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PRIOR REWARD CONTINGENCIES INFLUENCE THE CONTENTS OF WORKING  
MEMORY BY BIASING ATTENTION IN SPACE BUT NOT IN TIME: EVIDENCE  
FROM RECOGNITION OF SEQUENTIALLY VERSUS SIMULTANEOUSLY  
PRESENTED SETS OF ITEMS

BY

JONATHAN YUQUIMPO

THESIS

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Adviser:

Professor Aaron Benjamin

# Abstract

Attention is automatically drawn towards stimuli features that were previously associated with reward. The consequences of reward on memory are less clear, however. Two experiments investigate the effects prior reward associations have on encoding and recognition in visual working memory. In a training phase, participants searched for one of two colors of target, where one color had a greater reward contingency than the other. In a later task, participants studied sets of three symbols and made old/new judgments on a single test character. Critically, some lists contained a symbol that was presented in a previously rewarded color. Using drift-diffusion analysis, we found that targets that were displayed in high reward-associated color exhibited higher drift rates compared to targets presented a low-reward associated color, but only when the array when presented simultaneously (Experiment 1) and not sequentially (Experiment 2). This combination of results suggests that reward associations shape the distribution of visual-spatial attention but do not induce differential attention and rehearsal for the contents of working memory. Prior reward can influence the content of working memory, but only by a gatekeeping process and not by selective rehearsal.

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# Chapter 1

## Introduction

Rewards are powerful motivators underlying a wide range of human behaviors and cognitive processes, particularly attention [1]–[4]. Attention has traditionally been thought of as being driven by a combination of top-down, goal-directed processes and bottom-up, stimulus-driven processes. Yet a growing body of work now emphasizes the additional role of prior selection history, including reward-driven selection, as a third mechanism in the direction of selective attention [5]–[8]. The phenomenon of value-directed attentional capture (VDAC) reveals that previously learned stimulus-reward associations can automatically modulate attention, leading to higher attentional priority for reward-associated stimuli even when those reward attributes and reward associations are unrelated to the current task [9]. Here, we examine the unintended downstream effects of VDAC on encoding and memory, with specific attention paid to whether there are study conditions that enhance or inoculate against the deleterious effects of VDAC.

Value-driven attention capture has been frequently demonstrated using visual search tasks. In a common variant [9], participants search for an orientation-defined target and receive rewards depending on the color of the circle that surrounds the target line. Correct responses to a high-value colored target result in an 80% chance of a high reward (5¢) and a 20% chance of a low reward (1¢), with this contingency reversed for the low-value color. In a subsequent singleton detection task, the high- and low-rewarded colors from the training phase are presented as distractors. Results have shown that trials with high-value distractors lead to slower response times compared to trials with low-value distractors or trials including distractors with no previously associated value. These findings suggest that the magnitude of reward previously associated with a stimulus influences unintentional attention capture, independent of the physical saliency of the distractor stimulus [9].

The effects of VDAC can persist from days to months after training [10]–[13] and are evident even in contexts in which the reward-associated stimuli are task-irrelevant or counterproductive to an observer’s goals. In a study by Le Pelley, Pearson, Griffiths, *et al.* [14], participants in a visual search task had to fixate on a shape singleton while a colored distractor appeared elsewhere. The color of the distractor determined the amount of reward that could be earned in that trial, but gazing towards that distractor resulted in the omission of rewards on that trial. High-value distractors were found to capture oculomotor gaze more strongly than low-value distractors, even when participants were explicitly informed that gazing at the distractor would result in a penalty. Notably, the reward-associated stimulus was a to-be-ignored element with no prior selection history to account for its attentional capture. This experiment illustrates just how automatically VDAC can occur, and how resistant it is to cognitive control.

Given the powerful effects of reward on attention, it should be considered whether reward also exerts

effects on processes related to attention, such as working memory. Working memory shares common resources and is extensively involved with attention [15]–[21]. A particularly relevant function of attention is selecting or prioritizing what information is maintained in working memory [22]–[25]. The automatic biasing of attention towards rewarded stimuli may enhance memory of those items at the cost of reduced attention and memory capacity for unrewarded stimuli.

Several studies have explored the influence of reward on visual working memory. Gong and Li [26] reported a study in which participants completed a value-training procedure similar to Anderson, Laurent, and Yantis’s [9] visual search task. Afterwards, participants completed a change blindness task, which involved identifying whether the orientation of one of eight uniquely colored lines in a visual search display changed in orientation after a 1000–2500 ms retention interval. Participants showed enhanced detection sensitivity for lines displayed in a high-value color compared to lines displayed in a low-value color or colors without value.

Infanti, Hickey, and Turatto [27] showed that reward can also exert interference effects on memory. Participants in that experiment were shown an array of eight circles, each with a horizontally or vertically oriented line. One circle, a color singleton, was presented in a high-, low-, or no-value color learned from a prior reward training phase. Participants then had to identify the orientation of the line in a location that was probed after a 50 or 800 ms retention interval. The authors assessed whether the probe’s physical proximity to the color singleton affected accuracy. The authors found that interference was modulated by both the distance between the target and singleton and the singleton’s color. Interference was present when the target was near the color singleton, and was greater for high-value singletons compared to low-value and no-value singletons. Together, these findings demonstrate how reward can modulate attentional priority of stimuli, leading to enhanced working memory of rewarded items at the expense of memory for unrewarded items.

Researchers have put forth several theories to explain how reward acts on visual working memory. Some suggest that reward enhances visual processing [28], [29] or increases working memory capacity and maintenance [30], [31]. Others have argued that reward biases attentional allocation by inducing attentional trade-offs between items [32], [33]. Other research has also shown that overtly adjusting reward and punishment contingencies can influence response biases in old/new recognition tasks [34]. Taken together, there are clear reasons to believe that reward contingencies can influence memory by introducing shifts in attention. But it is less clear whether reward contingencies can affect further downstream processing once a stimulus has been encoded into working memory. Rewards may continue to exert effects of prioritization for rehearsal and maintenance in working memory, for example.

Here we explore this question by examining the effects of reward-biased attention on memory for items presented simultaneously (Experiment 1) and for items presented sequentially (Experiment 2). Items that are presented simultaneously compete with one another for spatial attention, while items that are presented sequentially compete for attention not in space but in time. If reward biases affect memory for sequentially presented sets, it would suggest that VDAC can shift the direction of attention not just in space but also by biasing attention and rehearsal within the content of working memory.

Aspects of the current experiments are motivated by other concerns about traditional VDAC procedures. First, many studies use similar stimuli between training and transfer phases. This methodological choice makes it hard to know if shifts in attentional or working memory priority in the transfer phase result from an inability or unwillingness to disengage from the prior task and the reward contingencies that it employs. Here, we use training and testing procedures that differ in more dimensions than traditional VDAC studies. Second, there is mixed evidence as to whether reward influences response bias. Gong and Li [26] demonstrated enhancements in discriminability but no changes in criterion placement towards rewarded stimuli. In contrast,

Bowen, Marchesi, and Kensinger [34] suggested that higher rewards elicit a liberal criterion shift, although the use of explicit reward contingencies in that study make their procedure quite different from those used by others. Furthermore, although reward associations clearly elicit increases in response time, it has largely been unexplored whether those shifts reflect speed-accuracy trade-offs or changes in response bias.

