



Supplementary Information for

Valuation of Knowledge and Ignorance in Mesolimbic Reward Circuitry

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Supplementary Information Text

Pilot data replicating the main behavioral findings. Behavioral data was collected in an independent sample of 26 participants. Sixteen of these participants completed the same choice task as the participants who were scanned. The remaining 10 completed a shorter version of the task which contained only one gain block and one loss block (30 trials each) in counterbalanced order. Given that these data were collected in London (UK), the monetary amounts offered in the task were in British pounds (£) instead of US dollars (\$). Twenty of these participants were not given the follow-up rating task, therefore data is only reported for the choice task. Results showed that similarly to **Fig. 2A**, participants selected the most informative option significantly more often for gain compared to loss trials (average gain= 83.67% \pm 18.04 (SD); average loss= 73.97% \pm 28.21 (SD); difference: $t(25)=2.97$, $P=0.006$; **Fig. S2A**). Similarly to **Fig. 2C**, the more likely participants were to win on gain trials the more they wanted to know the outcome (effect of probability of winning on information choice = 0.300 ± 0.46 (SD), $t(25)=3.31$, $P=0.003$, **Fig. S2B**); and the more likely they were to lose on loss trials, the less they wanted to know the outcome (effect of probability of losing on information choice = -0.354 ± 0.53 (SD), $t(25)=-3.40$, $P=0.002$, **Fig. S2B**). Similarly to **Fig. 2E**, there was also a significant positive effect of EV on information choice (mean slope= 0.119 ± 0.17 (SD), $t(25)=3.57$, $P=0.001$, **Fig. S2C**), such that the higher the EV of the lottery, the more participants wanted to know the outcome. Finally, similarly to **Fig. 2F** participants' valence-dependent preference for knowledge over ignorance translates to greater uncertainty about losses than gains (main effect of valence: $F(1,25)=5.51$, $P=0.027$), driven by trials with strong expectations (interaction between outcome probability and valence: $F(8,200)=2.02$, $P=0.046$, **Fig. S2D**).

General linear mixed-effect model of information choice. As shown in **Table S1**, the full model (Model 1) performed best in explaining participants' choices, winning over all other models (AIC=2359; BIC=2409.7; adjusted $R^2=0.81$). All fixed effects were found to be significant ($P(\text{info})\text{diff}$: estimate = 0.223 ± 0.057 (SE), $t(4176)=3.92$, $P=0.0001$; EV: estimate = 0.706 ± 0.196 (SE), $t(4176)=3.60$, $P=0.0003$; Uncertainty: estimate = 0.196 ± 0.067 (SE), $t(4176)=2.93$, $P=0.0034$; **Fig. S3**), confirming their effect on the decision to receive information.

Effect of block context on knowledge preference. When comparing behavior during gain and loss trials with low outcome probabilities, a crossover in knowledge preference is observed (**Fig. 2C-D**), with higher preference for knowledge when the probability of losses is low compared to when the probability of gains is low. We examined whether this reflects a context effect in which lotteries are evaluated relative to the value of the other lotteries available in the current block context. That is, while a 10% chance of gain has a higher expected value than a 10% chance of loss (EV = +0.1 vs -0.1), a 10% chance of gain is the worst-case scenario in its block (lowest chance of gain), while a 10% chance of loss is the best-case scenario in its block (lowest chance of loss).

To formally test for this effect, the full model was fitted to combined data from both gain and loss blocks as above, but adding a 'context value' regressor equal to +1 during the gain blocks and -1 during the loss blocks. All of the fixed effect estimates were significant, including the large positive effect of EV (estimate = 1.692 ± 0.348 (SE), $t(4175)=4.86$, $P<0.001$) and a significant negative effect of context value (estimate = -1.059 ± 0.298 (SE), $t(4175)=-3.55$, $P<0.001$). Thus, participants were more likely to prefer knowledge when the lottery's value was high (positive effect of EV), and especially when it was high relative to the values of the other lotteries available in the block (negative effect of context value).

Valence-dependent information seeking is not driven by Pavlovian conditioning. Could enhanced preference for knowledge on gain trials relative to loss trials result from Pavlovian conditioning? In other words, did the knowledge cue (green bar) become more rewarding in the gain block relative to the loss block, because of increased association with the word ‘win’? If valence-dependent information search was driven by Pavlovian conditioning, we would expect (i) that the knowledge would be more likely to be selected over time in the gain blocks and less likely to be selected over time in the loss blocks and (ii) that previous trial outcome will influence current choice. We tested these predictions, but did not find support for either.

