Reward differentially interacts with physical salience in feature-based attention

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A visual feature associated with reward can capture attention when it is neither physically salient nor task relevant. Although such findings suggest that reward acts similarly as physical salience, it is unknown whether reward works independently or interactively with physical salience to modulate attentional priority. Here, we first trained participants to associate two motion directions with high and low reward. During the test, we presented superimposed but perceptually separable stimuli that consisted of coherently and randomly moving dot fields, while manipulating the physical salience (low vs. high contrast) and reward history (low vs. high reward) of the coherent stimulus. Participants were instructed to identify speed-up targets on the coherent or random stimulus. We found that reward improved target detection in the coherent stimulus regardless of the physical contrast, whereas reward disrupted target detection in the random stimulus only when the coherent stimulus was of high contrast. Our findings thus suggest that goal-directed, feature-specific selection determines the pattern of interaction between reward and physical salience, such that they contribute either independently or interactively to attentional priority. We propose two possible mechanisms that can account for the intricate patterns of influence among multiple sources of priority.

Introduction

Visual scenes normally contain many objects at the same time. Humans need to select a subset of information for prioritized processing at a given time due to limited processing capacity. It is generally accepted that attentional selection can be guided by both top-down (directed by task goals) and bottom-up (driven by physical salience) processes (Posner & Petersen, 1990; Desimone & Duncan, 1995; Kastner & Ungerleider, 2000; Corbetta & Shulman, 2002; Connor, Egeth, & Yantis, 2004). However, this traditional dichotomy of attentional control has been challenged by recent studies that demonstrated reward contingency learned through past experience as another distinct source of selection priority (Awh, Belopolsky, & Theeuwes, 2012).

The reward-driven attentional effects have been widely examined in humans and monkeys on a variety of tasks (see reviews, Anderson, 2013, 2016; Chelazzi, Perlato, Santandrea, Della Libera, 2013; Le Pelley, Mitchell, Beesley, George, & Wills, 2016; Failing & Theeuwes, 2017). Studies have shown that reward can facilitate processing of physically salient (pop-out) targets (Kiss, Driver, & Eimer, 2009; Kristjánsson, Sigurjónsdóttir, & Driver, 2010), nonsalient conjunction targets (Lee & Shomstein, 2014) or complex visual targets that have no well-defined physical salience (Della Libera & Chelazzi, 2009). Moreover, a reward-associated distractor can capture attention when it is either physically salient (Hickey, Chelazzi, & Theeuwes, 2010; Anderson, Laurent, & Yantis, 2011a; Le Pelley, Pearson, Griffiths, & Beesley, 2015) or not (Anderson, Laurent, & Yantis, 2011b; Failing, Nissens, Pearson, Le Pelley, & Theeuwes, 2015; Hickey & Peelen, 2015). These findings have led to the suggestion that reward prioritizes its associated stimuli regardless of task goal in an analogous fashion as physical salience (Peck, Jangraw, Suzuki, Efem, & Gottlieb, 2009; Hickey et al., 2010; Anderson et al., 2011b; Failing & Theeuwes, 2017), and that reward and physical salience make independent contributions to attentional priority (Le Pelley et al., 2015; Failing et al., 2015).

Despite the theoretical contributions made to clarify the mechanism of reward-related attentional effects, how reward interacts with task goals and physical salience remains unclear. While previous findings, in particular those showing reward-based effects when reward contradicts the task goal (Hickey et al., 2010; Failing et al., 2015; Le Pelley et al., 2015), suggest that

Citation: Gong, M., & Liu, T. (2018). Reward differentially interacts with physical salience in feature-based attention. *Journal of Vision*, *18*(11):12, 1–12, https://doi.org/10.1167/18.11.12.

https://doi.org/10.1167/18.11.12 Received May 31, 2018; published October 16, 2018 ISSN 1534-7362 Copyright 2018 The Authors

reward-driven effects are not susceptible to top-down attentional control, it is worth noting that those studies often used singleton-based search tasks (e.g., search for a unique shape while reward-associated color served as distractors). Searching for a singleton likely downplays the role of attentional control for specific features, as demonstrated by studies manipulating search modes (Bacon & Egeth, 1994; Lamy & Egeth, 2003). Thus, tasks relying more on feature-specific selection might reveal different patterns of interactions between sources of attentional priority. Furthermore, from a methodological point of view, these prior studies have not systematically manipulated reward and physical salience within a single experiment; thus, they do not allow strong inferences regarding how these two sources of priority may jointly contribute to attentional selection. Given these considerations, it is important to examine how reward is combined with physical salience, especially under the control of goal-directed, feature-specific selection.

Here, we systematically manipulated reward and physical salience in a task that required feature-specific selection to determine how these two factors interact in shaping attentional priority. In brief, we first trained participants to associate low-level visual features (two motion directions) with high and low rewards, respectively. During a subsequent test session in which reward was no longer involved, we presented superimposed but perceptually separable stimuli that consisted of coherently and randomly moving dots. The spatial superposition enabled us to maximize the effects of feature-based selection without changes in spatial attention. We manipulated the physical salience (low vs. high contrast) and reward history (low vs. high reward) of only one of the stimuli (i.e., coherent motion) in a factorial design. Participants were instructed to detect or identify threshold-level speed-up events on a specific stimulus (i.e., coherent or random). Overall, we found that reward differentially interacts with physical salience depending on the allocation of feature-based attention, suggesting an intricate pattern of influences among the sources of attentional priority.