Because rewards may influence information processing, decision processes, or both, it is critical to use an analytic tool that enables precise separation of different components of the decision. The Drift-Diffusion Model (DDM; [35]) is a well validated tool for separating the effects of sensory processing, response caution, and bias. It leverages response time and accuracy data to describe the underlying decision-making processes of participants. In brief, the drift-diffusion model assumes binary decisions are driven by a noisy evidence accumulation process. Respondents start from an initial belief state and accumulating evidence moves the respondent towards one of two absorbing thresholds that each correspond to a choice. Evidence accumulates until a boundary threshold is reached, at which point the respondent makes the resultant choice.

This decision-making process is represented by four key parameters. Drift rate ( $v$ ) represents how quickly evidence is accumulated. Noisier sensory information or increased task difficulty decrease drift rate, while clearer sensory information and easier task difficulty increase drift rate. Boundary separation ( $a$ ) determines how much evidence is required before a decision is made. Higher boundary separation indicates a more conservative approach to decisions, prioritizing accuracy over speed. Lower boundary separation indicates an emphasis on speed. The third parameter, starting point ( $z$ ), reflects the bias the respondent has towards choosing one decision over another. For example, in a recognition-memory task in which "old" identifications are more frequent or carry greater incentives than "new" identifications, respondents may maintain a starting point closer to the boundary corresponding to choosing "old." Lastly, non-decision time ( $t$ ) reflects the time needed for all other processes unrelated to the decision, such as motor movements for key presses. There is a long tradition of fruitful use of the DDM in tasks involving attention and memory [36]–[40], and the structure of the DDM makes it easy to formulate testable hypotheses about how VDAC affects processing in sequential and simultaneous sets of to-be-remembered items.

## 1.1 The current experiments

The aim of these experiments is to examine the extent to which previous reward associations involuntarily influence working memory on a novel set of stimuli, and to use the DDM to evaluate whether those effects represent changes in information accrual or decision processes. We used the value-training procedure used in Anderson, Laurent, and Yantis [9] to train participants to associate one of two target colors, red or green, with higher or lower rewards. Then, in a subsequent visual working memory task, participants were presented with a simultaneous (Experiment 1) or serial (Experiment 2) display of three symbols and asked after a very brief delay whether a test item was included in the display or not. Critically, on some displays, one of the three to-be-remembered symbols was rendered in a reward-associated color. This colored symbol could either be the to-be-probed item, or it could be one of the non-probed items. This design allows us to contrast memory performance between trials where we might expect to see memory enhancement (when the target is colored) and memory interference (when a non-target is colored).

If reward enhances working memory, we expect to see higher drift rates towards probed items that are colored and lower drift rates towards probed items that are not colored but are co-presented with a colored non-target item. Alternatively, if reward association does not enhance memory, but instead changes response caution, we expect to see higher boundary separation for high-reward items compared to low-reward items.

# Chapter 2

## Experiment 1

### 2.1 Method

#### 2.1.1 Participants

One hundred eighteen undergraduate students from the University of Illinois Urbana-Champaign participated in exchange for course credit. Eleven participants were excluded because their accuracy during either the training or transfer phase was at or below chance level (50%). One participant was excluded due to data recording errors. This resulted in a final sample of 106 participants. We selected our sample size according to the lower bound of effect sizes found from a similar study by Sandry, Schwark, and MacDonald ([41]; Cohen's  $d = 0.35$ ). We estimated a need for 70 participants for a within-subjects design to achieve power of 0.8 at an alpha level of 0.05, but we continued sampling additional participants due to the availability of subjects at the time. All participants had normal or corrected-to-normal vision and normal color vision. All procedures were approved by the University of Illinois Institutional Review Board.

#### 2.1.2 Materials

The experiment was programmed in PsychoPy 6.2.0 (de Leeuw, 2015) and run on a Dell Optiplex using the Google Chrome web browser. Stimuli were presented on a 22in, 60Hz, 1080p Dell monitor viewed from a distance of approximately 70 cm. Responses were entered using a standard keyboard.

#### 2.1.3 Procedure

The experiment comprised two parts that took 1 hour in total to complete. The training phase was a visual search task similar to the value-driven attention capture task [9], but modified to award virtual points instead of money. The transfer phase used a visual short-term memory task. Participants were given 30-second breaks after every 50 trials during the training phase, and after every 60 trials during the transfer phase.

**Training Phase** The trial events for the training phase are illustrated in Figure 2.1A. The stimuli were presented against a grey background. Each trial started with a black fixation cross that lasted for a random uniform duration between 400–600 ms. Then, a search display appeared and remained on screen until a response was made or the trial timed out after 1000 ms. The search display consisted of six black lines (3.5 cm length) contained within six circles (5 cm diameter) arranged equidistantly along an invisible circle with



a diameter of 15.5 cm around the fixation cross. Five non-target circles were each presented in a unique color from the set black, blue, turquoise, pink, and yellow. The sixth (target) color was either red or green. For each participant, one of these target colors was assigned to be the high-value color, and the other was assigned to be the low-value color. The high-value color appeared in half of the trials, and the low-value color appeared in the other half. Each circle contained a short line segment. The line segment in the critical circle (the red or green circle) was oriented horizontally ( $0^\circ$ ) or vertically ( $90^\circ$ ). All other lines were randomly oriented diagonally to the left or right by  $45^\circ$ . Only one target was presented in each trial, and the target was equally likely to appear in any of the six positions.

Participants were instructed to look for the red or green circle and report the orientation of the line within the circle by pressing Z for a horizontal line and M for a vertical line. After each response, participants received feedback with a display (1000 ms) showing the number of virtual points they were awarded for that trial, as well as the total cumulative points that they had thus far earned in the experiment. Participants were awarded +2 points or +10 points for correct responses, and 0 points for incorrect responses or if they failed to respond within 1000 ms. Critically, the frequency of each of the rewards for correct responses depended on the color of the target. Responses to high-value targets had an 80% chance of receiving the higher reward and a 20% chance of receiving the lower reward, with the reverse contingency applied to low-value targets. Thus, the training phase assigned one color with a probabilistically higher value and the other with a lower value. Participants were instructed to earn as many points as they could, while emphasizing both speed and accuracy.

Participants completed 10 practice trials, with the option to repeat these trials, before proceeding to the experimental trials. The experimental trials consisted of 200 trials divided into 4 blocks, with a 30-second break screen displayed between blocks. The break screen provided feedback on the participant’s overall accuracy and the total number of points earned.

