Supplementary Note

Behavioral model

To infer the internal variables of monkey’s subjective decision-making, we used an econometrics model to approximate choice behavior. The model was generally formulated based on the discrete choice model in which the choice alternatives needed to be *mutually exclusive* (i.e., choosing one alternative implies not choosing the others), *exhaustive* (i.e., all possible alternatives are included), and *finite*. We adopted the conditional logit model that is the easiest and most widely used discrete choice model. Three axioms were required for the use of this logit model: (1) the subject is a utility-maximizing decision-maker, (2) utilities can be written as the linear sum of representative term and unobservable term, i.e., $U_+ + e_+$ and $U_\Box + e_\Box$, and (3) the unobservable term, $e_j (j = + \text{ or } \Box)$, is independently, identically distributed and forms, $P(e_j < \varepsilon) = \exp(-\exp(-\varepsilon))$. With the sampled monkey’s decision, we thus reversely inferred those subjective values. If there are two options (+ and □ targets), probability of choosing + targets can be written as $p_+ = 1/(1+\exp(-U_+ - U_\Box))$, where $U_+$ and $U_\Box$ are the representative utility of each option.

Our experimental condition satisfies the requirements for the discrete choice model. Two alternatives (e.g., approach and avoidance) in our experimental setup are mutually exclusive, exhaustive and finite. From the axioms, the logit formula further requires the *independence from irrelevant alternatives* (IIA) property for choice data. IIA is violated when the decision between two alternatives is affected by unobservable factor. In our experimental condition, potential factors are fully taken into account, and the decision is less likely to be critically affected by an identified factor. IIA requires that each choice has to be independent of other choices. In our experimental setup, offering $(x, y) = (\text{reward, airpuff})$ were randomly determined in each trials. The monkey thus knows the decision of current trial does not affect following offerings, and the
decision is mostly dependent on the current offering \((x, y)\). Therefore, the conditional logit model is considered to be at least an adequate approximation for modeling choice behavior, although further study is needed for better approximation.

**Supplementary Fig. 15** illustrates the procedure used to define those subjective values. For approach-avoidance decision-making, the first-order approximation with bias term was the best model to characterize the behavioral choice (**Supplementary Fig. 1** and **Supplementary Fig. 15g**). Then, \(U_+ - U_- = a_1x + a_2y + a_3\), where \(x\) was the length of red bar, \(y\) was the length of yellow bar, and \(a_1, a_2, a_3\) were the coefficients determined by the generalized linear model or logistic regression. The P-values for the coefficients of the first order-approximation were always less than 0.05, suggesting that each parameter of the model has significant meaning to account for the behavior. In the Ap-Av task, because an avoidance decision always led to a small amount of reward, the utility of avoidance is constant (i.e., \(U_- = U_{AV} = \text{constant}\)). In the actual data (**Supplementary Fig. 15a**), the decision boundary did not cross the origin point, \((x, y) = (0, 0)\), where the same small amount of reward (0.1 ml) was delivered after either approach or avoidance decisions. Although there was no difference in outcomes at this invariant point, the monkeys nevertheless tended to choose avoidance (**Fig. 2b**). We thus considered that there was a small intrinsic bias toward the avoidance decision, and represented it by \(-a_3 (>0)\). Accordingly, we modeled each utility as \(U_+ = U_{AP} = a_1x + a_2y\) (**Supplementary Fig. 15c**), and \(U_- = U_{AV} = -a_3\) (**Supplementary Fig. 15d**). Based on these utilities, we can derive the value of the chosen target, i.e., chosen value. This value can be written as \(E(u) = P_+U_+ + (1-P_+)U_-\), where \(P_+\) is 1 for an approach decision and 0 for an avoidance decision. We can also use the probability of choosing approach, \(p_+\), derived from the logistic model to characterize the chosen value. The weighted average, \(E_{util} = p_+U_+ + (1-p_+)U_-\) is called ‘expected utility’ in economics (**Supplementary Fig. 15f**). Following the definition in economics\(^7\), we use this ‘expected utility’ to characterize the decision-making. The expected utility corresponded to the continuous form of chosen value. The
expected utility was normalized to its maximum value. Because of this normalization, the expected utility derived by this procedure is relative value and only applicable in the Ap-Av task. Further, since unit of the expected utility is not expressed by the primary reward, the value cannot be interpreted in more realistic situations. We also introduced conflict in decision-making, measured by the entropy of the decisions, as \( H = -p_+ \log p_+ - (1-p_+) \log (1-p_+) \) (Supplementary Fig. 15e).

