Supplement

January 6, 2026

S1 Methods

S1.1 Complete task instructions

All participants received the following instructions, completed a practice version of the task, and completed an instruction comprehension quiz prior to beginning the main task. Those who failed the comprehension quiz more than once were allowed to complete the main task but were excluded from our data analysis. Instructions were presented both verbally via an audio track and in written form on the screen. The complete instructions were:

> *Page 1:* Howdy! In this experiment, you'll be an explorer traveling through space to collect space treasure. Your mission is to collect as much treasure as possible.
>
> *Page 2:* If you want to read more instructions, click on the green planet. If you want to go back and re-read the instructions on the last page, click on the blue planet. The planet you clicked will then be highlighted. Once it's been highlighted, press the space bar to lock in your choice.
>
> *Page 3:* As a space explorer, you'll visit different planets to dig for space treasure, these pink gems. The more treasure you dig up, the more bonus money you'll win!
>
> *Page 4:* When you've arrived at a new planet, you will dig once. Then, you get to decide if you want to stay on the planet and dig again or travel to a new planet and dig there. To stay and dig, press the letter 'A' on your keyboard. Try pressing it now!
>
> *Page 5:* Every time you dig up gems, there are less gems on the planet, so the more you dig on a planet the fewer gems you'll get with each dig. When gems are running low, you may want to travel to a new planet. Planets are very far apart in this galaxy, so it will take some time to travel between them. There are lots and lots of planets for you to visit, so you won't be able to return to any planets you've seen before. To leave this planet and travel to a new one, press the letter 'L' on your keyboard. Try pressing it now!
>
> *Page 6:* When you arrive at a new planet, the alien who owns the treasure mine on that planet will greet you! The better an alien takes care of their mine the

easier it is to dig for gems. Some aliens take better care of their mine than others. So, you won't get exactly the same amount of gems on each planet. What the alien looks like does not tell you anything about how many gems there are on the planet.

Page 7: If you don't make your choice fast enough, you'll have to wait a few seconds before you can make another one. You can't dig for more gems or travel to new planets. You just have to sit and wait.

Page 8: After digging and traveling for a while, you'll be able to take a break at home base.The game will last 20 minutes no matter what. You will visit home base every 5 minutes, so you will visit home base three times during the game.

Page 9: Are you ready to play a practice game? In this practice game, you'll be digging up barrels of gems. But, in the real game, you'll be digging up the gems themselves. You can start the practice game now or re-read the instructions.

Page 10: Great job on the practice game! Now, I'm gonna ask you some questions to make sure you understand the game.

Page 11: How do you win extra money?

- Visiting more planets
- Staying at home base longer
- Collecting more gems

Page 12: If they selected the correct answer, "Collecting more gems", then they were presented: That's correct. You win extra money by collecting more gems.
Page 12: If they did not select the correct answer, then they were presented: That's incorrect. You win extra money by collecting more gems.

Page 13 The length of this experiment...

- Depends on how many planets you've visited
- Is 20 minutes no matter what
- Depends on how many gems you've collected

Page 14: If they selected the correct answer, "Is 20 minutes no matter what", then they were presented: That's correct. The experiment is 20 minutes no matter what.
Page 14: If they did not select the correct answer, then they were presented: That's incorrect. The experiment is 20 minutes no matter what.

Page 15 You press what letter on your keyboard to travel to a new planet?

- A

- L

Page 16: If they selected the correct answer, "L", then they were presented:
That's correct. You press the letter L to travel to a new planet.
Page 16: If they did not select the correct answer, then they were presented:
That's incorrect. You press the letter L to travel to a new planet.

Page 17 The more you dig on a planet the fewer gems you'll get with each dig

- True
- False

Page 18: If they selected the correct answer, "True", then they were presented:
That's correct. The more you dig on a planet the fewer gems you'll get with each dig.
Page 18: If they did not select the correct answer, then they were presented:
That's incorrect. The more you dig on a planet the fewer gems you'll get with each dig.

Page 19 Does the alien tell you anything about how much treasure is on the planet?

- Yes
- No

Page 20: If they selected the correct answer, "No", then they were presented:
That's correct. The alien tells you nothing about how much treasure is on the planet.
*Page 20: If they did not select the correct answer, then they were presented:*That's incorrect. The alien tells you nothing about how much treasure is on the planet.

Page 21: If they did not miss any quiz questions, then they were presented: Good job! You're now ready to move on to the real game!
*Page 21: If they missed any quiz questions, then they were presented:*Oops, you missed some questions. Now that you've heard the correct answers. Try the quiz again!

Page 22 Now that you know how to dig for space treasure and travel to new planets, you can start exploring! Do you want to go over the instructions again or get started with the real game?

Page 23: If chose to go over the instructions, then they were presented: In this game, your goal is to collect as many gems as you can. That's how you will win bonus money. The entire game will last 20 minutes no matter how many gems you collect or how many planets you visit. To stay on a planet and dig again, press the letter A on your keyboard. To leave for a new planet, press the letter L.

The more you dig on a planet, the fewer gems you'll get with each dig which is why you might consider leaving for a new planet. When you arrive at a new planet, you'll be greeted by an alien. What the alien looks like does not tell you anything about how much treasure is on the planet.

