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² Supporting Information for

- ³ Overharvesting in human patch foraging reflects rational structure learning and adaptive
- ₄ planning

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Adaptive discounting provides a better account of overharvesting than temporal-difference learning

Both the adaptive discounting and temporal-difference learning models predicted overharvesting behavior on poor and neutral planets (Fig. 4B). To examine the question of which model better captured the *extent* of overharvesting observed in our participants, we assessed which model provided a better account of the data at a finer grain. Specifically, on the basis of our observation that overharvesting was greatest on poor and neutral planets following switches between planet type ("switch points") in the initial three blocks, we investigated how well each model captured this effect.

Methods. For each participant, we simulated the models of interest at the best fitting parameters for that participant's data. From this simulated data, we took the difference between the number of times they dug on a planet and that prescribed by MVT (planet residence time, or PRT relative to MVT). Positive values indicate overharvesting and negative underharvesting. Then, we separately averaged their PRT relative to MVT for planets at a switch point in planet type and planets not at a switch point. Finally, we took the difference between these two averages to quantify the extent overharvesting behavior changed at switch points. For each participant and model pairing, we repeated this procedure 50 times. We averaged over the the 50

²⁴ differences to produce a single value for each participant-model pairing.

Results. We found that the simulated behavior of both models at the best-fitting parameters demonstrated an increase in overharvesting at switch points, with differences significantly greater than 0 on average (Fig S1, one-sample t-tests: adaptive discount - t(115) = 8.63, p < .001; temporal-difference learning - t(115) = 3.11, p = .0024). Comparing the simulated models

 $t_{110} = 0.024$). Comparing the simulated models to subject behavior revealed that the the TD model overharvested significantly less than did subjects (two-sample t-tests:t(114)

 $_{29}$ = -2.75, p = .0065), while the adaptive discounting model showed a trend towards doing so (t(114) = -1.71, p = .089). When

 23 = -2.15, p = .0005), while the adaptive disconting model showed a trend towards doing so ((114) = -1.11, p = .005). When comparing the models directly, the adaptive discounting model overharvested significantly more - and, thus, was a significantly

better match to subject behavior - than TD (t(114) = 2.00, p = .046).



Fig. S1. Participants' overharvested to a greater extent on "switch point" planets, those in which a switch in planet type occurred. In simulation using the best-fitting parameters to subject behavior, both models increased their overharvesting at switch points, though to different degrees. The adaptive discounting model more closely aligned with the data, producing a larger increase in overharvesting than the temporal difference learning model. $\sim p < 0.1$, *p < 0.05, **p < 0.01, **p < 0.001