FIBRE BRAG Pilot Grant Proposal: Uncertainty in sequential patch-foraging across the lifespan

SIGNIFICANCE. Sequential decision making is ubiquitous in everyday life. Specifically, many choices humans make, whether as menial as deciding a restaurant to go to or as important as moving on to a new job, are based on the outcomes of previous, similar decisions. However, as humans progress through the lifespan, decision-making changes in distinct ways. Older adults often defer and delegate making decisions (Löckenhoff, 2019), or frame their choices around what is personally relevant (Hess et al., 2013) and less complex (Mata et al., 2007). More recently, differences in decision making for older adults have been attributed to deficits in learning and memory (Noh et al., 2023; Noh et al., 2026a). In line with this framework, we have recently shown that decisions in a sequential patch foraging task show fundamental differences across the lifespan, with older adult differences in decision making being explained by less structure learning (Chen et al., *under review*), mirroring in reverse the development of structure learning seen in children and adolescents (Harhen et al., 2026). However, it is unknown how differences in sequential decision making behavior are reflected in the brain, and specifically how neural representations of structure learning differ in aging. Here, we propose to examine this question using a novel model-based fMRI analysis approach that incorporates environmental uncertainty and structure learning in patch foraging decision making. If accepted, this study will help us better understand the reason behind systematic deviations in sequential choice behavior across the lifespan.

AIM 1: Determine the influence of uncertainty in state space learning during sequential decisions

***Premise*.** Sequential decision making has been studied under the framework of *patch-foraging*, where in order to make an optimal decision, humans are tasked with following the *Marginal Value Theorem (MVT)* (Charnov, 1976). The marginal value theorem, in short, asserts the correct time to leave a patch, such as a preferred restaurant or current company, is when the local reward rate diminishes below the global reward rate. While optimal, humans tend to overharvest (Harhen & Bornstein, 2023), or stay at a patch longer than the MVT would suggest, raising questions as to why humans consistently differ from the optimal solution. We posit that this systematic overstaying is a result of *environmental uncertainty*, and what seems like suboptimal behavior is instead rational state space learning. Our experiment tests this hypothesis by creating a patch foraging environment with a hidden but learnable state space; participants, in turn, would need to learn their environment and decrease their uncertainty through repeated sequential decisions.

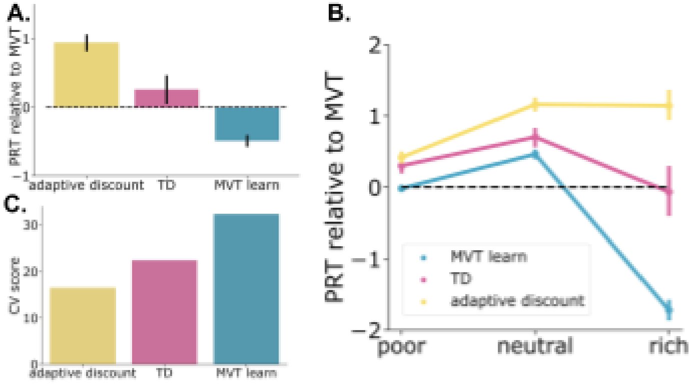

Figure 1. Adaptive discounting model compared to traditional MVT model and an adjacent model-free temporal discounting (TD) model. (A) Adaptive discounting shows more overharvesting compared to the comparison models, as well as (B) across each patch type. (C) Adaptive discounting model best fits participant data (n=117) compared to comparison models.

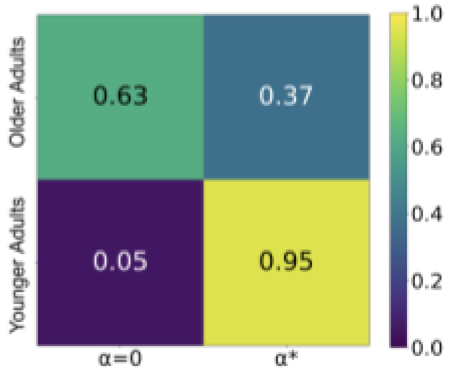

Figure 2. Protected exceedance probabilities of model likelihoods by age group. The α = 0 model does not account for structure learning, whereas the α^* (optimal) model does.

***What we know*.** As described in Harhen & Bornstein (2023), we created an uncertainty-weighted adaptive discounting model to represent participant choice in this task. In this model, we (1) utilize a Chinese Restaurant Process (CRP) to determine the number of clusters: The probability of a state belonging to a new cluster is proportional to our structure learning parameter (α). Also, (2) specific stay/leave decisions are modulated by a trial-by-trial uncertainty (U), where U is proportional to the expected value of staying on a current patch. We find that this model better reflects participant data (n=117; online) compared to the traditional MVT model as well as other model-free reinforcement learning models (temporal discounting) (Fig. 1C), and better accounts for participant overharvesting in different planet types (Fig. 1A, 1B). Additionally, younger adults (n=58; in-person) are better fit to the version of this model that accounts for optimal structure learning (α*) than one without any (Fig. 2B), highlighting that cognitively healthy adults tend to adaptively learn their state space when making sequential decisions (Chen et al., *under review*). Older adults, on the other hand, were found to be best fit by the model with no structure learning (Fig. 2), potentially explaining why older adults were not found to overharvest to the same degree as younger adults (ibid). This creates a testable question: does a lack of state space learning in later life drive observed differences in harvesting behavior? Neurally, patch foraging has been associated with activity in the dorsal anterior cingulate cortex (dACC), with monkey studies showing that the firing of dACC neurons predicts patch-leave behaviors (Hayden et al., 2011). Similar findings have been shown in humans (Kolling et al., 2012; Shenav et al., 2014), but existing neural studies of foraging do not account for representational uncertainty and how that may guide human behavior. This is especially significant because uncertainty during reinforcement learning has also been associated with ACC and prefrontal cortex (PFC) activity (Rushworth & Beherens, 2008), providing evidence that these two systems might be interconnected.