S1.2 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, we sampled ϵ from a narrower range, between 0 and 0.1, than the range we used in our fitting procedure, 0 to 1. We restricted the range of ϵ when simulating because both model and parameter recovery were expected to be poor for higher lapse rates. Each simulated dataset was fit to both models using the same procedure used for the empirical 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 S1: Bounds for parameters in each model.

To evaluate model identifiability, for each simulating model, we compared the proportions of simulated participants best fit by that model versus other models, as well as the protected exceedance probabilities (PXP) of the candidate models. PXPs estimate the likelihood that a given model is the most frequent best-fitting model within a group, while accounting for chance differences in model frequencies. We found that model identifiability was excellent (Fig S1). 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 (both PXPs = 1).

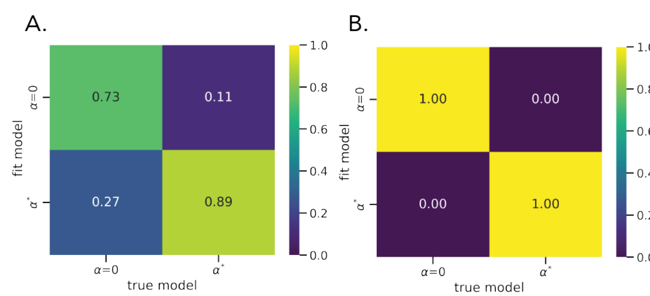


Figure S1: **Model recovery results. A.** Confusion matrix showing the proportion of simulated datasets best fit by the two models. **B**. Confusion matrix showing the protected exceedance probabilities for each pair of simulated and fit models. Across the datasets, the most frequent, best-fitting model is the model that was used to simulate the data.

To evaluate parameter recoverability, we examined the Spearman correlation between the parameters used to simulate the data and the parameters returned by our fitting procedure. For both models, recoverability varied across parameters (Fig S2). For datasets generated by the α^* model, parameters showed moderately good to good recoverability (γ_{base}: ρ=0.77; γ_{coef}: ρ=0.68; β: ρ=0.64; ϵ:ρ=0.64). For datasets generated by the $\alpha = 0$ model, parameter recovery was moderately good to good γ_{base}: ρ=0.85; β: ρ=0.74; ϵ:ρ=0.66)

To examine whether parameter recovery could be improved with additional data, we conducted a parameter recovery analysis using an extended version of the task with five blocks instead of four. Recovery improved for most parameters. For the α^* model, recovery for γ_{base} increased from 0.78 to 0.82, for β from 0.64 to 0.73, and for ϵ from 0.64 to 0.72. Recovery, however, for γ_{coef} remained unchanged at 0.68. For the $\alpha = 0$ model, recovery for γ_{base} increased from 0.75 to 0.89, for β from 0.74 to 0.77, and for ϵ from 0.66 to 0.68.

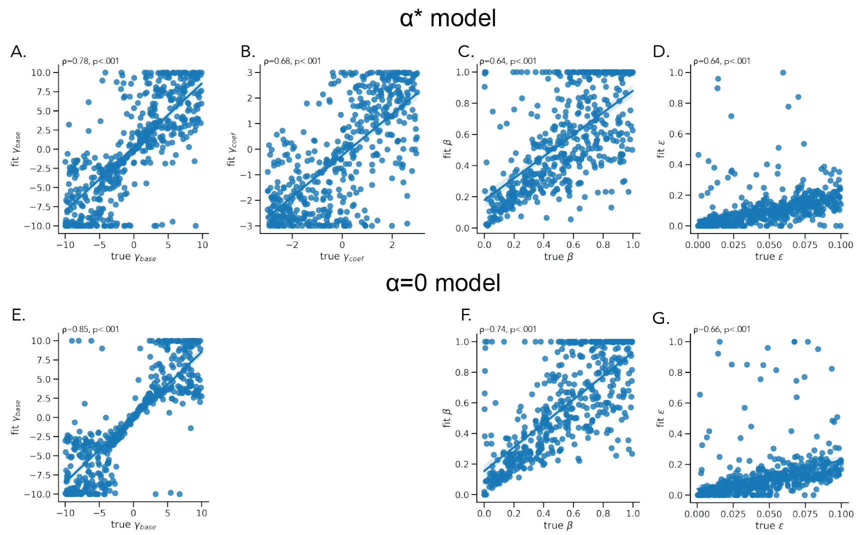


Figure S2: **Parameter recovery results.** Spearman correlations between simulated and recovered parameter values for the α^* and α=0 models ranged from .64 to .85, indicating moderately good to good recovery.

