Decision-making reference point biases in the dorsal anterior cingulate cortex

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Abstract

Probabilistic decision-making is shaped by various subjective factors such as **reward seeking**, **risk acceptance**, and **satisfaction**. One key but often overlooked component is **reference-point bias**—the evaluation of gains and losses relative to a shifting internal baseline tied to *current wealth status* [2]. To examine this, we introduced **incremental reference points** via the accumulation of *virtual tokens* leading to a **fluid jackpot reward**, and investigated their impact on behavior and **neural encoding** in the **dorsal anterior cingulate cortex (dACC)** of macaque monkeys. As tokens accumulated, trials neared jackpot completion. With higher token counts, monkeys made **faster and more accurate choices**, demonstrating **reference point-dependent behavior**. The dACC activity tracked **reward value** during offer presentation, with stronger encoding at higher token levels. In *easier trials*, where high-value options were clearer, both decision speed and reward encoding increased. These results highlight the **role of dACC** in *reward accumulation* and **reference-dependent** biases in decision-making.

Experimental Paradigm

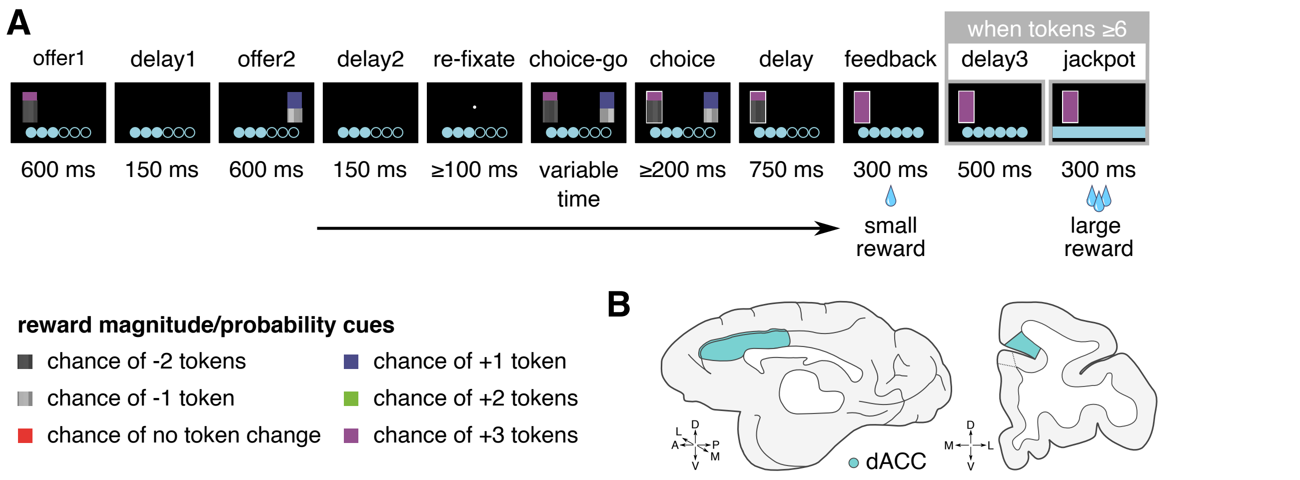

Figure 1. **A. Token-based decision-making task.** Two offers are sequentially presented (offer 1-2, 600 ms), interleaved by delays (delay 1-2, 150 ms). Subsequently, subjects re-acquire fixation to the center (re-fixate) for 100+ ms, and upon choice-go cue, they report the choice via gaze fixation for at least 200 ms (choice). A small fluid reward (100 µL) is provided in all trials. The accumulated tokens count (ATC) is displayed as initially unfilled circles, filled by tokens as they are collected. At 6 tokens count, subjects receive a "jackpot" reward (300 µL), and the count is reset. The height of the bar stimuli is informative of probability, and the color is informative of the magnitude. The probabilities color-cued by the height of top and bottom parts of the stimuli are drawn from binned uniform probability [10%, 30%, 50%, 70%, 90%]. The magnitudes included negative or positive virtual tokens [-2,-1,0,+1,+2,+3]. We included safe options where 0 or 1 tokens are achieved with 100% probability. **B. Recording sites covering the dACC.**

