Reward Segmentation During Feedback Improves Gambling Task Performance
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Accepted for publication in Decision on October 8, 2023

Abstract
Past research on reward-based decision-making documents deviations from optimal behavior that suggest insufficient sensitivity to rare outcomes. This insensitivity to rare events has often led to sub-optimal performance in gambling tasks. Participants tend to select options that provide frequent rewards, even though these same options sometimes give large-magnitude losses. In this study, we tested an experimental manipulation designed to enhance attention to the magnitude of choice outcomes, where outcomes were presented in segments of 100 points, rather than all at once. Performance in the segmented condition was compared to performance in the original condition, where reward amounts were not segmented. Participants in the segmented condition performed better than participants in the original condition in both a standard gambling task, involving both gains and losses, and a gains-only task where no losses were given. A third experiment indicated that the increase in instrumental responses, or button presses, for reward outcomes, was a critical factor that led to better performance in the reward segmentation conditions. We propose that the reward segmentation manipulation caused trials with rare, large-magnitude rewards to be perceived as additional trials associated with the rare option, which eliminated participants’ underweighting of rare events, leading to better performance. These results suggest that segmenting the presentation of rewards is a potential way in which decision-making behavior can be improved, particularly in cases where some outcomes are rare.

Key words or phrases: Decision-making, reward, reinforcement-learning, gambling tasks

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Introduction

Over the past several decades there has been much interest in reward-based decision-making, or reinforcement learning. This line of work examines how people learn to make the most rewarding choices based on previous feedback they have received, often using laboratory tasks designed to emulate characteristics of real-world choices that must be made every day. One phenomenon often seen in these types of experience-based decision-making tasks is that people are insufficiently sensitive to rare outcomes (Erev, Ert, & Yechiam, 2008; Erev, Ert, Roth, & Haruvy; Lin, Chiu, Lee, & Hsieh, 2007; Ludvig & Spetch, 2011; Barron & Yechiam, 2009). There is evidence that participants often make decisions by relying only on small samples from past experience, which leads to underweighting of rare events (Plonsky, Teodorescu, & Erev, 2015; Hertwig & Pleskac, 2010).

Insensitivity to rare events has been frequently examined using ‘gambling’ tasks like the Iowa Gambling task (IGT; Bechara, Damasio, Damasio, & Anderson, 1994) or the Soochow Gambling task (SGT; Chiu et al., 2008) where people repeatedly select from one of multiple decks of cards and they gain or lose points, or ‘money’, on each draw. In these tasks, the advantageous options provide frequent small losses, but occasionally also provide very large gains, leading to an overall net gain. The disadvantageous options are alluring because they frequently provide small gains, but then occasionally render large losses, leading to a net loss.

In prior work, participants have shown a preference for options that provide more frequent rewards, even though those options also give rare, large losses, compared to alternatives that give frequent losses, but rare large gains (Lin et al., 2007; IoDon et al., 2022). This leads to sub-optimal performance in these types of gambling tasks. Poor performance is especially apparent in the SGT, which was developed later than the IGT, with the goal of more neatly dissociating attention to frequent versus rare outcomes.1 In the SGT the disadvantageous decks give small gains on 80% of trials, and large losses on 20% of trials, while the advantageous decks give small losses on 80% of trials and large gains on 20% of trials. Data from published studies have consistently shown that participants initially prefer the disadvantageous decks, with a majority of participants still selecting the disadvantageous decks more than the advantageous decks after 100 trials (Byrne & Worthy, 2016, Don et al., 2022; Aite et al., 2012). People appear to select the decks with the most frequent gains and are less sensitive to the rare outcomes, or the net magnitude of rewards provided by each option over many trials.

Thus, prior work suggests that people may fail to attend to the magnitude of infrequent gains or losses. Gambling tasks have often been used to examine maladaptive or poor decision-making behavior in various clinical subgroups (e.g. Yechiam, Busemeyer, Stout, & Bechara, 2005; Sevy et al., 2007; Gaubert, Borg, & Chainay, 2022; Zeif & Yechiam, 2020). However, it appears that only a few studies have examined how performance might be improved on gambling tasks, or whether people can be induced to attend more to rare events, than they typically do. One of the few studies to address the issue of improvement on gambling tasks found that a dopamine D2 receptor antagonist improved performance in a rodent gambling task (Zeeb, Robbins, & Winstanley, 2009). In another study, with human participants, providing a hint led

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1 The IGT has two decks that give frequent gains (B & D), and two that give gains and losses with equal frequency (A & C). Decks C & D are optimal, and participants usually underperform by selecting Deck B too frequently. The Soochow Gambling task was developed so that both disadvantageous options give frequent gains, and both advantageous options give frequent losses (see Chiu et al., 2008).
to improved performance in the IGT (Fernie & Tunney, 2006). Another study found that a three-week program designed to boost emotional intelligence led to quicker learning (Alkozei et al., 2019). Buelow and colleagues also found evidence that shifting the focus to long-term outcomes can lead to improved performance in the IGT (Buelow, Okdie, & Blaine, 2013). However, this conclusion was based on a correlation between IGT performance and delay discounting behavior within participants, rather than a manipulation designed to improve long-term decision-making behavior.

The study that is the most similar in scope to the present work was conducted by Overman & Pierce (2013). They found that having participants physically turn over real, paper cards, rather than select virtual cards on a computer screen, led to improved performance in the IGT. They note that the original version of the IGT was conducted with real, rather than virtual cards (Bechara et al., 1994), but later versions that have used virtual cards have assumed that there is no difference from the original study. Overman and Pierce found about a 10% improvement in performance when real cards were used, compared to virtual cards.

The goal of the present study was to examine whether a manipulation of the way reward feedback is provided can improve performance in a virtual version of a gambling task. Following Overman and Pierce, 2013, we sought to test ways in which the presentation of feedback could lead to better engagement in the task, and, in turn, better learning, particularly for the rare outcomes. In the experimental condition, the presentation of rewards was segmented by presenting each reward in units of 100 points, rather than providing the entire magnitude of rewards at one time. This is analogous to being paid $1,000 by ten $100 bills rather than one $1,000 bill, for example. We hypothesized that this reward segmentation manipulation would enhance participants’ attention to the magnitude of gains and losses given in the task, because participants would perceive the segmented rewards as ‘mini-trials,’ which might enhance their sensitivity to the rare outcomes. Such enhanced sensitivity to outcomes was predicted to lead to better performance in the task. If our hypothesis is correct then it suggests that it is possible to enhance individuals’ attention to rare outcomes, leading to improved estimates of the long-term expected value of each option.