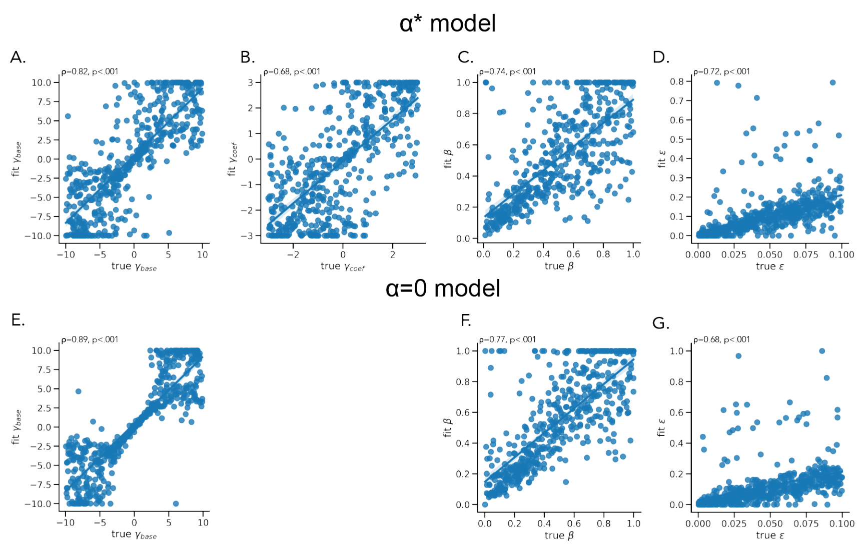


Figure S3: **Parameter recovery results with an additional block.** To determine whether parameter recovery would improve with more participant data, we conducted a parameter recovery analysis on a version of the task with an additional block. Here, Spearman correlations between simulated and recovered parameter values for the α^* and α=0 models are shown. The correlation coefficients ranged from .68 to .89. This is an improvement over from the parameter recovery results conducted on the version of the task our participants completed, in which the Spearman correlations ranged from .64 to .85.

S1.3 Free α parameter recovery

We initially attempted to fit α as a continuous free parameter ranging from 0 to 10. However, we were met with middling parameter recovery (Spearman's $\rho = 0.56$, Fig S4). Two aspects make fitting α as a free continuous parameter difficult. First, the task duration was shortened by six minutes relative to the young adult version (Harhen & Bornstein, 2023), substantially reducing the number of choices from which α could be inferred. Second, because the representation consists of discrete clusters, small changes in α do not translate into smooth changes in the inferred structure. As a result, nearby but distinct values of α can generate identical representations of the environment. For these reasons, we instead fit participants' behavior to two discrete models one with $\alpha = 0$ and another with $\alpha = 0.2$.

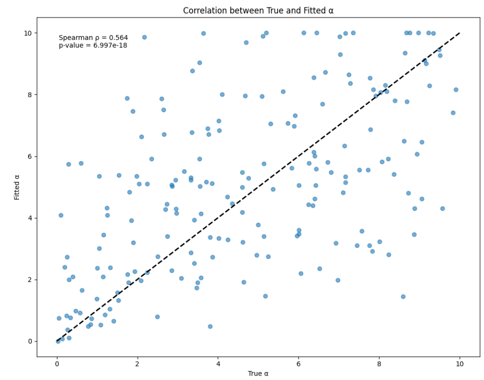


Figure S4: Spearman correlation between simulated and recovered α values when α was treated as a free parameter ranging between 0 and 10.

S1.4 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).

S2 Results

S2.1 Computational model-agnostic results

Table S2: 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 S3: Response 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 S4: 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.

S2.2 Computational model-fitting results

S2.2.1 Difference in AIC scores

Within each age group, participants varied in which model best fit their choices, with roughly a 60/40 split between the two models in all three groups. However, the AIC differences were larger in the child and adult groups, yielding more decisive PXPs in these age ranges.

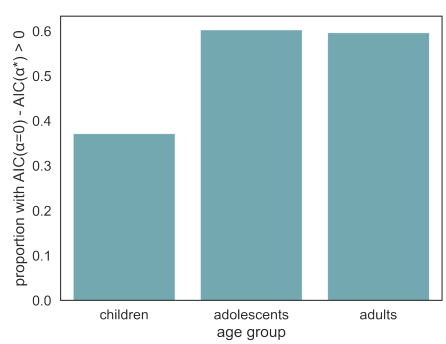


Figure S5: Proportion of participants in each age group with a positive AIC difference score.

S2.2.2 Correlation between age and γ_{coef} including only participants better fit by the α^* model

One potential concern is whether it is appropriate to analyze parameters from the α^* model for younger participants, for whom this model provided a poorer fit. In principle, such a mismatch could obscure a relationship between age and γ_{coef}. To assess this possibility, we simulated data from the $\alpha = 0$ model and fit it using the α^* model. Estimates of γ_{coef} derived from these simulations clustered more tightly around zero than estimates obtained from data generated by the α^* model (Fig. S6A). This pattern indicates that model mismatch should make observing an age-related differences in γ_{coef} *more* likely, rather thanless. Nevertheless, we observed no significant relationship between age in γ_{coef}, either in the full sample or when restricting analyses to participants whose behavior was better fit by the α^* model (Fig. S6B; $\rho = .058$, $p = .50$).

