

Supporting Information

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SI Note A

Study 1: Effect of Cognitive Reframing on Self-Reported Subjective Reward Value

Method. Participants. Data from 26 of the 198 participants were excluded due to missing data (4 participants), multiple survey responses from the same person (2 participants), unreasonably long/short completion times and/or straight-lining through the individual difference measures (6 participants), or consistently choosing either the immediate or delayed option on all trials (14 participants). Data exclusion did not differ by experimental condition. Table S1 presents the final number of participants in each group.

Analysis. All outcomes in our experiments involved obtaining monetary reward (of magnitude r) at some delay (d). We assumed that participants discount the value of future reward according to a hyperbolic function of the form

$$V = r(1 + kd)^{-1}, \quad [\text{S1}]$$

where V is the discounted subjective value. The discount rate, k , was our primary measure of interest.

For the subjective valuation task we estimated k by assuming that value (V) was indicated in a linear fashion by the position of the visual analog scale (VAS). We therefore estimated k by assuming that VAS values (S) were given by

$$S = S_0 + S_s \times V, \quad [\text{S2}]$$

where V is given by Eq. S1 above and S_0 and S_s together capture the linear transformation of value to VAS position. We obtained best fitting estimates of k for each participant and each framing condition (explicit-zero and hidden-zero) by finding values of S_0 , S_s , and k that minimized the sum-squared error between observed VAS values and those predicted by Eq. S2.

To obtain estimated discount rates for the choice task, we assumed that participants' decisions are approximated by a softmax decision function that depends on the relative value of the two options in each choice. Specifically, we assumed that the probability of choosing the first (smaller sooner) option is given by

$$P_1 = [1 + \exp(-\Omega(V_1 - V_2))]^{-1}, \quad [\text{S3}]$$

where Ω is a temperature parameter and captures how consistent (or noisy) choices are with the fitted discount function. V_1 and V_2 are the subjective values (derived from Eq. S1) of the first and second (larger later) choice options, respectively. Note that the probability of choosing the delayed reward is $P_2 = 1 - P_1$. We then estimated k and Ω by maximizing the likelihood of the observed choices for each participant in each framing condition. The likelihood function is given by

$$L(k, \Omega) = \prod_i P_i(\text{Choose } V_1)^J (1 - P_i(\text{Choose } V_1))^{1-J}, \quad [\text{S4}]$$

where J is an indicator function that is 1 when the participant chose V_1 and 0 when the participant chose V_2 .

SI Note B

Study 2: Effect of Cognitive Reframing on Neural Reward Representations

Method. We collected data from a total of 37 participants. Fourteen datasets were excluded from data analysis due to ex-

cessive head movements (10 participants), incomplete behavioral task (1 participant), or consistently choosing either the immediate or delayed option on all trials (3 participants).

Materials. Choice Pairs. We used a short block design (5 trials with the same framing in each block, with framing condition alternating across block), with a total of 60 trials (30 trials in each framing condition). In each trial, participants chose between a smaller immediate reward and larger delayed reward, presented either in a hidden-zero format or in an explicit-zero format (alternating between blocks, counterbalanced order across participants). As in study 1, participants were informed that one of their choices would be randomly selected to determine their compensation. All participants received an additional \$20 base compensation but were not informed of it before the experiment, so as not to influence their choice behavior. Following each choice, a yellow arrow was shown for 2 s to indicate that the response was recorded successfully. A 12-s interval followed each trial to allow the hemodynamic response to return to baseline. Discounting factors were calculated using the same procedure used in study 1. Imaging data were acquired on a 3T Siemens Trio scanner.

