Computational Modeling of Choice Frequency in Habitual Behavior: A Pre-Registered fMRI Study

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Abstract

Habits are integral to decision-making but can contribute to maladaptive behavior when they override goal-directed control. Previous research showed that past choice frequency influences current choice independently of reward history. However, many prior attempts to experimentally induce habitual behavior have failed to replicate (e.g., Gera et al., 2023), highlighting the need for robust behavioral paradigms. In this pre-registered fMRI study (N = 71), we aimed to replicate and extend previous behavioral findings to different behavioral situations. Moreover we aimed to investigate the neural mechanisms underlying frequency-based habitual behavior. Participants completed a modified version of the Reward Pairs task, where reward level and choice frequency were manipulated orthogonally. Behavioral data were best explained by a model combining reinforcement learning (RL) and a choice kernel (CK), confirming that both reward and choice history shape current choices. Our pre-registered univariate fMRI analyses are ongoing. So far, they revealed no significant neural correlates of RL or CK values in hypothesized regions of interest. While the behavioral findings reinforce the relevance of frequency-based habits, the neural data point to challenges in detecting their neural substrates using univariate BOLD analyses. Future work will examine whether these effects manifest through distributed neural patterns or in the functional connectivity between candidate brain regions.

Keywords: habit; decision-making; cognitive modeling; fMRI; reinforcement learning

Introduction

Habits are learned responses that operate with minimal deliberation, enabling efficient behavior under uncertainty. However, when left unchecked, they may undermine adaptive goal pursuit. Traditional accounts have attributed habit formation to stimulus-response associations arising from initial model-free reinforcement learning (RL), where action values are shaped by outcomes. Yet recent work (Nebe et al., 2024) demonstrated that choice repetition alone, captured by a reward-independent choice kernel (CK; Miller et al., 2019), can influence behavior, suggesting that habitual tendencies may emerge independently of value-based learning.

To examine the neurocomputational basis of frequency-driven habits, we conducted a pre-registered fMRI study (Fluhr et al., 2024) using a modified version of the Reward Pairs task, in which reward values and choice frequencies were manipulated independently. We hypothesized that (1) behavior would be best explained by a model integrating RL and CK mechanisms; (2) previous choice frequency would predict current choice in a test phase (with no feedback); and (3) RL and CK signals would map onto distinct neural circuits, with RL values reflected in ventral striatum and vmPFC, and CK values in dorsolateral striatum and parietal cortex.

Methods

Participants and Task Design

Seventy-one participants completed an fMRI-adapted version of the Reward Pairs task, a decision-making paradigm designed to isolate the effects of prior choice frequency (Nebe et al., 2024). The task consisted of two phases:

Learning Phase (2 blocks of 96 trials each): Participants made repeated, time-pressured choices between pairs of stimuli. Choice frequencies were experimentally manipulated independently of reward values. For example, among two stimuli associated with a reward of 7 points, one stimulus was more often paired with a stimulus providing 9 points and would therefore be chosen less frequently. By contrast, the other stimulus in the pair was more often presented with a stimulus providing 5 points and was therefore chosen more frequently. Participants received feedback for both chosen and unchosen stimuli at the end of each trial.

Test Phase (136 trials): Without feedback, participants made additional choices between the originally trained stimulus combinations, but for the first time also between pairs of stimuli with equal reward value and different choice frequencies during learning.

As compared to the original Reward Pairs task, stimulus presentation, timing, and jittered intertrial intervals were optimized for fMRI.

Behavioral Analyses

Four models were fitted to participants' choice data:

1. Random choice model.
2. RL model based on reward-driven value updates.
3. CK model capturing effects of past choice frequency.
4. Combined RL+CK model.

The RL model is based on the following Q-value update rule, based on rewards:

$$Q^k_{t+1} = Q^k_t + \alpha_q \cdot (r_t - Q^k_t)$$

While the CK model tracks choice history via the following update rule, based on actions:

$$H^k_{t+1} = H^k_t + \alpha_h \cdot (a_t - H^k_t)$$

Where:
– k: stimulus index
– t: trial index
– $\alpha_{q/h}$: learning rates for Q-values and H-values
– r_t: reward received at trial t
– a_t: action taken at trial t (1 if chosen, 0 otherwise)

In all models, choice probabilities were computed using a softmax function over the Q- and/or H-values.

Comparison of computational models was conducted with Bayesian Information Criterion (BIC). Choice data was also analyzed with a generalized linear mixed-effects model (GLME) to test the influence of past choice frequency.

Imaging

Functional data were acquired using a Philips Achieva 3T scanner. Preprocessing was done with fMRIPrep (Esteban et al., 2019) and included slice-time correction, spatial normalization, and nuisance regression (motion, CSF, WM, physiological). Trial-wise RL and CK values were used as parametric modulators in GLMs aligned to first stimulus presentation onset.

Regions of interest (ROIs) were defined a priori:

- RL signals: ventral striatum, vmPFC (Bartra et al., 2013).
- CK signals: dorsolateral striatum, parietal cortex (Guida et al., 2022).

Whole-brain exploratory analyses complemented the ROI-based approach.

Results

Behavioral Data

Comparison of computational models of choice behavior favored the RL+CK model (BIC = 481.87), outperforming RL-only (BIC = 497.48) and CK-only (BIC = 718.07) models. This suggests that participants relied on both reward learning and choice frequency. GLME analysis confirmed a significant main effect of prior choice frequency ($z = 2.875$, $p = 0.004$), replicating prior findings (Nebe et al., 2024).

Imaging Data

The ongoing pre-registered analyses so far revealed no significant effects of parametric RL or CK values at the group level in hypothesized ROIs. Exploratory whole-brain analyses at the time of the first stimulus presentation revealed no reliable clusters for either regressor at corrected thresholds.

Discussion and Conclusion

This study replicates behavioral and computational modeling evidence that both reward and choice history shape decision-making. Our univariate fMRI data so far yielded no robust neural correlates for either component in pre-registered ROIs. Frequency-based habit signals may be more distributed, subtler than anticipated, encoded as differences, or manifested through higher-order interactions not captured by univariate analyses.

Several factors may have contributed to the null results, including task timing, or the absence of incentive to compute subjective values during presentation of the first stimulus. These outcomes motivate follow-up analyses including additional parametric modulations (e.g., RL and CK difference or sum), multivariate approaches, and the investigation of functional connectivity between areas involved in value-based decision making.

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