S2.2.3 Results including all participants

A potential concern is that the age-related differences we report might depend on our chosen exclusion criteria. Multiple analyses point to this being unlikely. First, the exclusion rate was nearly uniform across the age range, with only a slightly lower rate among younger participants (Fig. S7A). Second, when we re-generated our modeling results with all participants, including those dropped, we obtained the same results as those reported in the main text (Fig S7B-D). The $\alpha = 0$ model continued to provide the best account of children's data, the α^* model remained

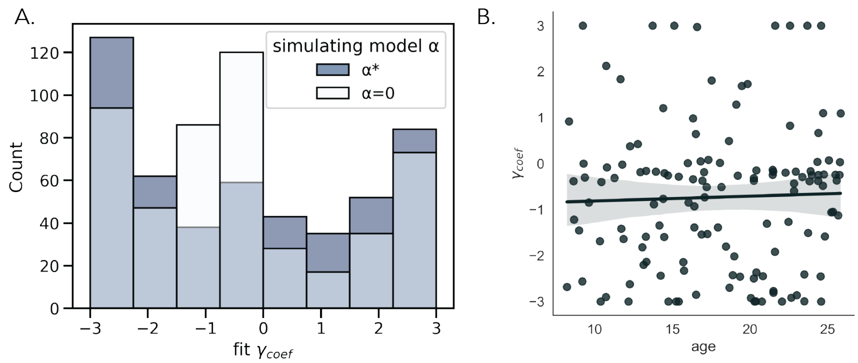


Figure S6: **A.** Comparison of the distributions of *fit* γ_{coef} parameters from data *generated* from the α^* model and the $\alpha = 0$ model in which, γ_{coef} is always set to 0. **B.** Even after excluding participants who were better by the $\alpha = 0$ model, we still found no significant relationship between age and γ_{coef} (Spearman's $\rho = .058$, $p = .50$

the best account for adults, and adolescents again fell in between these two groups. When examining the difference in AIC between the two models for each participant, we continued to observe a significant positive association age, with a nearly identical Spearman's ρ ($\rho = 0.21$, $p < .001$). Likewise, the relationship between age and the uncertainty-adaptive discounting parameter γ_{coef} remained insignificant ($\rho = -0.058$, $p = .32$). Together, these results indicate that our findings are robust to our choice of exclusion criteria.

S2.2.4 Model validation for individual participants sorted by age

To demonstrate that the model captures individual-level behavior as well as group-level patterns, we present plots comparing each participant's observed planet residence times, averaged across planet type, with the corresponding residence times predicted by the best-fitting model (α^* or $\alpha = 0$) using that participant's fitted parameters.

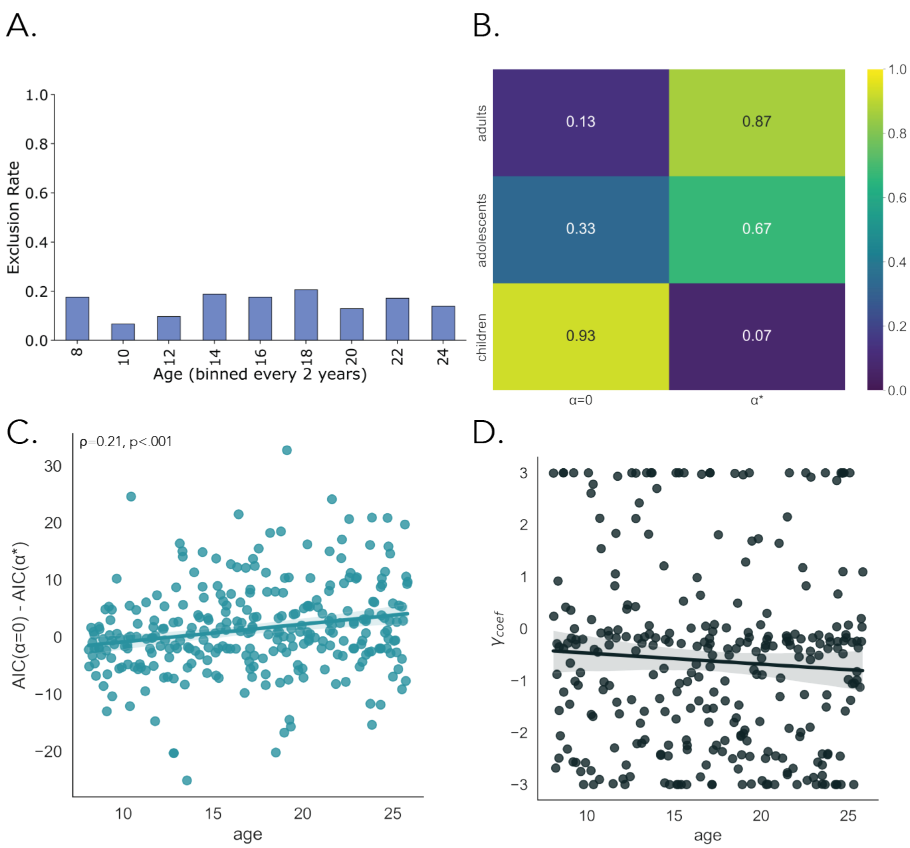


Figure S7: **Modeling results including excluded participants (N=297).** **A.** Proportion of participants excluded across the age range, binned in two-year intervals. Exclusion rates were nearly uniform across the range. **B.** Protected exceedance probabilities (PXPs) for each model with each age group. Consistent with the results presented in the main text, the α^* model best captured adults' choices whereas the α=0 model better captured children's choices. Adolescents showed a more mixed pattern. **C.** Difference in Akaike Information Criteria (AICs) between the $\alpha = 0$ and α^* as a function of age. The AIC difference increased with age, indicating that the older the participant, generally the better the α^* fit their choices over the $\alpha = 0$ model. **D.** Spearman correlation between age and the uncertainty-adaptive decision-making parameter, γ_{coef}. As in the main text, this association was not significant.

