Effort and Delay Discounting in a Foraging Environment 2

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## Research Questions

#### 3.1. Main question: Are decisions affected differently by equivalent time periods of pure delay, cognitive effort, and physical effort? Crucially, is this pattern different when individuals chose among all forms of effort?

## Hypotheses

#### 4.1. Single-option, accept/reject decisions will be influenced by within-subject manipulations of reward magnitude in line with a theoretical reward-maximizing strategy.

**4.1.1.** Participants will more frequently accept high-reward prospects than low-reward prospects. **4.1.2.** The pattern of acceptances will match that of groups that previously experienced each effort separately for an equivalent period of time.

#### 4.2. Prospect acceptance rates will differ across three within-subject conditions, in which the delays associated with rewards (a) are unfilled, (b) include a cognitive effort requirement, or (c) include a physical effort requirement. Each effort type will be paired with unfilled delay trials in a blocked manner.

**4.2.1.** Acceptance rates for unfilled-delayed trials will be higher than those for both physical and cognitive effort trials.

**4.2.2.** Acceptance rates for physical effort trials will be lower than those for cognitive effort trials.

**4.3.3.** Acceptance rates for unfilled-delay trials will not differ based on their pairing with each effort condition.

#### 4.3. Choices will be well fit by a computational model in which the subjective opportunity cost of time is free to vary across the four between-subject conditions.

**4.3.1.** Participants will display stable preferences, meaning that the reward amounts they accept in a given cost condition will be similar throughout the experiment.

**4.3.2.** Subject-specific opportunity cost (OC) estimates will vary inversely with acceptance rates. Thus, the unfilled-delay condition will produce higher OC estimates than both effort conditions, which in turn will show no differences between them.

## Analyses

#### 16.1. Tests of whether decision makers integrate reward information.

**16.1.1.** *To address hypothesis 4.1., A logistic regression will be fit for each participant in order to predict trial-wise acceptances, using reward amount as predictor. The resulting beta coefficients will be pooled across all participants, and we will perform a one-sample rank-sum test on each set of coefficients to examine whether the they are significantly positive or negative (compared to 0). If the group coefficients are significantly positive, it would mean that a predictor reliably increases the likelihood of acceptance. This will allow us to determine whether increments in reward amounts increased the likelihood of acceptance for each participant.*

**16.1.2.** *We will perform an extension of the logistic regression from 16.1.1., this time adding an autoregressive covariate containing the number of consecutive quits prior to a given trial. In this way, we will examine the possibility that participant choices were governed by recent quitting history rather than the experimental parameters (see 11.1.3.). Coefficients not significantly different from 0 will denote that a participant did not rely on recent quitting history.*

**16.1.3.** *A general linear model with constant, linear, and quadratic terms will be used to estimate the correspondence between proportion accepted (independent variable) and total earnings (dependent variable). No other covariates will be used, as this analysis is to confirm that over and under accepting are detrimental to total earnings.* ***The quadratic term will be defined as the squared deviation from the optimal overall acceptance rate?***

**16.1.4.** *To determine the optimality of the group’s decisions, we will perform two-sided one-sample t-tests to see if the proportion of acceptances for each time/reward combination was significantly different from the optimal rate (see 11.2.). This will result in 12 independent tests (3 reward amounts, and 4 cost types), so we will correct for multiple comparisons using False Discovery Rate (FDR).*

#### 16.2. Comparisons among the four delay and effort conditions.

**16.2.1.** *To compare preferences (hypothesis 4.2.), we will first perform a one-way ANOVA on the proportion of trials accepted using cost as a factor (controlling for subject-specific effects by regressing out participants or by mixed effect GLM?). In addition, we will do pairwise comparisons on the proportion completed among all 4 cost conditions using non-parametric permutation contrasts (6 tests). The same approach will be used for total earnings. This will give us an initial glimpse on the potential differences in cost among conditions. (****Maybe just do 16.2.3.)***

**16.2.3.** *We will compute the probability of accepting a trial with a mixed-effects logistic regression. Based on the task structure and our main question, our a priori model of interest will include cost condition and reward amount as fixed main effects, and subject ID as a random effect. Cost condition will be modeled with three categorical terms, with the fourth condition as the reference condition. We will run three versions of the model with different reference conditions, in order to test all pairwise differences among the four cost conditions. We anticipate significant main effects (coefficients different than zero) reward and cost condition. We hypothesize that the differences among cost conditions will follow the pattern described in 4.2. (****Think about the random-fixed organization, and whether the cost 2 one makes sense. Maybe this one should be random intercepts AND slopes)***

**16.2.4.** *Next, we will examine whether the a priori model from 16.2.3. outperforms both simpler and more complex models. Unlike the individual logistic regression fits in 16.1.1., a mixed-effects approach gives us a better goodness of fit measure for model comparisons. We will determine the best model (combination of predictors) using Akaike’s Information Criterion (AIC) to determine the model that minimizes the negative log-likelihood while penalizing the addition of parameters. The regression with each combination of predictors will be fitted in the following order: 1) intercept only; 2) condition only; 3) reward only; 4) condition and reward main effects (from 16.2.3.); and 6) adding a two-way interaction. We predict that model 4 will have the lowest AIC.*

#### 16.3. Modeling the subjective opportunity cost in each condition.

**16.3.1.** *Response times (RT) for quit responses will be presented in a descriptive manner in order to examine whether participants tended to quit early or late within individual trials. Each cost condition’s response time distribution will contain the pooled RT across participants, and we will display the empirical cumulative distribution functions for each condition. Short RT would suggest confident and stable decisions (in support of 4.3.1.).*

**16.3.2.** *In order to further examine choice stability (hypothesis 4.3.1.), we will compute each participant’s total proportion of acceptances pre- and post-midpoint. For each cost condition separately, we will fit a linear model that predicts post-midpoint acceptance from before-midpoint rates. We will report the slopes and 95% confidence intervals (CI) for each cost group. CIs containing 1 will denote that participants in that group produced consistent choices. (*. But think about this, because you can’t predict prepost per cost. What about paired permutations on the per-cost proportion accepted across participants? That way we can do per cost type)

**For the next 2, think about how to add a modulatory element to include cost type**

**16.3.3.** *To estimate the subjective opportunity cost (hypothesis 4.3.2.), we will use a logistic function to model each participant’s probability of completing a trial based on the difference between the delayed reward’s magnitude and the estimated opportunity cost (OC) for each cost type. OC will be computed as the product of a free parameter (gamma) and the handling time. Both gamma and the temperature parameter of the logistic function will be estimated at the subject level, independently for each subject.*

**16.3.4.** *We will cross-validate each subject’s OC value using the pre-midpoint data for estimation, and post-midpoint choices for testing. The estimates will be used to predict acceptances in the testing sample, and the mean percent correctly predicted will be reported for each group. This will also provide information on the stability of each participant’s choices (4.3.1.).*

**16.3.5.** *The OC estimates for each group will be compared using an ANOVA with condition as a factor. This will let us determine which cost type produced the highest discounting.*

**Additional ideas**

Also, find a way to compare the relative acceptance of waiting when paired with each effort. There might be a discrepancy in wait acceptance rates, which the data suggests might happen.

And think about an analysis where we check that the proportion of quits in the choice section vs handling time