings were displayed at all times, including when subjects were asked the happiness question.

Before each experiment, before the task instructions, we measured life happiness by asking subjects, "Taken all together, how happy are you with your life these days?" Subjects marked a point on a line to indicate their response, with the endpoints labeled "very unhappy" and "very happy." Subjects answered the question three times and we used the median response as their life happiness rating (mean = 66, range = 2–100). For some analyses, we split subjects from the fMRI experiment (after excluding two subjects for excessive head movement) into high (mean = 82, $n = 12$) and low (mean = 53, $n = 12$) life happiness groups. Subjects also completed the Beck Depression Inventory to quantify depression symptom severity (mean ± SD, 6.9 ± 5.9).

Smartphone-Based Experimental Task. Researchers at the Wellcome Trust Centre for Neuroimaging at University College London worked with White Bat Games to develop The Great Brain Experiment (www.thegreatbrainexperiment.com), available as a free download on iOS (Apple) and Android (Google) systems. One of these games was based on the task we used for the fMRI experiment. Subjects started the game with 500 points and made 30 choices in each play. In each trial, subjects chose between a certain option and a gamble with equal probabilities of two outcomes with the same three trial types as the laboratory-based experiments. Chosen gambles, represented as spinners, were resolved after a brief delay. Subjects were presented with the question, "How happy are you at this moment?" after every two to three trials. Subjects indicated their responses on a rating line and pressed a button labeled "continue" to proceed to the next trial. Subjects completed 30 choice trials and answered the happiness question 12 times in each play. Subjects were informed of their current task earnings during all choice trials. Each play started and ended with a happiness question.

Each trial of the smartphone-based experiment was randomly drawn from a list of 30 mixed trials, 60 gain trials, and 60 loss trials. The 30 mixed trials used 3 certain amounts in points (40, 55, 75) and 10 multipliers (0.2, 0.34, 0.5, 0.64, 0.77, 0.89, 1, 1.1, 1.35, 2). The 60 gain trials used 4 certain amounts (30, 35, 45, 55) and 15 multipliers (1.64, 1.7, 1.76, 1.82, 1.88, 1.94, 2, 2.06, 2.12, 2.18, 2.26, 2.4, 2.7, 3.2, 4). The 60 loss trials used the same amounts as the gain trials with 4 certain amounts (−30, −35, −45, −55) and the same 15 multipliers as used for loss trials. The maximum gain or loss for a single trial was 220 points.

fMRI Data Acquisition. All scanning was performed on a 3-Tesla Siemens Allegra scanner with a Siemens head coil at the Wellcome Trust Centre for Neuroimaging at University College

London. Functional images were taken with a gradient echo T2*-weighted echo-planar sequence [repetition time = 2.40 s, echo time (TE) = 30 ms, flip angle = 90°, 64 × 64 matrix, field of view = 192 mm, slice thickness = 2 mm with 1-mm gap]. A total of 40 axial slices were acquired in ascending order (in-plane resolution 3 × 3 mm). Four hundred seventy-five volumes were acquired in each of three sessions and the initial five volumes of each session were discarded to allow for steady-state magnetization. Slices were tilted at an orientation of −30° to minimize signal dropout in ventral frontal cortex. Anatomical images were T1-weighted (1 × 1 × 1 mm resolution). We also acquired a field map [double-echo FLASH, short TE = 10 ms, long TE = 12.46 ms, 3 × 3 × 3 mm resolution with 1 mm gap] for distortion correction of functional images. We used a pulse oximeter and breathing belt to collect physiological data during scanning.

Happiness Computational Models. We modeled moment-to-moment happiness for all ratings preceded by choices (20 per block) using models that assume an exponential decay of previous event influences and terms for certain rewards (CRs, in £), gamble expected values (EVs, average of the two possible outcomes), and reward prediction errors (RPEs, the difference between gamble outcome and EV). Alternative models included models without gamble expectations, with separate forgetting factors for different event types, with decay in prior trial influence modeled as the sum of two exponential functions, or with parameters related to the value of unchosen options. To verify that decay in previous event influence was best explained by an exponential function, happiness ratings were also regressed on separate elements of trial history. Data were modeled using events from up to seven prior trials.