We tested this hypothesis directly in Experiment 1, using the SGT. To foreshadow, we found that the reward segmentation manipulation, did indeed improve performance. In Experiment 2, we attempted to replicate this effect using an all-gains version of the SGT. The SGT involves gains and losses, and there is some debate over whether poor performance is due to loss aversion or to a lack of sensitivity to the magnitude of rewards (Erev et al., 2008). Experiment 2 was designed to remove losses, and to thereby remove any explanation of the findings that could be attributed to loss aversion. If we see similar patterns in behavior across Experiments 1 and 2, then it would seem to support the hypothesis that poor performance is due to insensitivity to rare outcomes, rather than loss aversion. In Experiment 3, we test the boundary conditions for the effects of our reward segmentation manipulation by comparing performance in the standard SGT to three alternative reward segmentation manipulations that differed from the one used in Experiments 1 and 2.

**Experiment 1**

Participants completed the SGT under either the original conditions where each gain or loss was presented at once on each trial, or in a segmented condition where each outcome was presented in increments of 100 points. On trials with large gains or losses participants would
first receive a gain or loss of 100 points, then they would be told that “there are still more gains or losses for this card. Click the card for more…” They would then be given another gain or loss of 100 points, until the full magnitude of the gain or loss for that trial was given. This manipulation was designed to better emphasize the magnitude of gains or losses given on each trial, and overcome participants’ insufficient attention to rare outcomes.

**Method**

**Participants**

We conducted a power analysis on the overall difference in optimal choices between the segmented and original conditions. Based on the assumption of a moderate effect size ($d = 0.50$) we would need 51 participants in each condition for 80% power at the $\alpha = .05$ level. Based on this value we planned to run the study until more than 102 participants had completed it. Our final sample size was 112 participants.

Participants were students from Texas A&M University who participated in the experiment for partial fulfillment of a course requirement. The experiment program randomly assigned participants to either the original or segmented condition. There were 52 participants in the original condition, 29 females and 23 males, and 60 participants in the segmented condition, 42 females, 17 males, and 1 who identified as other.

**Materials and Procedure**

Participants completed the SGT on personal computers in the lab. The experiment was programmed using Javascript, HTML, and Cascading Style Sheets (CSS), and run on a web-browser. JATOS, an open-source server software package for online studies, was used to host the Javascript-based experiment (Lange, Kuhn, & Filevich, 2015). The reward structure for the SGT is shown in Table 1. Decks A and B are disadvantageous, or ‘the bad decks’, because they yield a cumulative payoff of -500 points over every ten draws from each deck. Decks C and D are advantageous, or ‘the good decks’ because they have a cumulative payoff of 500 points over ten draws. However, the disadvantageous decks give gains on 80% of trials, while the advantageous decks give gains on only 20% of trials.

**Table 1**

*Reward Schedule for the Soochow Gambling Task*

<table>
<thead>
<tr>
<th>Draw from Deck</th>
<th>Deck A</th>
<th>Deck B</th>
<th>Deck C</th>
<th>Deck D</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>200</td>
<td>100</td>
<td>-200</td>
<td>-100</td>
</tr>
<tr>
<td>2</td>
<td>200</td>
<td>100</td>
<td>-200</td>
<td>-100</td>
</tr>
<tr>
<td>3</td>
<td>200</td>
<td>100</td>
<td>-200</td>
<td>-100</td>
</tr>
<tr>
<td>4</td>
<td>200</td>
<td>100</td>
<td>-200</td>
<td>-100</td>
</tr>
<tr>
<td>5</td>
<td>-1050</td>
<td>-650</td>
<td>1050</td>
<td>650</td>
</tr>
<tr>
<td>6</td>
<td>200</td>
<td>100</td>
<td>-200</td>
<td>-100</td>
</tr>
<tr>
<td>7</td>
<td>200</td>
<td>100</td>
<td>-200</td>
<td>-100</td>
</tr>
<tr>
<td>8</td>
<td>200</td>
<td>100</td>
<td>-200</td>
<td>-100</td>
</tr>
<tr>
<td>9</td>
<td>200</td>
<td>100</td>
<td>-200</td>
<td>-100</td>
</tr>
<tr>
<td>10</td>
<td>-1050</td>
<td>-650</td>
<td>1050</td>
<td>650</td>
</tr>
</tbody>
</table>

| Cumulative Payoff | -500 | -500 | 500 | 500 |


Note. See Chiu et al. (2008) for the full table which lists payoffs for the first 40 cards drawn from each deck. The above sequence of ten was repeated for all subsequent trials.

Participants were told that they would repeatedly select from one of four decks of cards, and they could gain or lose points on each draw. They were given 2,000 points to start the task with and their goal was to try to finish with at least 3,000 points by the end of the game. They were not given information on when the game would end, such as number of trials left, etc., and they were not playing for actual monetary payouts.

In the original condition participants were told that each time they drew a card, it would be turned over and the number of points gained or lost would be displayed. Gains were presented in green font and losses were presented in red. In the segmented condition, participants were told that each time they drew a card, it would be turned over and reveal a number of points gained or lost, but that some cards may have multiple numbers of outcomes. For the cards with multiple outcomes, participants were told to keep clicking on the card deck to see all of the outcomes for that card.

The decks were labeled “A,” “S,” “K,” and “L.” These labels were based on the layout of the keys on the keyboard; however, participants selected from the decks by clicking on one with the mouse. In this way they made a choice on each of 100 trials. On the right side of the screen “Bank:$” was listed, followed by the number of points participants had currently earned. The locations of the decks listed in Table 1 as “A-D” were randomly determined for each participant, and analyzed below as A-D for clarity, and consistency with prior studies.

