**METHODS**

No statistical methods were used to pre-determine sample sizes, but our sample sizes are similar to those reported in previous publications.

Data distribution was assumed to be normal but this was not formally tested

Data collection was performed blind to the conditions of the experiments.

Cues were pseudo-randomly sampled.

**Animals**

All experimental procedures were performed in accordance with the ILAR Guide for the Care and Use of Laboratory Animals and were approved by the Animal Care and Use Committee of the National Institute of Mental Health. Two male monkeys (Macaca mulatta, W – 6.7 kg, age 4.5yo, V – 7.3 kg, age 5yo) were used as subjects in this study.

**Decision-making task**

Monkeys were trained to perform a decision-making task while they were seated in front of a computer screen. In this task, animals had to choose to either reject or accept a reward offer that differs in reward size (drops) and delay time. Different reward offers were indicated by different pretrained visual cues that indicate different combinations of reward size (2, 4 or 6 drops) and delay time (1, 5 or 10s).

On each trial, animals had to first touch the bar and hold it for 500ms. Next, a small red square was presented at the center of the screen for 500ms. After that, one of the 9 visual cues was presented behind the red square at the center of the screen. The center square stayed red for a discrete random period at one of the five levels (1.5, 2, 2.5, 3 or 3.5 seconds) before it became purple. Animals reported their decisions by either releasing the bar anytime during the red period to reject the current offer or between 200 and 1200 ms after the purple square was presented to accept the offer. If the animal rejected the offer, a new trial started immediately. If the animal accepted the offer, the purple square became green and liquid reward of the indicated size was delivered after the indicated delay. The visual cue was turned off during reward delivery. If the monkeys released the bar before cue onset, within 200ms of presentation of the purple square onset or if they never released the bar during the trial, an error cue appeared on the screen for 1000 ms and the trial was considered an error. After an error trial the same cue was presented in the next trial. Error trials from both animals were excluded from the analysis.

**Data collection**

A noncommercial software REX (version XXX) was used to control simuli in the decision-making task. A commercial software Ripple grapevine (version XXX) was used for neural recordings. A custom software WangSpikeSorter (version 1.0.0) was used to perform offline spike sorting.

**Computation of choice consistency and decision evidence**

Choice consistency is quantified by the entropy of choices. The entropy of choices is defined as the entropy of a Bernoulli process in which binary choices are generated with probability and . Specifically, the choice entropy can be written as a function of the probability that animals accept the offer, .

Decision evidence on the other hand is estimated by the drift rate in the drift diffusion model. The amount of evidence for choice of option at time can be estimated by 1:

FC is the fraction of correct (preferred for that cue) choices, in this case .

The drift rate for each cue, , was then estimated as

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Where, is a non-decision time and is the reaction time minus the non-decision time. The non-decision time is not immediately available in this task. However, previous work has shown that non-decision time is under 200 ms. Therefore, we calculated evidence under a series of non-decision times (0, 50, 100, 150, and 200ms), and examined correlations in evidence, across cues, for different values of non-decision time. For the extreme values (0 vs 200ms), the calculated drift rates are correlated at R = 0.99, p < 0.01. Since estimated drift rates using different non-decision-times are strongly correlated, we adopted the average of the 5 sets of estimated drift rates as the final estimate for drift rates.

The accept decision times are not immediately available, since animals make accept decisions by not releasing the bar when the cue is presented, until the center red square turns purple which happens 1.5-3.5s after cue onset. Note that accept decision time is different from the accept response time analyzed in Fig. 1F, which instead measures the bar release reaction time after the red dot turns purple. Therefore, we inferred the accept decision times using the regression between entropy and reaction time for reject choices, and then using the entropy for accept choices. We carried out this approximation in two ways. First, we fit a linear model between reject RT and entropy for each session and estimated the accept decision time based on the session-specific regression model. Second, we fit a linear model between reject RT and entropy by pooling data from all sessions and estimate the accept decision time based on the pooled regression model. Results using either approach were similar.