Our model (model 1) contained separate terms for CR, gamble EV, and gamble RPE with influences that decay exponentially over trials. Thus, writing t as trial number, w_0 as a constant term, weights w_1, w_2, and w_3 to capture the influence of the three event types respectively, $0 \leq \gamma \leq 1$ as a forgetting factor that makes events in more recent trials more influential than those in earlier trials, CR_j as the CR if chosen instead of a gamble on trial j, EV_j as the EV of a gamble (average of the two possible outcomes) if chosen on trial j, and RPE_j as the RPE [difference between the gamble reward (GR) and the gamble EV] on trial j if the gamble was chosen, we get

$$\text{Happiness}(t) = w_0 + w_1 \sum_{j=1}^{t} \gamma^{t-j} CR_j + w_2 \sum_{j=1}^{t} \gamma^{t-j} EV_j + w_3 \sum_{j=1}^{t} \gamma^{t-j} RPE_j.$$

Models with exponential constraints were fit using nonlinear least squares using the optimization toolbox in MATLAB (MathWorks, Inc.). The forgetting factor γ is closely related to the time constant estimated when fitting an exponential function to weights for individual trials estimated using linear regression (Fig. S1). We used one-sample t tests to determine whether parameter weights were different from zero on average and we used paired t tests to compare different parameter weights. In the case of the weights estimated from a single rating from each subject in the smartphone data (Fig. 3*C*), we used a permutation test and fit 10,000 random shuffles of the happiness ratings to generate the null distributions.

To verify that happiness depends not only on rewards but also on expectations, we fit an alternative model (model 2) in which expectation terms were omitted and GR_j is the GR received on trial j if the gamble was chosen:

$$\text{Happiness}(t) = w_0 + w_1 \sum_{j=1}^{t} \gamma^{t-j} CR_j + w_2 \sum_{j=1}^{t} \gamma^{t-j} GR_j.$$

To verify that happiness is best explained by influences that decay exponentially in time with a single forgetting factor for all event types, we fit alternative models in which influences decayed according to the sum of two exponential functions with different forgetting factors (model 3) or with separate forgetting factors for each event type (model 4).

There was broad variability in the forgetting factor estimated in model 1 across subjects [$\gamma = 0.61 \pm 0.30$ (mean ± SD), range 0–0.97]. Thus, we also fit linear regression models to estimate the influences of previous rewards and expectations without constraining the decay in influences to take any particular functional form. We fit linear regression models with the same event types as in model 1 and with terms for one, two, or seven previous trials (models 5, 6, and 7, respectively). Average parameter estimates from models 1 and 7 are shown in Fig. S1.

The quality of fits for nine behavioral models is summarized in Table S1. There was considerable variability in how subjects used the rating scale (mean ratings SD was 16, range = 6–29). To prevent subjects with greater rating variability from having a disproportionate effect on the model comparison, we z scored ratings before performing model fits. Because we used z-scored ratings, we also omitted the constant term w_0 from these fits. We evaluated the models using Bayesian model comparison techniques (1, 2). We computed Bayesian Information Criterion (BIC) values for each model fit in individual subjects and summed BIC across subjects. BIC penalizes for parameter number and the model with the lowest BIC is the preferred model. Because the relative BIC value of different models is important and not the absolute size, we also computed BIC values for each model relative to the BIC value for model 1 to simplify comparison. Model 1, with influences decaying according to a single exponential function and weights for CR, EV, and RPE, was the overall preferred model according to BIC.