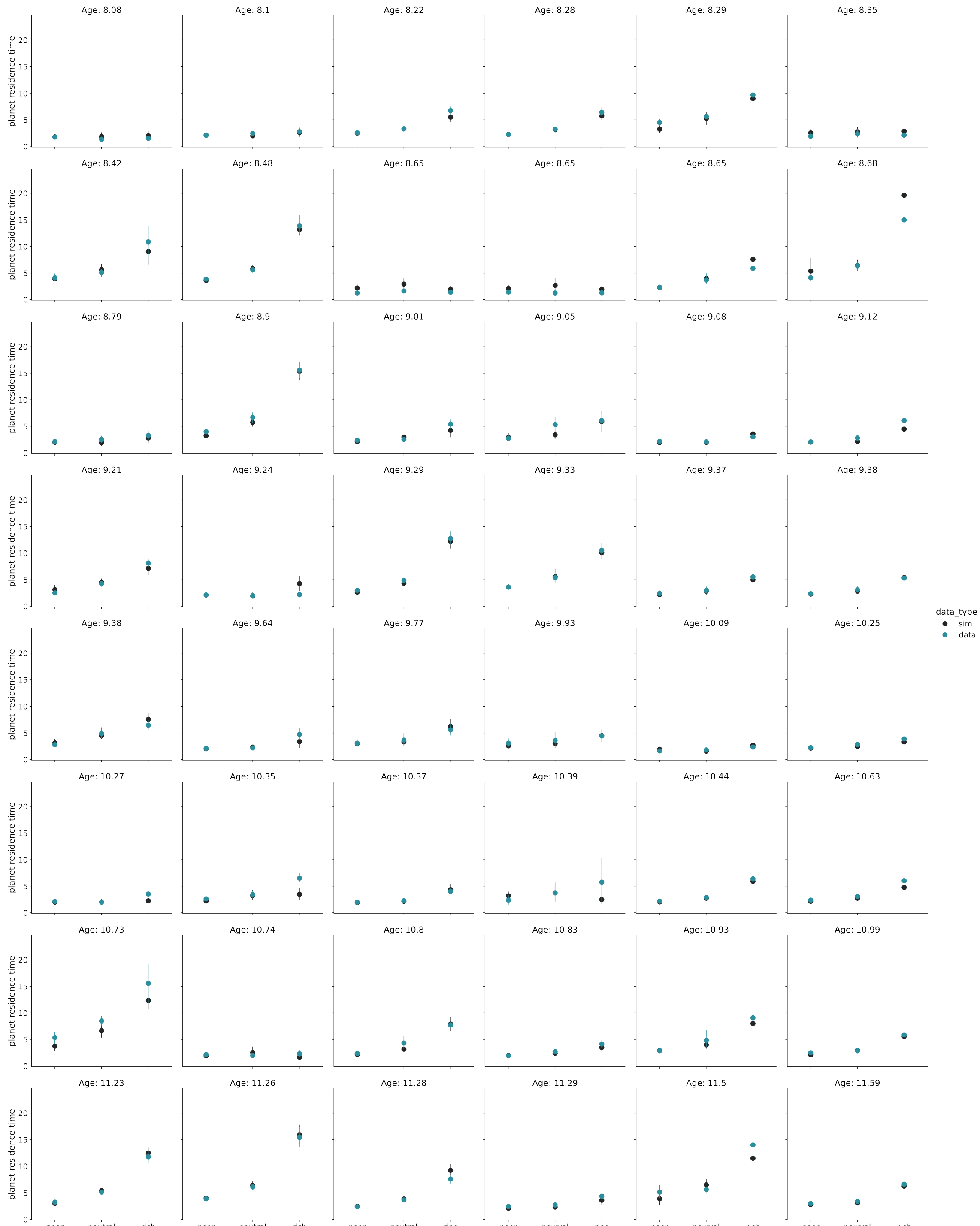
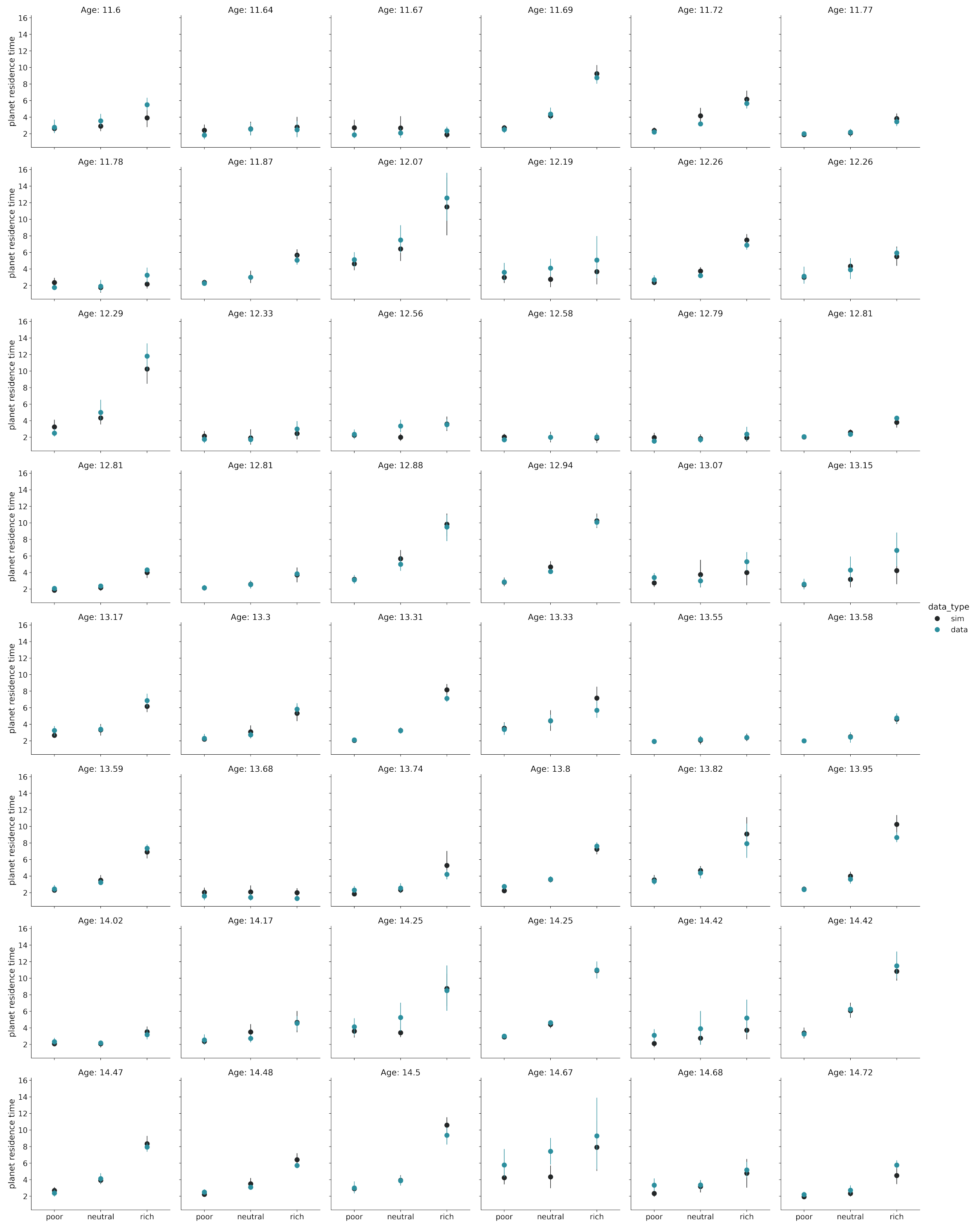


