Age-related differences in structure learning drive foraging behavior in a multimodal patch-leaving task

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Abstract

Prior work has shown that older adults exhibit reduced exploratory tendencies relative to younger adults (Chin et al., 2015; Wiegand & Wolfe, 2021; Wolpe et al., 2025). Explanations for this pattern include that older adults' choices are less sensitive to underlying reward values (Noh et al., 2023), are simply more "noisy," or overly sensitive to uncertainty (Mata et al., 2013). Recently, the idea that over-exploitation reflects suboptimal choice processes has been called into question by a series of studies that examine how exploration relates to learning environment structure (Harhen & Bornstein, 2023; Harhen et al., 2026; Zhang et al., 2026). A prediction that follows from this line of work is that older adult decisions reflect differences in learning and memory, rather than decision strategies (Noh et al., 2023, 2026b, 2026a). We examined this hypothesis using a sequential patch leaving task with multiple patch types. We fit a computational model that distinguished latent learning from uncertainty-adaptive reward sensitivity. Across 111 participants (53 older, 58 younger), we found that older adults were less likely to overharvest relative to younger adults. Critically, older adult behavior was best explained by a model that lacked sensitivity to latent structure. These findings suggest that age-differences in exploration may be due to an inability to distinguish between options of varying rewards.

Introduction

In standard patch-leaving tasks, humans generally choose to stay in a patch longer than is mathematically optimal as described by the Marginal Value Theorem (MVT) (Charnov, 1976).

Notably, though older adults overharvest even more (Mata et al., 2013), they can still adjust their foraging strategy in response to different task characteristics (Mata et al., 2009), which may suggest that the tendency to overstay is not due to poor decision-making but rather to learning and memory differences in this population (Noh et al., 2026a). Previous studies that showed overstaying behavior (Chin et al., 2015; Wiegand & Wolfe, 2021; Wolpe et al., 2025) did not include a latent environment structure; variable patch types (i.e., variable reward distributions) were either not present (Wiegand & Wolfe, 2021), determined pseudo-randomly (Wolpe et al., 2025), or the choice of patch type was determined by the forager themselves (Chin et al., 2015), making it difficult to assess the role of learning and memory in patch-leaving tasks. Thus, we implemented a patch leaving task with a latent environment structure to examine the hypothesis that older adult behavior differs from younger adults due to a reduced capacity for structure learning.

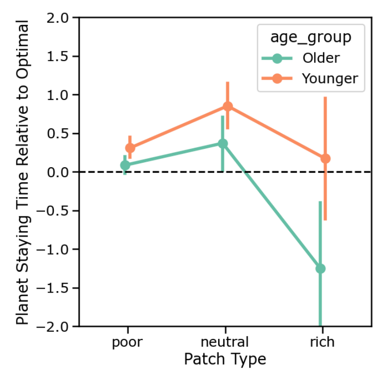

Figure 1: Planet residence time (PRT) relative to Marginal Value Theorem (MVT)

Materials and Methods

Patch-leaving Task We adopted a patch leaving task with multiple patch types, (Figure 2), to assess people's ability to learn structure in their environment (Harhen & Bornstein, 2023). 111 participants (53 older adults, ages 65-83; 58 younger, ages 18-35) across four 7-minute blocks, were instructed to maximize collected treasure by deciding whether to stay, earning immediate but depleting rewards, or leave, incurring a time cost to reach a new (undepleted) patch. For each new planet, depletion rate was sampled from a beta distribution centered on planet type: poor, neutral, or rich, with means of 0.2, 0.5, and 0.8, respectively (Figure 2b). As in naturalistic environments, transitions were more likely to lead to a planet of the same type (Figure 2c).