The only-some-gamble-outcomes-shown behavioral experiment allowed us to verify the role of both reward expectations and RPEs in determining happiness. In this experiment, expectations can affect happiness whenever gambles are chosen but RPEs can affect happiness only when gamble outcomes are revealed. To verify that happiness depends on RPEs, we fit an alternative model that includes a term for the EV of all chosen gambles but omits the RPE term. Instead the model includes a term GR_j equal to the GR received on trial j if the gamble was chosen and the outcome revealed and equal to zero otherwise:

$$\text{Happiness}(t) = w_0 + w_1 \sum_{j=1}^{t} \gamma^{t-j} CR_j + w_2 \sum_{j=1}^{t} \gamma^{t-j} EV_j^{choice} + w_3 \sum_{j=1}^{t} \gamma^{t-j} GR_j.$$

We used an additional model to dissociate expectation effects at choice and outcome that included an additional term equal to the gamble EV when the gamble outcome was revealed and zero otherwise:

$$\text{Happiness}(t) = w_0 + w_1 \sum_{j=1}^{t} \gamma^{t-j} CR_j + w_2 \sum_{j=1}^{t} \gamma^{t-j} EV_j^{choice} + w_3 \sum_{j=1}^{t} \gamma^{t-j} GR_j + w_4 \sum_{j=1}^{t} \gamma^{t-j} EV_j^{outcome}.$$

If happiness is positively affected by RPEs, then because RPE is equal to GR minus EV, the weight w_4 will be negative and anticorrelated with w_3 across subjects.

We fit two additional models that included terms related to the value of unchosen options that might capture influences on happiness of the decision difficulty or regret for not obtaining the best available outcome. Model 8 included a term for the difference between the values of the chosen and unchosen options with the EV as the gamble value. If the weight for this term is positive it might capture the relief of having an easy decision or the regret of having possibly made a poor decision. Model 9 included a term for how much better the outcome could have been if the other option had been chosen. When the certain option was chosen, this term was equal to the gamble gain amount minus the certain amount. When the gamble was chosen and lost, this term was equal to the certain amount minus the gamble loss amount. The term was zero when the subject won the gamble. This quantity relates to the potential regret that could be felt due to a decision. If regret decreases happiness, the weight for this term would be negative.

We also fit an additional four utility-based behavioral models, using established procedures (3) to estimate utilities (Table S2). Each model contained a loss aversion coefficient λ, and curvature parameters of α for the gain domain and β for the loss domain assuming a power function transformation. We fit a model in which α and β were constrained to be identical and a model in which they could be different. We used the following equations to transform objective gain and loss magnitudes into utilities:

$$\text{utility}(\text{gain}) = \text{gain}^{\alpha}$$
$$\text{utility}(\text{loss}) = -\lambda(-\text{loss})^{\beta}.$$

We then fit the following model of happiness using utilities rather than objective magnitudes:

$$\text{Happiness}(t) = w_0 + w_1 \sum_{j=1}^{t} \gamma^{t-j} CR_j^{utility} + w_2 \sum_{j=1}^{t} \gamma^{t-j} EV_j^{utility} + w_3 \sum_{j=1}^{t} \gamma^{t-j} \left(GR_j^{utility} - EV_j^{utility} \right).$$

In the first two models, we used individual choice data to estimate the best parameters in accounting for economic preferences. Parameters α and β were constrained to be identical in model 10 and were allowed to differ in model 11. The probability of gamble acceptance was computed using a noise parameter μ and the softmax equation. Parameters were fit by the method of maximum likelihood. We then applied those parameter estimates to transform objective amounts into utilities before fitting the happiness model.

We fit two additional utility-based models in which we simultaneously estimated happiness model parameter weights and utility parameters λ, α, and β without reference to choice data. Parameters α and β were constrained to be identical in model 12 and were allowed to differ in model 13. Results including model comparisons are shown in Table S2.

fMRI Data Analysis. We used SPM8 (Wellcome Trust Centre for Neuroimaging) for fMRI data analysis. Images were preprocessed using standard procedures [echo planar image unwarping using field maps, slice-time correction to the first volume, motion correction, spatial transformation to the Montreal Neurological Institute (MNI) template, spatial smoothing with a Gaussian kernel (8-mm full-width at half-maximum)].