Figure S6: Comparison of individual participants' data to model-generated data produced using their best-fitting parameters. Participants are ordered by increasing age.



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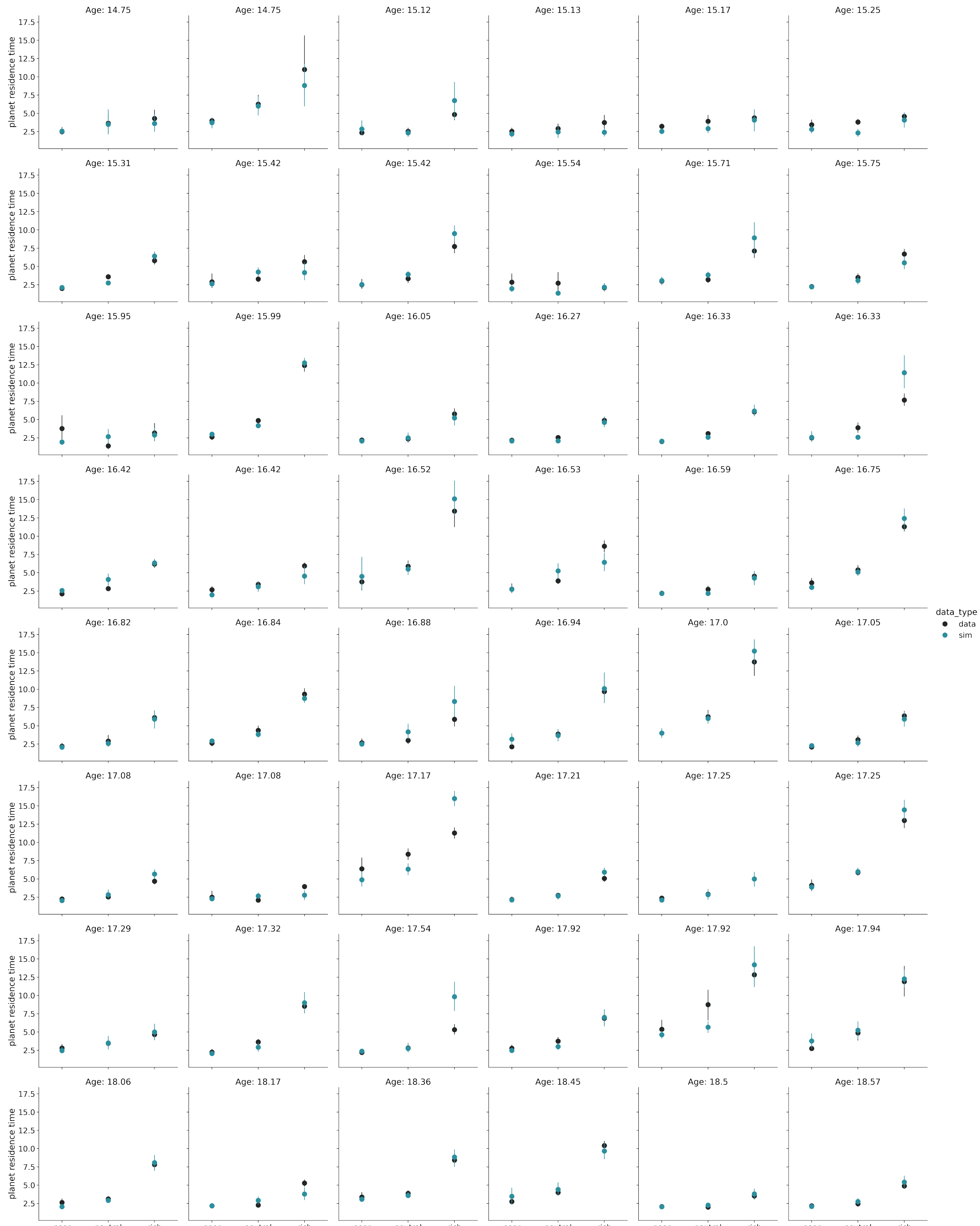

