Eye-tracking based Bayesian inference for adaptive decision making and planning processes in a dynamic environment

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Abstract:

In dynamically evolving environments, effective planning is crucial for guiding decisions toward optimal goals and adjusting them as conditions change. However, the underlying neurocognitive mechanisms of planning remain elusive, as these processes are not directly observable through behavior. Previous studies have largely focused on simplified decision-making tasks, often limited to static environments or single-goal scenarios. Here, we introduce a novel arithmetic paradigm that requires multi-step planning and flexible goal switching in a dynamic, multi-goal context. Using eye tracking data, we estimated the utility of each goal and modeled goal switching in real time using a Bayesian framework, capturing individual differences in how participants integrate new information into decisions. High-performing participants were more likely to adjust their choices based on updated utilities and engaged in forward planning when initial plans became infeasible. Moreover, model-derived goal switching probabilities reliably predicted activity in brain regions associated with reward processing and value-based decision-making. These findings suggest that adaptive goal switching is supported by neurocognitive processes that continuously track the evolving utility of multiple goals.

Keywords: Eye-tracking, Bayesian, Adaptive decision-making, Planning, Dynamic environment

Introduction

Adaptive decision-making is fundamental to higher cognitive processes, requiring the continuous updating of goals and plans in response to environmental changes (Hunt et al., 2021; De Martino et al., 2023). However, previous studies have primarily examined the formation of single plans within a stable environment (Callaway et al., 2022) and pursuit of fixed goals (van Opheusden et al., 2023). Moreover, most decision-making research has focused on planning as an end-to-end process (Matter et al., 2022; Eluchans et al., 2023), often overlooking the moment-by-moment formation and updating of plans and decisions (Gordon et al., 2025).

In this study, we developed a novel arithmetic task that requires adaptive decision-making and real-time planning. We implemented an eye-tracking-based Bayesian model that predicts adaptive goal switching from participants' eye-gaze patterns, allowing us to capture shifts in internal utility estimates that occur dynamically over time in changing environments.

We hypothesized that high-performing participants would more effectively integrate available information, leading to more accurate adaptive goal switching. Furthermore, we predicted that fluctuation in model-estimated goal-switching probabilities would correlate with neural activation in the reward- and value-related regions, including the medial prefrontal cortex (mPFC), anterior cingulate cortex (ACC), nucleus accumbens (NAcc), and insular.

Methods

Task design

Participants (N=58) performed a novel calculation task in an fMRI scanner. On each trial, they selected three numbers and two operators from items on the screen to formulate valid equations that matched one of two predefined target numbers (Fig. 1). Each trial was divided into two stages: planning and execution. During the planning stage, participants were given 60 seconds to generate and report up to three plans. In the subsequent execution stage, they selected items sequentially to implement their chosen plan. However, after each selection, the values of unselected number items changed with a probability of 0.35. Following each number change, participants were given 4 seconds to observe the new state and reported which target number they were currently pursuing. The penalty for each trial was defined as the difference between the selected target at the final step and the output of the constructed equation. Overall task performance was calculated as the inverse of the cumulative penalty across 32 trials.

Task goal: Use three numbers and two operators to approximate one of two target numbers as closely as possible.

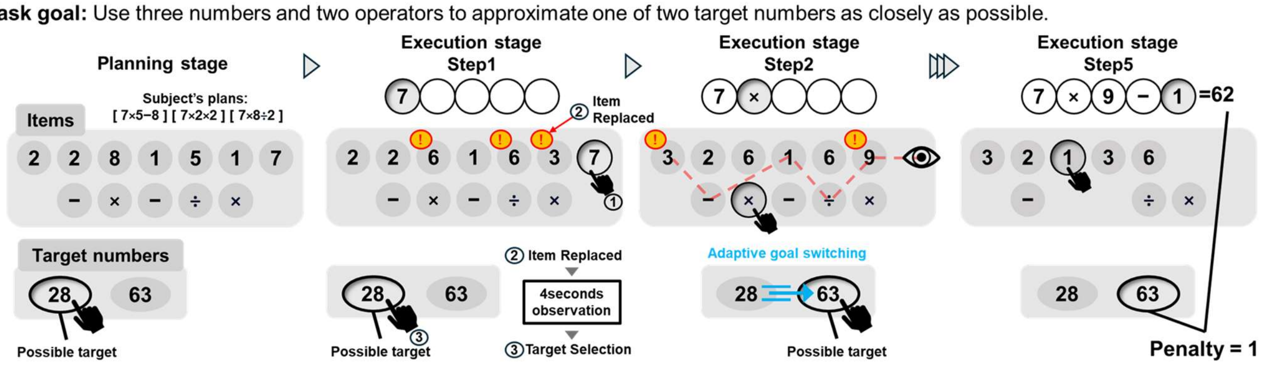

Figure 1. **Task Design.** Participants were presented with seven numbers, five operators, and two target numbers. They reported up to three plans to reach one of the targets. During the execution stage comprised five steps, participants could no longer view their previous plans. At each step, unselected number items were randomly changed, and participants observed the new items for 4s, followed by 2s to select which target to pursue. The penalty for each trial was defined as the difference between the final selected target and the output of their equation.