We estimated parameters of three general linear models (GLMs) using regressors for option presentation, button press, gamble outcome, happiness question, and initial button press to register a happiness response. Six additional regressors captured residual movement-related artifacts and 18 additional cardiac and respiratory regressors corrected for physiological noise. In all GLMs, the regressor for the happiness question was parametrically modulated by the z-scored happiness rating.

In the first GLM, separate regressors at option presentation and gamble outcome for the two to three trials preceding each rating were parametrically modulated by the z-scored happiness rating subsequently given at the next probe question. In the second-level analysis these two regressors were weighted equally in computing the total effect. In the second GLM, the option presentation regressor was instead parametrically modulated by chosen CR magnitude and chosen gamble EV. The gamble outcome regressor was parametrically modulated by the RPE. These parametric regressors replaced the parametric happiness rating regressors at option and outcome onset in the first GLM. In the third GLM, the RPE term was split into separate parametric regressors for GR and gamble EV, but the GLM was otherwise the same as the second GLM. Parametric regressors were not orthogonalized in the design matrix, ensuring that parameter estimates were not confounded by spurious correlations due to signals related to other regressors (4). Statistical significance was determined at the group level using a random-effects analysis. All analyses used a voxel-wise significance threshold of $P < 0.001$ and a corrected significance threshold of $P < 0.05$ based on a family-wise error (FWE) cluster-level small-volume correction centered on coordinates from previous studies. Images were thresholded at $P < 0.005$ for display purposes only.

Because previous studies indicate that the ventral striatum represents reward-related signals and the right anterior insula plays a role in interoception and emotion, our a priori hypothesis was that these areas would be involved in our study. We performed a small-volume correction using 8-mm spheres at MNI coordinates from prior studies (5, 6) (left ventral striatum: −10, 12, −8; right ventral striatum: 10, 12, −8; right anterior insula: 39, 5, −14). Further analysis was performed on regions of interest (ROIs) defined as all voxels significant in the group-level analyses at $P < 0.001$, uncorrected. Striatal parameter estimates were also extracted from an independent bilateral ROI of 6-mm spheres at the ventral striatum coordinates used for small-volume correction. In addition to using cluster-level corrections, we also computed the FWE-corrected P value for peak voxels. For the relationship between happiness and neural responses during preceding events, the peak voxels in left and right ventral striatum remained significant after FWE correction (left ventral striatum: $P = 0.002$; right ventral striatum: $P = 0.022$) and the effect of the happiness question was also significant in the peak voxel in the right anterior insula ($P = 0.008$).

We used the Multilevel Mediation and Moderation Toolbox in SPM (7, 8) to perform the mediation analysis. We first estimated parameters for z-scored happiness ratings for the only-some-gamble-outcomes-shown behavioral experiment and used the median parameter weights (w_1, w_2, w_3, γ) to make happiness predictions from behavioral data for the fMRI experiment. In each individual, we calculated the first eigenvariate for the ventral striatum ROI defined in the group-level analysis at $P < 0.001$ from the first GLM. We deconvolved this time course to estimate neural activity for each task event, and used the out-of-sample forgetting factor γ to weight neural activity to make happiness predictions. Neural predictions were mean subtracted for each block and the predictions concatenated. The multilevel mediation analysis analyzed for each of the 24 subjects (after excluding 2 subjects for excessive motion), 60 behavioral predictions, 60 neural predictions (the mediator), and 60 happiness ratings. We tested whether the neural predictions from either ventral striatum ROI mediated the relationship between the behavioral predictions and the happiness ratings (see the mediation path diagram in Fig. S5). The relation between behavioral predictions and happiness ratings controlling for the mediator (neural predictions) is referred to as path "c′" (the direct effect). We estimated the relationship between happiness predictions and neural predictions (path "a") and the relationship between neural predictions and happiness ratings (path "b") controlling for happiness predictions. Thus, path a and b identify two separable processes that contribute to happiness ratings. A mediation test (path "ab") examines whether the inclusion of the mediator (neural predictions) explains a significant amount of the covariance between happiness predictions and happiness ratings. We used multilevel path analysis with bootstrap significance testing to determine two-tailed uncorrected P values from the bootstrap confidence intervals for the path coefficients (see ref. 8 for details on the method).