In addition to using closed-form formulas to calculate drift rates as stated above, we also directly fit two variants of the drift diffusion model (DDM), vanilla DDM and DDM with collapsing bound, directly to the trial-by-trial reaction time and choice data. Since we only have access to trial-by-trial reaction time for reject trials, analysis was restricted to reject trials. Model-fitting was carried out using a recently published python library pyDDM (version 0.6.1)2. Drift rates estimated using all three methods (closed-form solution, vanilla DDM, and DDM with collapsing bound) significantly correlate with each other in both animals (Supplementary Fig. S9).

For correlation of reaction time and choice-entropy, the reaction times were z-scored within each session. For plotting purposes, the z-scored reaction times were transformed to the overall reaction times, by multiplying by the overall average (i.e., across session) standard deviation and adding the overall average reaction time. This transformation does not affect the statistics, because all values were multiple by the same constant, and the same constant was added to all values.

For the combined reaction time regression, we have

Both interactions between entropy and monkey, and between p(accept) and monkey were included in the model. A random effect of session was included to account for variations of RTs across sessions. The dependent variable here is reaction time, for both accept trials and reject trials. Reaction time for reject trial is the interval between cue onset and bar release while the square is red. Reaction time for accept trials, on the other hand, measures the response time between when the red square turns purple and bar release.

**Analysis of single unit responses**

ANOVAs were applied to the single unit data to assess response association in sliding windows (50ms bin, 50ms steps) time locked to offer cue onset. The dependent variable was the spike count in each time bin. The ANOVA included main effects of choice, delay time, reward size, and interactions between delay time and reward size. A separate ANOVA was carried out which included the main effects of cue accept probability and choice.

**Dimensionality reduction of population activity and decoding analysis**

All population analyses were conducted on simultaneously recorded neurons from a single session from a single animal. We performed dimensionality reduction using Principal Component Analysis. The mean spiking activity of each neuron was computed for each visual cue and each choice in 50 ms bins from 0 to 1000 ms after cue onset. This led to 18 time series of mean firing activity for each neuron. The time-series for the different conditions were then appended into one long vector for each cell, and the covariance matrix across simultaneously recorded neurons from a single session was then computed. The first 20 principal components of the covariance matrix were kept for further analysis as they explained above 60% of the total variance. Including additional dimensions did not increase decoding performance for predicting monkeys’ choices (Supplementary Fig. S4).

A linear Support Vector Machine classifier was used to predict trial-by-trial variations in three task variables (choice, delay time and reward size) separately based on the first 20 principal component scores at each time bin. We used a 10-fold cross validation to evaluate the accuracy of the classifier.

In order to estimate and visualize the attractor dynamics of the population activity, we further projected the 20-dimensional neural data (based on Principal Component Analysis as described above) onto a single dimension, the choice dimension. The choice dimension was defined by the Support Vector Machine classifier and was the dimension perpendicular to the separating hyperplane in the SVM classifier. An alternative way of defining the choice was by computing the difference between the average population activity vector in the 20-dimensional subspace for accept vs reject trials. Results using this alternative definition were included in the supplementary material.

**Estimation of the energy landscape in the 1-dimensional neural subspace**

We reconstructed the energy landscape by numerically estimating the flow field in a 1-D space, and then spatially integrating the flow field 3. Thus, we assume the neural dynamics of the population activity , are governed by a first-order (at this point potentially nonlinear) system,

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And then defined the spatial derivative of the potential function ,

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For a first order system, . Therefore, the potential function, , which we assume exists, is given by the spatial integral of the time derivative.

To estimate the time derivative, we defined the population activity in the 1-D subspace at time and trial as . We first computed the expected value, **,** of the time derivative of population activity at binned spatial locations and time , with the expectation taken over trials, .