(i) When examining correlations between time (trial number) and proportion of times the most informative offer was selected (calculated on each trial as the percentage of participants who made that choice), separately for each block, there was no significant correlation in any of the blocks (Gain Block 1: $R(30)=-0.086$, $P=0.65$; Gain Block 2: $R(30)=-0.272$, $P=0.15$; Loss Block 1: $R(30)=-0.124$, $P=0.51$; Loss Block 2: $R(30)=-0.212$, $P=0.26$; **Fig. S4A-D**).

(ii) To test if the outcome on the previous trial influenced choices, a general linear model predicting choice (1,0) was run which included current expected value (from -0.9 to +0.9) and previous outcome cue (coded as 1 for ‘WIN’, 0 for ‘ZERO’ and -1 for ‘LOSE’). The regression was run using all trials for which the previous trial delivered an informative outcome cue (‘WIN’, ‘ZERO’, or ‘LOSE’), and using all participants who chose knowledge and ignorance at least once on those trials. Results show that decisions to know were driven by current EV (mean $\beta=0.562 \pm 1.15$ (SD), $t(26)=2.53$, $P=0.018$, **Fig. S4E**) but **not** by the previous outcome cue (mean $\beta=-0.069 \pm 0.78$ (SD), $t(26)=-0.46$, $P=0.65$). Finally, we directly correlated these parameter betas with a measure of the bias in knowledge search, the difference in information choice between gain and loss trials across individuals. Again, there was a significant effect of current trial EV ($R(27)=0.623$, $P=0.001$, **Fig. S4F**), but not of previous trial outcome cue ($R(27)=-0.218$, $P=0.27$).

This suggests that increased preference for knowledge on gain compared to loss trials was not the result of the cue itself acquiring rewarding properties via Pavlovian conditioning.

Valence-dependent information seeking is not driven by confusion between absence of information and absence of outcome. One may wonder if participants confused absence of information (i.e. the ‘XXXX’ cue) with absence of outcome (not winning nor losing). This is highly unlikely. First, if participants confused no information with no outcome, they should be selecting ignorance in the loss domain at a much higher rate than they did and significantly above knowledge. However, this was not the case – only 13.8% of participants in Experiment I and 2.4% of participants in Experiment II selected ignorance on a majority of trials when the outcome was likely to be negative (loss trials in Experiment I, market going down in Experiment II). Excluding these subjects did not change the behavioral findings (Experiment I: higher propensity to select knowledge on gain than loss trials: $t(30)=2.48$, $P=0.019$; significant effect of EV on choice: $t(30)=2.91$, $P=0.007$; Experiment II: significant fixed effect of signed market changed on signed WTP for information: estimate = 1.142 ± 0.55 (SE), $t(7890)=2.07$, $P=0.039$). This is a very strong indicator that subjects did not think they could avoid a negative outcome altogether by not knowing about it. Second, in both experiments outcome uncertainty is a significant predictor of choice to obtain knowledge. If participants believed that no information meant no outcome, their choices should not be sensitive to outcome uncertainty. Third, instructions in both studies clearly stated that the amount received at the end of the study would be equal to the accumulated earnings (Experiment I) or to the portfolio value on one randomly selected trial (Experiment II) **regardless** of whether the participant observed the outcome or not. Finally, in the second half of Experiment II, participants reported their expectations about their portfolio value before selecting whether to

receive information, suggesting that they did not think their choice could freeze their portfolio but rather understood that their portfolio value had already changed.