1. Schwarz G (1978) Estimating the dimension of a model. *Ann Stat* 6(2):461–464.
2. Burnham KP, Anderson DR (1998) *Model Selection and Inference* (Springer, New York).
3. Sokol-Hessner P, et al. (2009) Thinking like a trader selectively reduces individuals' loss aversion. *Proc Natl Acad Sci USA* 106(13):5035–5040.
4. Andrade A, Paradis AL, Rouquette S, Poline JB (1999) Ambiguous results in functional neuroimaging data analysis due to covariate correlation. *Neuroimage* 10(4):483–486.
5. Pessiglione M, Seymour B, Flandin G, Dolan RJ, Frith CD (2006) Dopamine-dependent prediction errors underpin reward-seeking behaviour in humans. *Nature* 442(7106):1042–1045.
6. Lewis GJ, Kanai R, Rees G, Bates TC (2014) Neural correlates of the 'good life': Eudaimonic well-being is associated with insular cortex volume. *Soc Cogn Affect Neurosci* 9(5):615–618.
7. Wager TD, Davidson ML, Hughes BL, Lindquist MA, Ochsner KN (2008) Prefrontal-subcortical pathways mediating successful emotion regulation. *Neuron* 59(6):1037–1050.
8. Atlas LY, Bolger N, Lindquist MA, Wager TD (2010) Brain mediators of predictive cue effects on perceived pain. *J Neurosci* 30(39):12964–12977.

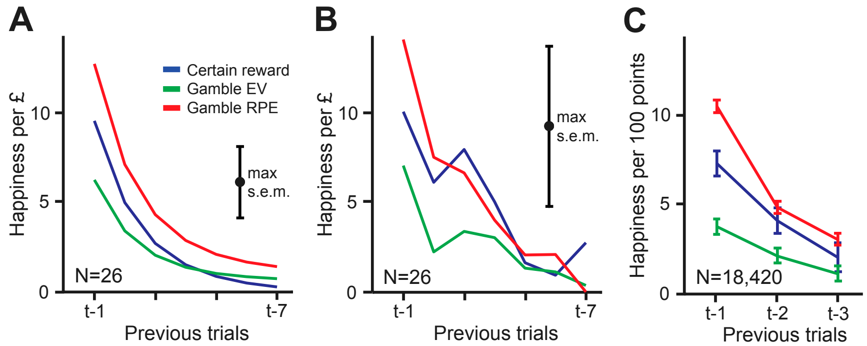

Fig. S1. Effect of previous trials on happiness ratings. (*A*) Mean weighting function across subjects ($n = 26$ subjects, 1,560 ratings) in the fMRI experiment for model 1 with influences constrained to decay exponentially. (*B*) Mean parameter estimates across subjects in the fMRI experiment for model 7, a linear regression with weights for seven previous trials. The time constant of an exponential function fit to parameter weights at the group or individual level is closely related to the forgetting factor γ estimated in exponential models. (*C*) Parameter estimates from a single happiness rating following the first two to three trials ever played by a subject ($n = 18{,}420$ subjects, 18,420 ratings) in the smartphone experiment for a linear regression with weights for three previous trials. The maximum SEM for all means is indicated for the fMRI experiment. The SEs for all parameters are indicated for the smartphone experiment.

