Title: Effort and Delay Discounting in a Foraging Environment

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Abstract

Both delay and effort (i.e. physical and mental) have been shown to reduce the value of prospects, such that people tend to opt for less valuable outcomes if they can avoid waiting or exerting effort. Effort demands can influence the amount of time until an outcome is received, but to this date no study has tried to dissociate these factors under equivalent scales. In this project, participants foraged for rewards under either pure delay or effortful conditions, with time-until-outcome being matched for both. While I expected the effort group to accept fewer trials overall, the data showed the opposite. This finding is at odds with previous literature (suggesting that effort can boost the value of outcomes) and encourages further study into the value-modulating properties of effortful demands.

Introduction

Decisions lie at the actionable core of human experience. Much of what we see in others, such as the way they dress or what they eat, can be conveyed as a result of their choices. An important aspect of such decisions involves weighing the value of an outcome against the cost incurred in obtaining it. This cost-value interaction has many forms and characteristics, such as the allocation of monetary resources, or the uncertainty of obtaining an outcome versus a sure gain. A considerable amount of work has been focused on understanding the nature of value (Schultz, 2015). Cost, on the other hand, is less understood. A prevalent idea is that effort can act as a discounting factor, meaning that it reduces the perceived value of prospects. Indeed, effort has been shown to be an actively avoided cost that devalues rewards, so that decision makers prefer small rewards tied to low demands over large rewards that require high effort (Massar et al., 2015). Importantly, this effect is independent from the amount of errors made in the task (Apps et al., 2015; Kool et al., 2010).

In the animal literature, the amount of effort a subject is willing to exert for a reward can be probed by increasing the ratio of responses required per each reinforcement until an animal refuses to work for the reward (Richardson & Roberts, 1996). Although findings from such studies have provided important information about the cost of effort in general, controversy regarding the particular nature of cognitive and physical effort persists (Westbrook & Braver, 2015). This debate has motivated investigators to characterize these types of effort more precisely (Schmidt et al., 2012; Walton et al., 2006). However, even though effort can be seen as cost in and of itself (Botvinick et al., 2009), in ecological scenarios the magnitude of effort required by a task often affects the amount of time that is spent performing it. For example, going through an additional section of one's tax return involves weighing both the mental effort and the extra time it takes against the reward attained. This is an important consideration. Multiple studies show that delayed rewards are discounted, so that having to wait longer for an outcome makes it less rewarding (Ainslie, 1975; Frederick et al., 2002; Green et al. 1994; McClure et al., 2004). Additional investigations suggest that delay is discounted in a qualitatively similar fashion to physical (Prévost et al., 2010) and mental effort (Massar et al., 2015), but that the magnitude of discounting varies between cost types. Although these studies have examined cost differences by combining time with physical or cognitive effort, there is currently no evidence on how participants would actively choose between all three types of cost. Moreover, these studies use different scales for effort and timing (e.g. the participant can either wait for weeks to be rewarded, or type 50 words backwards-an effortful task), thus retaining the time confound of effortful tasks. Finally, recent findings demonstrate that cost related to physical and mental effort is computed differently in the brain (Hosking et al., 2014; Kurniawan et al., 2011; Westbrook & Braver, 2015), thus highlighting the need to examine these effects simultaneously. Because of this, it is important to understand if and how effort acts as a source of cost that is distinct from delay, and how this dissociation is represented in people's choices. The overarching aim of this project is to use behavioral and neuroimaging methods to investigate the potential differences in cost between time, cognitive effort, and physical effort. However, the results presented here pertain to behavioral pilot data that is limited to cognitive effort and pure delay. These attributes are examined in a between-subject manner in order to provide a baseline that will guide future within-subject examinations. In particular, we explore how participants behave when faced with a foraging task. There are two main hypothesis in this project: 1) Participants should be less likely to accept low-reward and/or long-delay/effort trials; and 2) Participants in the cognitive group will accept fewer trials overall.

