Supplementary Materials

September 30, 2025

1 Methods

1.1 Instructions

The instructions and the instruction comprehension quiz can be found at the following link: `https://github.com/noraharhen/Harhen-Budiono-Hartley-Bornstein-2025-Foraging/blob/main/run_exp/foraging_instructions.pdf`

1.2 Identifying α^*

We sought to compare the α=0 model, which assumes all planets belong to a single type, with a model that would acquire a veridical representation of the environment. To identify the value of α that would most likely yield a veridical representation of the environment, we performed a grid search over α values, from 0 to 2, in increments of 0.1. For each α value, we simulated 1,000 datasets, across a range of other model parameters. Specifically, γ_{base}, γ_{coef}, β were uniformly drawn within the bounds detailed in Table S1, while ϵ was fixed at 0.01. We found that α=0.2 produced the greatest proportion of datasets with a veridical representation of the environment.

To verify that the task structure did not incentivize use of one model over the other, we compared the total rewards earned by the α=0 and the α=0.2, or α^*, model across the 1,000 simulated datasets. The reward distributions were largely similar, with the α=0 model earning an average total reward only 1.13% more than the α^* model (α=0: 8831.59 gems, α^*: 8733.32 gems).

1.3 Model and parameter recovery

To determine the recoverability of the two models and their parameters, we simulated datasets for 500 participants under each model. Temporal discounting parameters, γ_{base} and γ_{coef}, as well as the inverse softmax temperature, β, were uniformly sampled within the bounds specified in Table S1. Given that higher lapse rates (ϵ) result in increasingly random behavior, ϵ was sampled from a narrower range, between 0 and 0.1. We restricted the range of ϵ because both model and parameter recovery were expected to be poor for lapse rates exceeding the upper bound. Each simulated dataset was fit to both models using the same procedure used for the empirical data.

For each simulating model, we evaluated model identifiability by examining the proportion of participants best fit by each model and the most frequent best-fitting model within the group based on protected exceedance probabilities (PXP). Model identifiability was strong (Fig 1): the true, simulating model was identified as the best-fitting model for the majority of simulated participants (α=0: 73%, α^*: 89%), and as the most frequent best-fitting model for the group, according to protected exceedance probabilities (both PXPs = 1).

To evaluate parameter recoverability, we examined the Spearman correlation between the parameters used to simulate the data , and the parameters identified by our fitting procedure. For both models, recoverability varied across parameters (Fig 2). For datasets generated by the α^* model, γ_{base} showed good recoverability (ρ=0.77),

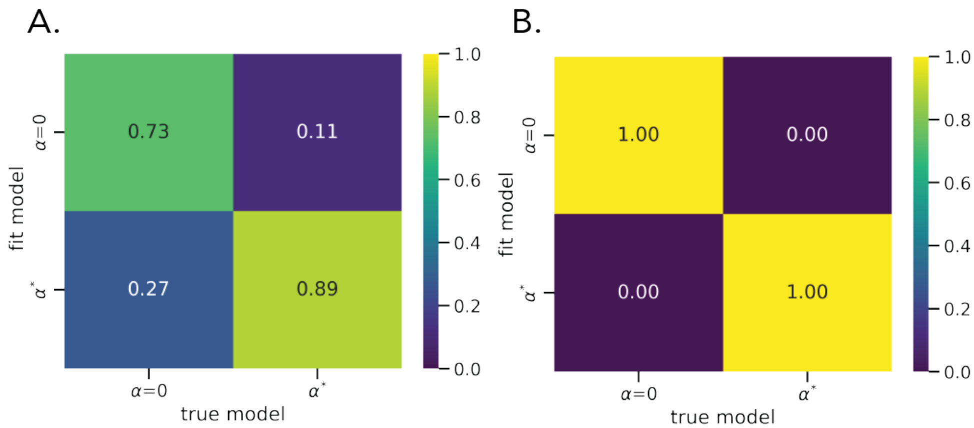

Figure 1: **Model recovery results. A.** Confusion matrix showing the proportion of simulated datasets best fit by the two models. **B**. Confusion matrix showing the protected exceedance probabilities for each pair of simulated and fit models. Across the datasets, the most frequent, best-fitting model matches the model that was used to simulate the data.

Model	Parameter	Bounds
α^*	γ_{base}	-10,10
	γ_{coef}	-3,3
	β	0,5
	ϵ	0,1
α=0	γ_{base}	-10,10
	β	0,5
	ϵ	0,1

Table 1: Bounds for parameters in each model.

while γ_{coef}, β, and ϵ showed moderate recoverability (γ_{coef}: ρ=0.68; β: ρ=0.64; ϵ:ρ=0.64). The α=0 showed a similar pattern of recovery to the α^* model, but achieved had slightly better recovery overall, likely due to having fewer parameters. For the datasets generated by the α=0 model, γ_{base} showed good recoverability (ρ=0.85), while β, and ϵ both showed moderate recoverability (β: ρ=0.74; ϵ:ρ=0.66).