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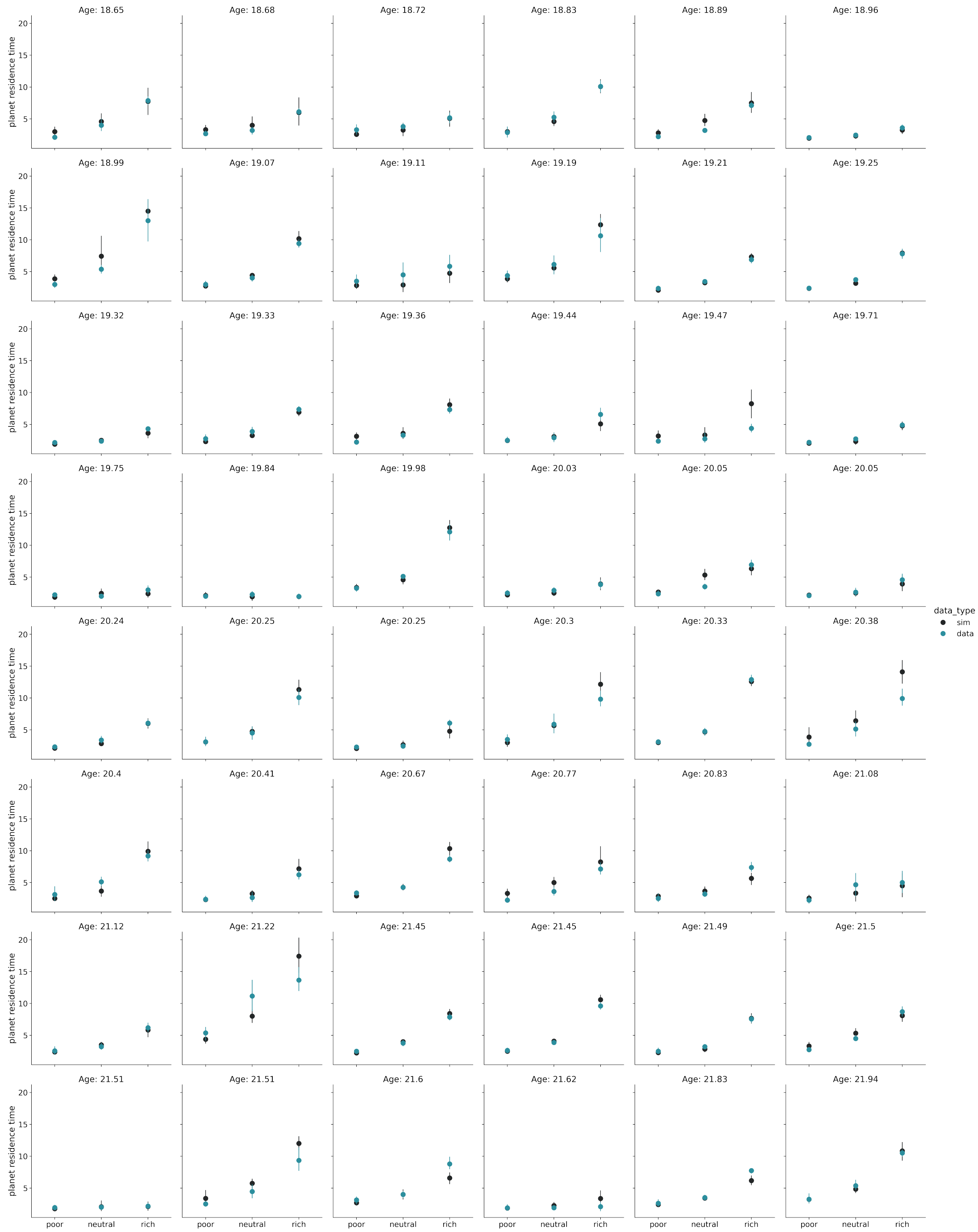