Reference-dependent value

Expected value

$$EV = v^t p^t + v^b p^b = v^t p^t + v^b(1-p^t)$$

Risk

$$R = (v^t - EV)^2 p^t + (v^b - EV)^2 (1-p^t)$$

Utility Function

$$u(v, ATC) = \begin{cases} [v - r(ATC)]^{\gamma(ATC)} & v \geq r(ATC) \quad \text{(gains)} \\ -\lambda(ATC)[v - r(ATC)]^{\gamma(ATC)} & v < r(ATC) \quad \text{(losses)} \end{cases},$$

$$r(ATC) = \frac{6 - ATC}{1 + e^{-\kappa_0(ATC - \kappa_1)}}, \lambda(ATC) = \lambda_0 + \lambda_1 ATC + \lambda_2 ATC^2, \gamma(ATC) = \gamma_0 + \gamma_1 ATC$$

Behavioral analyses

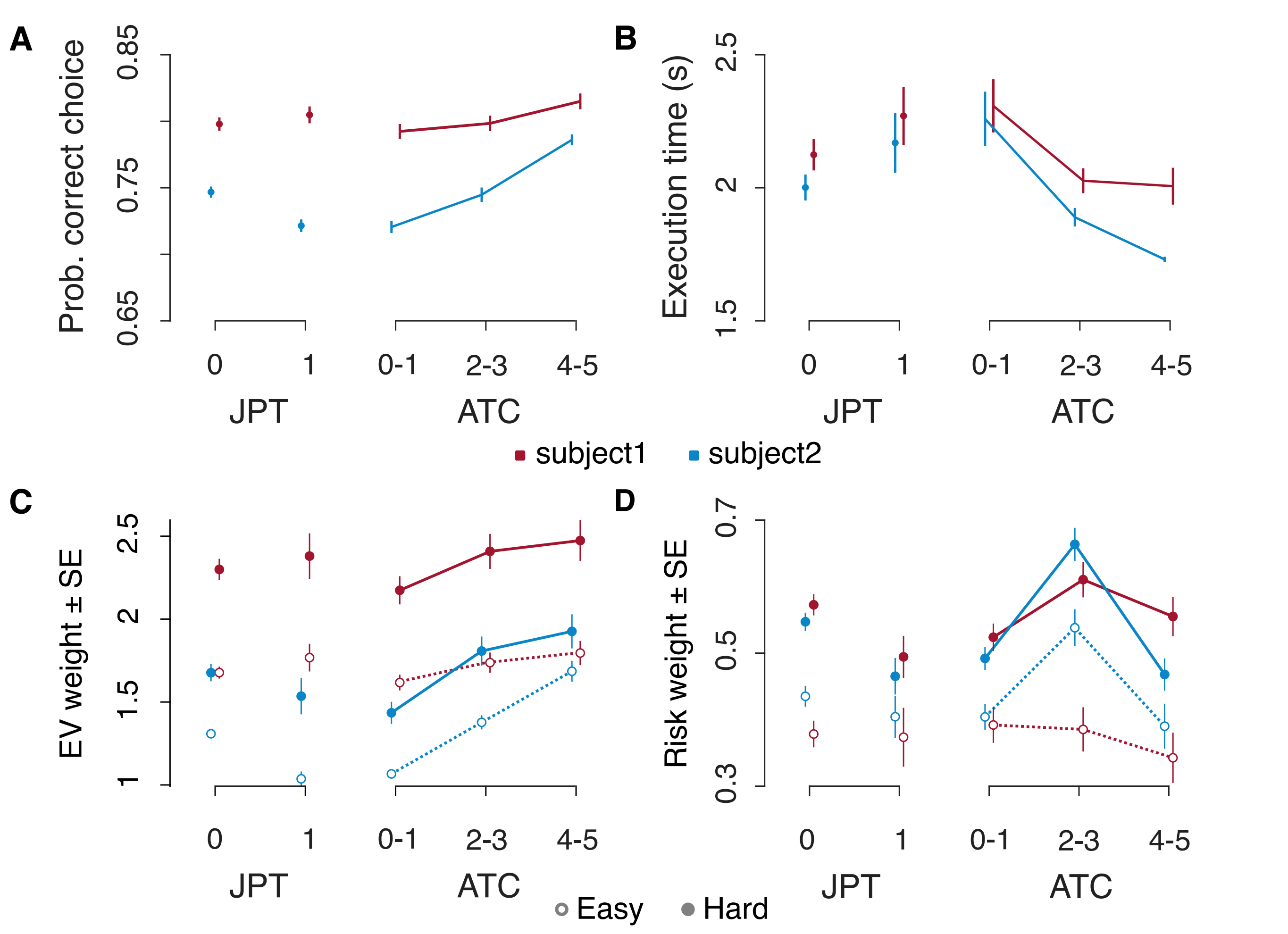

Figure 2. **A. Probability of correct choice.** Choices for the option with best EV (mean ± s.e.m.) for binned values of JPT (Jackpot on Previous Trial) and ATC (Accumulated Tokens Count) in the two subjects. **B. Trial Execution time.** Choice execution time (mean ± s.e.m.) from trial start to choice report, for JPT and ATC bins in the two subjects. **C-D. Logistic weights of EV and R.** The choice is regressed as $logit(ch = 1) = \beta_0 + \beta_1(EV_1 - EV_2) + \beta_2(R_1 - R_2)$ to compute β_1 (C) and β_2 (D) for JPT and ATC bins in the two subjects. Easy: Δ_{EV} ≥median(Δ_{EV}), Hard: Δ_{EV} <median(Δ_{EV}), where $\Delta_{EV} = |EV_1 - EV_2|$.

