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Research report

Neural signatures of experience-based improvements in deterministic decision-making

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HIGHLIGHTS

- Covariates derived from decision and learning models identify common neural regions.
- Feedback provides performance information monitored by a prefrontal network.
- Choice-outcome learning improves decision evidence via the basal ganglia.
- Choice-outcome learning drives a shift toward stimulus-driven decision-making.

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ABSTRACT

Feedback about our choices is a crucial part of how we gather information and learn from our environment. It provides key information about decision experiences that can be used to optimize future choices. However, our understanding of the processes through which feedback translates into improved decision-making is lacking. Using neuroimaging (fMRI) and cognitive models of decision-making and learning, we examined the influence of feedback on multiple aspects of decision processes across learning. Subjects learned correct choices to a set of 50 word pairs across eight repetitions of a concurrent discrimination task. Behavioral measures were then analyzed with both a drift-diffusion model and a reinforcement learning model. Parameter values from each were then used as fMRI regressors to identify regions whose activity fluctuates with specific cognitive processes described by the models. The patterns of intersecting neural effects across models support two main inferences about the influence of feedback on decision-making. First, frontal, anterior insular, fusiform, and caudate nucleus regions behave like performance monitors, reflecting errors in performance predictions that signal the need for changes in control over decision-making. Second, temporoparietal, supplementary motor, and putamen regions behave like mnemonic storage sites, reflecting differences in learned item values that inform optimal decision choices. As information about optimal choices is accrued, these neural systems dynamically adjust, likely shifting the burden of decision processing from controlled performance monitoring to bottom-up, stimulus-driven choice selection. Collectively, the results provide a detailed perspective on the fundamental ability to use past experiences to improve future decisions.

1. Introduction

Decision-making is fundamentally influenced by past experiences. On a daily basis, we face numerous decisions requiring us to draw upon learned information to optimize our choice selection. This underlying information is acquired through experience, often by using feedback to assess the quality of decisions. Feedback thus provides a critical link between decision outcomes and mnemonic information that influences future choices. However, the processes and neural substrates that translate feedback into improved decision-making remain poorly understood.

The present study investigated how the neural systems that process feedback can influence subsequent decision-making behavior. Specifically, we used computational models of learning and choice selection to investigate how feedback influences decision-making

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in the context of repeated choice experiences with deterministic outcomes. In such contexts, feedback from a single choice can provide sufficient information to optimize future decisions involving the same choice. For example, if a student guesses that Harrisburg is the capital of Pennsylvania and is then told this answer is correct, the student gains valuable information that may help for later choices. In practice, however, the retrieval of learned information can be faulty, so repetition is typically required to attain optimum performance. These considerations, wherein outcome feedback and choice selection are conceptually linked, suggest that feedback processing and decision-making share a common set of neural substrates. We sought to characterize these substrates using functional magnetic resonance imaging (fMRI) combined with model-informed data analysis.

This work is guided by a literature on perceptual decisions and the impact of noisy sensory input, such as in tasks wherein subjects decide whether a noisy image depicts a face or a house [33,21,80] or whether a cloud of dots with partial motion coherence is drifting leftward or rightward [70]. These perceptual decision processes are well characterized by sequential sampling models, such as the drift-diffusion model [59,61]. In this class of model, a decision-variable accumulates evidence for or against a choice—when this value reaches a threshold, a decision is executed. As one makes a perceptual choice, competing sensory evidence is evaluated until a stopping criterion is reached. This process has been conceptually mapped onto physiological measures, wherein the firing rate of neurons modulates in a manner analogous to parameters within drift-diffusion models [31,70,60,64,27]. Parallel neuroimaging work in humans has identified fMRI signatures of comparable processes [54,55,90,39,40] and connected these signatures directly to drift-diffusion parameters [7,80]. Thus, the processes encapsulated by drift-diffusion models are neurally plausible and carry specific cognitive interpretations for underlying neural correlates based on past work.