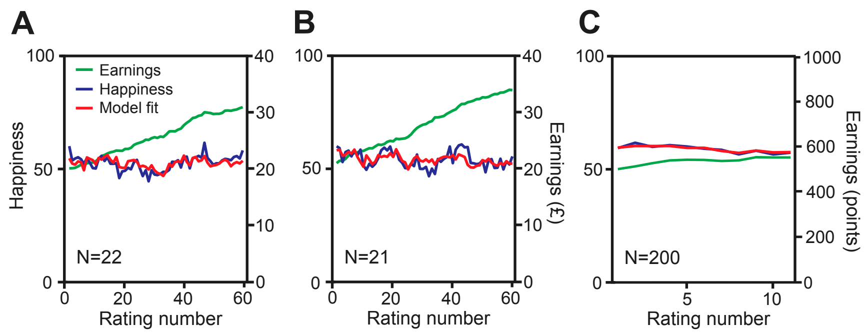

Fig. S2. Effect of previous rewards and expectations on happiness ratings in two behavioral experiments. (*A*) Cumulative task earnings, happiness ratings, and happiness model fits across subjects ($n = 22$) in the current-earnings-always-shown behavioral experiment. (*B*) Cumulative task earnings, happiness ratings, and happiness model fits across subjects ($n = 21$) in the only-some-gamble-outcomes-shown behavioral experiment. (*C*) Average cumulative task earnings, happiness ratings, and happiness model fits from the first 30-trial 12-rating play from the first 200 participants to complete the smartphone experiment. Overall, participants ($n = 18{,}420$) earned 564 ± 246 points (mean ± SD), a significant increase in wealth from an initial 500 point endowment [$t(18{,}419) = 35.2$, $P < 0.0001$], but happiness decreased over the experiment [initial happiness: 62 ± 20, final happiness: 57 ± 23 (mean ± SD), $t(18{,}419) = -26.2$, $P < 0.0001$].

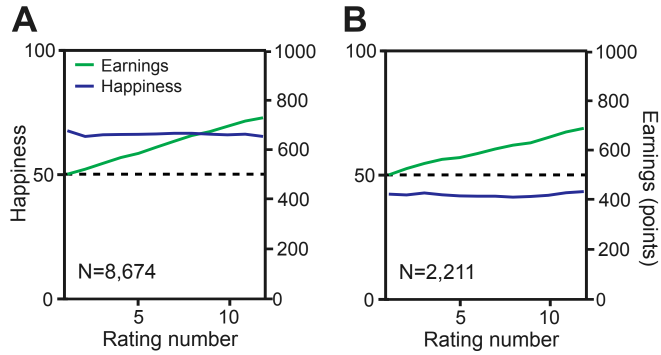

Fig. S3. Happiness in subjects in the smartphone experiment with mean happiness above or below the midpoint. (*A*) Average cumulative task earnings and happiness ratings in participants in the smartphone experiment who both increased their wealth from an initial 500-point endowment and had a mean happiness above the midpoint [n = 8,674, happiness: 66 ± 13, earnings: 727 ± 163 points (mean ± SD)]. (*B*) Average cumulative task earnings and happiness ratings in participants who both increased their wealth from an initial 500-point endowment and had a mean happiness below the midpoint [n = 2,211, happiness: 42 ± 9, earnings: 687 ± 149 points (mean ± SD)]. Despite a very significant increase in wealth [$t(2{,}210) = 59.3$, $P < 0.0001$], there was only a modest increase in happiness (initial happiness: 42 ± 17, final happiness: 43 ± 19 [mean ± SD), $t(2{,}210) = 1.9$, $P = 0.051$].

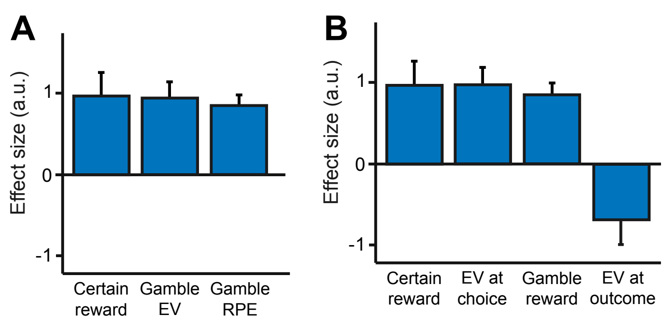

Fig. S4. Neural responses in an independent ROI in the ventral striatum. (*A*) Blood-oxygen-level-dependent (BOLD) activity in the ventral striatum at the time of task events was correlated with the same parametric task variables that explained changes in happiness (all $P < 0.005$; Fig. 2*A*). (*B*) When the gamble RPE term was separated into its components (GR and gamble EV at outcome), BOLD was positively correlated with GR and negatively correlated with gamble EV at outcome in the same way that those variables were related to changes in happiness (all $P < 0.05$; Fig. 2*D*). Error bars represent SEM.