Information choice reaction times. Participants' average choice reaction time was 0.772 sec (\pm SD 0.199, range: [0.484, 1.289]). Reaction times were faster on gain trials compared to loss trials (mean RT for gain trials: 0.755 sec \pm SD 0.201; mean RT for loss trials: 0.789 sec \pm 0.209; $t(37)=2.095$, $P=0.043$). When testing for an interaction between choice (most vs least informative option) and context (gain vs loss) on participants who had a measure of RT in all 4 conditions, we found a main effect of choice ($F(1,23)=5.60$, $P=0.027$), such that people were faster to choose knowledge (the most frequent choice) than ignorance, but no interaction with valence ($F(1,23)=0.37$, $P=0.55$). Averaged across participants, there was a negative effect of EV on reaction time (mean slope = -0.045 ± 0.096 (SD), $t(35)=2.79$, $P=0.009$). Given these results, we ran a control analysis to ensure that the VD-IPE signals observed in the brain were not driven by differences in reaction times. We defined a GLM that was the same as the one described in the main text (GLM 1) except that we added reaction time on each trial as an additional parametric modulator at the time of knowledge/ignorance cues (in addition to EV, IPE and VD-IPE; with all four parametric modulators competing for variance). Our results remained the same, with significant VD-IPE tracking in VTA/SN (mean beta = 0.117 ± 0.29 (SD), $t(32)=2.33$, $P=0.026$) and significant correlation between VD-IPE tracking in NAc and behavior ($R(33)=0.377$, $P=0.031$). Running the same model as above but removing RT as a parametric modulator and instead changing the stick function (duration=0) to a duration equal to RT on every trial also showed significant VD-IPE tracking in VTA/SN (mean beta = 0.142 ± 0.26 (SD), $t(32)=3.19$, $P=0.003$). These control analyses suggest that our results are not due to RT.

VD-IPE signals are not influenced by participants' choice patterns. We ran a control analysis to ensure that our results could not be explained by choice rather than by valence. This was done by running the same GLM described in the main text (GLM 1), except that choice (coded as 1 when high information probability offer was selected and 0 when low information probability offer was selected) was added as an additional parametric modulator of the BOLD signal at the time of knowledge/ignorance cue. All four regressors (EV, IPE, VD-IPE, Choice) competed for variance. The VD-IPE signal in VTA/SN remained significant (mean beta = 0.117 ± 0.248 (SD), $t(32)=2.72$, $P=0.01$) as did the correlation between VD-IPE signal in the NAc and behavior ($R(33)=0.384$, $P=0.027$). Next we examined whether BOLD signal in the ROIs tracked a "choice-IPE" parameter which is equal to IPE tracked positively when participants choose the high information probability offer, but negatively when participants choose the low information probability offer. This variable was added as the parametric modulator of the BOLD signal at the time of knowledge/ignorance cue in a new GLM (all other regressors were the same as in GLM 1). As expected, choice-IPE was not significant in the VTA/SN (mean beta = 0.030 ± 0.204 (SD), $t(32)=0.831$, $P=0.41$) and its tracking in the NAc did not correlate with behavior across individuals ($R(33)=0.077$, $P=0.67$). These control analyses suggest that our results cannot be explained by choice rather than valence.

OFC response to the opportunity to gain knowledge has no detectable dependence on valence and choice. To test whether the response to knowledge versus ignorance cues observed in the medial OFC (**Fig. 5**) is valence-dependent or valence-independent, we used our trial-by-trial model presented in the main text to extract BOLD response in the OFC functional cluster (averaged across the 49 voxels of the cluster) separately for each delivery of a knowledge or ignorance cue. We then entered these betas into a mixed-effects general linear model with fixed and random (participant)

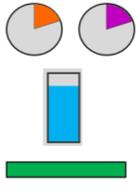
effects of cue (knowledge vs ignorance), fixed and random effects of EV, fixed and random EV*cue interaction, as well as fixed and random intercepts. As expected this revealed a significant main fixed effect of cue (stronger response to knowledge versus ignorance cues; $t(3824)=4.351$, $P<0.001$), but no fixed interaction between cue and EV ($t(3824)=0.479$, $P=0.63$) and no main fixed effect of EV ($t(3824)=0.852$, $P=0.39$), suggesting that the OFC response to the opportunity to gain knowledge is valence-independent.

Another interesting question is whether the OFC response to knowledge cues varies with participants' decisions, in other words does OFC respond similarly after participants chose knowledge (choose the most informative option) versus ignorance (choose the least informative option)? To test this, we ran a mixed-effects general linear model with fixed and random (participant) effects of cue (knowledge vs ignorance), fixed and random effects of choice (most vs least informative option selected), fixed and random choice*cue interaction, as well as fixed and random intercepts. Again, as expected, we found a significant main fixed effect of cue (stronger response to knowledge versus ignorance cues; $t(3824)=3.206$, $P=0.001$), but no fixed interaction with choice ($t(3824)=0.039$, $P=0.97$) and no main fixed effect of choice ($t(3824)=1.01$, $P=0.31$), suggesting that OFC responds to the delivery of knowledge cues over ignorance cues regardless of participants' choice to receive information.