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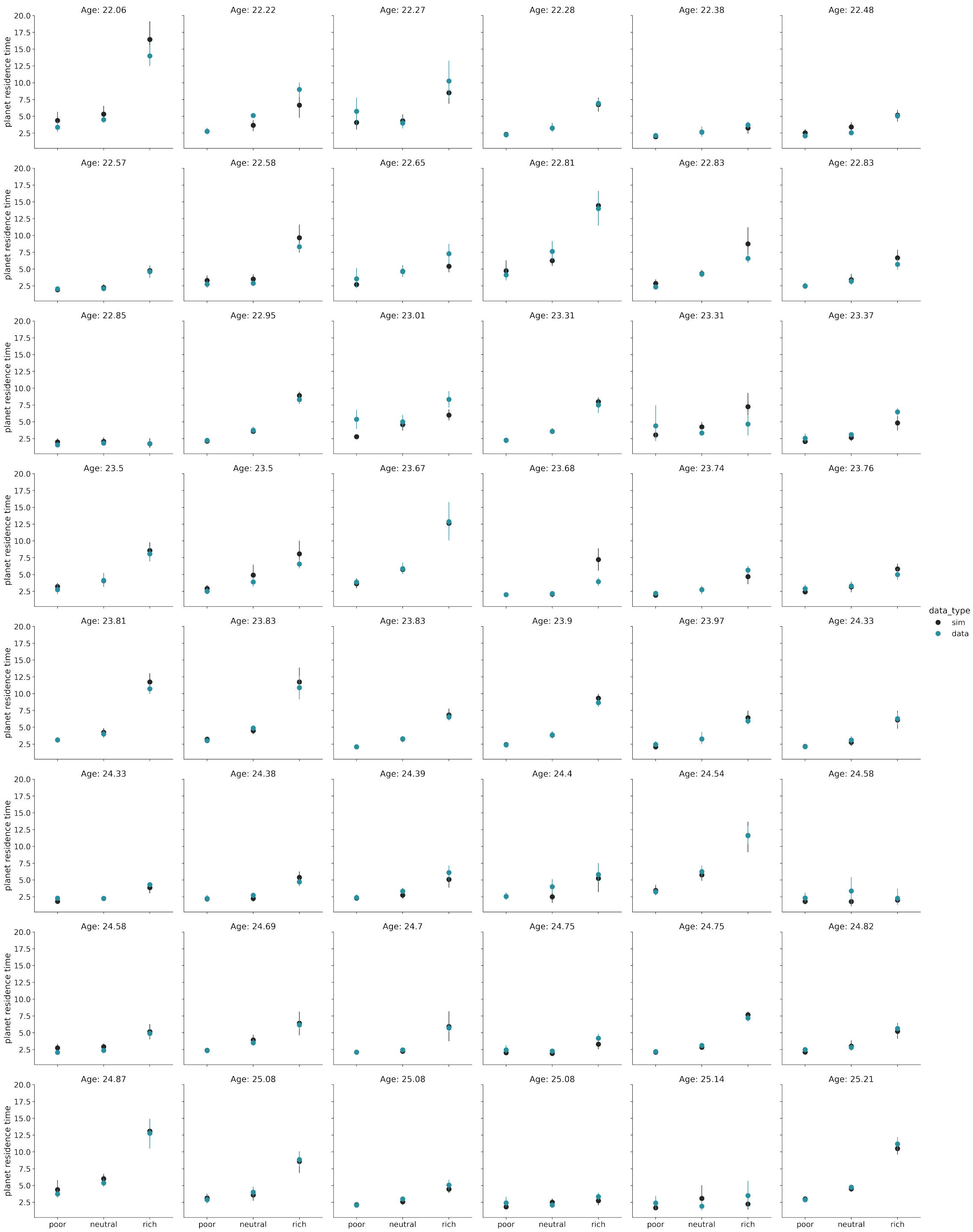

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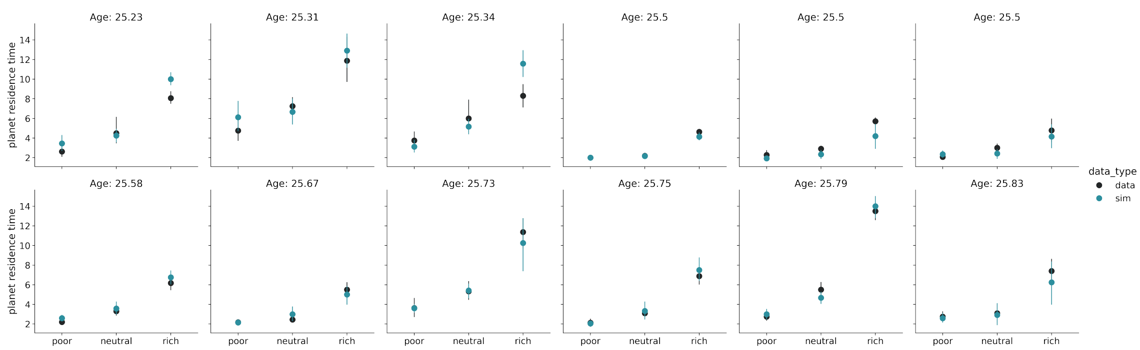

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