***What we don't know*. How does patch uncertainty modulate dACC activity during stay/leave sequential decisions?** It is unclear how the dorsal anterior cingulate cortex interacts with foraging uncertainty, and whether its neural activity is correlated with trial-by-trial uncertainty. If it has to do with environmental uncertainty, we expect to see age-differences in dACC activation as well. **How does patch overharvesting as a function of rational structure learning impact the neural circuits involved in foraging decisions?** Although ACC activity seems to reflect patch-leaving (Kolling et al., 2012), forward planning and structure learning reflect vmPFC activity (Benoit et al., 2014) as well as fronto-temporal neural circuits (Andersen & Cui, 2009). Utilizing our adaptive uncertainty-based model allows us to determine the magnitude of one's planning horizon as a function of their uncertainty. **How are differences in state space learning reflected in neural activity when foraging?** Given the robust age-related differences in optimal structure learning (Chen et al., *under review*), we expect distinct neural activity when the two age groups make sequential decisions.

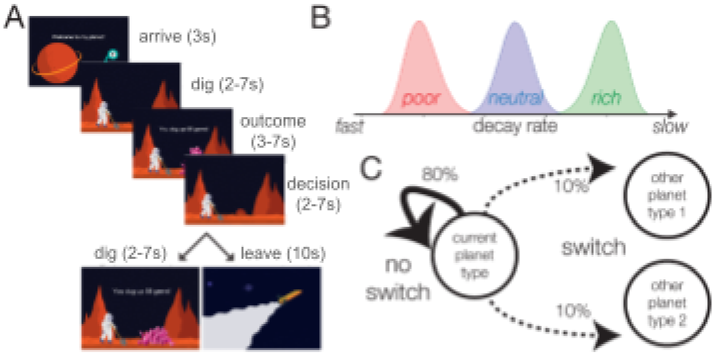

Figure 3. Structured foraging task from (Harhen & Bornstein 2023). (A) Task structure for patch-foraging task. (B) Decay rate for each planet type. (C) Transition distribution for each planet type.

TASK DESIGN. **Structured patch foraging task**. Participants travel to different planets and mine for space gems across 4 ~7-minute blocks. On each trial, participants decide between staying to dig from a depleting gem mine or incurring a time cost to travel to a new planet (Fig. 3A). Reward outcome and decision are jittered using an exponential transform, with both jitters centered at 4 seconds. **Environment Structure.** Planets vary in their richness (the rate at which they exponentially decay with each dig) (Fig. 3B). There are 3 planet types: poor, neutral, and rich, which differ in decay rates. **Environment dynamics.** A new planet has an 80% probability of being the same type as the prior planet ("no switch"), and a 20% probability of being of a different type (Fig. 3C). Upon leaving a patch, there was an 80% chance of the participant transitioning to a patch of the same type. Critically, this structure is not conveyed to participants, requiring them to infer it from experience. Our prior work (Harhen & Bornstein, 2023) suggests that individuals follow optimal strategies and adapt their planning depth (how many steps they look ahead when estimating the value of staying and leaving) to their uncertainty about the number of patch types in the environment.

ANALYSIS. Measure how representational uncertainty maps onto ACC activity during foraging. According to our adaptive discounting model, uncertainty (U) is calculated per participant at the trial level. We plan to run a first-level parametric modulation to see how brain activity, specifically in the dACC and vmPFC, varies as a function of environmental uncertainty. Our model suggests that planning horizons broaden as participants get more certain about their patch type (Harhen & Bornstein, 2023), so we expect to evaluate other planning networks in this first level analysis. **Evaluate functional connectivity of frontotemporal networks during state space learning.** While we expect to see ACC activity during foraging per prior literature (Hayden et al., 2011; Kolling et al., 2012), our infinite mixture model suggests participants engage in adaptive structure learning, providing evidence of potential interactions between the two networks. Crucially, we would expect to only see this interaction in younger adults, highlighting that age-related differences in harvesting can be explained by differences in planning. **Model-based representational similarity analysis.** In order to evaluate if patches are clustered according to patch type, we plan to run an RSA on initial planet decay trials to see how they are represented in both structure and non-structure learners. Structure learners should progressively develop differentiable representations, in correspondence with the uncertainty predicted by our model.

PARTICIPANTS AND FUNDING. We will recruit 25 healthy adult participants, 13 between the age range of 18-35 and 12 above the age of 65. We will ensure every participant is cognitively normal (neuropsychological tests in the age-expected range), in good health (no major medical conditions), and free of MRI contraindications. While 25 participants will not be enough to achieve our final target power, it will provide us with a pilot analysis to motivate future funding. We budget 1 hour scanning sessions for each participant, which at the current rate of $600/hr would cost $15000.

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