**Transfer Phase** The working-memory transfer phase was administered immediately following the training phase and is summarized in Figure 2.1B. Each trial began with a 400–600 ms fixation cross. Then a search array with three symbols was displayed for 750 ms. The items were positioned equidistant from the fixation along an invisible circle with a diameter of 15.5 cm. We used a set of 90 unique symbols taken from the Brussels Artificial Character Sets [42], which are a set of standardized characters that simulate features of various alphabets without being recognizable to participants. The goal of using these stimuli was to minimize verbal recoding of the memoranda. Within each trial, three symbols were randomly selected without replacement from the total stimulus set. Across trials, symbols could be repeated. Most symbols were presented in black, but on some trials, one character was displayed in red or green. No rewards were accrued and color had no bearing on the task.

Following a stimulus mask and a retention interval of 1000 ms, a test item was displayed with a prompt instructing participants to identify the test symbol as old (meaning it was included in the previous set) by pressing the Z key, or new (meaning it was a new item that was not included in the previous set) by pressing the M Key. After each response, feedback was displayed for 1500 ms with “Correct” for correct responses or “Miss” for wrong or late responses.

To maximize the number of critical trials, we adjusted the number of old versus new trials and the number of color-present to color-absent trials. There were 144 old trials and 96 new trials. Of the old trials, 36 had no color, 54 had a high-reward-colored symbol present, and 54 had a low-reward-colored symbol present. Of the new trials, 24 had no color, 36 had a high-reward-colored symbol present, and 36 had a low-reward-colored

symbol present. The colored item, and the test item (for old displays) were equally likely to appear in any of the three study positions. Because the ratio of old to new trials was kept consistent across color-present and color-absent trials, participants could not strategically use the presence or position of a colored item to enhance accuracy.

Participants completed 10 practice trials with the option to repeat the set of practice trials before proceeding to the experimental trials. The experimental trials consisted of 240 trials divided into 4 blocks, with a 30-second break screen displayed between blocks. The break screen provided feedback on the participant’s cumulative accuracy in percentage correct.

## 2.2 Results

### 2.2.1 Behavioral Performance

We used t-tests and ANOVA tests with Greenhouse-Geisser corrections as our primary analysis of behavioral data. The Bayes factors ( $BF_{10}$ ) presented here indicate the ratio of evidence in favor of the alternative hypothesis; values greater than one indicate evidence favoring the alternative, and values less than one indicate evidence favoring the null. We interpret Bayes factors greater than 3 and less than 0.33 as our criteria for evidence of the alternative and null hypotheses, respectively [43]. Bayes factors were calculated using BayesFactor version 0.9.12-4.2 [44] in R with default Cauchy settings of 0.707 for priors.

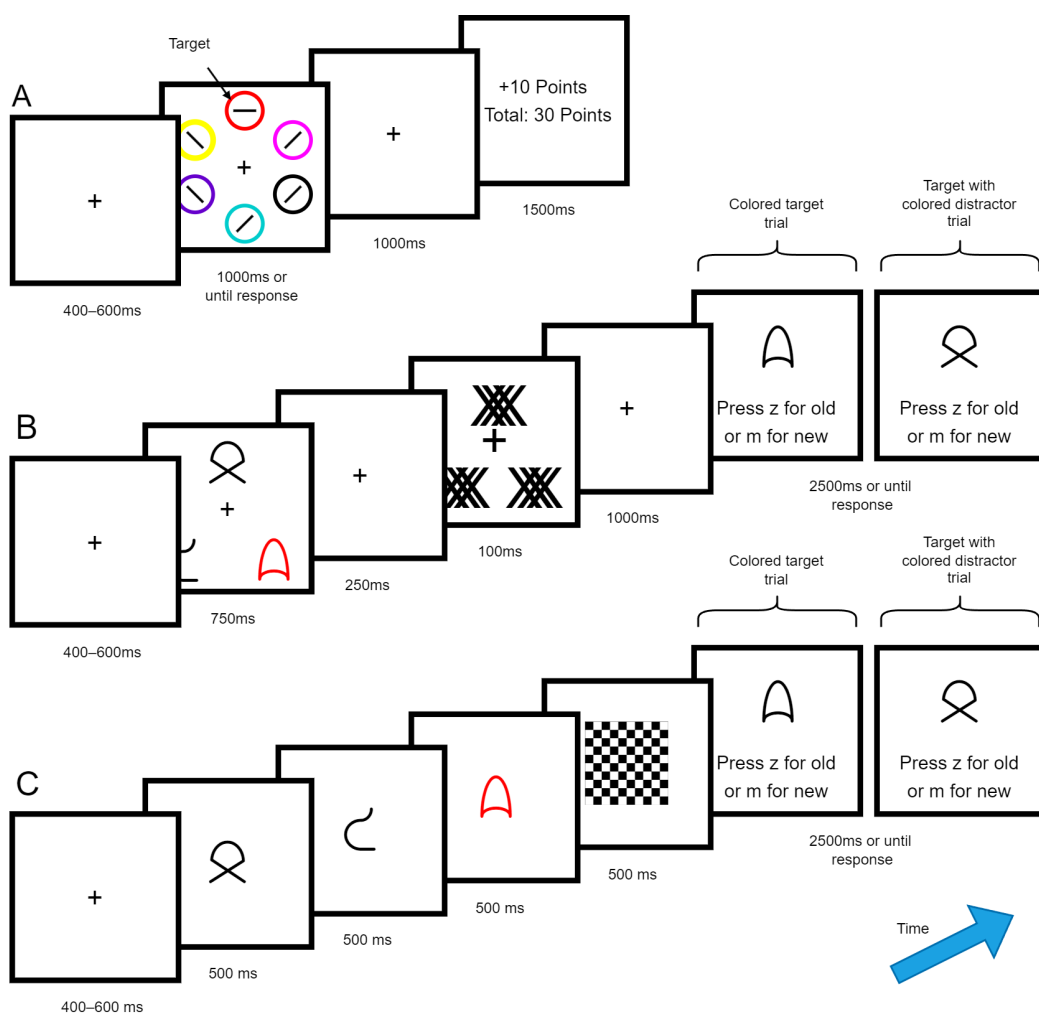
**Training Phase** Mean performance in accuracy and response time (RT) is illustrated in Figure 2.2. Participants improved in accuracy ( $F(2.52, 264.45) = 46.07, p < 0.001, BF_{10} = 3.71 \times 10^{21}$ ) and RT ( $F(2.43, 254.76) = 70.27, p < 0.001, BF_{10} = 2.86 \times 10^{31}$ ) across the four blocks of the experiment. However, there were no significant differences in accuracy or response time between the high and low-reward conditions.

**Transfer Phase** For the recognition task, performance was analyzed based on two factors: reward color (high, low, and control) and color-target correspondence (colored target versus target paired with a colored lure). In “colored target” trials, the target item is the colored item among the set of three items in a trial, whereas in “target with colored lure” trials, the target item is not the colored item in the trial, and a different non-target item is colored (see Figure 2.1C). In the control condition, no items are colored. In the examination of the effects of color-target correspondence, the analysis was restricted to old trials because new trials do not present any target item to distinguish.