Figure 1 shows sample screenshots of the experiment for each condition. In the segmented condition outcomes would be presented in units no greater than 100 points. As stated above, if the magnitude of the reward on a given trial was larger than 100 points, participants were told: “There are still more gains or losses for this card. Click the card for more…” Another 100 points would then be shown, alongside the original 100 points. The 100-point increments would be added in two columns on the overturned card until the total reward was given, according to the reward schedule shown in Table 1. After the total number of points had been given participants were told: “That is all of the gains or losses for that card. Press/Click the Box to Continue.” Note that the total magnitude of the rewards was not shown as a single number in the segmented condition, but instead several values of 100 or -100, or in some cases 50 or -50, would be shown on each trial.

After participants completed 100 trials of the experiment, they were given feedback about whether they reached the goal and thanked for their participation in the study.
Figure 1: Sample screenshots of the experiment for participants in the segmented (left) and original condition (right) of the Soochow Gambling Task.

Data Analysis

We used Bayesian analysis methods such as the R package brms for mixed effects regression models (Bürkner, 2017), and JASP (jasp-stats.org) for Bayesian t-tests and ANOVAs. Bayes Factors were computed in JASP using the default Cauchy priors. We considered a Bayes Factor of 3 or more to be analogous to a critical threshold, or ‘significant,’ although Bayes Factors can be interpreted continuously as the odds in favor of the alternative hypothesis (Wagenmakers et al., 2018). Bayes Factors less than 1 indicate more support for the null than the alternative hypothesis, and a Bayes Factor less than 1/3 would suggest moderate support for the null hypothesis (analogous to a $BF_{10}$ of 3 in favor of the alternative hypothesis). In addition to Bayes Factors we also report effect sizes. Prior work suggests that a Bayes Factor of 3 is a more conservative statistical threshold than a frequentist test at the alpha = .05 level, and that effect sizes provide additional information beyond that provided by Bayes Factors or p-values (Wetzels et al., 2011). For mixed effects models fit using brms, we considered an effect ‘significant’ if the 95% highest credible interval (HDI) did not include zero (Nalborczyk et al., 2019; Byrne et al., 2020).

To compute the optimal points possible in the task, we assumed that an optimal observer would select Decks A and B four times each, gaining a total of 1,200 points; they would then select Deck D for the remaining 92 trials, earning a total of 4,300 points, for 5,500 total. To compute the points for the poorest possible performer; we assumed that they would select from Decks C and D four times each, losing 1,200 points; then they would select from Deck B for 92 trials, losing 4,300 points, for a total loss of 5,500 points. To compute the proportion of optimal points each participant earned, we took $P$, the net points earned over the entire task and
subtracted the minimum number of points, then divided that value by the range of possible points: \((P + 5,500)/(11,000)\).

**Results**

We first divided the data into 25-trial blocks and computed the average proportion of optimal deck selections (Decks C or D) in each block. These are shown in Figure 2. Participants in the segmented condition made more optimal choices in each block than participants in the original condition. To examine whether the groups differed significantly in how often they selected the best decks, we ran a mixed effects logistic regression model using R’s *brms* package. Optimal choices were predicted from the interaction between condition and block, with random intercepts for each participant. The coefficient for the interaction term was not significantly different from zero, \(b = -.07, SE = .04, HCI = [-.15, .01]\), which suggests roughly equal rates of improvement in the task across conditions.

**Figure 2.** Proportion of choices from decks C and D in 25-trial blocks of the task. Error bars represent standard errors of the mean.

Because there was no interaction, we next ran a simpler model without an interaction term, where optimal choices were predicted from the additive effects of block and condition, with random intercepts for each participant. There were significant effects for both block, \(b = .43, SE = .02, HCI = [.39, .47]\), and condition, \(b = .45, SE = .16, HCI = [.12, .77]\). Participants in both conditions improved over the course of the experiment, but participants in the segmented consistently outperformed participants in the original condition. The odds ratio for participants in the segmented condition selecting from the advantageous decks compared to participants in the original condition was 1.57 to 1; participants in the segmented condition were about 1.57 times more likely to select from one of the advantageous decks than participants in the original condition.

We also conducted a Bayesian t-test to examine the overall difference in the optimal choices between groups, across all blocks. This test revealed moderate support for the hypothesis that the two groups differed in their proportion of optimal choices, \(BF_{10} = 4.60, d = \)
Participants in the segmented condition ($M=45\%$) selected one of the optimal decks on 9% more trials than participants in the original condition ($M=36\%$). Participants in the segmented condition lost an average of 382 points across the task, while participants in the original condition lost an average of 1,105 points. An optimal observer would gain a total of 5,500 points across the task, while the worst possible performance would lead to a loss of 5,500 points. Participants in the original condition earned 40% of the points an optimal observer would earn, while participants in the segmented condition earned 47% of the optimal points possible.

Next, we examined the proportion of choices made by each option across all blocks. These are plotted for each condition in Figure 3. The data show a clear pattern where participants in the segmented condition selected disadvantageous deck A less often and advantageous deck C more often than participants in the original condition. We conducted Bayesian t-tests to determine if the groups differed in how often they selected each deck. The difference in deck A choices showed extreme support for the alternate hypothesis that the groups differed, $BF_{10} = 511.11$, $d = .81$, and there was moderate support for a difference in deck C choices, $BF_{10} = 6.19$, $d = .53$. There was moderate support for the null hypothesis that participants in the two conditions did not differ in deck B ($BF_{01} = 3.89$, $d = .14$) or deck D choices ($BF_{01} = 4.05$, $d = .13$).

![Proportion of choices from each deck across the entire task. Error bars represent standard errors of the mean.](image)

We also computed transition matrices that represented, for each deck, the proportion of trials where each deck was chosen on the next trial. These proportions were computed for each participant and then averaged within each condition; they are shown in Table 2. The main
diagonal, in bold, indicates repeat choices, and the other values reflect switch trials. The main difference between conditions is that when participants in the original condition selected Deck A, they selected Deck A again on 57.1\% of the next trials, while the segmented condition selected Deck A repeatedly on only 39.3\% of trials. This difference indicates extreme support for the hypothesis that the two groups differed on this measure, $BF_{10} = 1,922.58$, $d = .88$. These results are similar to those presented in Figure 3 above, and suggest that participants in the segmented condition switched away from Deck A much more often than participants in the original condition.