Willingness to pay for knowledge and ignorance varies with the valence of expected knowledge. For the stock market task (Experiment II), we describe in the main text the results of a mixed effects model showing that people's willingness to pay for knowledge over ignorance is predicted by the signed market value. In particular, the greater the increase in the market the more participants are willing to pay for knowledge, and the greater the decrease the more they are willing to pay to remain ignorant. As mentioned in the main text, there was a second significant predictor of willingness to pay: absolute market change (estimate = 1.546 ± 0.47 (SE), $t(8090)=3.29$, $P=0.001$; **Fig. 6C**). The other control factors did not have significant effects. In particular, there was no significant effect of last known portfolio value (estimate = 0.07 ± 0.32 (SE), $t(8090)=0.22$, $P=0.83$). This shows that information seeking behavior was not related to the portion of the current portfolio's value that participants knew with certainty, but rather to the portion of its value that they were uncertain about (i.e. the effects of recent market changes), for which gaining new information could influence their beliefs. In addition, there was no significant effect of the cursor's starting position on the screen (estimate = 0.42 ± 0.54 (SE), $t(8090)=0.77$, $P=0.44$). This shows that behavior was not biased by the details of the bidding display (e.g. participants made similar bids regardless of where the bidding cursor started on the scale). Finally, two other factors had effects at trend level: the number of trials since last information was revealed (estimate = 0.736 ± 0.42 (SE), $t(8090)=1.77$, $P=0.077$) and trial number or time elapsed since the beginning of the task (estimate = 1.677 ± 0.89 (SE), $t(8090)=1.89$, $P=0.059$). In other words, there were trends for people to be more willing to pay to receive information the longer the time since they last received information, and the longer the time since the start of the task.

It is of interest that in Experiment 2, in contrast to Experiment 1 (**Fig. S4A-D**), we observe a trend for information to be sought out more over time. It may be that Experiment 2 provides a more sensitive behavioral measure for the value of information than Experiment 1 (because participants need to pay for information and its avoidance) or promotes learning of information preferences over time (because participants track a time-varying market and the trial outcome distributions are not explicitly cued). Future studies will be required to examine the robustness of this temporal effect and its possible source.

A.



Pie: Probability of win (orange) / Probability of loss (magenta)

Blue bar: Probability of informative outcome cue

Green bar: Knowledge cue, always followed by informative outcome cue

WIN/ZERO/LOSS

Informative outcome cue (indicating outcome on current trial)



Red bar: Ignorance cue, always followed by non-informative outcome cue

XXXX

Non-informative outcome cue (outcome on current trial not revealed)

B.

Cue	RPE (Reward Prediction Error)	IPE (Information Prediction Error)	VD-IPE (Valence-Dependent Information Prediction Error)
 (Knowledge cue)	~	1 - 	 * (1 - )
 (Ignorance cue)	~	0 - 	 * (0 - )
Win/Zero/Loss (Informative outcome cue)	Win/Zero/Loss - 	~	~
XXXX (Non-informative outcome cue)	~	~	~

Fig. S1. Presentation and definition of symbols, cues and signals used in the study and analysis. (A) Symbols and cues used in the task are described. Color associations (orange/magenta and green/red) were counterbalanced across individuals. (B) Definition of prediction error signals. Reward prediction errors (RPEs) are calculated as the signed difference between actual and expected outcome and should be observed at the time of informative outcome cues. Information prediction errors (IPEs) are calculated as the signed difference between delivery of knowledge cue (1 or 0) and expected likelihood of knowledge cue, and should be observed during the presentation of the knowledge cue (green bar) and ignorance cue (red bar). Valence-dependent IPEs (VD-IPEs) are calculated as the IPE multiplied by the outcome's expected value. These represent errors in the expected gain of desirable knowledge and thus depend both on the likelihood of receiving information and on the desirability of the expected outcome.