In the Ap-Ap task (Supplementary Fig. 15h), following the results of the model selection procedure (Supplementary Figs. 1 and 15n), we adopted the first-order approximation model without bias term (Supplementary Fig. 15i) as the best model (Supplementary Fig. 15n). Then, \( U_+ - U_\Box = a_1 x + a_2 y \), where \( x \) was the length of red bar, \( y \) was the length of yellow bar, and \( a_1, a_2 \) were the coefficients determined by the logistic regression. Given that the monkeys were fully trained on this task, we considered that the monkeys had acquired the association between the cross target and red cue and the association between the square target and yellow cue. Then, \( U_+ \) became a function of \( x \) and \( U_\Box \) became a function of \( y \). Based on this assumption, we modeled \( U_+ = a_1 x \) (Supplementary Fig. 15j) and \( U_\Box = -a_2 y \) (Supplementary Fig. 15k). Therefore, the value of the chosen target, or the expected utility, became \( E(u) = p_+ U_+ + (1-p_+) U_\Box \), where \( p_+ \) is the probability of choosing + (Supplementary Fig. 15m). In addition, the conflict in decision-making could be modeled by entropy as \( H = -p_+ \log p_+ - (1-p_+) \log (1-p_+) \) (Supplementary Fig. 15l).

**Stepwise regression**

We performed multiple regression analyses to characterize the neuronal activities during the cue period in the Ap-Av and Ap-Ap tasks. In order to derive a proper combination of
variables that linearly parameterized the neuronal activity, we introduced a stepwise regression method using the “stepwisefit” function of Matlab (Mathworks, Natick, MA). Stepwise regression is a systematic method for adding and removing terms from a multiple linear model based on a series of F-tests. The method begins with an initial model and then compares the explanatory power of incrementally larger and smaller models. At each step, the P-value of an F-statistic is computed to test models with and without potential term. The criterion for statistical significance of F-test was set at \( P < 0.05 \).

For the analysis in the Ap-Av task shown in Fig. 3a of the main text, the explanatory variables we chose were Rew (offered reward by red bar), Ave (offered airpuff strength by yellow bar), Eutil (expected utility modeled in the Ap-Av task), Cho (approach=1, avoidance=0), Cho*Rew (chosen reward or interaction of choice and red bar), Cho*Ave (chosen airpuff or interaction of choice and yellow bar), Conf (conflict in decision) and RT (reaction time). To choose these variables, in another analysis, we also performed a pilot stepwise regression by adding ‘option utility’ (i.e., \( U_{AP} \) and \( U_{AV} \)) to the variables mentioned here. We found that none of the pACC units identified uniquely represented \( U_{AP} \) or \( U_{AV} \). We therefore did not use ‘option utility’ as the regression variable for the following analyses.
References


Supplementary Fig. 1. Bayesian information criterion (BIC) used to find the best model to characterize the behavioral choice. BIC is defined as $\text{BIC} = -2\log L + k \log N$, where $L$ is the likelihood of the model, $k$ is the number of free parameters, and $N$ is the number of trials in a given session. With a conditional logit model (Supplementary Note), we approximated the choice behavior by representative utilities $U_+$ and $U_-$. Then, we modeled the behavior by the probability of choosing the cross target: $p_+ = 1/(1 + \exp(-(U_+ - U_-)))$. Using multivariate and multinomial logistic regression analysis, we estimated the function $f(x, y) = U_+ - U_-$. Based on the monkey's decision, the models we compared were the following:

- M0 (1st-order approximation without bias): $f(x, y) = a_1 x + a_2 y$,
- MC (1st-order approximation with bias): $f(x, y) = a_1 x + a_2 y + a_3$,
- MCI (1st-order approximation with interaction): $f(x, y) = a_1 xy + a_2 x + a_3 y + a_4$,
- M2 (2nd-order approximation): $f(x, y) = a_1 x^2 + a_2 xy + a_3 y^2 + a_4 x + a_5 y + a_6$,
- M3 (3rd-order approximation): $f(x, y) = a_1 x^3 + a_2 x^2 y + a_3 xy^2 + a_4 y^3 + a_5 x^2 + a_6 x + a_7 y + a_8$.