Methods

Subjects

A total of 22 healthy subjects (age 18-23; 13 female) were recruited from Psychology 101 classes through the Boston University SONA system. Participants were told to acquire as many points as possible during the task. After the task, subjects were questioned on their within-task behavior, and all mentioned that they followed a specific strategy that they developed early on in the task. We thus found no reason to exclude any participants for this analysis. In the foraging task, participants faced individual trials in which they wait a given amount of time for a reward (the handling time). If the reward amount was not worth the time, the participant could quit the trial by pressing a key, forfeit the reward, and wait a different amount of time (traveling time) to try a new (and potentially more rewarding) trial. Participants were shown the total amount of points they can earn at the beginning of each trial (5, 10, or 25 points, uniformly distributed). These amounts were explicitly disclosed during the practice session in order to avoid any confusion about the possible reward amounts throughout the experiment. The total experiment time was divided into six 7-minute blocks. Each block had one of three predefined combinations of handling and travel times, all of which added up to 16 seconds (handling times could be 2, 10, or 14 seconds long). All three timing combinations were shown in a semi-random order, once before and after a break, and each was visually disclosed to the participant at the beginning of each block. Subjects were divided into two groups: the "wait" group passively waited during the handling time, while the "cognitive" group completed a random sequence of two-second-long cognitive tasks that collectively lasted the equivalent of the handling time. This kind of task switching is demonstrably effortful (Apps et al., 2015; Kool et al., 2010). If a participant made more than two errors during the handling time, they were forced to travel (forced travel trials were not included in decision-related analyses). This contingency was added to guarantee engagement.

Calculating optimal behavior

Having predefined handling, traveling, and reward amounts allowed me to compute the optimal behavior for each block. In the foraging literature, the possible per-trial reward is often weighed against the per-second rate of reward (Constantino & Daw, 2015). This is called the opportunity rate. By multiplying the opportunity rate by the handling time, decision makers can estimate the opportunity cost of time. This measure conveys the richness of the environment, and is equivalent to the participant contemplating how much they could be making instead of waiting for the current reward. The resulting optimal behavior was to accept everything when the handling time was 2 seconds, accept 10 and 25 points when it was 10 seconds, and to only accept 25-point trials when it lasted 14 seconds.

Statistical analyses

Choices are taken to be I.I.D. Bernoulli random variables (0 = quit, 1 = accept). Due to the non-gaussian nature of the data (choice and proportion of completed trials), as well as the small sample sizes, I gave preference to non-parametric permutation analyses when possible (i.e. when I am comparing an overall measure between both groups). KS test was used to compare response time distributions for all participants, since response times tend to have non-Gaussian distributions. In order to get a general sense of the difference for all combinations of experimental factors, I performed a repeated-measures ANOVA, using handling time and rewards as within-subject factors. To check for the importance of each parameter, I performed model selection on a set of logistic regressions that predicted the proportion completed by each subject across conditions. The GLM was performed using a quasibinomial distribution to account for overdispersion due to proportion data. ANOVA was used to compare the nested models, using a chi-squared distribution to evaluate reduction in deviance. Finally, I performed an auto-regressive process to identify whether participants were merely being influenced by the number of skips they had consecutively performed. Since this analysis was performed per-subject, individual choices were used, and thus I fully assumed a binomial distribution. I dwell on the specifics of each analysis and their assumptions in the results.

Results

Performance errors and outliers

In the effort condition, participants were forced to travel if they made more than 2 mistakes in a trial. To check if any participant showed significant struggles, I computed the inter-quartile range for the proportion of trials in which each participant was forced to travel (inter-quartile range = 0.18). A single outlier was found. However, due to the small sample size, and the fact that the participant had a clear strategy (disclosed post-experiment), I decided to retain this outlier for all analyses.

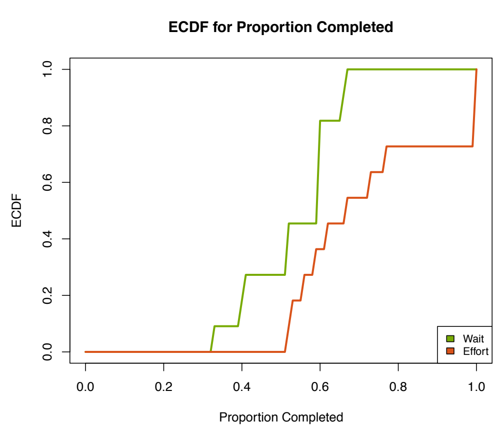

Figure 1. ECDFs for the proportion completed per group.