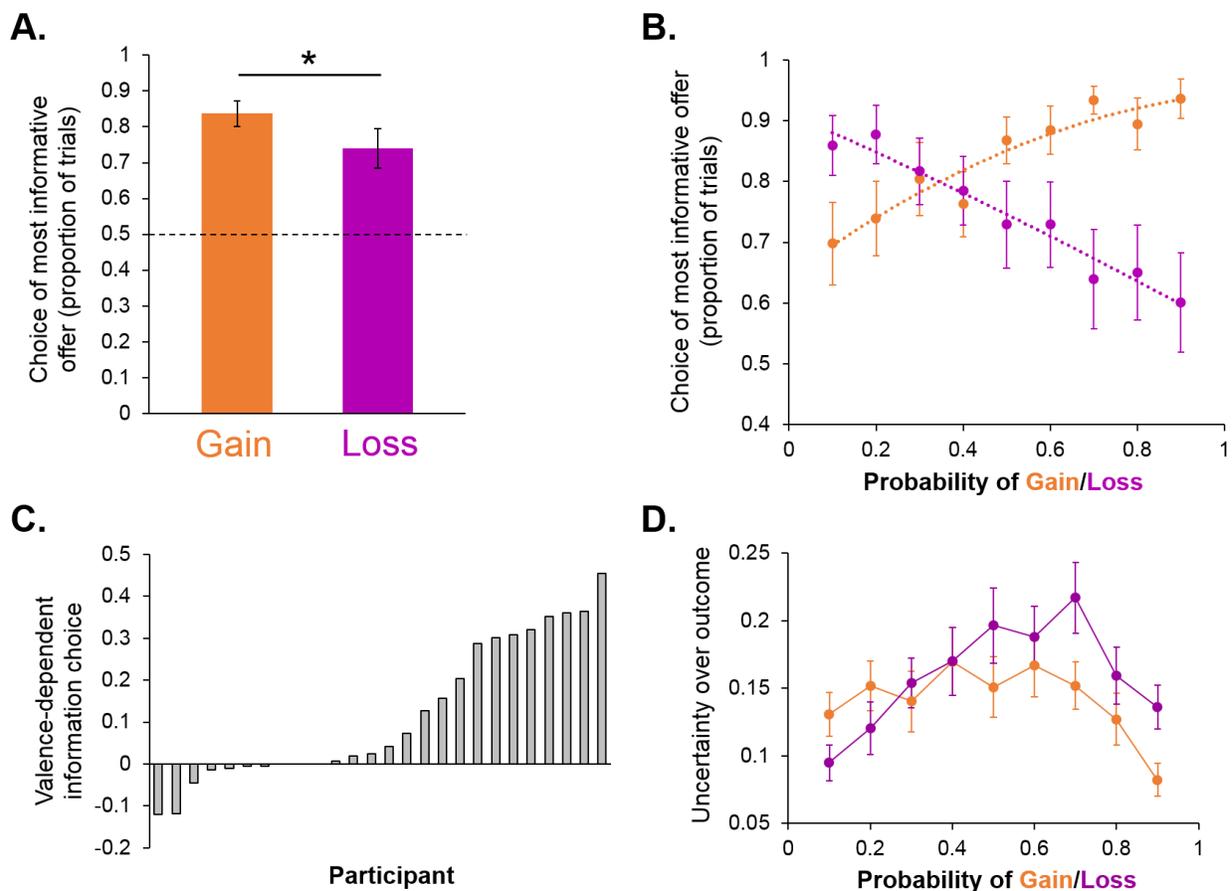


Fig. S2. Replication of valence-dependent preference for knowledge findings in a pilot sample. Behavioral data on the information choice task was collected for an additional 26 participants, showing replication of the main behavioral findings. **(A)** The propensity to select the most informative option was higher in gain relative to loss trials. **(B)** Choice of information increased with likelihood of winning (orange curve) and decreased with likelihood of losing (purple curve). The trendline represents 2nd order polynomial fit (gain trials: $R^2=0.908$; loss trials: $R^2=0.958$). **(C)** There was a positive effect of lottery expected value (EV) on decisions to know, calculated for each individual participant as the slope between EV and the proportion of times they selected the most informative offer. **(D)** Uncertainty over outcomes following the presentation of informative/non-informative cues was calculated for each trial as 0 when information was delivered and as the standard deviation of the lottery when information was denied, then averaged separately for gain and loss trials across participants. Participants' valence-dependent information seeking strategy led to a greater degree of uncertainty about losses than gains, especially on trials for which outcome probability was equal or greater than 50%. Error bars represent ± 1 SEM. Two-tailed t-test: * $P < 0.05$.