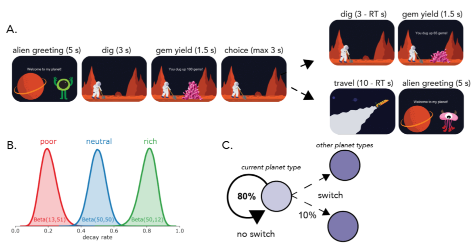

Figure 2: Patch-Leaving Task. (a) A series of stay-leave decisions (b) Each planet type has a unique decay rate distribution, where the poor, neutral, and rich planet types sample from means at 0.2, 0.5, and 0.8, respectively. (c) Displays transition probabilities between planets, where for each leave trial there is an 80 percent chance of seeing the same planet type.

Adaptive Discounting Model We applied a computational model that captures two factors absent from single-patch foraging: structure learning and uncertainty-sensitive adaptive discounting (Harhen & Bornstein, 2023; Harhen et al., 2026; Zhang et al., 2026). Structure learning was modeled as an *infinite mixture model* classifying the current patch type based on observed rewards and prior beliefs about underlying structure, controlled by a structure sensitivity parameter α (Equation 1). We fit the model using two fixed alpha values: 0 and 0.2. $\alpha = 0$ assumes no new planet types are inferred, and thus no structure learning or uncertainty-adaptive discounting. In contrast, $\alpha = 0.2$ (α^*) allows for structure learning and was chosen because it most often recovered the true underlying structure (Harhen et al., 2026).

$$P(k) = \begin{cases} \frac{n_k}{N+\alpha} & \text{if k is old} \\ \\ \frac{\alpha}{N+\alpha} & \text{if k is new} \end{cases} \tag{1}$$

Then, the entropy of this classification decision (U) factors into the discounting rate of future rewards: higher uncertainty of the patch type results in more discounting. Within this discounting computation, there are two free parameters, γ_{base} and γ_{coef}: prior discounting without uncertainty and the influence of uncertainty on discounting, respectively (Equation 2).

$$\gamma_{effective} = \frac{1}{1 + e^{-(\gamma_{\text{base}} + \gamma_{\text{coef}} * U)}} \tag{2}$$

Protected Exceedance Probabilities We used Bayesian model selection (BMS) to determine which model best fit each age group (Stephan et al., 2009). Specifically, we compared models on the basis of the *protected exceedance probabilities* (PXP) of each model for each age group (Rigoux et al., 2014).

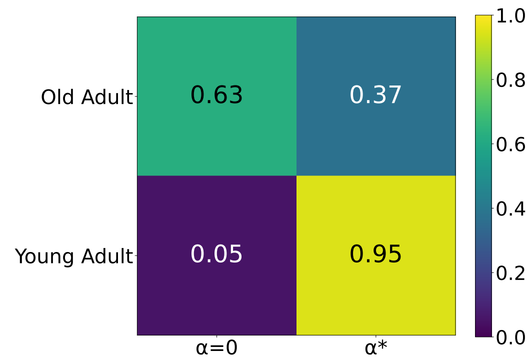

Figure 3: Protected exceedance probabilities of model likelihoods by age group. The $\alpha = 0$ model does not account for structure learning, whereas the α^* model does.

Results

Older adults were better fit by the $\alpha = 0$ model (PXP=0.63 vs. 0.37), implying that they perform minimal amounts of structure learning during the task, despite the latent environment structure. In contrast, younger adults are overwhelmingly better fit by the α^* model (0.95 vs. 0.05).

Discussion

We find that older adults' behavior in a patch foraging task is consistent with deficits in structure learning relative to younger adults. Specifically, older adults more often fail to distinguish patches of differing reward values, as demonstrated by a starkly different value of the structure sensitivity parameter (α). However, older adults did not differ in their use of the reward information to make decisions. Older adults may have different information encoding and maintenance costs, leading to a preference for a simplified representation of the environment (Zhou & Bornstein, 2024; Zhou et al., 2025).

The trends observed in older adults mirror previous research done by Harhen et al. (2026), in which children (8-12 y/o) show reduced capacities for structure learning.

This behavior could arise from a distinct mechanism compared to younger adults, who may represent the environment more simply due to a prior for simplicity. Future work should examine neurological and cognitive correlates of age-related differences in environment representation.

Acknowledgements

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