Proportion Completed

The most basic question that guides this project is which group accepted more trials. Under the present framework, the condition that triggered the least acceptances can be argued to be the costliest. Unexpectedly, the wait group had a smaller proportion of completed trials (M = 0.53, SD = 0.11) than the effort group (M =0.72, SD = 0.19). Figure 1 shows the ECDFs for the proportion completed by each group.

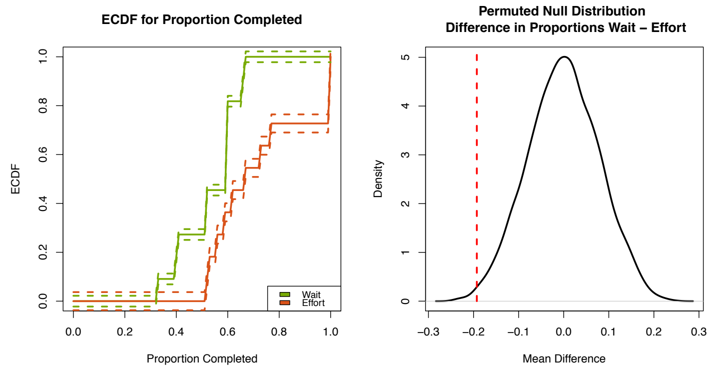

Figure 2. Left: ECDF for the proportion completed per group, with bootstrapped CIs. Right: Null distribution from the permuted differences in means between groups (wait minute effort), and the actual difference marked in red.

The small size of the samples makes any distinction difficult to perceive, and the estimates unreliable. To overcome this shortcoming I took a handful of steps. First, I bootstrapped the mean proportion for each group separately (5000 iterations), so I could get a better estimate of the mean through CIs (which were computed based on the 0.025 and 0.975 quantiles). The bootstrapped statistics for the wait (M = 0.53, lower CI = 0.47, upper CI = 0.59) and effort (M = 0.72, lower CI = 0.62, upper CI = 0.84) were then used to re-plot the ECDF (Figure 2, left). It can now be seen that the CIs do not overlap, suggesting a true difference between these groups. To formalize this comparison, I performed a permutation test on the mean difference in proportions between both groups (relabeling the data through 5000 iterations). The estimated null distribution of this difference is shown in Figure 2 (right). This distribution was plotted as an example. Further permutations will not be plotted. The resulting p-value was 0.0088, thus rejecting the null hypothesis that the difference between these groups would be 0. Just to be clear, from now on the p-values will mean the probability of finding a statistic at least as extreme as the one observed under the null distribution. Finally, I used Cohen's D to estimate the effect size of this comparison, which yielded a value of −1.22. This shows that the effort group completed a significantly larger amount of trials overall than the wait group.

Total Earnings

Next, it was of interest to examine each group's total earnings. As seen on figure 3 (left), the effort group earned slightly less (median = 1780, SE = 75.3) than the wait group (median = 1835, SE = 37.01). A permutation analysis of differences in median earnings per group indicated a trend (p = 0.07; Cohen's D = 0.79). The figure on the right shows a nonlinear relationship between acceptance rates and total earnings. A linear model was performed to estimate this relationship, using the total earned as

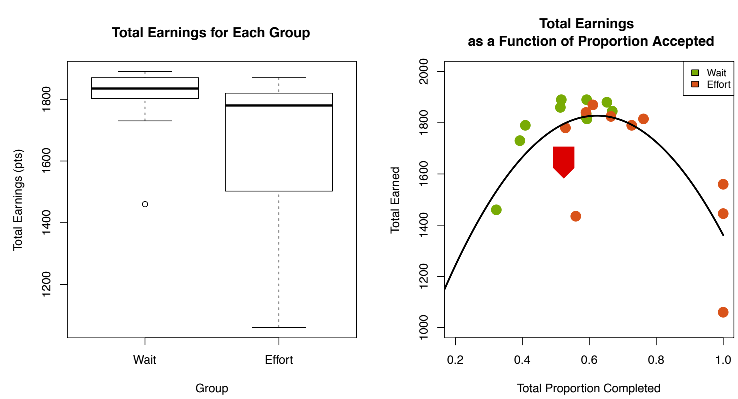

Figure 3. Left: box plot of earnings for each group. Right: earnings as a function of completed trials. Linear fit shows that both linear (β = 4078, SE = 1013, p < 0.001) and quadratic form (β = -3275, SE = 715, p <0.0001) of the proportion predicted the total earned.