Mean accuracy and response time (RT) by color-target correspondence is summarized in Figure 2.2C. Across all trial types, there were no significant changes in accuracy over the four experiment blocks, but there was a decrease in response time ( $F(2.51, 263.88) = 22.06, p < 0.001, BF_{10} = 1.36 \times 10^{10}$ ). There was a significant effect of reward color on accuracy ( $F(1.93, 202.63) = 3.33, p = 0.039, BF_{10} = 0.68$ ), but Holm-Bonferroni post-hoc analysis revealed no significant differences between colors ( $p > 0.059$  for all comparisons). Similarly, there were no significant effect of color on response time.

Comparing between color-target correspondences (colored targets vs. targets with colored lures), we found a main effect of target correspondence on accuracy ( $F(1, 105) = 5.20, p = 0.025, BF_{10} = 3.08$ ). Participants were less accurate on *target with colored lure* trials compared to *colored target* or control trials. Holm-Bonferroni post-hoc analysis revealed a significant difference between low-uncolored target trials versus high-colored target trials  $t(105) = -3.004, p = .020$ . However, we found no interaction between target

Figure 2.1: Experimental design. (A) Visual search task. Participants reported the orientation of the line inside the red or green circle. Awarded points a correct response were probabilistically higher for one color over the other. (B) Memory task for experiment 1. A to-be-remembered set of 3 symbols elements was presented and followed by a yes/no recognition judgment for a test symbol. On some trials, one of the symbols was rendered in a color previously associated with the high or low reward target. (C) Memory task for experiment 2. A series of 3 symbols were presented individually followed by a recognition trial. On some trials, one of the symbols was rendered in a color associated with the high or low reward target.



correspondence and reward color. We also found no effect of target correspondence on response time, nor an interaction between reward color and target correspondence.

## 2.2.2 Drift-diffusion analysis

To examine the influence of reward on the latent decision processes involved in recognition memory, we used a Bayesian hierarchical drift-diffusion model (HDDM v0.9.8; [45]). This Python package estimates DDM model parameters across experimental conditions while also constraining individual parameter estimates according to group-level estimates. These parameter estimates are quantified in the form of a posterior distribution from a Markov chain Monte-Carlo (MCMC) sampling method. This allows us to test for significant differences in parameter estimates directly on the obtained posterior distributions.

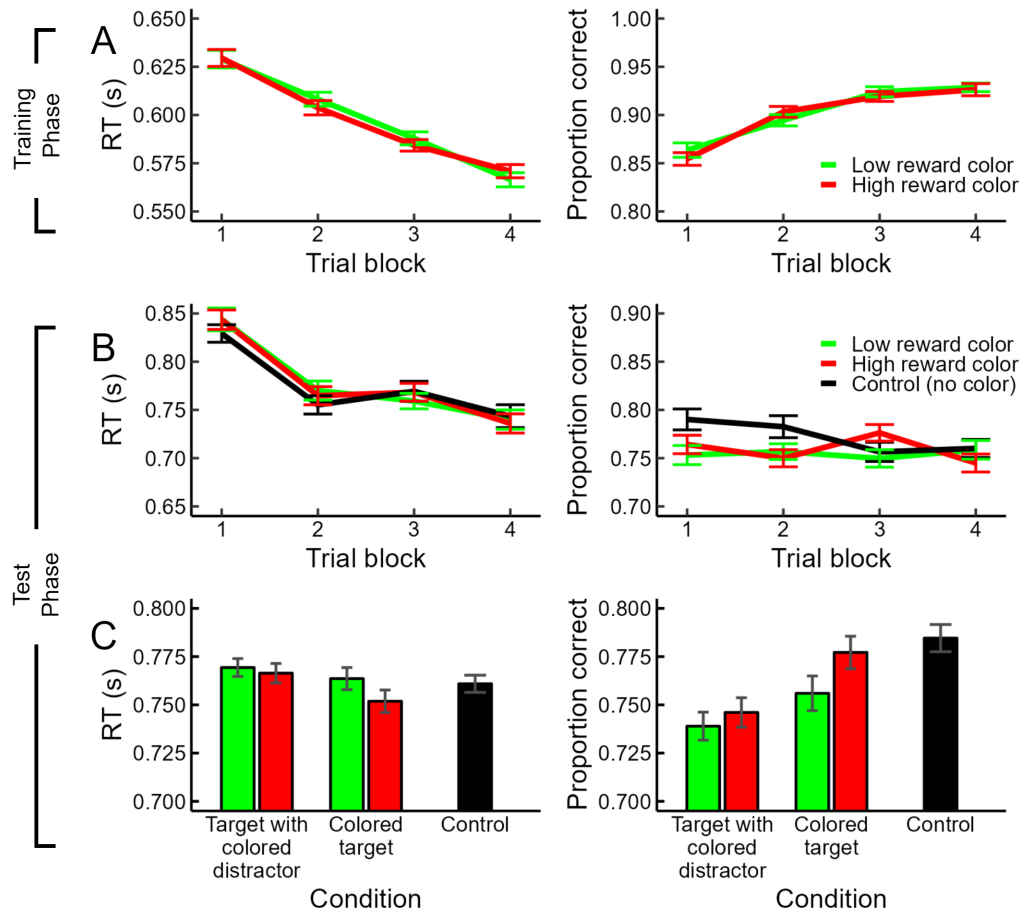
To estimate within-subject effects in HDDM, we used the *HDDMRegressor* function. The control condition was set as an intercept and the four conditions (high-colored target, low-colored target, target with high-colored lure, and target with low-colored lure) were dummy-coded. Our hypothesis is focused on how reward associations influence information search processes and response conservatism. Thus, for this analysis, we allowed the parameters for drift rate and response threshold to vary by condition. Non-decision time was fixed across conditions and the starting point was fixed at 0.5 (halfway between the two boundaries). We ran 5000 samples and discarded the first 500 as burn-in. We also assigned 5% of the most extreme RTs to an outlier distribution.

The parameter estimates for drift rate and boundary separation by trial type and reward color are summarized in Table 2.1 and the posterior parameter distributions are shown in Figure 2.3. Posterior distributions are compared by computing the degree of overlap. This overlap is denoted by the Bayesian probability  $p(\text{hypothesis})$  which expresses the probability of the stated hypothesis being true. For example, when testing the hypothesis that high reward results in a higher drift rate than the control condition ( $p(v_{\text{high target}} > v_{\text{control}})$ ), a probability of .95 would indicate a 95% chance of the hypothesis being true, whereas a probability of .05 would indicate a 95% chance of the converse ( $p(v_{\text{control}} > v_{\text{high target}})$ ) being true. A probability of .5 indicates both hypothesis are equally likely, and constitutes a null result. We consider  $p > .95$  and  $< .05$  as a threshold for significance.