Importantly, under the drift-diffusion framework, the source of information to be evaluated for a decision can derive from any of a number of systems (e.g., sensory, memory, etc.). Since the underlying information being evaluated is the distinguishing characteristic of mnemonic versus perceptual decisions, the predictions of drift-diffusion models should hold for decisions wherein evidence is based on information gathered from experience. To support this extension, Yang and Shadlen [95] trained monkeys to associate shapes with reward probabilities, and using a modified weather prediction task, linked changes in the firing rates of parietal neurons to the integration of probabilistic decision evidence acquired from training. In humans, Wheeler and colleagues [91] demonstrated similar modulations of fMRI activity in occipital, temporal, and parietal regions that corresponded to sequences of presented probabilistic evidence. In both cases, decision evidence derived directly from arbitrary stimulus-response associations acquired through learning, supporting the link between drift-diffusion principles and decision-making in non-perceptual domains. On top of this, Frank et al. [23] offered a direct connection by showing that changes in estimates of outcome reward (via probabilistic reinforcement learning) correlated with changes in model-estimated decision thresholds and that this relationship could be traced to activity in thalamic and medial frontal regions. The study's approach, however, focused on specific cortico-striatal connections and did not directly consider the broader influence of feedback on decision processes or a feedback-based learning framework. Taken together, key findings from simple perceptual decisions seem to translate to the mnemonic domain, but the larger intersection between memory and decision-making remains unclear.

One fundamental unknown is how feedback influences decision-making processes and improves later behavior. This is especially applicable for deterministic or quasi-deterministic decisions, where the available choices always or nearly always produce the same outcome. Tricomi and Fiez [82,83] made progress on this front by examining decision-making across multiple rounds of a paired-associate learning task. They found that feedback influenced both explicit and implicit memory, which together seemed to drive learning and subsequent decision-making. However, the Tricomi and Fiez work did not consider model-based connections between behavioral and neuroimaging data, and therefore could not draw inferences in the context of computationally defined feedback and decision-making processes.

The current study takes this next step by investigating the influence of feedback on decision processes during a concurrent discrimination learning task. In this task, subjects are presented with a pair of items, wherein one is arbitrarily designated as the correct choice, and the other as incorrect. After selecting an item, subjects see feedback that indicates the value of the choice (i.e., a correct or incorrect choice). With repeated experience of the items, subjects accrue mnemonic information and gain proficiency in making correct choices. At the same time, subjects could also accrue all of the mnemonic information necessary for perfect performance from a single decision experience. Thus, concurrent discrimination offers a meaningful framework with which to study how the encoding and accrual of past experiences translate into improved decision-making.

To capture these feedback-based learning influences, we implemented a reinforcement learning model alongside the drift-diffusion model. Reinforcement learning describes how a history of outcomes, built up for individual choices, creates a prediction of an outcome's value that can be used to drive choice selection. Errors between the expected versus observed outcomes (reward prediction error, RPE) are used to adjust the expected value of a choice (EV) toward a more accurate representation of the actual result. Thus, measures derived from reinforcement learning can explain aspects of feedback processing in terms of a learning signal (RPE) and the consequence of that learning (EV). Neurally, these signals have been shown to be distinct and separable: in the context of probabilistic learning, each signal tends to localize to different areas, such as sub-regions of the basal ganglia and orbitofrontal cortex [66,67]. In the case of deterministic learning, such as concurrent discrimination, reinforcement learning should be equally applicable. In an extreme case, where mnemonic encoding and retrieval processes are entirely noise-free, the RPE signal from an initial choice should drive sufficient learning to ensure optimal choice selection for a future episode. Reinforcement learning can capture this type of single-trial learning, such that the initial RPE updates the EV to ensure future accuracy. While deterministic learning can be plausibly captured by reinforcement learning models, the extent to which estimates of RPE and EV exhibit the same neural localization and dissociations compared to probabilistic choice learning remains an open question. Regardless, like the drift-diffusion model, reinforcement learning has a set of distinct cognitive predictions that correspond to a set of distinct neural correlates.

Thus, the two models each describe aspects of learning and decision-making that, when combined, could offer unique leverage for understanding how feedback influences decision-making behavior, and how this influence is implemented neurally. The drift-diffusion model describes how information is evaluated to drive decision-making, whereas reinforcement learning describes how feedback shapes that information. As such, each model can distinguish between performance-related effects (e.g., boundary in the diffusion model and RPE in reinforcement learning) and evidence-related effects (e.g., drift-rate in the diffusion model and EV in reinforcement learning). When applied to neural data, these two models can be leveraged to identify regions associated with performance and evidence monitoring, versus regions that provide evidence to decision-making processes.