Table 2

Transition Matrix Between Decks for Each Condition

<table>
<thead>
<tr>
<th>Original Condition</th>
<th>Deck A</th>
<th>Deck B</th>
<th>Deck C</th>
<th>Deck D</th>
</tr>
</thead>
<tbody>
<tr>
<td>Deck A</td>
<td>.57</td>
<td>.25</td>
<td>.09</td>
<td>.09</td>
</tr>
<tr>
<td>Deck B</td>
<td>.35</td>
<td>.42</td>
<td>.04</td>
<td>.14</td>
</tr>
<tr>
<td>Deck C</td>
<td>.27</td>
<td>.24</td>
<td>.32</td>
<td>.17</td>
</tr>
<tr>
<td>Deck D</td>
<td>.26</td>
<td>.20</td>
<td>.18</td>
<td>.36</td>
</tr>
<tr>
<td>Segmented Condition</td>
<td>Deck A</td>
<td>Deck B</td>
<td>Deck C</td>
<td>Deck D</td>
</tr>
<tr>
<td>Deck A</td>
<td>.39</td>
<td>.29</td>
<td>.18</td>
<td>.14</td>
</tr>
<tr>
<td>Deck B</td>
<td>.32</td>
<td>.41</td>
<td>.13</td>
<td>.14</td>
</tr>
<tr>
<td>Deck C</td>
<td>.23</td>
<td>.24</td>
<td>.33</td>
<td>.20</td>
</tr>
<tr>
<td>Deck D</td>
<td>.25</td>
<td>.21</td>
<td>.20</td>
<td>.34</td>
</tr>
</tbody>
</table>

Note: Each row indicates the prior choice; each column indicates the proportion of responses to each deck on the next trial. Bold values along the main diagonals indicate repeat choices.

Finally, we next examined the average response times for participants in each condition. We first removed response times that were more than two standard deviations above the overall mean response time across participants. This removed 283 of the 11,200 total trials in the data set. Figure 4 shows the average response times in each of four 25-trial blocks, for participants in each condition. Response times tended to decrease over the course of the task, and participants in the segmented condition consistently took longer to respond than participants in the original condition. A Bayesian mixed effects model predicting response times from the additive effects of condition and block, with random intercepts for participants, indicated strong effects for both predictors: condition, $b = 179.21$, $SE = 64.03$, $HCI = [57.31, 306.38]$; block, $b = -202.47$, $SE = 8.33$, $HCI = [-218.68, -185.71]$. 
Fig. 4. Average response times for participants in each condition. Error bars represent standard errors of the mean.

We also ran a similar model predicting response times from the interaction between condition and block, with random intercepts for participants. This model showed a significant condition by block interaction, $b = -58.96$, $SE = 16.12$, $HCI = [-90.61, -26.34]$. The difference in response times between conditions was much larger during the early part of the task. Participants in the segmented condition reduced their response times over the course of the task more than participants in the control condition.

**Discussion**

Participants who performed the SGT with the reward segmentation manipulation made more advantageous deck selections than participants who performed the task under standard conditions. Participants in the original condition showed a strong preference for disadvantageous Deck A, while participants in the segmented condition were much more likely to have switched away from Deck A, after sampling from it, switching following 60.7% of Deck A choices, compared to only 42.9% for participants in the original condition.

We believe that these results are consistent with our hypothesis that the segmented reward presentations would be perceived as additional trials, and this would counteract participants' insufficient sensitivity to rare outcomes. The segmentation manipulation likely enhanced participants attention to the rare large losses (-1,050) provided by deck A, and to the rare large gains (1,050) provided by Deck C. The improved attention to the rare losses provided by Deck A may have led participants in the segmentation condition toward a pattern of selecting A on some trials, for the large common reward of 200, but being more likely to switch away from that deck because of the anticipated large losses that would come from repeatedly selecting it.

We also observed that response times were slower for the segmented condition than for the original condition. Although, we did not have specific predictions about the segmented condition taking longer to respond that the original condition, the longer response times may have been due to more deliberation over which deck to select. It’s also possible that the longer
response times were simply due to participants in the segmented condition needing a longer psychological refractory period after having longer trials, and more button presses than participants in the original condition (Smith, 1967; Welford, 1952).

A remaining question following Experiment 1 is whether the advantage we found for the segmented condition was due to enhanced attention to the rare large losses provided by Decks A and B, or whether the manipulation heightened attention to both rare gains and rare losses. Many researchers have used tasks like the SGT to examine how information about reward valence (gain vs. loss) versus reward magnitude (small vs. large) affects subsequent decision-making behavior (Yeung & Sanfey, 2004; Delgado, Locke, Stenger, & Fiez, 2003; Meadows, Gable, Lohse, & Miller, 2016; Wu & Zhou, 2009). Some researchers have proposed that loss aversion is important for good performance in the task, because participants have to learn to avoid the large losses from the disadvantageous decks (Lin, Chiu, & Huang, 2009; Upton, Kerestes, & Stout, 2012; Byrne & Worthy, 2016; Don et al., 2022; Aite et al., 2012). However, other researchers have argued that what is commonly described as ‘loss-aversion’ is actually better described as insensitivity to rare outcomes (Erev et al., 2008; Gal & Rucker, 2018).

To examine whether the segmentation manipulation would enhance attention to rare gain outcomes only, in Experiment 2, we had participants perform a gains-only version of the SGT (detailed below), with the same reward segmentation manipulation used in Experiment 1. If participants performed well in Experiment 1 because of enhanced attention to the rare losses, then there should be no advantage for participants in the segmented condition in Experiment 2, because the task is gains-only. However, if the segmentation manipulation led to enhanced sensitivity to rare events, regardless of valence, then it should also lead to improved performance in Experiment 2.

**Experiment 2**

**Method**

**Participants**

Participants were students from Texas A&M university who participated in the experiment for partial fulfillment of a course requirement. The experiment program randomly assigned participants to either the original or segmented condition. We planned for similar sample sizes as in Experiment 1. There were 54 participants in the original condition, 40 females and 14 males, and 60 participants in the segmented condition, 42 females, and 18 males.