the dependent variable and the proportion completed (and its quadratic form) as predictors. All of the terms significantly predicted cumulative earnings ($p < 0.0001$), with an R^2 of 0.52 (estimating the variance explained by the model). This is in line with the nature of the experiment, as participants should cautiously balance rewards with opportunity cost, and both under- and over-acceptance were non-optimal.

Response Times (RT)

After checking for acceptance and earnings, another question is how fast participants were in making decisions (as they could quit at any point during the handling time). Perhaps participants were unclear about the experimental procedures, or changed their minds mid-trial. To account for this, I pooled all the response times for quit trials (since they are representative of a participant's choice to leave) across participants for each group. With these two vectors, I plotted their respective ECDFs (Figure 4) and bootstrapped 95% CIs. As it can be seen, most decisions were made before the first second, with the wait group being slightly slower.

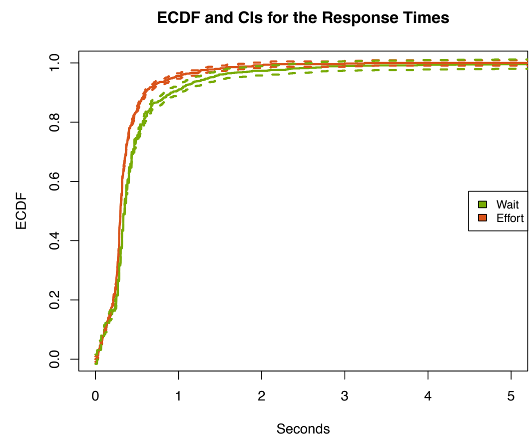

Figure 4. ECDF of pooled response times. Responses were quick overall, with the wait group being slightly slower.

Lastly, I performed a KS test to check if the difference between these distribution was not 0. The test proved significant ($D = 0.19$, $p < 0.001$), although this difference is not behaviorally very relevant for the present study (millisecond differences are inconsequential when we are interested in seconds). I confirmed this result by means of permutation analysis on median RTs ($p < 0.0001$; Cohen's $D = 0.25$). The small effect size also speaks to the potential lack of true differences between groups at this level. The overall quick response times indicate that participants had a clear idea of what rewards were worth their time and effort. This is in agreement with the post-experiment questionnaire, in which participant explained very specific strategies that they followed throughout the session.

Proportion per handling-reward combination

The analyses above give us a general sense of the characteristics of each group. However, it is also necessary to asses whether decision makers were influenced differently at each timing and reward combinations, and how these factors varied by group. First, I was interested in seeing differences as a whole. Figure 5 shows the proportion accepted (and standard error) for all these combinations.

This plot portrays some important features: the first hypothesis was supported, as we can see that participants accepted fewer trials for smaller rewards and longer handling times. On the other hand, and perhaps expectedly, we can see that the effort group accepted more trials than the wait group in all cases. This is contrary to the second hypothesis. In order to analyze these differences, I ran a 2-way repeated measures ANOVA to see how participants in each group performed at each combination of handling times and rewards. Since all three factors are relevant to the question, and since at this point I was interested in mean differences, I did not perform model selection. Main effects were found for group ($F(1,186) = 5.36$, $p < 0.05$), handling time ($F(1,186) = 30.045$, $p < 0.0001$), and reward amount ($F(1,186) = 81.08$, $p < 0.0001$). A handling by reward interaction was also found ($F(1,186) = 9.42$, $p < 0.005$), indicating that participant tendencies to accept higher rewards were reduced by longer handling times. This was somewhat expected, since the optimal behavior was to forage selectively for higher rewards as the handling time increased, and participants were fairly sensible to this structure. This analysis opens the door to another important consideration: the optimality of each group's behavior. Since the reward-maximizing choices can be calculated, I overlaid them on figure 5 (in grey).