Neural analyses

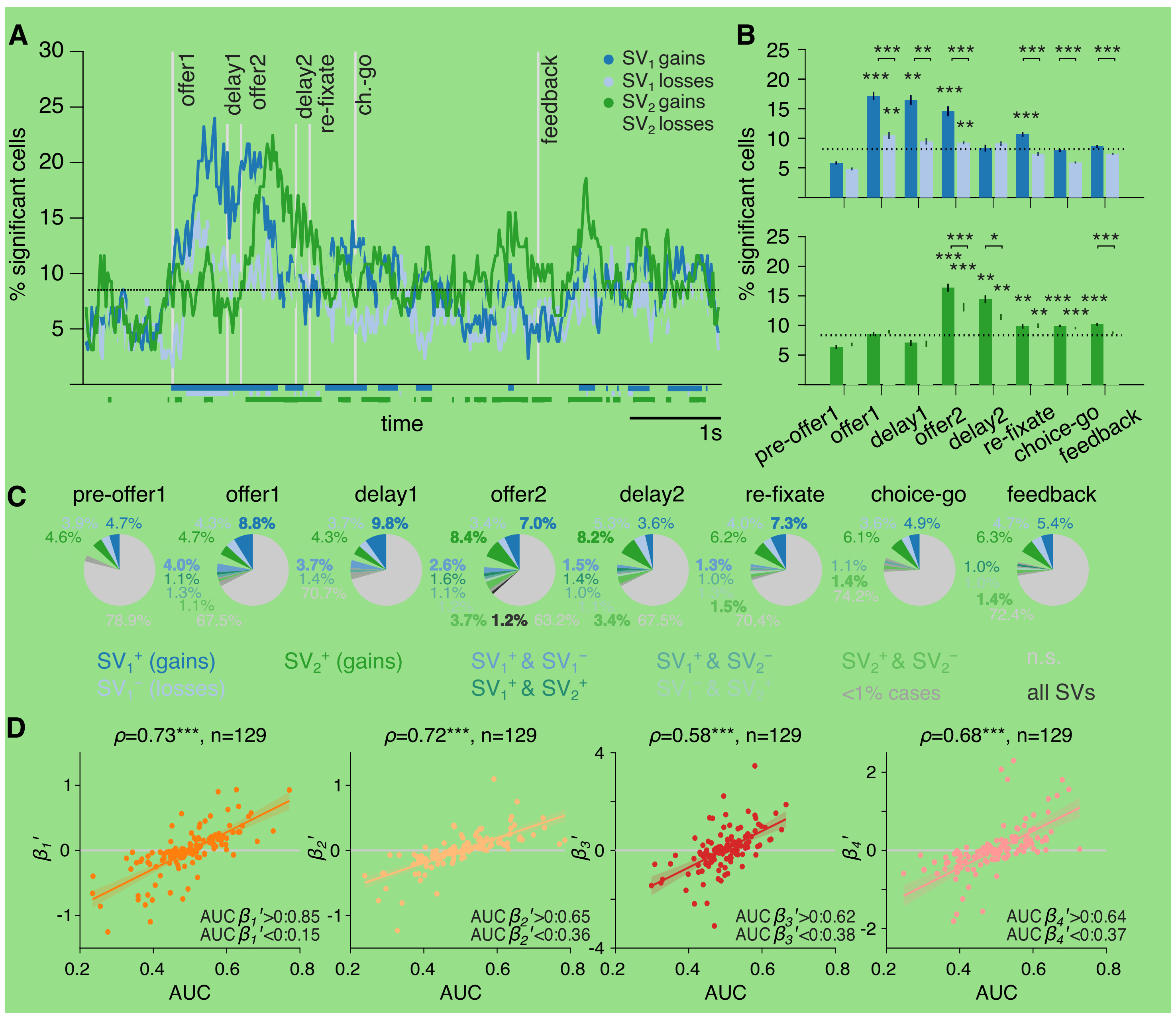

Figure 3. **A. Neural encoding of reference-dependent SVs.** Fractions of cells significantly encoding SV_1, SV_2 for gains/losses, with 95th percentile from shuffled data as baseline (dotted line). **B. Epoch-averaged fractions.** Mean ± s.e.m. of significant fractions across task epochs. One-tailed signed-rank tests compare to shuffled baseline or gains vs. losses (*p<0.05, **p<0.01, ***p<0.001). **C. Exclusive vs. simultaneous encoding.** Epoch-averaged fractions of cells encoding only one or both SVs; bold indicates significance above shuffled control. **D. Neural encoding and behavioral readout.** Correlations between spike-rate model weights (β_1'–β_4') and AUCs for choice prediction (subjects combined, n=129; ***p<0.001).

Neural encoding and behavioral readout

The Subjective Value is defined for gains (SV^+) and losses (SV^-)

$$\begin{aligned} SV^+ &= \beta_0 + \beta_1 EU^+ + \beta_2 VU^+, \\ SV^- &= \beta_0 + \beta_1 EU^- + \beta_2 VU^-, \\ EU^+ &= \mathbb{E}[u(v^t, ATC)]|_{u(v^t,ATC) \geq r(ATC)} + \mathbb{E}[u(v^b, ATC)]|_{u(v^b,ATC) \geq r(ATC)}, \\ VU^+ &= VAR[u(v^t, ATC)]|_{u(v^t,ATC) \geq r(ATC)} + VAR[u(v^b, ATC)]|_{u(v^b,ATC) \geq r(ATC)}, \\ EU^- &= \mathbb{E}[u(v^t, ATC)]|_{u(v^t,ATC) < r(ATC)} + \mathbb{E}[u(v^b, ATC)]|_{u(v^b,ATC) < r(ATC)}, \\ VU^- &= VAR[u(v^t, ATC)]|_{u(v^t,ATC) < r(ATC)} + VAR[u(v^b, ATC)]|_{u(v^b,ATC) < r(ATC)}. \end{aligned}$$

The moving-average spike-rate $\eta_k(t)$ for the k^{th} cell at each 20 ms bin t is fit to

$$\eta_k(t) = \beta_0^+(t) + \beta_1^+(t) SV_1^+ + \beta_2^+(t) SV_2^+ \quad \eta_k(t) = \beta_0^-(t) + \beta_1^-(t) SV_1^- + \beta_2^-(t) SV_2^-$$