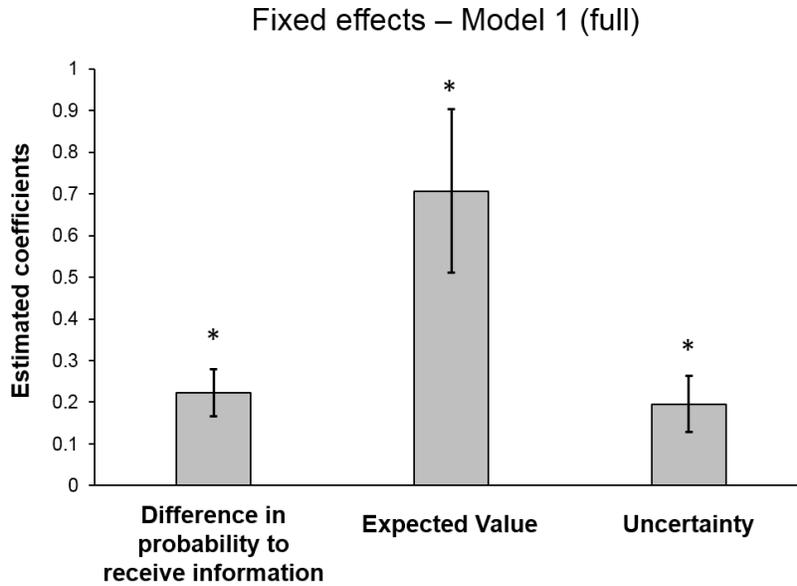


Fig. S3. Fixed effects on decisions to receive information. A general linear mixed-effects model was run to predict people’s choices of most informative option. Three factors were included in the model as fixed and random effects, with participant as the random variable: the difference in probability to know between the two information offers, outcome expected value (EV) and outcome uncertainty (calculated as the standard deviation of the outcome distribution). The model also included fixed and random intercepts. All three factors were z-scored before inclusion in the model. A fixed intercept and a random intercept were also added. Estimated coefficients, depicting the fixed effect of each factor, are plotted. Error bars represent \pm SE estimated by the model; * $P < 0.05$.