Eye-tracking based Bayesian model

To predict adaptive goal switching, we developed a Bayesian inference model using eye movement data (N=37) recorded during the task (60Hz video). Before each item replacement, the target number selected in the previous step was treated as the prior belief (Fig. 2.A left). The likelihood was derived from the computed utility for each target based on participants' fixations on number items (excluding the target number) during the observation period (Fig. 2.A. middle). The utility was computed as the minimum penalty across all possible equations involving each fixated number item—calculated for each target and its position in the equation (2nd or 3rd: Fig. 2.B). The posterior belief was defined as updated beliefs after the item replacement (Fig. 2.A right). Both prior and posterior beliefs were modeled as beta distributions, updated with each fixation. We optimized two learning rate parameters (w1, w2 in Fig 2.B) for each participant using a grid search algorithm. Model performance was assessed using leave-one-trial-out cross-validation, evaluating how accurately the posterior probability predicted participants' actual switching decisions.

To examine how participants' real-time goal utility computation is represented in brain activity, we conducted parametric GLM analysis using the probability of selecting an alternative target (switching probability) over the 4-second observation period as a regressor (Fig. 2.C, *P(alternative target)*).

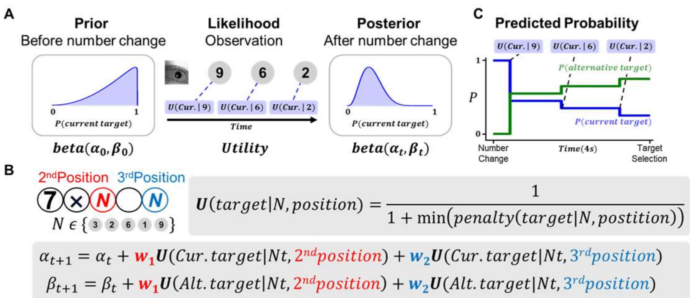

Figure 2. A. Adaptive goal switching was modeled using a Bayesian framework, where the prior belief about the current target utility, $U(target)$, was updated based on the likelihood derived from fixated items (N_t). This yielded a posterior beta distribution, capturing belief updates over time. **B.** Utility was defined by the penalty incurred for each target given the fixated number. This utility varies depending on the fixated number's position in the equation with unique learning rate parameters. The coefficients α and β indicate inferred probabilities of selecting the current vs. alternative target, respectively. **C.** The model predicted the probability of selecting each target based on real-time utility estimates, with the posterior probability serving as the model's prediction of participants' target selection.

Results

We focused our analysis on execution step 2, a critical decision point where items changed, yet participants could still adjust their plans (Fig.1). Task performance was significantly correlated with participants switching their target only when the utility for the current target had been diminished (Fig 3.A, R= 0.28, p=0.046). This finding suggests that accurate computation of the relative utility associated with each target number is essential for adaptive behavior.

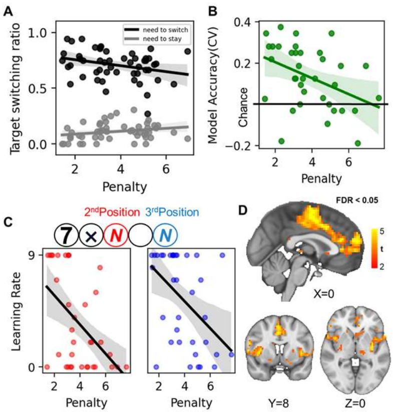

Figure 3. A. High-performing participants selectively switched targets when the utility of the current target was low, and maintained their selection when it remained high. **B.** Our Bayseian model outperformed chance in predicting target selection, correlating with the participants' task performance. **C.** Learning rates for both the 2nd and 3rd number positions positively correlated with task performance. **D.** A parametric GLM analysis showed that model-derived goal-switching probabilities were represented in the mPFC, ACC, NAcc, and insula.

The eye-tracking-based Bayesian model performed significantly above chance level, with its accuracy positively correlated with participants' task performance (Fig 3.B; R=0.41, p=0.012). Moreover, both learning rates used to update the likelihood in the Bayesian inference showed significant positive correlations with performance (Fig 3.C; left: R=0.50, p=0.002, right; R=0.47, p=0.003). Notably, these correlations emerged only when participants' initial plans became invalid due to number changes. The positive correlation for the learning rate of the number at the 3rd position suggests that, when adaptive decision-making was required, high-performing participants engaged in strategic forward planning, integrating utility information up to the final step in the equation to select the optimal target.

Furthermore, parametric GLM analyses revealed that neural activity in mPFC, ACC, NAcc, and insular tracked fluctuations in the model-estimated goal-switching probabilities (Fig 3. D, FDR<0.05). This suggests that these brain regions are involved in continuously evaluating the need for adaptive goal switching based on dynamic utility estimates. These individual differences in behavior and neural activity were only observed at step 2.

Conclusion

We introduced a novel sequential planning and decision-making paradigm that provides insight into adaptive behavior in dynamic environments. Using an eye-tracking-based Bayesian model, we characterized goal-switching behavior and found that high-performing participants effectively monitored goal utility and flexibly adjusted their plans in real time. Neural activation in the mPFC, ACC, NAcc, and insula tracked fluctuations in model-predicted goal-switching probability, highlighting their role in adaptive planning and decision-making.

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