2 Results

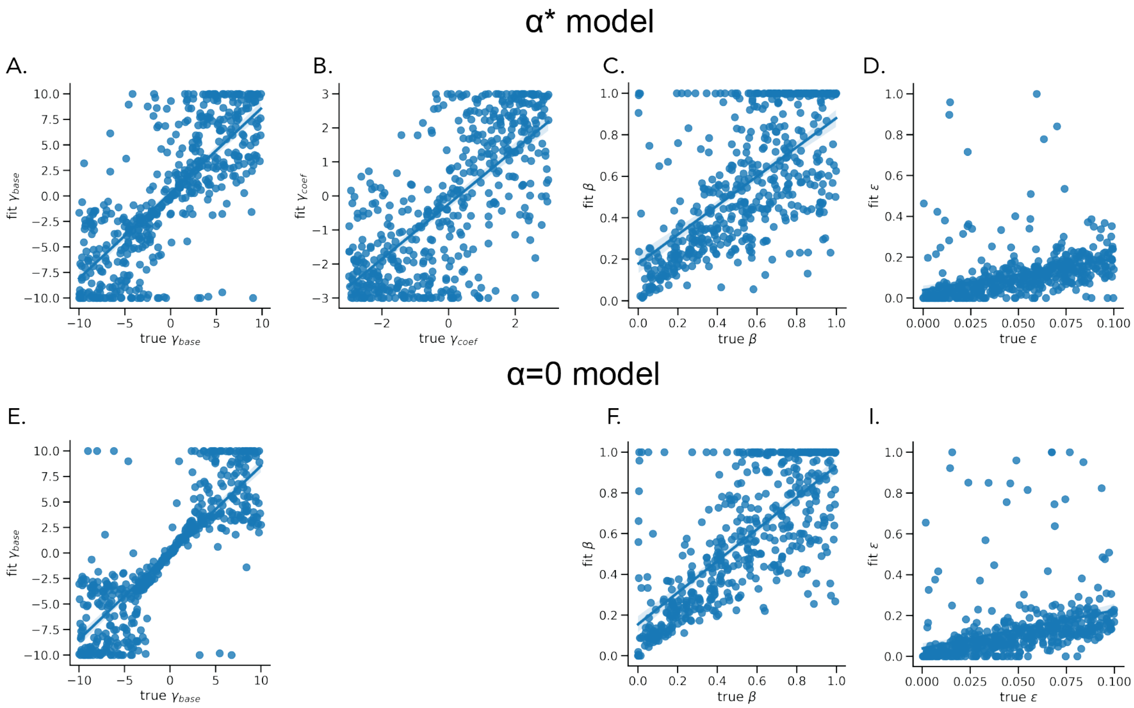

Figure 2: **Parameter recovery results.** Spearman correlations between simulated and recovered parameter values for the α^* and α=0 models ranged from .64 to .85, indicating moderate to good recovery.

Table 2: Overharvesting and planet richness

Parameter	β	SE	df	t-value	p-value
intercept	1.30	0.081	235.63	15.96	$< .001$
age (z-scored)	0.059	0.082	245.48	0.72	.47
poor galaxy	-0.63	0.052	307.32	-12.05	$< .001$
rich galaxy	-0.42	0.13	245.17	-3.15	.0018
planet number	-0.24	0.050	238.88	-4.85	$< .001$
age x poor galaxy	-0.045	0.52	303.05	-0.86	.39
age x rich galaxy	0.36	0.13	245.01	2.68	.0078
age x planet number	-0.060	0.050	238.48	-1.19	.24
poor galaxy x planet number	0.067	0.47	346.64	1.43	.15
rich galaxy x planet number	-0.26	0.060	229.28	-4.29	$< .001$
age x poor galaxy x planet number	0.017	0.047	342.11	0.37	.71
age x rich galaxy x planet number	-0.058	0.061	228.50	-0.96	.34

Full results from a mixed effects model regressing planet type, planet number, and age on the difference between the participants' actual planet residence time and the MVT-optimal residence time. We did not find any interaction between age, planet number, and richness on overharvesting.

Table 3: Reaction times

Parameter	β	SE	df	t-value	p-value
intercept	-0.0086	0.013	878.7	-0.66	0.51
age (z-scored)	-0.0022	0.013	889	-0.17	.87
switch point	0.049	0.023	255.5	2.09	.038
planet number	-0.049	0.012	8551	-4.072	$< .001$
age x switch point	0.0083	0.023	256.3	0.38	.71
age x planet number	-0.024	0.012	8555	-1.99	.047
switch point x planet number	0.014	0.024	8711	0.60	.55
age x switch point x planet number	-0.019	0.024	8717	-0.78	.44

Full results from a mixed effects model regressing presence of a switch in planet type, planet number, and age on reaction times (z-scored within participant and log-transformed). We also did not find any baseline differences in reaction time nor interaction between age, switch point, and planet number.

Table 4: Overharvesting and uncertainty

Parameter	β	SE	df	t-value	p-value
intercept	0.71	0.11	256.2	6.50	$< .001$
age (z-scored)	0.22	0.11	256.0	2.03	.043
switch point	0.31	0.039	8410	7.84	$< .001$
planet number	-0.31	0.043	280	-7.29	$< .001$
age x switch point	-0.0094	0.039	8410	-0.24	.81
age x planet number	0.018	0.043	278.2	0.41	.69
switch point x planet number	-0.078	0.042	8414	-1.85	.065
age x switch point x planet number	-0.11	0.042	8412	-2.65	.0082

Full results from a mixed effects model regressing presence of a switch in planet type, planet number, and age on on the difference between the participants' actual planet residence time and the MVT-optimal residence time. In the absence of a switch point, overharvesting similarly occurred as did its decrease with experience.