**Drift rates** Drift rates were higher for high-reward targets than for low-reward targets ( $p(v_{\text{high target}} > v_{\text{low target}}) = 0.97$ ). Furthermore, drift rates were lower for low-reward targets than for control trials ( $p(v_{\text{control}} > v_{\text{low target}}) > .99$ ), but were not lower for high-reward targets compared to control trials ( $p(v_{\text{control}} > v_{\text{high target}}) = 0.86$ ). For target with colored lure trials, there was no difference between high or low reward colors ( $p(v_{\text{high lure}} > v_{\text{low lure}}) = 0.77$ ) but drift rates for both conditions were lower than the control ( $p(v_{\text{control}} > v_{\text{high lure}}) = 1.00$ ;  $p(v_{\text{control}} > v_{\text{low lure}}) = 1.00$ ). Comparing colored targets against targets with colored lures, there were greater drift rates for high-reward targets than targets paired with a high-reward lure ( $p(v_{\text{high target}} > v_{\text{high lure}}) = 0.98$ ), but there was no difference for low-reward targets compared to targets paired with a low-reward lure ( $p(v_{\text{low target}} > v_{\text{low lure}}) = 0.72$ ).

**Boundary separation** For colored target trials, there was no difference in boundary separation between high and low conditions ( $p(a_{\text{high target}} > a_{\text{low target}}) = .53$ ), nor was there a difference between both reward conditions and the control ( $p(a_{\text{control}} > a_{\text{high target}}) = .87$ ;  $p(a_{\text{control}} > a_{\text{low target}}) = .89$ ). For target with colored lures trials, there was no difference between high and low conditions ( $p(a_{\text{high lure}} > a_{\text{low lure}}) = .43$ ), nor was there a difference between both color conditions and the control ( $p(a_{\text{control}} > a_{\text{high lure}}) = .49$ ;

Figure 2.2: Behavioral results for Experiment 1. (A) Response time and accuracy for the training phase by trial block. Each block represents 50 trials. (B) Response time and accuracy for the transfer phase by trial block. Each block represents 60 trials. (C) Response time and accuracy for the transfer phase by reward color and target-color correspondence.



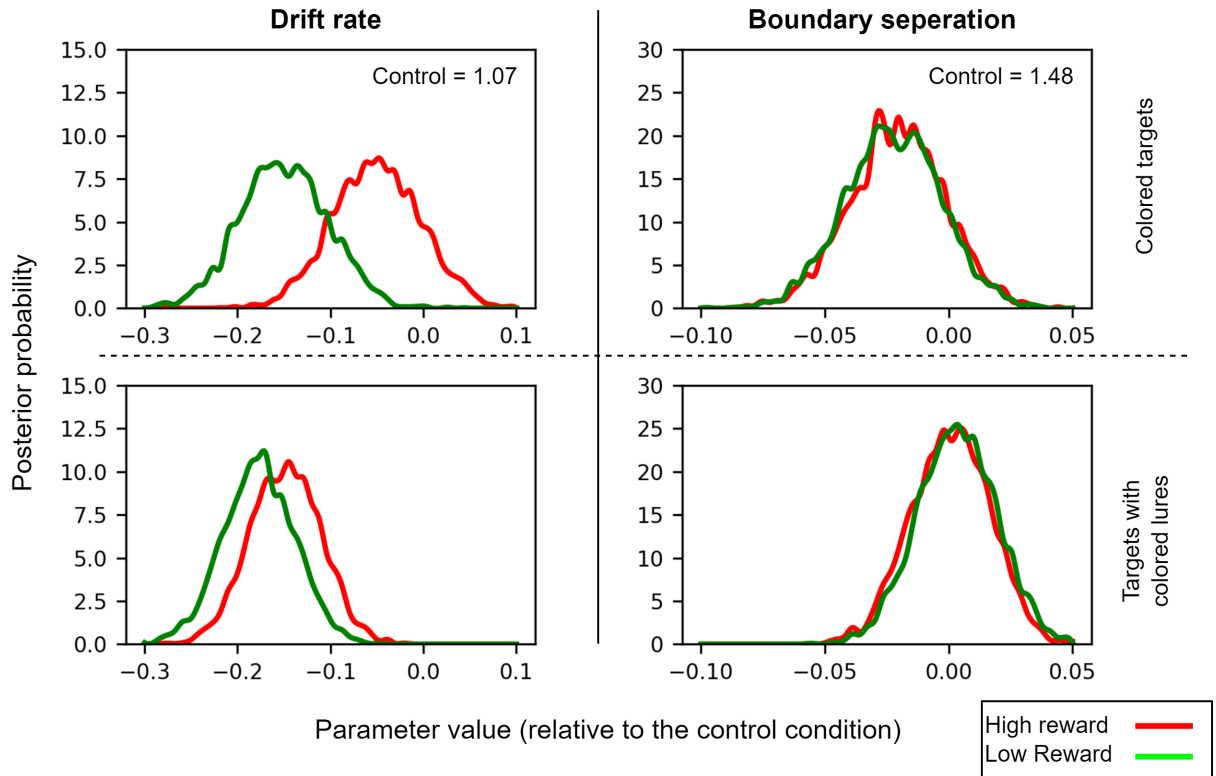
$p(a_{control} > a_{low\ lure}) = .43$ ). In comparing colored targets against targets with colored lure trials, we found no difference between colored targets and targets with colored lures for either high or low reward colors ( $p(a_{high\ target} > a_{high\ lure}) = .13$ ;  $p(a_{low\ target} > a_{low\ lure}) = .09$ )

## 2.3 Discussion

The aim of Experiment 1 was to investigate the impact of reward-associated colors on visual working memory for a novel stimulus. The experimental design enabled us to explore scenarios where a reward color served as the eventual target and also cases where it was not. We employed a drift-diffusion model to disentangle the distinct effects of drift rate, which reflects the speed of information accumulation, and response boundary, which characterizes response conservatism.

Influences of reward were apparent in the drift-diffusion analysis. High reward led to enhanced information processing compared to low reward, suggesting that reward magnitude influenced the distribution of attention during study and consequent degree of encoding into working memory. The fact that reward overall reduced

Figure 2.3: Posterior distributions for drift rate and boundary separation (columns) by target-color correspondence (rows) for Experiment 1.



*Note.* Parameter estimates are expressed relative to the control condition.

Table 2.1: Mean parameter estimates for drift rate, boundary separation, and non-decision time by reward condition and reward-color correspondence for Experiment 1.

Parameter	Condition	Mean Estimate	Lower Bound	Upper Bound
Drift rate	High reward colored target	<b>1.02</b>	0.81	1.23
	Target with high reward colored lure	<b>0.92</b>	0.73	1.11
	Low reward colored target	<b>0.92</b>	0.71	1.13
	Target with low reward colored lure	<b>0.89</b>	0.70	1.09
	Control	<b>1.07</b>	0.95	1.19
Boundary separation	High reward colored target	<b>1.46</b>	1.37	1.54
	Target with high reward colored lure	<b>1.48</b>	1.40	1.56
	Low reward colored target	<b>1.46</b>	1.37	1.54
	Target with low reward colored lure	<b>1.48</b>	1.40	1.56
	Control	<b>1.48</b>	1.43	1.53
Non-decision time	Fixed across conditions	<b>0.37</b>	0.33	0.41

*Note.* Lower and upper bound indicate the 2.5<sup>th</sup> and 97.5<sup>th</sup> quartiles, respectively.

processing efficiency likely reflects a disruptive effect of a color singleton in the array; high reward seems to have mitigated that disruptive effect. When a study item was colored that did not eventually serve as the test item, there were no differences as a function of color.