(a) Mean BIC in the Ap-Av task. BIC values calculated for each session were averaged. MC (first-order approximation with a bias term) produced the lowest BIC, and was chosen as the best model among the models that we compared. This result indicates that the monkeys' choice behavior could best be modeled by a simple subtraction of cost from benefit. Error bars indicate the standard error of the mean. (b) Mean BIC in the Ap-Ap task. The simplest M0 model (first-order approximation without a bias term) produced the lowest BIC, and was chosen as the best model.
Supplementary Fig. 2. Effects of anxiolytic drug administration on decision-making performance. We administered diazepam to two monkeys during performance of the two tasks. The approach-avoidance and approach-approach decisions were compared between blocks of trials before and after drug administration (200 or 250 trials each). (a) Effect of diazepam in the Ap-Av task averaged over sessions. Diazepam treatment increased the monkey’s approach decisions in the Ap-Av task by 7%, as measured by the size of significant change in decision in the decision matrix (i.e., the matrix of decision relative to offered reward and airpuff, $W = 20\%$; see Methods). (b) Regression analysis showed that the increase in approach decisions was significantly correlated with doses of diazepam ($r^2 = 0.57$, $P < 0.001$). Compared to negligible change in decision induced by saline injection (0 mg/kg), approach decisions were increased significantly by diazepam at 0.1, 0.25 and 0.4 mg/kg (two-tailed t-test, $P < 0.05$). (c, d) The approach-approach decisions were not affected by diazepam treatment at any dose that we used.
Supplementary Fig. 3. Neural activity in the pACC during performance of two decision-making tasks. We recorded the activity of 1065 well-isolated single units in the pACC and adjoining medial prefrontal cortex with chronically implanted electrodes as two monkeys performed alternating 150-trial blocks of the Ap-Av and Ap-Ap tasks (Methods). (a-c, e) Population activity of units in zone dorsal to cingulate sulcus (a), the ventral bank of the anterior cingulate sulcus (b), the ventral part of the pregenual ACC (c), and the dorsal bank of the anterior cingulate sulcus (e). Each panel shows population activity of all units recorded during the Ap-Av (red) and Ap-Ap (blue) tasks. Yellow shading indicates the cue period. (d) Cortical distribution of recorded units. Circle sizes indicate numbers of total units (gray) and those with responses during the cue period (black) per electrode track. Neurons in the pACC zone dorsal to the cingulate sulcus (a) and in the deep part of the pregenual anterior cingulate cortex (c) tended to be less responsive to cues during the Ap-Av and Ap-Ap tasks. In the dorsal zone (e) and in the ventral bank of the cingulate sulcus (b), subpopulations of the units also exhibit responses to other task events in both Ap-Av and Ap-Ap tasks, and were primarily activated in the cue period when the monkeys watched the cues that guided their decisions.
Supplementary Fig. 4. Stepwise regression of cue-related units in two decision-making tasks. Stepwise regression is a systematic method to find a proper combination of regression variables by their explanatory power (Supplementary Note). We chose 6 observable variables for the regressors: the length of red bar (Sr), length of yellow bar (Sy), target choice (Cho), reaction time (RT), push or pull joystick movement (Mv), and task condition (Tk; Ap-Av or Ap-Ap). (a) Results of stepwise regression. The Y-axis indicates the number of recorded units best characterized by single or combinations of the variables indicated by black squares in the matrix below. Green bars show the number of units affected by Tk. Yellow bars show the number of units affected by Mv (push/pull). Blue bars show the number of units affected by other terms. (b) Correlation coefficients among variables used in the analysis in a. (c) Correlation coefficients among the variables used for the classification in the Ap-Av task shown in Fig. 3a of the main text. Among 875 cue-related units, 761 (87.0%) could be significantly well accounted for by the regression models produced by this procedure (F-test, $P < 0.05$). Of these, 518 units (68.1%) were characterized by linear combination of variables including Tk, and 139 units were modeled solely by Tk. Among the units whose activity was modulated by the task version, many (379, 73.2%) were also dependent on other variables, suggesting that they did not simply encode the task difference but encoded the variables that were different between two tasks. Contrary to the strong influence of Tk, Mv was barely influential. Activity of only 58 units were explained by factors including Mv (7.6%), and only 5 (0.7%) were solely dependent on Mv. For the analyses reported in the main text, we therefore neglected the effect of Mv and analyzed neuronal activities in the Ap-Av and Ap-Ap tasks separately.