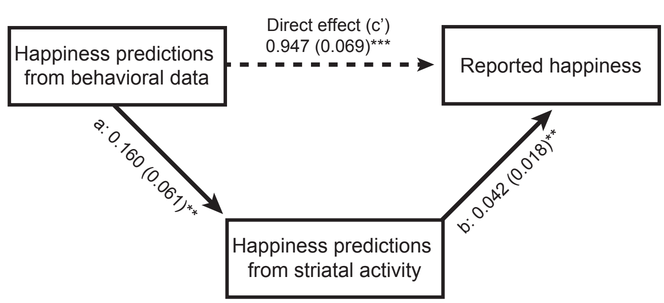

Fig. S5. Mediation path diagram for happiness predictions from striatal activity. Happiness predictions from behavioral data were made using out-of-sample median parameter weights ($w_1 = 0.52$, $w_2 = 0.35$, $w_3 = 0.80$, $\gamma = 0.72$) for subjects ($n = 21$) in the only-some-gamble-outcomes-shown behavioral experiment. Reported happiness ratings were highly correlated with behavioral predictions ($P < 0.001$; median $r^2 = 0.43$). Happiness predictions were made from the neural data in the nonindependent happiness ventral striatum ROI by weighting striatal activity by the out-of-sample forgetting factor ($\gamma = 0.72$). Reported happiness ratings were correlated with neural predictions ($P < 0.003$). Striatal activity showed a positive path "a" effect ($P < 0.01$), indicating higher neural predictions when behavioral predictions were higher. Striatal activity also showed a positive path "b" effect ($P < 0.01$) controlling for behavioral predictions, and a positive path "c′" effect ($P < 0.001$). There was no significant mediation (path "ab," $P = 0.25$). We repeated the mediation analysis for the independent ventral striatum ROI and obtained a similar result (path a, $P < 0.05$; path b, $P < 0.05$; path c′, $P < 0.001$; path ab, $P = 0.97$). Reported happiness ratings for the independent ROI were also correlated with neural predictions ($P < 0.003$). Mean standardized path coefficients are shown with SEs. $^{**}P < 0.01$, $^{***}P < 0.001$.

Fig. S6. Life happiness across sessions. Life happiness ratings were collected before the fMRI experiment and the only-some-gamble-outcomes-shown behavioral experiment (median 53 d apart; range, 3–162 d). The two measures were correlated ($r = 0.68$, $P < 0.001$, $n = 21$) and this correlation remained significant in subjects with at least 30 d between sessions ($r = 0.60$, $P < 0.05$, $n = 12$). Life happiness ratings were also correlated between the fMRI experiment and the current-earnings-always-shown behavioral experiment 14–17 mo later ($r = 0.70$, $P < 0.05$, $n = 11$). There was a weak positive relationship between life happiness and average momentary subjective well-being in the task ($r = 0.32$, $P = 0.11$, $n = 26$). Life happiness ratings from the fMRI experiment were inversely correlated with Beck Depression Inventory (BDI) scores that quantify depression-related symptoms (Spearman's $\rho = -0.54$, $P = 0.005$, $n = 26$). There was no relationship between BDI scores and right anterior insula parameter estimates for happiness ratings ($r = -0.062$, $P = 0.77$).