**Materials & Procedure**

The materials and procedures were identical to Experiment 1, except for the gains-only reward structure, which is shown in Table 2. We designed this reward structure so that, as in Experiment 1, the disadvantageous decks (A & B) offered better rewards than the advantageous decks (C & D) on 80% of trials. For the rare outcomes that occurred on 20% of trials, the disadvantageous decks gave the smallest rewards possible (0 and 200), while the advantageous decks gave the largest rewards possible (1300 and 1500). The advantageous decks yielded 5000 points over ten trials, while the disadvantageous decks yielded only 4000.
Table 3
Reward Schedule for the Gains-Only SGT

<table>
<thead>
<tr>
<th>Draw from Deck</th>
<th>Deck A</th>
<th>Deck B</th>
<th>Deck C</th>
<th>Deck D</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>500</td>
<td>450</td>
<td>300</td>
<td>250</td>
</tr>
<tr>
<td>2</td>
<td>500</td>
<td>450</td>
<td>300</td>
<td>250</td>
</tr>
<tr>
<td>3</td>
<td>500</td>
<td>450</td>
<td>300</td>
<td>250</td>
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<tr>
<td>4</td>
<td>500</td>
<td>450</td>
<td>300</td>
<td>250</td>
</tr>
<tr>
<td>5</td>
<td>0</td>
<td>200</td>
<td>1300</td>
<td>1500</td>
</tr>
<tr>
<td>6</td>
<td>500</td>
<td>450</td>
<td>300</td>
<td>250</td>
</tr>
<tr>
<td>7</td>
<td>500</td>
<td>450</td>
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<td>8</td>
<td>500</td>
<td>450</td>
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<td>9</td>
<td>500</td>
<td>450</td>
<td>300</td>
<td>250</td>
</tr>
<tr>
<td>10</td>
<td>0</td>
<td>200</td>
<td>1300</td>
<td>1500</td>
</tr>
</tbody>
</table>

Cumulative Payoff | 4000 | 4000 | 5000 | 5000 |

*Note.* The above sequence of ten was repeated for all subsequent trials.

For the reward segmentation condition, rewards were again presented in units of 100, except if there were fewer than 100 points left, when participants would receive the remaining 50 points for that trial. Note that this manipulation led to a different number of button presses for rare outcomes in this experiment, compared to Experiment 1. In Experiment 1, the rare gains and losses (1050, 650, -650, -1050) would lead to the most segments of rewards. In this experiment, the large rare gains for Decks C & D (1300 & 1500) led to the most button presses, but the small rare gains for Decks A & B (0 and 200), led to the fewest button segments.

**Results**

Figure 5 shows the average proportion of optimal deck selections in each block. Participants in the segmented condition made more optimal choices in each block than participants in the original condition. We next ran a multilevel model where optimal choices were predicted from the interaction between condition and block, with random intercepts for each participant. The coefficient for the interaction term was significantly different from zero, $b = -0.14$, $SE = 0.04$, $HCI = [-0.21, -0.07]$. Participants in the segmented condition performed much better than participants in the original condition, early in the task, but participants in the original condition were performing almost as well by the end of the task.
To test for an overall effect of condition, we ran a simpler model without an interaction term, where optimal choices were predicted from the additive effects of block and condition, with random intercepts for each participant. There were significant effects for both block, $b = .29, SE = .02, HCI = [.25, .32]$, and condition, $b = .46, SE = .18, HCI = [.10, .79]$. The odds ratio for participants in the segmented condition selecting from the advantageous decks compared to participants in the original condition was 1.58 to 1.

We also conducted a Bayesian t-test to examine the overall difference in the optimal choices between groups, across all blocks. This test revealed moderate support for the hypothesis that the two groups differed in their proportion of optimal choices, $BF_{10} = 6.17, d = .52$. Participants in the segmented condition ($M=47\%$) selected one of the optimal decks on 10% more trials than participants in the original condition ($M=37\%$). Participants in the original condition earned an average of 43,117 total points, which was 39% of the optimal total points, while participants in the segmented condition earned an average of 44,231 points, which was 50% of the optimal total points.

Next, we examined the proportion of choices made for each option, across all blocks. These are plotted for each condition in Figure 6. As in Experiment 1, participants in the segmented condition selected disadvantageous Deck A less often and advantageous Deck C more often than participants in the original condition. However, participants in the segmented condition appeared to also show a greater preference for advantageous deck D than participants in the original condition. We conducted Bayesian t-tests to determine if the groups differed in how often they selected each deck. These tests revealed that the differences in Deck A ($BF_{10} = 2.02, d = .43$), C ($BF_{10} = 1.19, d = .38$) and D choices ($BF_{10} = 1.18, d = .37$) were only weak or
anecdotal. The difference in Deck B choices showed moderate support for the null hypothesis that the groups did not differ, $BF_{01} = 4.40$, $d = .10$.

![Figure 6](image)

**Figure 6.** Proportion of choices from each deck across the entire Gains-only task. Error bars represent standard errors of the mean.

The transition matrices between deck choices are shown in Table 4. As in Experiment 1, the most notable discrepancy was in repeated Deck A choices. Participants in the original condition selected Deck A on 57.4% of trials following a Deck A choice, compared to only 43.5% for participants in the segmented condition. A Bayesian t-test indicated moderate support for the hypothesis that the two groups differed in consecutive Deck A choices, $BF_{10} = 3.45$, $d = .48$. Participants in the segmented condition also made fewer consecutive Deck B choice (25.5%) than participants in the original condition (35.2%), but a Bayesian t-test indicated only weak or anecdotal support for the difference, $BF_{10} = 1.62$, $d = .41$. 
### Table 4

*Transition Matrix Between Decks for Each Condition in Experiment 2*

<table>
<thead>
<tr>
<th>Original Condition</th>
<th>Deck A</th>
<th>Deck B</th>
<th>Deck C</th>
<th>Deck D</th>
</tr>
</thead>
<tbody>
<tr>
<td>Deck A</td>
<td>.57</td>
<td>.17</td>
<td>.13</td>
<td>.12</td>
</tr>
<tr>
<td>Deck B</td>
<td>.32</td>
<td>.35</td>
<td>.17</td>
<td>.16</td>
</tr>
<tr>
<td>Deck C</td>
<td>.31</td>
<td>.18</td>
<td>.33</td>
<td>.19</td>
</tr>
<tr>
<td>Deck D</td>
<td>.30</td>
<td>.20</td>
<td>.20</td>
<td>.30</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Segmented Condition</th>
<th>Deck A</th>
<th>Deck B</th>
<th>Deck C</th>
<th>Deck D</th>
</tr>
</thead>
<tbody>
<tr>
<td>Deck A</td>
<td>.44</td>
<td>.21</td>
<td>.18</td>
<td>.17</td>
</tr>
<tr>
<td>Deck B</td>
<td>.28</td>
<td>.26</td>
<td>.25</td>
<td>.22</td>
</tr>
<tr>
<td>Deck C</td>
<td>.27</td>
<td>.21</td>
<td>.31</td>
<td>.21</td>
</tr>
<tr>
<td>Deck D</td>
<td>.26</td>
<td>.22</td>
<td>.27</td>
<td>.26</td>
</tr>
</tbody>
</table>

Note: Each row indicates the prior choice; each column indicates the proportion of responses to each deck on the next trial. Bold values along the main diagonals indicate repeat choices.