The interval . Then we took the spatial integral over these time derivatives to get the potential function at location and time ,

The integral results in an arbitrary constant. Potentials were always set to 0 at the center of the 1-D decision space.

**Linear dynamics analysis**

Furthermore, we fit a linear dynamical system model to estimate the retraction coefficient for each reward offer. Here we assume that in the low-D space(s) the dynamics could be approximated as a first-order linear system in which we model both fixed-point dynamics and evidence input to the system. This gives the following equation:

Here is the activity at time , and is zero-mean Gaussian white noise. The coefficients characterize the depth of the attractor, with larger values corresponding to deeper attractors. The coefficient characterizes the strength of the evidence, and is the fixed point of the undriven dynamics () which also corresponds to the choice-related component of the fixed-point.

This model was fit to activity projected into the 1-D choice dimension, averaged in 50 ms bins. Thus, the activity in a 50 ms bin, was used to predict the activity in the next 50 ms bin, . The model was fit to data from all correctly executed trials. From this regression, the retraction coefficient was extracted.

Parameter recovery analysis of the linear dynamical model suggests that our model can be robustly fit to the data (Supplementary Fig. S19). We also performed posterior predictive checks to see if our model could qualitatively capture the differences in energy landscape that we observed in Fig. 4. In this analysis, we start with the recorded neural activity at the -1000ms bin, then simulated bin-by-bin the population activity in the next time bin using our fitted model. The noise term in the model is sampled from the empirical distribution of residuals from the model. Our model could indeed qualitatively capture the data (Supplementary Fig. S20).

We also fit a variant of the equation given as:

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In this equation, is a cue-specific term reflecting evidence accumulation. We fit as a constant, and then subsequently correlated with .

**Multi-dimensional linear dynamics analysis and calculation of curls**

A multi-dimensional version of the linear dynamics analysis was also estimated in a 3-D subspace. A principal component analysis was performed on the residual neural activity orthogonal to our 1-D choice dimension. The 3-D subspace was then composed of the choice dimension and the first two principal components of the residual activity.

Here and are 3 dimensional vectors and represent the population activity at time . The 3 x 3 matrix is the recurrent matrix. is the fixed point for choice . is the constant drift for cue . is zero-mean Gaussian white noise. Because the dynamics were non-stationary, the model was fit to a moving window of 3 time bins from each trial. The window was advanced by 50 ms, and 3 bins of 50 ms were fit, etc. Thus, for each time window, we used 3 consecutive time bins from each trial, and all valid trials, for one regression fit. This gave us temporal resolution on the change in dynamics, while also providing pooling over time within each trial (3 time bins) to increase statistical power.

Eigen values of the recurrent matrices were computed for each cue . Correlations between the eigenvalues and choice entropy were computed.

The 3-dimensional curl around the population activity in the 3-D subspace was computed as . Here represents the element of the recurrent matrix at the row and column.

**Data Availability**

Data from the manuscript can be found in the following figshare repository.

Wang, Siyu; Falcone, Rossella; J. Richmond, Barry; Averbeck, Bruno (2023). data for "Attractor dynamics reflect decision confidence in macaque prefrontal cortex". figshare. Dataset. <https://doi.org/10.6084/m9.figshare.21701282>

**Code Availability**

Data and codes will be made publicly available upon publication.

**Methods-only references**

1 Costa, V. D., Kakalios, L. C. & Averbeck, B. B. Blocking serotonin but not dopamine reuptake alters neural processing during perceptual decision making. *Behav Neurosci* **130**, 461-468 (2016). <https://doi.org:10.1037/bne0000162>

2 Shinn, M., Lam, N. H. & Murray, J. D. A flexible framework for simulating and fitting generalized drift-diffusion models. *Elife* **9** (2020). <https://doi.org:10.7554/eLife.56938>

3 Strogatz, S. H. *Nonlinear dynamics and Chaos : with applications to physics, biology, chemistry, and engineering*. (Addison-Wesley Pub., 1994).