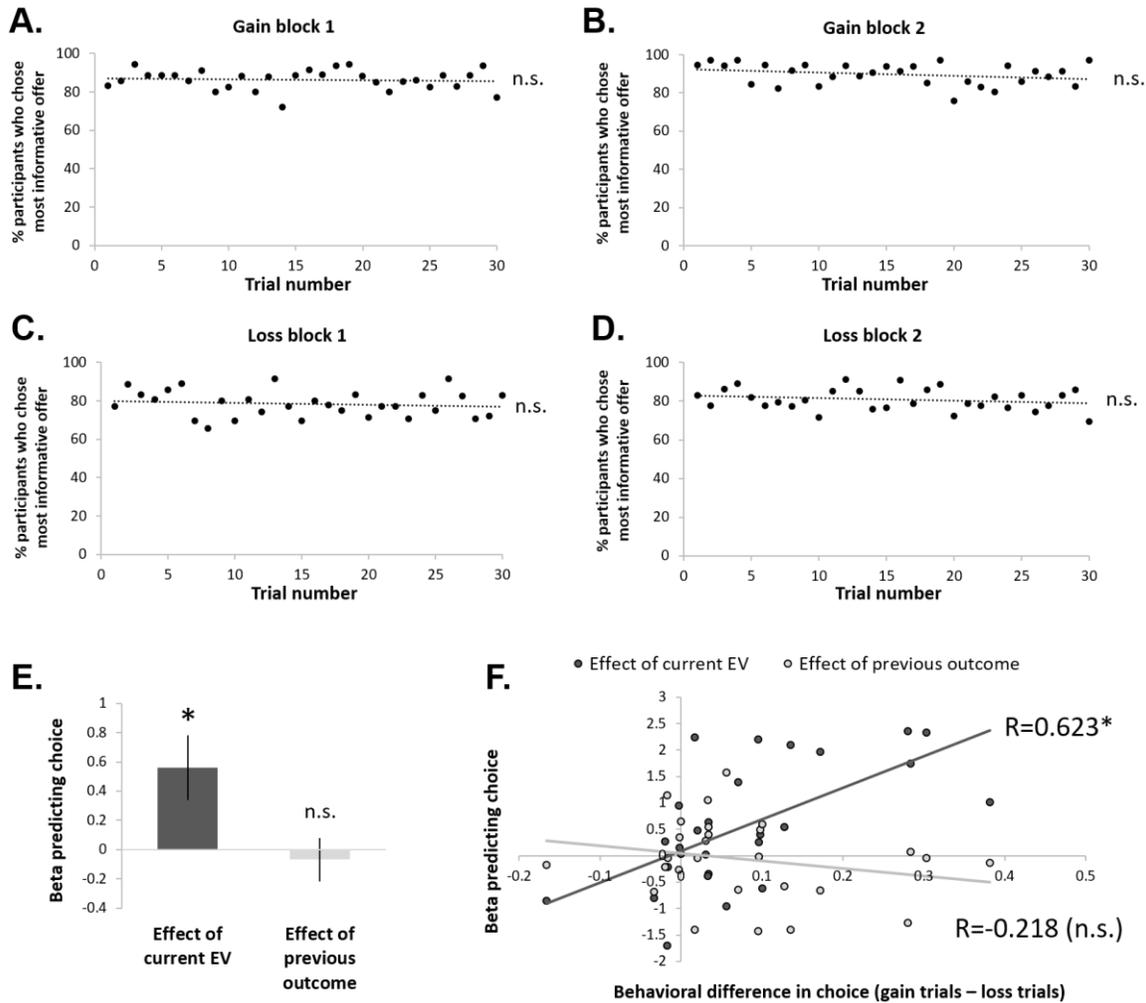


Fig. S4. Tests for Pavlovian conditioning. (A-D) Propensity to choose the most informative option was calculated for each trial across all participants and plotted over time separately for each block, showing no effect of time on decisions to know in any of the blocks. (E) Second, a logistic regression model was run for all participants who showed variability in choice (N=27) predicting their choice from current EV and from previous outcome. Previous outcome cue (“WIN”, “ZERO” or “LOSE”) had no effect on participants’ subsequent choice, (F) nor did it explain people’s preference for knowledge in the gain domain over the loss domain, thus arguing against Pavlovian conditioning as an explanation for our results. Error bars represent ± 1 SEM. Two-tailed t-test: * $P < 0.05$.