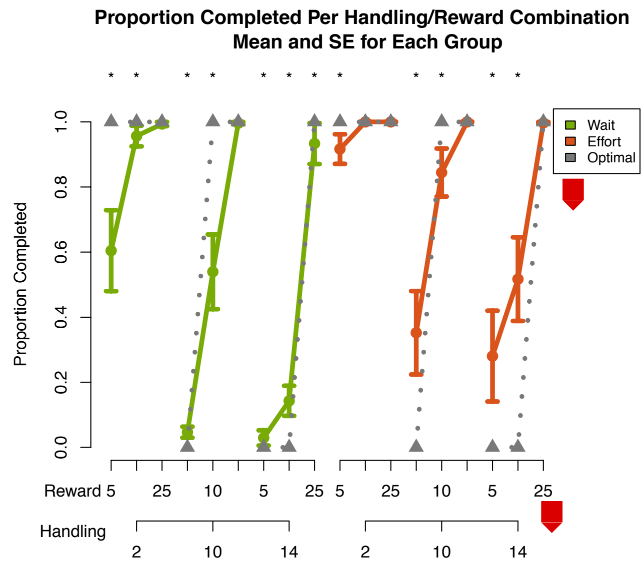

Figure 5. Proportion completed and standard errors for each combination of handling and reward amounts, for each group separately. Optimal choices in grey. Asterisks mark significant deviations from optimality.

The first aspect to note is that both groups show some level of sensitivity to the optimal behavior for each handling time. While there are no perfect matches, each group's choice behavior at each handling time was more similar to its corresponding optimal behavior than to any other ones. This suggests that participants were able to integrate the parameters of the task in a sensible way. Second, the effort group was closer to optimality for the 2 second handling time, while the wait group better approximated optimality at 14 seconds. In addition to these insights, we can ask quantitatively which group deviated the most from this ideal.

Deviation from optimality

The following analysis relies on a set of assumptions. First, I assumed that participants knew what the overall optimal acceptance was (partially supported by post-experimental interviews). If we consider optimal acceptances to be the null distribution against which the optimality of acceptance rates can be evaluated, then we could use the probability of finding the observed acceptance rate using a binomial distribution for each reward/handling combination. Second, since probabilities of 1 and 0 for the binomial distribution would yield absolutes, I assumed that complete certainty was impossible, and thus changed 1 to 0.999 and 0 to 0.001. This way, I calculated the probability of seeing a proportion of acceptances given that the null probability was either 0.999 or 0.001. Importantly, since I was interested in the group as a whole, I pooled the total number of acceptances and total trials across participants in each group (organized by reward and handling time combinations). The resulting probabilities were transformed into p-values and adjusted for multiple comparisons using the Benjamini & Yekutieli method (FDR), and evaluated at an alpha of 0.05.

The asterisks on figure 5 mark significant differences from optimality. This analysis confirms what was visually evident (given the SEM bars). Further it shows to some extent that the wait group was overall less optimal than the wait group. However, given the shape of acceptance rates and their actual distances from optimality, I would still argue that the wait group was more optimal at longer handling times, while the inverse was true for the effort group.

Logistic regression

The analyses above were meant to get a sense of performance differences between groups while assuming that all experimental parameters were relevant, but I was also interested in estimating the importance of each factor in predicting choice. Such predictions can often be done with linear models. However, due to the non-Gaussian nature of the proportion of choices, I decided to run a logistic regression to predict the proportion of trials completed per subject using group, handling time, and reward amount as predictors. Due to the overdispersion of the proportion data, I chose to use a quasibinomial family when computing the GLM.

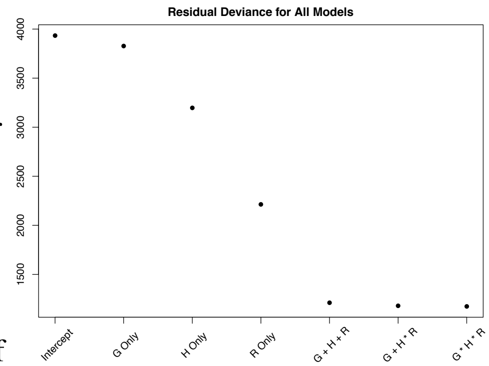

Figure 6. Residual deviance for each model. The model with all main effects was chosen. G = group, H = handling, R = reward.