Figure 7 plots the average response times for participants in each condition. Participants in the segmented condition responded slower early in the task, during blocks 1 and 2, but they responded slightly faster than participants in the original condition during block 4. We ran a multilevel regression model predicting response times from the interaction between condition and block, with random intercepts for participants. This model indicated a significant interaction effect between condition and block, $b = -150.18, SE = 22.40, HCI = [-194.68, -106.37]$, consistent with the crossover pattern of the data. A similar model with only additive effects of condition and block showed a significant effect of block, $b = -223.58, SE = 10.99, HCI = [-245.42, -201.66]$, but no overall effect of condition, $b = 124.53, SE = 79.05, HCI = [-29.42, 282.93]$. 

![Average Response Time By Condition](image_url)
**Figure 7.** Average response times for participants in each condition. Error bars represent standard errors of the mean.

**Discussion**

In Experiment 2 participants performed a gains-only version of the SGT, and we again found an advantage for participants who were given our reward segmentation manipulation over participants who performed the task under the original conditions. The pattern of the data is very similar across Experiments 1 and 2, which suggests that the segmentation manipulation enhanced attention to rare outcomes, rather than just attention to losses, as opposed to gains. We also again observed the pattern where participants in the original condition selected deck A more than participants in the segmented condition, and they were less likely to switch away from deck A.

We also found a similar pattern in response times to that found in Experiment 1. Participants in the segmented condition took longer to respond, although this difference was only found early in the task. By block 4, participants in the original condition were taking slightly longer to respond than participants in the segmented condition.

As in Experiment 1, Deck A offered the lowest possible outcome (0) of all decks, although there were no losses. It should be noted that unlike Experiment 1, where participants received the worst outcome of -$1,050 in eleven segments (ten segments of -100 and one segment of -50), in Experiment 2 the worst outcome of 0 had only one button press associated with it. The pattern of results was remarkably similar across the two experiments, which suggests that the segmentation manipulation was not due to simply pressing the button for one option more than others, or action selection (Don & Worthy, 2021; Sutton & Barto, 1998; Thorndike, 1911), since the response button for deck A was only pressed once when receiving the worst outcome of 0 in Experiment 2. However, it is worth noting that Decks C and D gave very large rare gains of 1,300 and 1,500, which were presented in 13 and 15 reward segments, respectively. We propose that these reward segments were perceived as additional trials, which heightened participants sensitivity to these rare outcomes. The rare outcome trials for Decks A and B that gave the smallest gains of $0 and $200, may have been more noticeable to participants in the segmented condition because of their contrast with the common outcome trials and the rare outcomes for Decks C and D, which had many more reward segments. The difference in the number of reward segments across trials may have generally increased participants’ attention to rare outcomes.

**Experiment 3**

Experiments 1 and 2 provided evidence for a reliable improvement in two variants of the SGT from reward segmentation manipulation. In Experiment 3, we aimed to test the limits of the reward segmentation manipulation by teasing apart its components. Compared to the standard, or original SGT condition, our reward segmentation manipulation involved: a.) more button presses per trial, on average, b.) more time per trial, on average, and c.) serial presentation of rewards, compared to the single presentation of the reward on each trial in the original condition. In the present experiment we ran three experimental conditions, along with an original condition, that was identical to Experiment 1, and we used the reward structure for the standard SGT.

For the three experimental conditions, none of them included additional button presses on each trial, which was a component of the segmentation manipulation in Experiments 1 and 2.
Thus, all three experimental conditions included only one response per trial. In the original-timed condition, the total magnitude of reward for each selection was shown, but the outcomes of larger magnitude were shown for a longer period of time (details below). In the segmented-timed condition, rewards were presented in the same segmented manner as in Experiment 1, but the participant only pressed the button once each trial. Segmented rewards were shown one second apart from each other, so that the total feedback time was equated between the segmented-timed and original-timed conditions. Finally, in the segmented-simultaneous condition, rewards were shown in 100-unit segments, but all segmented rewards were presented simultaneously, following choices on each trial. Feedback time in this condition was consistent across all trials (2000 ms), and consistent with the original condition. Thus, the only difference between the original and segmented-simultaneous condition was that rewards were shown in separate 100-unit amounts in the latter condition.

Method

Participants A total of 219 participants performed the task, and were randomly assigned to one of the four between-subjects conditions. There were 49 participants in the original condition, 30 females and 19 males; 52 participants in the original-timed condition, 33 females, and 18 males, and 1 participant who selected ‘other’; 63 participants in the segmented-simultaneous condition, 38 males and 25 females; 55 participants in the segmented-timed condition, 37 males, 17 females, and one participant who selected ‘Prefer not to answer.’

Materials & Procedure

The basic methods were the same as in Experiment 1, except for the changes in the manner in which feedback was presented. The differences in feedback presentation between each condition and the original condition are detailed below.

Original-Timed Condition: Feedback was presented for one second per 100 points gained or lost on each trial. Thus, a gain or loss of 1,000 points would be shown for ten seconds, but a gain or loss of 200 points would only be shown for two seconds. For additional increments of 50 points, the reward presentation would last for an additional second. Rewards were not segmented in this condition; the total reward amount was shown for the entire duration of the feedback.

Segmented-Timed Condition: Feedback was presented for one second per 100 points, as in the original-timed condition; however, it was shown in segments of 100 points. Participants made one button press per trial; then rewards would be shown in 100-point segments, with a new segment appearing every one second.