to extract the fraction of cells significantly encoding each of the SV variables.

The Area Under the Curve (AUC) is computed by predicting choices on the product of time-average $\langle \beta(t)' \rangle$ estimated on train data as $\eta_k(t) = \beta_0'(t) + \beta_1'(t)(EU_1^+ - EU_2^+) + \beta_2'(t)(EU_1^- - EU_2^-) + \beta_3'(t)(VU_1^+ - VU_2^+) + \beta_4'(t)(VU_1^- - VU_2^-)$ and EU, VU variables from test data. Pearson's correlation is computed between cell-wise AUC and $\langle \beta'(t) \rangle$.

Results

We found that subjects made token-based decisions using a **reference-dependent strategy**, where the **number of accumulated tokens** acted as a dynamic reference point. When **jackpot attainment was possible**, choices reflected a **goal-directed comparison** to the remaining tokens needed. When the jackpot was unattainable, choices were made by selecting the option yielding the **highest expected token amount**. Closer proximity to the jackpot led to **improved performance**, marked by **higher accuracy and faster responses**. At the neural level, **gains relative to the reference** were linked to a **higher fraction of value-encoding neurons**, whose **tuning correlated more strongly with behavioral readout** analyzing choice prediction AUC and spike-rate model weights.

References

[1] Demetrio Ferro, Tyler Cash-Padgett, Maya Zhe Wang, Benjamin Y Hayden, and Rubén Moreno-Bote. Gaze-centered gating, reactivation, and reevaluation of economic value in orbitofrontal cortex. *Nature Communications*, 15(1):6163, 2024.

[2] Daniel Kahneman and Amos Tversky. Prospect theory: An analysis of decision under risk. *Econometrica*, 47(2):263–291, 1979.

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