Supplementary Fig. 5. Cue-period activity of each neuronal type relative to the length of red bar (x-axis) and the length of yellow bar (y-axis). Units were classified based on their activity in the Ap-Av task using the stepwise regression (Supplementary Note and Fig. 3a) as: Rew (pos) units (a), Rew (neg) units (b), Ave (pos) units (c), Ave (neg) units (d), Eutil (pos) units (e), Eutil (neg) units (f), Cho (pos) units with activity correlated with approach decision (Cho=1; g), Cho (neg) units with activity correlated with avoidance decision (Cho=0; h), ChoRew (pos) units (i), ChoRew (neg) units (j), ChoAve (pos) units (k), ChoAve (neg) units (l), Conf (pos) units (m), Conf (neg) units (n), RT (pos) units (o), and RT (neg) units (p). Each plot shows the matrix of average firing rates during the cue period in the Ap-Av (left) and Ap-Ap (right) tasks according to the color scale at right (\(10^3\) Hz). Black line indicates decision boundary. ChoRew and ChoAve, respectively, represent the amount of chosen reward and the strength of chosen airpuff. Conf indicates the degree of conflict in decision, and RT indicates the reaction time. Units that were positively (pos) and negatively (neg) correlated with the regressors were categorized separately.
Supplementary Fig. 6. Multidimensional scaling. To search for a comprehensive property that accounts for different patterns of pACC unit activity, we used classical multidimensional scaling (MDS or principal coordinate analysis) and extracted the principal feature characterizing the similarity in the firing patterns of different types of units. We quantified the similarity of the firing patterns based on the matrices of firing rate of each type of unit shown in Supplementary Fig. 5. We defined the correlation distance between type \( i \) and type \( j \) as \( d_{ij} = 1 - r_{ij} \), where \( r_{ij} \) is the Pearson’s correlation coefficient between the matrices of the firing rates of type \( i \) and type \( j \). (a) Matrix of correlation distances between different types of units \( (D = \{d_{ij}\}) \). (b) Results of dimensionality reduction done by classical MDS, producing the configuration matrix \( Y \). MDS was applied to \( D \) to obtain \( Y \) that represented the distances of the correlations from their mean in each feature dimension. (c) The eigenvalue of \( Y^*Y \) representing the explanatory power of each feature dimension. The principal feature could characterize most of the neuronal activity properties. (d, e) Plots illustrating the locations of different neuronal types in the principal (d) and secondary (e) features. In the primary feature dimension (d), units clustered within two distinctive regions were categorized into two types (P-type and N-type). P-type units consisted of units whose activities were positively correlated (over 0.5) with the principal feature. These units were correlated with Rew (pos), Eutil (pos), Cho (pos), Cho*Rew (pos), Cho*Ave (pos), Conf (neg), and RT (neg). N-type units, by contrast, had activities that were negatively correlated (less than –0.5) with the principal feature, and their correlations were greater for Rew (neg), Eutil (neg), Cho (neg), Cho*Rew (neg), Cho*Ave (neg), Conf (pos) and RT (pos). This classification corresponded to the result of k-means clustering \( (k = 3 \text{ and } 4) \). (f) The absolute values of regression coefficients of Rew and Ave for each unit. The inset shows the mean coefficients for each type of units (arrows). Eutil and Cho were affected by Rew and Ave, suggesting that aspects of both reward and aversion contributed to the representation of Eutil and Cho units.
Supplementary Fig. 7. Examples of N-type (a-c) and P-type (d-f) units. (a, d) Raster plots. Time zero (labeled at the bottom of b, e) represents cue onset. Blue, yellow and red dots indicate response onset (RS), airpuff onset (A), and reward delivery (RWD), respectively. (b, e) Spike density function for different types of decisions made by the monkey during the Ap-Av (top) and Ap-Ap (bottom) tasks. Dark red and blue lines indicate the activity that was followed by avoidance and approach decisions, respectively. Light red and blue lines indicate activities followed by choices of square and cross, respectively. (c, f) Cue-period activity during performance of the Ap-Av (top left) and Ap-Ap (top right) tasks. Each datum was transformed to have the standard decision boundary and was convolved with a square window (W = 20%). Black line contours indicate significant difference from the mean (t-test, \( P < 0.05 \)). The bottom panel shows differences between the two tasks in t-scores. Black line contours indicate significant difference between them (\( P < 0.05 \)). The spike density function of N-type unit (b) shows that its activity was enhanced during the cue period, and that this enhancement was greater in the Ap-Av task when the monkey subsequently chose avoidance. The cue-period activity increased for the visual cue that subsequently led to avoidance (c, top left). In the Ap-Ap task, the activity was high when the offered reward was low (c, top right). Firing rates in the two tasks were significantly different (c, bottom), indicating that the neural activity did not simply represent stimulus-response associations (e.g., the visual properties of the cue or target selection process). The P-type unit (e) showed increases in activity during the cue-period, but was relatively less active when the monkey subsequently chose avoidance. The activity was dependent on the amount of reward offered by the visual cue (f). The difference in activity between the Ap-Av and Ap-Ap tasks was significant, suggesting that this unit, also, did not simply represent stimulus-response associations.