To choose between these nested models I performed forward selection, comparing each model's residual deviance (D) with the next. I used ANOVA to evaluate the difference in deviance against a χ^2 distribution (with df equal to the difference in number of parameters). This showed that the model with group, handling, and reward as main effects was the last to make significant contributions to the prediction ($D = 1210$, $p < 0.001$). I calculated a pseudo-R^2 by subtracting the ratio of the residual deviance over the null deviance from 1, which yielded a moderate 0.69. Figure 6 shows the residual deviance for each model. The resulting logistic model showed a significant main effect of group as a factor (wait, $\beta = -1.65$, $SE = 0.32$, $p < 0.0001$), indicating that the odds of accepting a trial for the wait group are 80% lower than for the effort group (odds are equal to $\exp(-1.65) = 0.192$). I also found a significant main effect of handling time ($\beta = -0.36$, $SE = 0.040$, $p < 0.0001$), suggesting that as the handling time increases, the odds of acceptance decrease by 30% (odds = 0.70). Finally, reward amounts also played a significant role in predicting choice ($\beta = 0.32$, $SE = 0.034$, $p < 0.0001$), showing that as rewards increase, the odds of acceptance are boosted by 37% (odds = 1.37). Interestingly, these results match what was found using a regular binomial GLM and AIC for comparisons. In order to visualize these results (figure 7), I computed the probability of acceptance for each combination of factors, given by the following equation (with group being either 0 for effort, and 1 for wait):

$$\frac{e^{(\beta_0+Group*\beta_1+Handling*\beta_2+Reward*\beta_3)}}{1+e^{(\beta_0+Group*\beta_1+Handling*\beta_2+Reward*\beta_3)}}$$

Expectedly, as the handling time increased, higher rewards were needed to increase the probability of acceptance, regardless of group. Importantly, we can see that the wait group required higher rewards than the effort group to accept a trial regardless of handling time. In the present context, the significance of these results is two-fold: First, participants acted as predicted by the first hypothesis, integrating all experimental parameters adequately. Second, they estimated the cost of time to be higher than the effort group did. Figure 7 (right) also shows the residuals from the model, which suggested an overall good fit (with the exception of that extreme

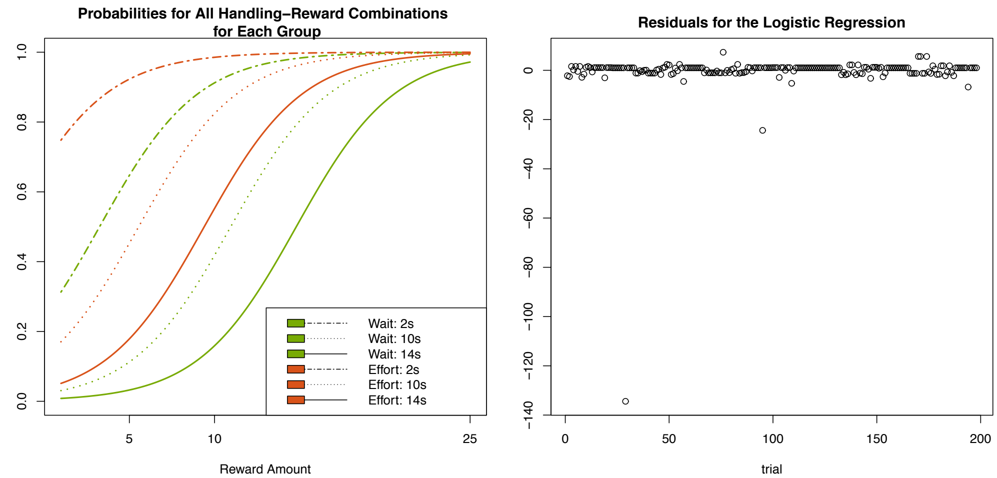

Figure 7. Left: sigmoidal functions depicting the probability of accepting a trial for each group, distinguished per handling-reward combination. Right: residuals from the chosen model.

residual point, which persisted across models. I could not identify what was triggering it by manually inspecting the data either).