Segmented-Simultaneous Condition: Participants made one button press per trial, and were shown the amount gained or lost in segments of 100 units, all presented simultaneously. Feedback was shown for two seconds on each trial. Thus, participants made a response and the total reward was shown, but broken down into segments of 100 units.
Results

The proportion of optimal choices in each 25-trial block are plotted in Figure 8. We ran a Bayesian mixed effects logistic regression where optimal choices were predicted from the interaction between condition and block on each trial, with random intercepts for each participant. Because there were four conditions, this model contained three coefficients for the interaction terms and three for the lower order effect of condition. We used the original condition as the reference group, so that each interaction term and lower order term for condition indicated the difference between the original condition and one other condition.

The only interaction term that was significantly different from zero was the term between the original and the segmented timed condition, $b = -0.33, SE = 0.04, HCI = [-0.41, -0.25]$. The highest credible intervals for the interaction between the original condition and the original-timed ($HCI = [-0.14, 0.03]$), and segmented-simultaneous conditions ($HCI = [-0.16, 0.00]$) included zero, indicating no difference in rate of learning compared to the original condition. The interaction with block between the original condition and the segmented-timed condition appears to be due to a lower rate of learning in the segmented-timed group. By the last 25-trial block, participants in the segmented block group were selecting from the optimal decks less than participants in the other groups.

We next ran an additive model without the interaction term from the model above. This model indicated an effect of block, $b = 0.50, SE = 0.014, HCI = [0.48, 0.53]$, but no differences in optimal choices between the original condition, and any of the other three conditions (original-timed 95% HCI = [-0.21, 0.58], segmented-simultaneous 95% HCI = [-0.31, 0.46], segmented-timed 95% HCI = [-0.46, 0.30]). A leave-one-out (LOO) comparison using widely applicable information criterion (WAIC) between the additive model, and the model that included the interaction terms between condition and block suggested that the interaction-term model fit the data better than the additive model ($elpd-diff = -40, se-diff = 9.5$).
Participants in the original-timed condition lost an average of 365 points, or 47% of the optimal total points, participants in the segmented-simultaneous lost an average of 734 total points, or 43% of the optimal points, participants in the original condition lost an average of 855 points, or 42% of the optimal total points, while participants in the segmented-timed condition lost an average of 1,333 total points, or 38% of the optimal total points.

Figure 9 plots the proportion of selections from each deck across all trials. Numerically, the segmentation manipulations led to fewer deck A choices compared to the original condition, but the differences were very small. A Bayesian ANOVA indicated strong support for the null model, or no difference in A choices between conditions, $BF_{01} = 10.99$, $\eta^2_p = .01$. Thus, the manipulations used in this study did not lead to significantly fewer A choices, like those used in Experiments 1 and 2. Interestingly, a Bayesian ANOVA for the proportion of deck D choices showed moderate support for the alternate hypothesis of a difference between groups, $BF_{10} = 3.78$, $\eta^2_p = .06$. Participants in the original condition selected Deck D on only 13.9% of trials, while participants in the other three conditions made between 19%-23% deck D responses, with chance being 25%.

The transition matrices between decks for each condition are shown in Table 4. Although there was no significant difference in the overall proportion of A choices, a Bayesian ANOVA showed a strong effect of condition for the proportion of repetitive A choices, $BF_{10} = 385.11$, $\eta^2_p = .10$. Participants in the original condition selected deck A on 59% of trials following an A choice, while the other conditions made fewer consecutive A choices, most notably with participants in the segmented-timed condition repeatedly selecting deck A 40% of
the time. This difference in consecutive A choices is similar to that found between the original and segmented conditions in Experiment 1 and 2.

Table 5

| Transition Matrix Between Decks for Each Condition in Experiment 2 |
|-----------------|-------|-------|-------|-------|
|                 | Deck A | Deck B | Deck C | Deck D |
| Original        | .59    | .22    | .11    | .08    |
| Original-Timed  | .54    | .27    | .10    | .09    |
| Seg-Simultaneous| .50    | .29    | .11    | .11    |
| Seg-Timed       | .40    | .31    | .13    | .15    |

Note: Each row indicates the prior choice; each column indicates the proportion of responses to each deck on the next trial. Bold values along the main diagonals indicate repeat choices.

A Bayesian ANOVA for Deck C indicated a strong difference between conditions, $BF_{10} = 95.52$, $\eta_p^2 = .09$. Interestingly, the original condition tended to repeat following a deck C choice the most (45%), while the other conditions made fewer consecutive C choices, particularly for participants in the segmented timed-condition, who only repeated a deck C choice on 19% of trials. There was no difference in consecutive deck B choices, $BF_{01} = 7.90$, $\eta_p^2 = .02$, or deck D choices, $BF_{01} = 2.42$, $\eta_p^2 = .03$, however there was only weak or anecdotal support for the null hypothesis for consecutive deck D choices, whereas there was moderate support for the null hypothesis, indicating that there was no difference among groups on consecutive deck B choices.

The average response times are plotted in Figure 10. A total of 23 of 21,900 response times were excluded for being more than two standard deviations above the overall mean. We ran a multilevel regression model with response time predicted from the additive effects of block and condition, with random intercepts for participants, and with the original condition as the reference group. This model indicated a significant effect of block, $b = -159.27$, $SE = 10.89$, $HCI = [-180.46, -137.21]$. The coefficient for the difference in response times between the original and the original-timed conditions was also significant, $b = 182.06$, $SE = 86.53$, $HCI = [16.59, 347.64]$, but the difference in response times between the original and segmented-timed
condition was not significantly different from zero, \( b = 140.22, SE = 84.14, HCI = [-28.43, 307.72] \). There was little difference in response times between the original and segmented-simultaneous conditions, \( b = 2.58, SE = 81.84, HCI = [-158.97, 159.98] \).

![Figure 10](image.png)

Figure 10. Average response times for each condition in Experiment 3. Error bars represent standard errors of the mean.

One thing to note is that the conditions with the quickest response times (original and segmented-simultaneous) also had the shortest trial lengths, with only one presentation of reward in these conditions. The other two conditions, original-timed and segmented-timed, had longer feedback periods.