Supplementary Fig. 8. Mean frequency of error trials in relation to visual cues. (a, b) Frequency of omission errors (i.e., failure to respond within the response period) made by two monkeys as they performed the Ap-Av (a) and Ap-Ap (b) tasks. The overall omission error rates were 3.36% for the Ap-Av task and 2.79% for the Ap-Ap task. (c, d) Frequency of commission error (i.e., premature termination of trial by cessation of fixation during the cue-period) in the Ap-Av (c) and Ap-Ap (d) tasks. The overall error rates were 2.13% for the Ap-Av task and 2.02% for the Ap-Ap task. Omission errors occurred frequently when the offered reward and aversions were low (Ap-Av) or when the two offered rewards were low (Ap-Ap). In such conditions, their reaction times also increased, suggesting low motivation to perform the task (Fig. 2c, f of the main text).
Supplementary Fig. 9. Histological identification of one effective site. We confirmed histologically the location of an electrode used to deliver microstimulation that produced a significant change in monkey A's decision in the Ap-Av task. The electrode was kept in place, and electrolytic lesions were made by delivering 10 µA cathodal current for 20 s through each electrode following the completion of the experiments. The monkey was then deeply anesthetized with an overdose of sodium pentobarbitol and was perfused with 0.9% saline followed by 4% paraformaldehyde in 0.1M phosphate buffered saline. Microelectrode tracks were identified in 45 µm-thick coronal sections cut on a freezing microtome. (a, b) Nissl-stained coronal sections at ca. AP 36 (right hemisphere). The track, indicated by thick arrows, passed through the medial wall cortex and terminated at site C in the ventral bank of the cingulate sulcus. (c) Microstimulation (70 µA) at this site increased avoidance choice in the Ap-Av task. The microstimulation was applied with bipolar electrodes with the cathode located at site and the anode located 1 mm caudal to the cathode at the same depth. Right panel shows the zone of increased avoidance, as calculated using Fisher’s exact test ($P < 0.05$), that covered 13.1% of the total data matrix ($W = 20\%$). (d) No stimulation effect was found at this same site during performance of the Ap-Ap task.
Supplementary Fig. 10. Standardization procedure to compare and combine data across daily sessions. For analyses of population neuronal activity (Fig. 4a, b, f, g and Supplementary Fig. 5) and average behavioral performance (Fig. 7b, c, e), we needed to compare data across different daily sessions. Within a single session, the decision boundaries were stable, but there were small day-to-day variations in these boundaries. We thus performed the standardization procedure by transforming the behavioral data before we accumulated them across sessions. We linearly resized the parameter \( x \) for the transformation as follows: We assumed that the decision boundary of stimulation-off trials is \( ax+by+c = 0 \), and transformed it to the standard boundary, \( a_0 x+b_0 y+c_0 = 0 \). In the space of \((x, y)\), where \( x \) is reward amount (0 < \( x < 1 \) or 0 < \( x < 100\% \)) and \( y \) is airpuff strength (0 < \( y < 1 \) or 0 < \( y < 100\% \)), if an \( x \) is on the decision boundary, it should be transformed to be on the standard decision boundary. Function \( X_a(y) = -(c+by)/a \) indicates the distance from the y-axis to the decision boundary. Function \( X_b(y) = -(c_0+b_0 y)/a_0 \) indicates the distance from the y-axis to the standard decision boundary. For every datum, \((x, y)\) that was to the left of the decision boundary (i.e., \( ax+by+c > 0 \), red region), we re-sized \( x \) in accordance with the proportion of \( X_a/X_b \) and transformed it as \( x' = x X_a/X_b \). Similarly, if a datum \((x, y)\) was to the right of the decision boundary (i.e., \( ax+by+c < 0 \), blue region), we used the function \( X'_a(y) = 1+(c+by)/a \) (i.e., the distance between the line \( x=1 \) and the decision boundary) and the function \( X'_b(y) = 1+(c_0+b_0 y)/a_0 \) (i.e., the distance between the line \( x=1 \) and the standard decision boundary). The transformation then becomes \( x' = (1-x) X'_a/X'_b \). The standard decision boundary could be arbitrarily determined, and we set it so that it passes through (0.05, 0) and (0.5, 1). We confirmed that the results with standardization were similar to those without standardization, suggesting that the day-to-day variations were negligible.