Sequential effects

Finally, I was curious about whether there were sequential effects. One could think that quitting too many times consecutively would increase the probability of accepting any reward (in fear of skipping too much and lowering the amount of points they get overall). I checked for this possibility by creating a vector with the number of consecutive quits that happened before each trial, and used it as a predictor in a binomial GLM. This auto-regressive process was performed on each subject separately, using choice as the dependent variable and the quit-run vector as a predictor. While sequential quits were significantly predictive of choice for a couple of subjects ($p < 0.05$), the effect sizes were minimal. Deviances barely changed, if at all, and none of them were significantly reduced from the null deviance (evaluated under a χ^2 distribution). This indicates that previous trials had little bearing on choices. Instead, as seen above, participants focused mainly on the experimental parameters.

Conclusion

In this project I investigated the possible value-discounting effects of cognitive effort and passive delay. I utilized data from a modified foraging task, in which participants decided whether to accept or skip a rewarding trial based on the richness of the environment. The original hypothesis stated that having to perform cognitive tasks during the delay would be extra aversive, making participants estimate the opportunity cost of time as higher than it truly is. However, the present findings demonstrate that effort might not always discount the value of a reward, although it nonetheless affects a subject's ability to evaluate rewards.

My results suggest that performing cognitive tasks while waiting for a reward facilitates optimality in short delays, whereas passive waiting promotes it during long intervals. In general, participants that performed tasks had a marked tendency to over-accept rewards, even when the choice was detrimental to their overall earning rate. This is contrary to our original hypothesis, and perhaps counterintuitive in the presence of previous literature (Kool et al., 2010). Although the present data does not provide further insights into why this might be, there are some ideas that might account for this behavior. One reason could be that participants are motivated to complete trials due to their accurate performance in the cognitive tasks. Such effects have been reported before under the name of ‘learned industriousness’ (Eisenberger & Cameron, 1996). In addition, the tasks themselves might have proven entertaining, and thus intrinsically rewarding. Such an effect could also contribute to a misinterpretation of the trial-wise elapsed time. In other words, our foraging experiment might have accidentally captured the notion that time goes by faster when you are busy. Notably, supervised training and self-reported strategies argue against the possibility of the effort group being unable to act optimally due to task distractions. Response time and optimality analyses also help us discard distraction effects.

Some limitations remain to be addressed. For example, the fact that participants immediately experienced each condition could limit the scope of our results. Discounting effects are known to vary in magnitude depending on the relative temporal position of the options, especially when they are far into the future (Green et al., 1994). Another shortcoming is the lack of monetary rewards. It is possible that participants were not motivated enough by earning points. Perhaps more importantly, comparing effortful and passive waiting between subjects does not give us a full picture of their relative costs. In the future, this task will give each subject the option to forage through both conditions. In addition, a measure of physical activity (e.g. hand grip) will be included in order to further tease apart the relative cost of time and effort (the study’s original plan). First, however, I will replicate the current study, this time using monetary rewards. While the current results look promising, it is important to remember that this was a minimally-sampled pilot study, which limits its power. Perhaps more importantly, even with sufficient power and low p-values, the current study still risks a high false positive rate if the prior odds of finding this difference are against the alternative hypothesis (Benjamin et al., 2017; Nuzzo, 2014). This is a complicated issue to solve at the moment, especially since the present findings go against a literature that expects cognitive effort to provoke fewer responses than passive delays.

Despite these limitations, the current behavioral task was geared to provide a baseline of the cost of each discounting type, thus giving us a reference that can guide future within-subject manipulations. The ongoing study has broad implications for understanding cost. First, discriminating between cost features can have fruitful clinical applications, helping us better understand motivational dysfunctions associated with mood disorders (Westbrook & Braver, 2015). Second, by incorporating both physical and cognitive effort in the context of time for the first time, it will provide an opportunity to determine the specific influence of each type of effort in discounting value. This result can directly benefit fields such as economics and learning theory, particularly by clarifying the extent to which physical and mental effort can be interchangeably used in studies of valuation.

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