In the analysis of response boundary, no significant differences were observed between high- and low-reward colors or between the rewarded colors and the control condition, regardless of whether the colored item was the target or a lure. This result suggests that the effects of reward on memory representation primarily act on evidence accumulation processes rather than on decision processes that affect response conservatism.

The enhancement in drift rate for high-reward colors is consistent with the view that prior reward acts to influence attention. Early or prolonged direction of gaze and attention to a high-reward stimulus in the study set increases the probability and durability of encoding into visual working memory [24], [46]–[48]. It also decreases encoding of other elements in the display, as revealed by the effects of colored items that did not serve as targets.

In Experiment 2, stimuli were presented in a continuous stream centered at a single location on the screen. This procedure removes the opportunity for VDAC to influence memory by drawing the subject’s gaze; if reward contingencies are still seen in memory for sequentially presented lists, it would suggest that those reward contingencies continue to exert effects on the content of working memory beyond the initial direction of attention.

# Chapter 3

## Experiment 2

### 3.1 Methods

#### 3.1.1 Participants

Seventy students from the University of Illinois Urbana-Champaign participated in this study in exchange for course credit. Seven participants were excluded from analysis for performing at or below chance level in either the training or transfer phase of the experiment. One participant was excluded due to technical problems with data recording. The sample size was selected according to the lower bound of effect sizes found from a similar study [41] (Cohen’s  $d=0.35$ ). We estimated needing 70 participants to achieve power of 0.8 at an alpha level of 0.05 in a within-subjects design. All participants had normal or corrected-to-normal vision and normal color vision. All procedures were approved by the University of Illinois Institutional Review Board.

#### 3.1.2 Materials

The experiment was programmed in PsychoPy 6.2.0 (de Leeuw, 2015) and was run online. Participants accessed the study on their own personal computers through a secure link on the university server. Screen resolutions below 720p were excluded from participation.

#### 3.1.3 Procedure

Experiment 2 was similar to Experiment 1, except for some changes in the transfer phase, which are summarized in Figure 2.1C. Following a 400–600 ms fixation cross, participants were briefly presented with a stream of 3 symbols, one after another, with each lasting 500 ms and positioned in the center of the display. The symbols were the same set of characters from Experiment 1. Symbols were primarily presented in black, but on some trials, one character was displayed in red or green. However, color was not relevant to the task. The stream of symbols was followed by a 500 ms stimulus mask and the test item. Like experiment 1, participants responded with Z to indicate that the test item was an old symbol or M to indicate that the item was a new symbol. Participants received feedback with *correct* or *miss* depending on their response but they did not receive any points in the transfer phase.

There were 120 old trials and 80 new trials. Of the old trials, 30 had no color, 45 had a high-reward colored symbol present, and 45 had a low-reward-colored symbol present. Of the new trials, 20 had no color, 30 had a high-reward-colored symbol present, and 30 had a low-reward-colored symbol present. The



colored item, and the test item (for old lists) were equally likely to be in any of the three positions. As in Experiment 1, the ratio of old to new trials was kept consistent across color-present and color-absent trials so that participants could not use the presence or position of a colored item to inform the recognition judgment.

Participants completed 10 practice trials with the option to repeat the set of practice trials before proceeding to the experimental trials. The 200 experimental trials were evenly divided into 4 blocks, with a 30-second break screen showing the participant’s cumulative accuracy in-between each block.

## 3.2 Results

### 3.2.1 Behavioral Performance

**Training Phase** Mean accuracy and response time are shown in Figure 3.1. Accuracy increased ( $F(2.69, 164.16) = 16.91, p < 0.001, BF_{10} = 1.04 \times 10^7$ ) and RT decreased ( $F(2.16, 132.04) = 28.70, p < 0.001, BF_{10} = 2.05 \times 10^{12}$ ) over the four blocks of the experiment, but there was no significant difference in accuracy ( $t(61) = -0.6, p = 0.6, BF_{10} = 0.161$ ) or response time ( $t(61) = -1, p = 0.2, BF_{10} = 0.325$ ) between the high and low-reward conditions.

**Transfer Phase** There was no effect of block on accuracy ( $F(2.94, 179.49) = 0.82, p = 0.482, BF_{10} = 0.0534$ ), but there was a significant decrease in response time over the four experiment blocks ( $F(1.98, 120.77) = 5.20, p = 0.007, BF_{10} = 12.3$ ). We found no effect of reward color on accuracy ( $F(1.95, 118.91) = 0.32, p = 0.719, BF_{10} = 0.0727$ ) or response time ( $F(1.99, 121.14) = 0.29, p = 0.747, BF_{10} = 0.0704$ ), with Bayes Factors indicating substantial support for the null hypothesis in both cases. There were also no differences between conditions in the final block on accuracy ( $F(1.96, 119.67) = 0.36, p = 0.698, BF_{10} = 0.0772$ ) or response time ( $F(1.87, 113.93) = 0.20, p = 0.802, BF_{10} = 0.0452$ ).

There was no effect of target correspondence on accuracy ( $F(1, 61) = 0.08, p = 0.779, BF_{10} = 0.143$ ), and no interaction between target correspondence and reward color ( $F(1, 61) = 0.01, p = 0.773, BF_{10} = 0.198$ ). There was also no effect of target correspondence on response time ( $F(1, 61) = 1.49, p = 0.227, BF_{10} = 0.322$ ), nor an interaction between reward color and target correspondence ( $F(1, 61) = 2.41, p = 0.126, BF_{10} = 0.617$ ).