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**Supplementary Fig. 11.** Effects of microstimulation on response reaction times (RTs) during performance of the Ap-Av task. (a) Slow, gradual changes in the RT over the course of each daily session for monkey S (red) and monkey A (blue), suggesting that any stimulation effects should overlap the slow motivation-derived changes in RT that can occur without stimulation. Data were smoothed using a moving-average filter with a 50-trial bin-width. (b, c) Difference in RTs between the stimulation-on and stimulation-off trial blocks shown individually for monkey S (b) and monkey A (c). We subtracted the slow component from the raw data and then added the mean RT for the session, assuming that the subtraction removed any direct effects of microstimulation on the RT as well as any slow motivation-induced RT changes. Each RT datum was standardized before performing statistical tests. Dotted black line indicates the decision boundary. Changes induced by stimulation are represented by t-scores. Solid black line contours indicate significant differences (two-tailed t-test, \( P < 0.05 \)). RT increased significantly in the high-conflict conditions, in which the monkeys sometimes had to change their decisions, suggesting an indirect stimulation effect on high-conflict decision-making.
Supplementary Fig. 12. Results of two control experiments. After we found effective stimulation sites, we ran following control experiments without moving electrodes. (a) Stimulation effects were not dependent on temporal order of daily sessions. We observed no stimulation-induced changes in the second Ap-Ap sessions, but avoidance increased in the last Ap-Av sessions. One set of experiments was done with monopolar electrodes, and the other with bipolar electrodes. (b, c) Microstimulation did not induce changes in skin conductance. We recorded skin conductance from monkey’s hand while we delivered electrical microstimulation to the effective sites. The session started with a 30-min rest period (black dotted line), after which we began the microstimulation period for 20 min (black line), followed by another 20-min period during which we gave a mild aversive stimulus to the monkey (green line). Red vertical lines mark the onset and offset of microstimulation (60 trains of pulses with 20-s intervals, biphasic leading cathode, 70 µA, for 1 s with 200 Hz). We observed little change in skin conductance after the electrical microstimulation. In the last period, we clapped our hands nearby the monkey, mildly pinched her tail using clothespins (strength: 2.5 kg, size: 7 mm by 20 mm), and delivered airpuffs to her nose (1 s, 10 psi) at time 0 (blue vertical line). (b) Example of the skin conductance change for a single session at an effective site (6-7 mm deep from the surface). (c) Change in skin conductance average over 5 sessions at 5 effective sites.
Supplementary Fig. 13. Effect of anti-anxiety drugs on stimulation-induced anxiety-like state (orange line with circle terminals in Fig. 8a). We examined the effect of diazepam administration on the behavioral changes induced by microstimulation at an effective stimulation site. In this experiment, monkey S performed 600 trials of the Ap-Av task during a single session divided into three blocks: stimulation-off (200 trials), stimulation-on (200 trials), and stimulation-on after drug administration (200 trials). Microstimulation (150 µA) was repetitively applied during the cue period of the second and third blocks, and diazepam (0.25 mg/kg, IM) was administrated as a single intramuscular injection during the trial interval between the second and third blocks. Each block lasted ca. 55-60 min. (a) Decision matrix for the first 200-trial block without stimulation or drug. (b) Decision matrix for the second trial block during which microstimulations (150 µA) were applied repeatedly in the cue period. (c) Decision matrix for the third trial block after diazepam administration (IM, 0.25 mg/kg) with microstimulations delivered as in b. (d) Difference between the first (a) and second (b) trial blocks represented by t-score (two-tailed t-test). Black outlines enclose values with significant differences in decision (Fisher’s exact test, $P < 0.05, W = 30\%$). Microstimulation increased avoidance by 17.2%. (e) Difference between the first (a) and third (c) trial blocks. Microstimulation plus diazepam administration increased approach by 13.7%. (f) Summary of these effects. Microstimulation increased avoidance, but the same microstimulation following diazepam administration increased approach. For this instance, the effect of ventral bank microstimulation on the behavior was reversed by the diazepam administration.
Supplementary Fig. 14. Size of smoothing window did not affect the conclusions. Choosing the appropriate size of the spatial smoothing window ($W$) involves a trade-off relationship with the number of trials in a given session. When the trial number is low, the data matrix becomes sparse, requiring a fairly large $W$. On the other hand, too large $W$ renders the data matrix too coarse and reduces the spatial resolution of the data. Because the number of trials in a single session was determined by the monkeys, it was difficult to estimate the proper size of $W$ and whether $W$ could affect the conclusion. We therefore systematically tested whether the size of $W$ could affect the distribution of effective sites. The panels show the effects of microstimulation on decision-making as analyzed with three sizes of smoothing window: 10% (a), 30% (b) and 40% (c). The x-axis in the plots indicates the distance from the midline (ML = 0), and the y-axis indicates the depth from the cortical surface as measured at the time of electrode implantation. The results for both hemispheres of the two monkeys are shown. The size of the circles indicates the magnitude of changes in decision observed, in percentages, as indicated (red-orange hues: increased in avoidance; blue hues: increase in approach). Circle centers represent the locations of monopolar electrodes or mid-points between bipolar electrode pairs. Black dots: sites with less than 3% change. A larger window size increased the span of coverage on the matrix and thus increased the number of data for each element of the matrix. Although these estimates were affected by $W$, effective sites were only observed in the localized pACC zone in the ventral bank of the anterior cingulate sulcus, irrespective of the size of $W$. 