**General Discussion**

None of the three segmentation manipulations in Experiment 3 led to better performance than the original condition, and the segmented-timed manipulation led to poorer performance near the end of the task. We did however, observe that participants in the experimental conditions made fewer consecutive A choices, which was consistent with Experiments 1 and 2. The segmented-timed condition participants switched about 60% of the time following an A choice, compared to about 41% of switch trials following A choices in the original condition. However, curiously, participants in the segmented-timed condition selected from deck B more than the other conditions and participants in this condition seldom selected from deck C on consecutive trials. While there were some differences in behavior across conditions, particularly from examining the transition matrices, the manipulations used in Experiment 3 did not seem to produce nearly as strong effects as the manipulation used in the first two experiments.

We also observed that, at least early in the task, response times were longer for participants in the segmented conditions in Experiment 1 and 2. In Experiment 3 we found that response times were longer for the two conditions that had the longer trials, the original-timed and the segmented-timed conditions. This suggests that, across the three experiments, longer trials led to longer lags in responding on successive trials. We did not have specific predictions about how our segmentation manipulation would affect response times, but future work could explore this issue further. For example, one remaining question is whether longer trials simply
led to longer response times, or whether the longer trials from the segmentation manipulations led to more processing of reward outcomes on each trial, which led to slower responding on succeeding trials.

The key difference between the segmentation manipulation used in Experiment 1 and 2, compared to the manipulations in Experiment 3, is that there were no additional button presses in the latter conditions, but button presses were a part of the segmentation manipulation in the first two experiments, where it led to better learning, compared to the original condition. This suggests that the additional button presses were critical for the successful performance brought about by the segmentation manipulation. We propose that the inclusion of additional button presses in the first two experiments was critical for creating the perception that participants were performing additional trials, which enhanced their attention to rare outcomes, and improved performance. As noted above, the results of Experiment 2 suggest that it is not necessary for rare outcomes to be directly associated with more reward segments; the different number of button presses across trials appears to be sufficient for enhancing participants’ sensitivity to rare outcomes.

One limitation of our study is that we did not collect physiological data such as galvanic skin response (GSR). In Bechara and colleagues’ original (1994) study, healthy control participants showed an increased anticipatory GSR before picking from the disadvantageous decks, but patients with vmPFC damage showed no GSRs when selecting from these decks. An open question for future research is whether the segmentation manipulation leads to heightened anticipatory GSR responses. If participants are more sensitive to rare outcomes, then they may develop stronger aversive emotional responses to picking the disadvantageous decks. We also did not collect any self-report data that may have indicated that participants in the segmented condition felt more engaged in the task, or that they were more aware of the rare outcomes, relative to participants in the original condition – this also could have provided further support to the hypothesis that reward segmentation enhances sensitivity to rare outcomes. Future work should test reward segmentation manipulations to assess whether they lead to larger anticipatory GSRs or differences in other measures of motivation or task engagement, compared to participants who perform the task under standard conditions.

The precise computational mechanisms by which the segmentation manipulation from Experiments 1 and 2 improved performance are also still unclear. Future work could test computational models on these, and other data to provide a mechanistic account of how reward segmentation improves performance in tasks like the SGT. One possibility is that the additional button presses for rewards of larger absolute magnitude led to improved memory for those rewards. This would mean that, for Experiment 1, the rare, large magnitude rewards that were given on only 20% of draws from each deck would be remembered more, because of the instrumental act of pressing the button more often for those rewards. However, this would not be the case for Experiment 2. Here the rare rewards for Decks A and B (0 and 200) would be associated with fewer button presses than the frequent rewards (500 and 450). Although, for Decks C and D, the rare rewards (1300 and 1500) would be associated with more button presses than the frequent rewards (300 and 250). Thus, for Decks A and B, the rare low rewards would be less likely to be remembered than the frequent high rewards.

An alternative possibility, is that the additional button presses from the segmentation manipulation led to an improved attentional state that led to better memory for rare outcomes.
This is similar to the instrumental control explanation above, but the improved memory for rare rewards is not directly tied to the number of button presses associated with each reward. Participants may have simply been more engaged in the task and more attentive to the rare outcomes, and this led to better memory for rewards that occurred less frequently. As stated above, the rare small gains for Decks A and B in Experiment 2 may have stood out for being so short, compared to all other trials, and this could have enhanced participants’ sensitivity to those outcomes. The results of Experiment 3 suggest that the additional button presses were critical to the segmentation manipulation, but it may be that the different amount of button presses across trials drew participants’ attention to reward outcomes more than the single button press per trial in the original condition.

It is important to note that we have only used one type of reward segmentation manipulation, where rewards were presented in segments of 100 points. It is an open question whether we would see such improvements in performance with more segments of smaller rewards, such as 50 or 25-point segments, or fewer segments of more points such as 150 or 200-point segments. It’s possible that with too few segments, participants would not perceive as many additional trials, and would still be insensitive to rare outcomes. With too many reward segments, participants might feel that the task is too cumbersome or tedious. A critical question for future work is to identify the minimal level of reward segmentation that is needed to achieve the desired improvement in performance.

The results of this study have important practical implications. The presentation or distribution of monetary payoffs or other rewards can enhance attention to rare outcomes. Including such a reward presentation manipulation appears to have helped participants perform the task better than is normally seen in similar laboratory studies. Our results suggest that something can potentially be done to counteract participants’ insufficient sensitivity to rare outcomes, that has often been observed in decision-making tasks like the SGT or IGT (Lin et al., 2009; Upton et al., 2012; Byrne & Worthy, 2016; Don et al., 2022; Aite et al., 2012). Breaking up the distribution of large gains or losses, and enhancing attention to them by presenting rewards in smaller units, can improve performance, particularly when some outcomes are rare. Similar manipulations of reward-based feedback could be used in other situations to improve learning.

Future work should also examine whether similar reward presentation manipulations, like the segmentation manipulation used in the present study, can improve performance in other types of cognitive tasks. The SGT, used in the present study, involves a manipulation of how frequently different outcomes are presented; would a reward segmentation manipulation also improve learning in tasks where all outcomes were presented with equal frequency? Additionally, could other forms of learning, such as category-learning, be improved by a similar reward segmentation manipulation? A recent paper from our lab showed that some reward structures facilitate better category learning than others (Cornwall, Davis, Byrne, & Worthy, 2022). Similarly, it is possible that performance on memory or attentional control tasks could be improved by manipulating the presentation of reward-based feedback. Thus, there are many avenues for future work to explore how performance can be improved in cognitive tasks, like the gambling task we observed improvement on in this work.
References