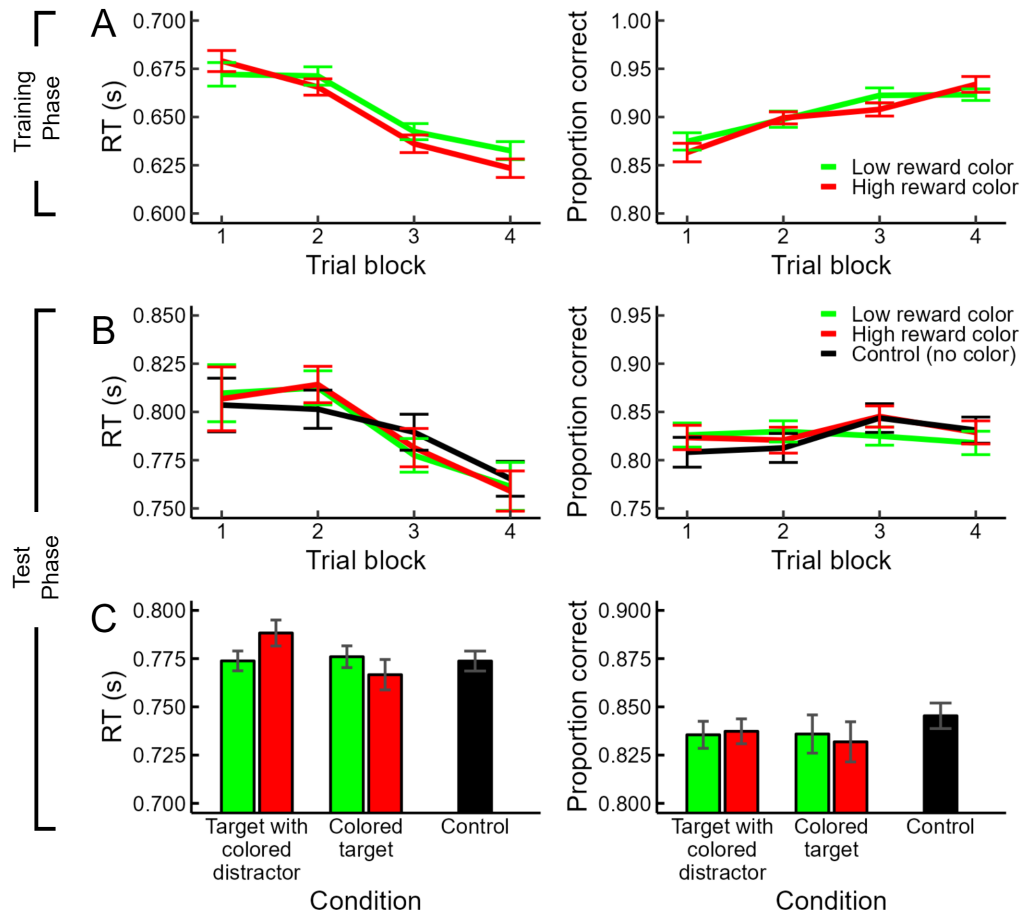
### 3.2.2 Drift-diffusion analysis

The parameter estimates for drift rate and boundary separation by trial type and reward color are summarized in Table 3.1 and the parameter distributions are shown in Figure 3.2.

**Drift rate** There were no differences in drift rates between high-reward targets and low-reward targets ( $p(v_{high\ target} > v_{low\ target}) = .43$ ) and neither reward-colored target condition differed from the control condition ( $p(v_{control} > v_{high\ target}) = .89; p(v_{control} > v_{low\ target}) = .84$ ). For target with colored lures lists, there was no difference between high and low reward colors ( $p(v_{high\ lure} > v_{low\ lure}) = .53$ ) nor was there a difference between either target with colored lure condition and the control condition ( $p(v_{control} > v_{high\ lure}) = .76; p(v_{control} > v_{low\ target}) = .78$ ). Comparing colored targets against targets with colored lures, there no differences for high and low-reward colors ( $p(v_{high\ target} > v_{high\ lure}) = .26; p(v_{low\ target} > v_{low\ lure}) = .34$ ).

**Boundary separation** For colored target lists, there was no difference in boundary separation between high and low conditions ( $p(a_{high\ target} > a_{low\ target}) = .34$ ) and neither reward-colored target conditions differed

Figure 3.1: Behavioral results for Experiment 2. (A) Response time and accuracy for the training phase by trial block. Each block represents 50 trials. (B) Response time and accuracy for the transfer phase by trial block. Each block represents 60 trials. (C) Response time and accuracy for the transfer phase by reward color and target-color correspondence.

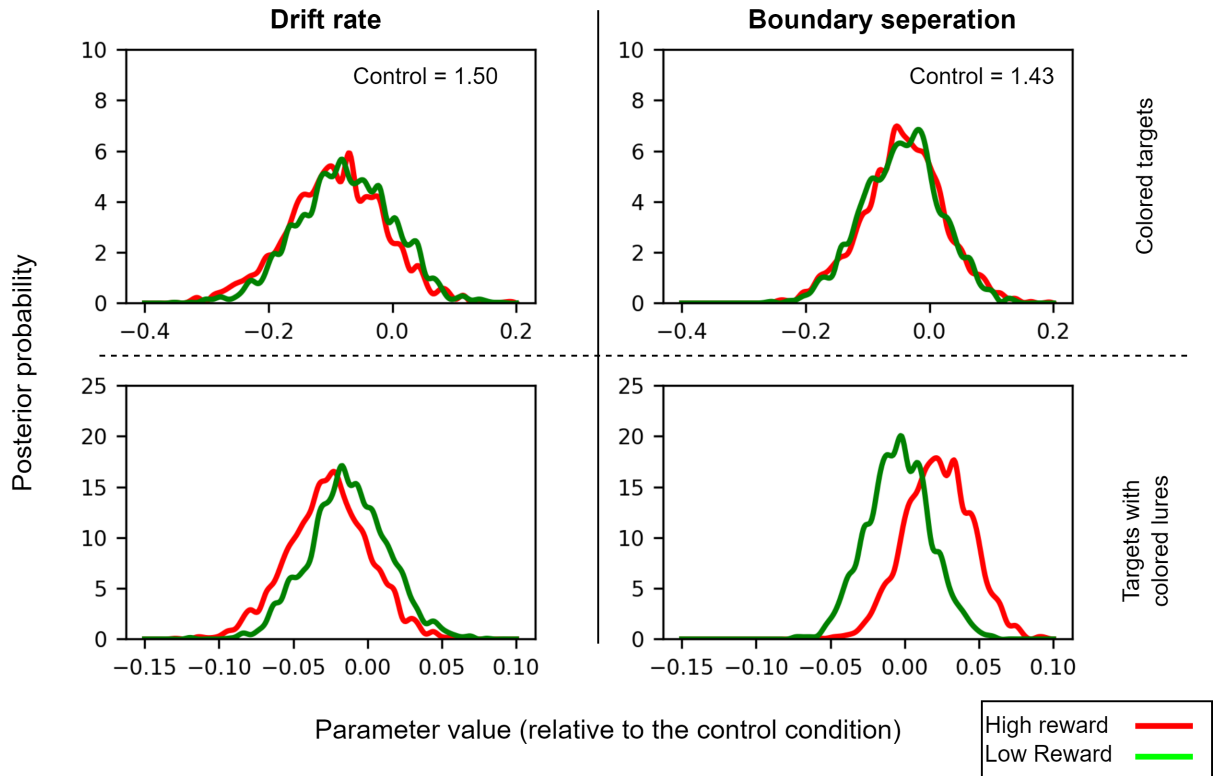


from the control condition ( $p(a_{control} > a_{high\ target}) = .84$ ;  $p(a_{control} > a_{low\ target}) = .70$ ). For target with colored lures lists, there was no difference between high and low reward colors ( $p(a_{high\ lure} > a_{low\ lure}) = .88$ ) nor was there a difference between either target with colored lure condition and the control condition ( $p(a_{control} > a_{high\ lure}) = .17$ ;  $p(a_{control} > a_{low\ target}) = .59$ ). Comparing colored targets against targets with colored lures, high-reward-colored targets had less boundary separation than targets with high-reward-colored lures ( $p(a_{high\ target} < a_{high\ lure}) = .96$ ). However, given the marginal level of significance, and the failure to obtain an analogous result in any other conditions, a cautious interpretation of this result is warranted. Lastly, there was no difference for low-reward-colored targets and targets with low-reward-colored lures ( $p(a_{low\ target} > a_{low\ lure}) = .37$ ).