Table S1. Quality of behavioral fits for happiness models for the fMRI experiment

Model no.	Parameters per subject	Mean r^2	Median r^2	Model BIC	BIC – BIC_{model_1}
1	4	0.46	0.49	−671.6	0.0
2	3	0.39	0.44	−556.3	115.4
3	5	0.47	0.50	−610.0	61.6
4	6	0.48	0.50	−553.4	118.2
5	3	0.26	0.24	−215.9	455.7
6	6	0.36	0.33	−141.3	530.4
7	21	0.57	0.56	767.1	1438.8
8	5	0.48	0.50	−632.3	39.3
9	5	0.48	0.51	−624.0	47.6

BIC measures are summed across the 26 subjects. Model fits for model comparison were performed with *z*-scored happiness ratings to prevent subjects with greater rating variability from having a disproportionate impact on the results. Our model (model 1) contains separate terms for CRs, gamble EVs, and gamble RPEs with influences that decay exponentially. Model 2 omits expectations and has terms for CRs and GRs. In model 3, influences decay according to the sum of two exponential functions. In model 4, each of the three event types has a separate forgetting factor. Linear regression models with the same event types as model 1 with terms for 1, 2, or 7 previous trials (models 5, 6, and 7, respectively) were also fit. Model 8 includes a term for the difference between the value of the chosen and unchosen options using the gamble EV as the gamble option value. This parameter was not different from zero on average ($P = 0.43$). Model 9 includes a term for how much better the outcome could have been by choosing the other option (equal to zero when the outcome was the gamble gain). This quantity relates to the potential regret that could be felt due to a decision. This parameter was no different from zero on average ($P = 0.31$).

Table S2. Quality of behavioral fits for utility-based happiness models for the fMRI experiment

Model no.	Parameters per subject	Mean r^2	Median r^2	Model BIC	BIC – BIC_{model_1}
1	4	0.46	0.49	−671.6	0.0
10	4*	0.46	0.50	−683.9	−12.3
11	4*	0.46	0.50	−675.8	−4.2
12	6	0.48	0.53	−531.9	139.7
13	7	0.49	0.53	−439.0	232.6

BIC measures are summed across the 26 subjects. Model fits for model comparison were performed with *z*-scored happiness ratings, to prevent subjects with greater rating variability from having a disproportionate impact on the results. Model 1 is identical to model 1 in Table S1. For models 10 and 11, choice data were used to estimate the best parameters for explaining economic preferences. Parameters α and β were constrained to be identical in model 10 and were allowed to differ in model 11. The average model fit for model 1 was pseudo-r^2 = 0.43 and the mean ± SEM parameters were $\mu = 0.30 \pm 0.18$, $\lambda = 1.43 \pm 0.22$, and $\alpha = 1.02 \pm 0.06$. The average model fit for model 2 was pseudo-r^2 = 0.47 and the mean ± SEM parameters were $\mu = 0.25 \pm 0.11$, $\lambda = 1.70 \pm 0.27$, $\alpha = 1.05 \pm 0.05$, and $\beta = 1.01 \pm 0.06$. The quality of these fits suggests that subjects chose in a manner consistent with standard economic models. Average loss aversion coefficients greater than 1 are consistent with loss aversion in our population. We used the model parameter estimates for the individual subjects in the fMRI study to fit the utility-based happiness model.

*There were three and four additional parameters per subject for models 10 and 11, respectively, but these parameters were fit on the choice data separately and so the BIC values for computing happiness do not penalize for these additional parameters. Compared with model 1, the fit was better for 13 of the 26 subjects for model 11 and better for 12 of 26 subjects for model 12, suggesting that the extra complexity of the utility-based approach did not improve fits in the majority of subjects. Models 12 and 13, which incorporated utility parameters into the happiness model, similarly resulted in only modest improvements not justified by the increase in parameter number.

Table S3. Out-of-sample happiness model predictions

Dataset	No. of subjects	RPE model median r^2
fMRI experiment (individual model fits)	26	0.49
Behavior: only some gamble outcomes shown (median fMRI experiment parameters)	21	0.29
Behavior: current earnings always shown (median fMRI experiment parameters)	22	0.33
The Great Brain Experiment (median fMRI experiment parameters)	18,420	0.24

Model fits and predictions were performed with *z*-scored happiness ratings. Individual model fits were estimated for data from the fMRI experiment. Median parameter weights from the fMRI experiment model fits were used to make out-of-sample predictions for the two laboratory-based behavioral experiments and the smartphone-based experiment. The results demonstrate a high degree of out-of-sample validity.