For each participant, intertemporal choices were generated according to the following procedure based on equivalence discount rates (k_{eq}). Specifically, indifference between an immediate reward of magnitude r_1 and a delayed reward of magnitude r_2 available at delay d occurs when

$$r_1 = r_2(1 + k_{eq}d)^{-1} \quad [\text{S5}]$$

or

$$k_{eq} = (r_2/r_1 - 1)d^{-1}. \quad [\text{S6}]$$

To accurately estimate discount rates within each format across participants, the set of k_{eq} that defined the indifference point for each choice pair for each participant were selected to span a range of discount rates (k) that encompasses those expected in our participant population, based on our review of the literature. Specifically, the 30 values of k_{eq} were randomly drawn from a normal distribution with mean 5.3×10^{-3} and SD 2.7×10^{-3} . The value of immediate options was drawn from a uniform distribution with maximum \$15 ($\mu = \9.00, $\sigma = \$3.97$). Delays were similarly drawn from a uniform distribution with maximum 100 d ($\mu = 52$ d, $\sigma = 24.67$ d). The magnitude of delayed outcomes were determined by k_{eq} : $r_2 = r_1(1 + k_{eq}d)$. Overall, the explicit-zero and hidden-zero formats were composed of 30 choices each and were equated by designing individual choices so that they used the same set of 30 k_{eq} values. The values r_1 , r_2 , and d differed somewhat between formats and across participants due to the stochastic procedure by which they were generated. However, there were no systematic differences in choice values that could potentially affect our results. Mean reaction time for choices was 2.25 s ($SD = 1.07$ s) and did not differ between conditions (Wilcoxon signed rank test, $P = 0.72$).

Functional Magnetic Resonance Imaging Data Acquisition. High-resolution ($1 \times 1 \times 1$ mm³) T1-weighted anatomical images of each participant's brain were obtained first. For functional images, T2-weighted echo planner images were acquired with repetition time of 2 s (acquired $\sim 30^\circ$ off of the AC-PC line to minimize susceptibility effect in orbitofrontal cortex; TE = 30 ms, flip angle = 90° , 37 total slices with 2-mm slice gap, 64×64 matrix, voxel

dimensions = $3 \times 3 \times 3 \text{ mm}^3$). Five additional volumes at the beginning of series were acquired to allow for steady-state magnetization and were subsequently discarded. Data were analyzed using SPM5 (Statistical Parametric Mapping; Wellcome Department of Cognitive Neurology). We performed slice timing correction before analysis and aligned data to correct for head movement. Images were smoothed with an 8-mm full width at half maximum Gaussian kernel. Volumes were normalized to Montreal Neurological Institute template and were resampled at $4 \times 4 \times 4 \text{ mm}^3$ resolution.

Analysis and Results. We fit discount rates (k) for participants separately for hidden-zero and explicit-zero trials (Eqs. S3 and S4). To summarize the effect of framing on each participant's valuation of reward outcomes, we borrowed the model developed by Loewenstein and Prelec (1) to describe the valuation of sequences of rewards. For our task, sequences are (i) relevant only in the explicit-zero frame and (ii) always include two outcomes of which one is always of zero magnitude. In these conditions, the Loewenstein–Prelec model reduces to

$$V_1 = r_1 - \varepsilon \gamma r_1 \text{ for immediate rewards} \quad [\text{S7}]$$

and

$$V_2 = r_2(1 + kd)^{-1} + \varepsilon \gamma r_2 \text{ for delayed rewards,} \quad [\text{S8}]$$

where ε is an indicator variable that is 1 for explicit-zero and 0 for hidden-zero. We estimated γ by finding parameter values that maximize the likelihood function expressed in Eq. S4, including choices made in both the explicit- and hidden-zero frames.

Functional Magnetic Resonance Imaging Analysis. We analyzed functional magnetic resonance imaging data as events with two conditions: choices presented in a hidden-zero format and choices presented in an explicit-zero format. Hemodynamic response amplitudes were estimated using a general linear model, with each choice modeled using a boxcar function (with duration given by response time) convolved with a standard hemodynamic response function. Best fitting response amplitudes can therefore be interpreted as brain activity relative to the rest period between trials. We included choices as separate parametric regressors to factor out potential brain activity that occurs as a result of behavioral responses independent of the experimental manipulation. Group results were calculated using t tests, with individual brain responses treated as random variables. Presentation order (i.e., starting in the hidden-zero vs. explicit-zero format) had no effect on brain activity or behavior.