### 3.3 Discussion

Experiment 2 aimed to investigate whether the previously observed changes in drift rate seen in Experiment 1 would persist in a task where all stimuli were presented temporally in a single location. The persistence of

Figure 3.2: Posterior distributions for drift rate and boundary separation (columns) by target-color correspondence (rows) for Experiment 2.



*Note.* Parameter estimates are expressed relative to the control condition.

Table 3.1: Mean parameter estimates for drift rate, boundary separation, and non-decision time by reward condition and reward-color correspondence for Experiment 2.

Parameter	Condition	Mean Estimate	Lower Bound	Upper Bound
Drift rate	High reward colored target	<b>1.41</b>	1.16	1.46
	Target with high reward colored lure	<b>1.46</b>	1.28	1.54
	Low reward colored target	<b>1.42</b>	1.20	1.49
	Target with low reward colored lure	<b>1.45</b>	1.29	1.52
	Control	<b>1.50</b>	1.33	1.66
Boundary separation	High reward colored target	<b>1.40</b>	1.32	1.43
	Target with high reward colored lure	<b>1.45</b>	1.43	1.51
	Low reward colored target	<b>1.41</b>	1.35	1.45
	Target with low reward colored lure	<b>1.42</b>	1.38	1.46
	Control	<b>1.43</b>	1.35	1.51
Non-decision time	Fixed across conditions	<b>0.45</b>	0.42	0.48

*Note.* Lower and upper bound indicate the 2.5<sup>th</sup> and 97.5<sup>th</sup> quartiles, respectively.

this effect would suggest that the influence of VDAC extends beyond its effects on the distribution of spatial attention.

The drift-diffusion analysis revealed no differences in drift rates between high and low-reward-colored targets, as well as no differences between either reward-colored target condition and the control condition. Furthermore, there were no differences in drift rate between colored targets and targets with colored lures.

The results of Experiment 2 qualify the conclusions drawn in Experiment 1. By presenting stimuli in a fixed location, Experiment 2 eliminated the effect of color-target correspondence on accuracy observed in Experiment 1. The differences in drift rate observed in Experiment 1 were no longer present in Experiment 2. This combination of results aligns with the hypothesis that the effects of reward operated principally on the direction of gaze in Experiment 1.

## Chapter 4

# General Discussion

The present research investigated the effects of reward-associated colors on visual working memory for novel stimuli using a drift-diffusion approach. This methodology advances our understanding of how reward impacts attention and visual working memory by separating differences in information accumulation processes from changes in response caution. Our findings revealed that while reward modulates the initial visual-spatial allocation of attention and the subsequent encoding of items into visual working memory, it does not appear to influence the maintenance of those items in working memory.

In Experiment 1, we found that that targets displayed in a high reward-associated color had greater drift rates compared to targets displayed in a low reward-associated color. This difference reflects an enhancement of information processing towards the high reward-colored items, consistent with previous research [26], [27]. This outcome aligns with the notion that reward shapes spatial attention and gaze in ways that affect the likelihood of encoding items into visual working memory [31], [33], [49]. However, the spatial-visual arrangement of the stimuli does not decisively distinguish whether these observed enhancements in processing stem exclusively from early attention processes or from changes in the maintenance of those items within working memory.

Experiment 2 extends our investigation by demonstrating that when items were presented at a singular, fixed location, the differences in drift rates between the two reward-colored trials and the control were eliminated. This manipulation effectively prevented participants from deliberately shifting their gaze towards reward-colored items. The results suggest that, while reward may indeed impact the spatial distribution of attention, it exerts no discernible effect on the attention or maintenance of items within working memory over time. This is further supported by the absence of any interference effects from colored items when they were presented as a lure, which would have been expected if reward shifted working memory priority.

These findings diverge from previous studies reporting memory enhancements towards reward-colored items [31], [32] and memory interference effects from such items [27]. Particularly, Sandry and Ricker [32] noted clear enhancements in accuracy and response time towards rewarded items presented within a similar three-item list. However, it should be noted that their study directly linked a higher reward contingency to colored memoranda, potentially incentivizing participants to prioritize the maintenance of those items. In the current Experiment 2, the color of the item was unrelated to the task and thus any differences in maintenance strategies could only be due to previously acquired reward associations.

Our work also contributes evidence regarding the scope of influence that reward associations can exert on responses directed at diverse stimuli. Studies using the VDAC paradigm conventionally use similar sets of

stimuli through the training and test phases [9], [14], [26], [27]. Often, these studies utilize the same array of circles, with only minor differences introduced in the test phase. Despite the deliberate use of novel symbols during the transfer phase of Experiments 1, we still observed an impact on the processing of these stimuli. It is worth noting, however, that other research has also shown VDAC to be highly context-specific [50]. Thus, it could be beneficial to conduct further studies aimed at understanding the degree to which VDAC effects transfer between stimuli and contexts of increasing dissimilarity.

With respect to boundary separation, our study yielded no substantial evidence to support the idea that reward influences response boundaries, barring a single marginally significant outcome in Experiment 2. This set of results suggests that, in the memory task, reward did not significantly alter participants' preference for quicker or accurate responses across conditions. This pattern is evident in the degree of overlap shown in Figures 2.3 and 3.2. However, it is important to remember that we did not intentionally emphasize speed or accuracy differently between reward conditions. Hence, while we cannot entirely rule out the possibility that previously learned speed-accuracy tendencies might carry over into other task-irrelevant contexts, we can tentatively conclude that reward associations alone are insufficient to induce meaningful changes in response caution.

Lastly, although analyzing target-present trials has shed light on the impact of reward on drift rate and boundary separation, it falls short of adequately disentangling reward strength and color-target correspondence from old-new response biases. To date, just one study [34] has demonstrated that reward structures could induce a liberal response bias shift (i.e., more likely to endorse an "old" response), but little exploration has been undertaken into the mechanisms by which reward might influence response bias and whether such effects extend to other task-irrelevant contexts. Further studies are needed to better understand this consequence of reward.

Previous literature has extensively demonstrated the interplay between reward and attention [4], [9], [33], [49] and between attention and visual working memory [15]–[17], [25], [48]. Our findings contribute a nuanced understanding of the flexibility and constraints inherent in the relationship between reward, attention, and visual working memory. While prior reward associations influence attention towards novel stimuli, and thereby influence early encoding, we have found little evidence that reward operates beyond that stage on the selective rehearsal or maintenance of items in working memory.

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