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Supplementary Fig. 15. Definitions of expected utility and degree of conflict in the Ap-Av task (a-g) and in the Ap-Ap task (h-n). (a) Choice behavior in a single Ap-Av session. Blue squares indicate avoidance, and red crosses indicate approach. (b) First-order approximation of the behavioral choice. \( p(x,y) \) is the modeled probability of choosing approach, where \( x \) is the length of red bar, and \( y \) is the length of yellow bar. (c) Utility of choosing approach (\( U_{AP} \)) derived from the modeled behavior. (d) Utility of choosing avoidance (\( U_{AV} \)). (e) Degree of conflict in decision-making derived from the entropy, \( H = -p \log p - (1-p) \log (1-p) \). (f) Expected utility or subjective value of chosen option, derived from \( E(u)=pU_{AP}+(1-p)U_{AV} \). (g) BIC of multiple models. First-order approximation with a bias term was the best model to characterize the choice behavior of this Ap-Av session. (h) Choice behavior in a single Ap-Ap session. (i) First-order approximation without a bias term. (j) Utility of cross target (\( U_+ \)). (k) Utility of square target (\( U_\square \)). (l) Degree of conflict in decision. (m) Expected utility or subjective value of chosen option derived from \( E(u)=pU_++(1-p)U_\square \). (n) BIC of multiple models. First-order approximation without a bias term was the best model to characterize the choice behavior of this Ap-Ap session. See Supplementary Note for detail.