Nuisance regressors included the choice rendered (1 for immediate and -1 for delayed in each explicit- and hidden-zero formats) and head movement (six regressors; estimated during preprocessing). Choices were modeled as events with variable duration matched to the reaction time for each decision. These regressors were generated separately to estimate mean activity during the choice period for the explicit- and hidden-zero formats. Our primary analysis contrasted differences in brain activity during the choice period in the hidden-zero versus explicit-zero presentation formats ($\beta_{\text{hidden}} - \beta_{\text{explicit}}$). To factor out the effect of choice behavior, we included a regressor for the choice in each trial (1 for choosing the immediate smaller reward and 0 for choosing the delayed larger reward). This analysis revealed the differences between how participants' brains processed rewards (and reward sequences) in each presentation format and therefore serves as the heart of our neuroimaging analysis. The results are shown in Fig. 2A; specific coordinates of brain regions identified in the contrast are provided in Table S2.

A second analysis estimated mean choice-related brain activity relative to baseline and identified the right dorsolateral prefrontal cortex (dlPFC) and the right pPC [46–46 58] as shown in Fig. 2C. Although these regions were clearly involved in intertemporal decision-making, there were no differences in activity between the hidden- and explicit-zero formats for the right dlPFC ($t[22] = 0.15$, $P = 0.88$) or for the right pPC ($t[22] = 0.64$, $P = 0.53$).

Because the dlPFC was of specific interest, we performed a separate region of interest analysis using the locations reported in previous studies: left IPFC [–48 15 24] from ref. 2 and right IPFC [44 44 16] from ref. 3. Mean β values were calculated within an 8-mm-radius sphere surrounding these locations and compared across hidden- and explicit-zero presentation formats. We found no differences in responses for left IPFC ($t[22] = 0.02$, $P = 0.98$) or for right IPFC ($t[23] = 0.64$, $P = 0.53$).

SI Note C: Equivalence Discount Rate

Each choice in the experiment has an equivalence discount rate, k_{eq} (Eq. S6). Of course, each participant is presumed to discount future rewards with an individual-specific discount rate, k , that is generally not equal to k_{eq} . For trials in which k_{eq} is greater than the actual discount rate, k , the participant should select the larger-later outcome. For trials in which k_{eq} is less than the actual k , choices should favor the smaller-immediate alternative. The farther k_{eq} is from a participant's discount rate, the easier the choice should be. The equivalence discount rate therefore characterizes a choice in the sense that participants should have equal preferences for the smaller-immediate or larger-later outcomes for trials with the same k_{eq} .

SI Note D: Ruling out Cognitive Load as an Alternative Explanation of Hidden Zero Effect

A potential concern with our studies may be that cognitive demands for performing the tasks may differ for the hidden- and explicit-zero choice frames, resulting in differential cognitive load that is responsible for changes in choice patterns. This concern is partially ameliorated by the fact that reaction times did not differ between conditions ($P = 0.72$; see above), suggesting that cognitive demands were not different across choice frames. Nonetheless, the amount of information presented to participants is greater in the explicit-zero frame than in the hidden-zero frame, potentially serving as a source of additional cognitive load that may affect the decision-making process. If the explicit-zero frame does indeed increase the cognitive load associated with the task, two possible consequences may follow. First, greater cognitive load may increase discount rates (4). This possibility cannot account for our results, because we found lower discount rates in the frame potentially associated with greater cognitive demand (i.e., lower k for explicit- relative to hidden-zero frame). Second, greater cognitive load may lead to noisier, more random, and less systematic responding, potentially increasing the number of smaller-sooner choices in a manner that can be mistaken as greater rates of temporal discounting. In our analyses, we explicitly modeled random noise in responding with a temperature parameter in the assumed choice function (*Materials and Methods*). Best fitting temperature parameters did not differ between the hidden-zero and explicit-zero frames in the choice task (Wilcoxon signed rank test, $P = 0.48$). Moreover, best fitting discount rates (k) account for a similarly high percentage of choices in both the hidden-zero (96.78%) and explicit-zero (96.81%) choice frame (Wilcoxon signed rank test, $P = 0.95$).

SI Note E: Potential Effects of Repeating Monetary Values and Delays

Repeating the use of the same monetary values and delays across tasks within participants was beneficial because it allowed a more straightforward comparison of behavior across tasks and presentation frames. However, it also created the risk that participants