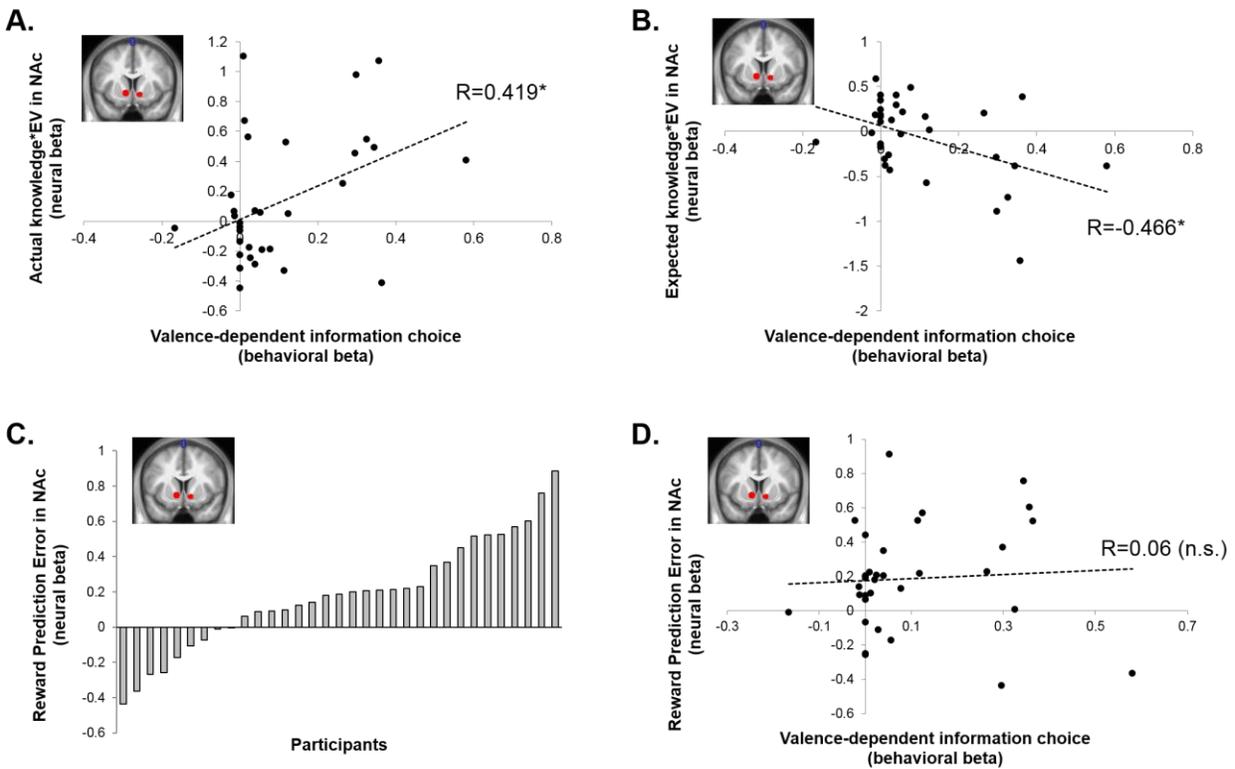


Fig. S5. Valence-dependent information choice correlates with individual components of the VD-IPE signal in NAc, but not with the RPE signal. (A-B) Each component of the VD-IPE in the NAc ROI, extracted at the time of knowledge/ignorance, was associated with behavior in the expected way: (A) positive correlation between behavior and the first VD-IPE component (Actual opportunity to gain knowledge*Expected Value) and (B) negative correlation between behavior and the second VD-IPE component (Expected opportunity to gain knowledge*Expected Value). (C) Individual participants' parameter estimates of Reward Prediction Error (RPE) in the NAc at the time of informative outcome cue. This effect was significant at the group level, suggesting that traditional RPEs are coded in the NAc. (D) The strength of this RPE signal in the NAc ROI was not correlated with individual differences in valence-dependent information seeking decisions.

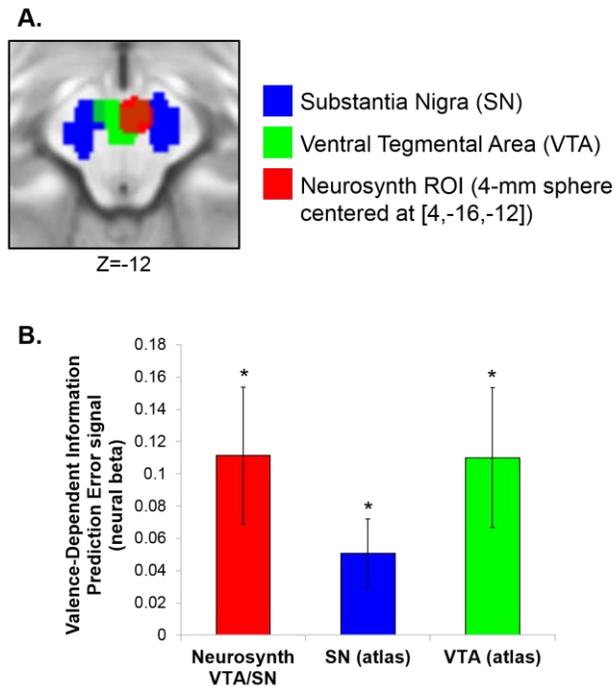


Fig. S6. Anatomical localization of the midbrain ROI. (A) Overlaying the midbrain ROI (in red) on top of an anatomical atlas (32) that separates the ventral tegmental area (VTA; in green) from the substantia nigra (SN; in blue) indicates that the midbrain ROI, derived from Neurosynth ‘reward’ map, overlaps with both the SN and the VTA. (B) Extracting the VD-IPE signal from each of these ROIs shows significant VD-IPE tracking in both the SN (mean beta=0.051 ± 0.12 (SD), $t(32)=2.38$, $P=0.024$) and the VTA (mean beta=0.11 ± 0.25 (SD), $t(32)=2.55$, $P=0.016$). For reference, the red bar (VD-IPE signal in Neurosynth VTA/SN ROI) is the same result as reported in the main text (mean beta=0.111 ± 0.244 (SD), $t(32)=2.63$, $P=0.013$).

Model No	Fixed effect factors	Random effect factors (grouping: participants)	AIC	BIC	Adjusted R²
1 (Full)	-Intercept -Difference in probability to receive information -Expected Value -Uncertainty	-Intercept -Difference in probability to receive information -Expected Value -Uncertainty	2359*	2409.7*	0.8099
2	-Intercept -Expected Value	-Intercept -Expected Value	2386.5	2411.8	0.7647
3	-Intercept -Uncertainty	-Intercept -Uncertainty	2695.6	2720.9	0.2880
4	-Intercept -Difference in probability to receive information	-Intercept -Difference in probability to receive information	2692.7	2718.1	0.2974
5 (Null)	Intercept	Intercept	2710.2	2722.9	0.2844

Table S1. Generalized linear mixed-effects models of decisions to receive information. Model fits calculated using Akaike Information Criterion (AIC), Bayesian Information Criterion (BIC) and adjusted R², all show that the best-fitting model was the full model. AIC and BIC values were summed across participants. Lower AIC and BIC values indicate better fit. * indicates the winning model.