Experiment 1

The purpose of this experiment is to examine the relationship between reward and physical salience in a paradigm that isolated feature-based attention. We first established associations between reward and coherent motion direction in the training session. Then, in a subsequent test session, we asked participants to attend to either the coherent or random stimulus in a detection task in separate blocks. This task thus allowed us to examine how reward and physical salience contribute to priority through attentional benefit (i.e., attend-to-coherent) or cost (i.e., attend-to-random).

Methods

Participants

Twenty-two individuals (13 women, 9 men; mean age = 21.59) participated in the experiment. The sample size was comparable to those of previous behavioral studies examining the reward-based associative learning (Raymond & O'Brien, 2009; Anderson et al., 2011b; Le Pelley et al., 2015; Sha & Jiang, 2016). Using this sample size and a pre-defined effect size (η_p^2) of 0.1, the minimal effect size of reward history as reported by several prior studies (Della Libera & Chelazzi, 2009; Raymond & O'Brien, 2009; Gong & Li, 2014; Sha et al., 2016; Anderson & Halpern, 2017), a power analysis in G*Power (Faul, Erdfelder, Lang, & Buchner, 2007) showed that this sample size would give over 99% power to detect an effect. All participants had normal or corrected-to-normal vision and were right-handed. They were undergraduate and graduate students at Michigan State University. Participants were paid for their participation at $10/hr with an extra bonus of up to $10 based on their performance during training session. Participants gave informed consent according to the study protocol approved by the Institutional Review Board at Michigan State University.

Stimuli and apparatus

The stimulus was comprised of moving dots (dot size: 0.1°, 2.5 dots/deg^2, base speed = 2.5°/s) drawn in an annulus (inner radius = 1.5°, outer radius = 6°) and centered on a white fixation cross against a dark background (luminance: 1.4 cd/m^2). When a dot moved out of the aperture, it was wrapped around to reappear from the opposite side to conserve the dot density. We used two types of motion stimuli, coherent and random motion. The dots in the coherent stimulus moved in a particular direction (i.e., upper-left or upper-right 45°) at 100% coherence, while the dots in random stimulus moved in random directions. In the training session, we presented either a single coherent or random dot field in separate blocks. In the test session, we presented a compound stimulus in which a coherent and a random dot field were superimposed. All dots within a single dot field had the same luminance; across trials dots could assume three possible luminance levels: high (101.1 cd/m^2), medium (45.0 cd/m^2), or low (11.3 cd/m^2), with the associated Weber contrast at 70.2 (high), 31.1 (medium), and 7.0 (low).

Stimuli were generated using MGL (http://gru.stanford.edu/mgl/), a set of custom OpenGL libraries implemented in MATLAB (MathWorks, Natick, MA).

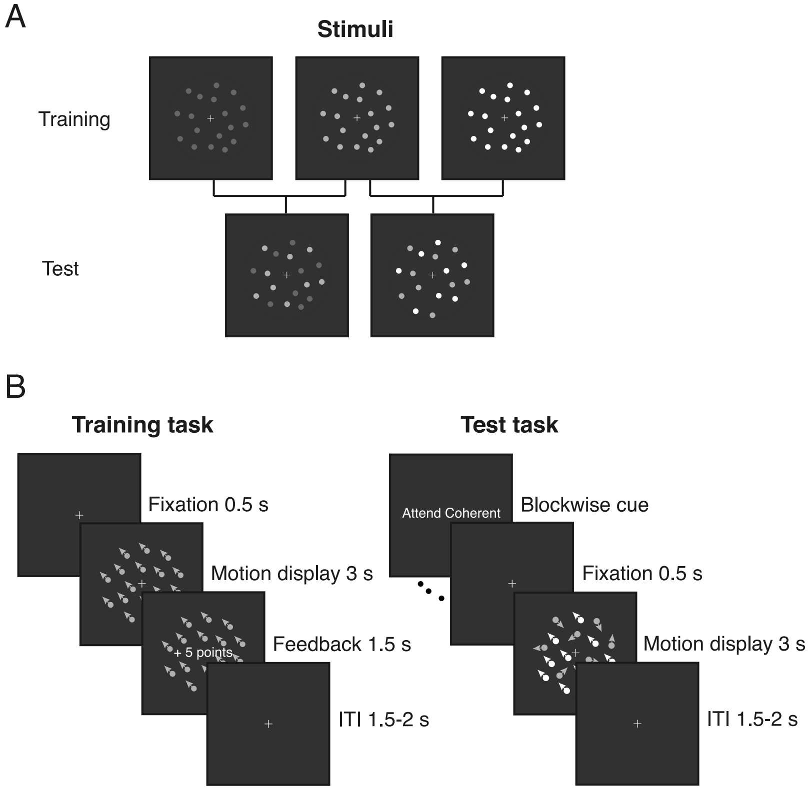

Figure 1. Schematic trial sequences in Experiment 1. (A) The motion stimuli used in the training and test sessions. In the training session, all dots had the same luminance (contrast) within a single dot field, which consisted of either coherently moving or randomly moving dots. These dots can have three possible contrast levels across trials (from left to right: low to high contrast). In the test session, a high- or low-contrast coherent dot field and a medium-contrast random dot field were superimposed. (B) Trial sequence in the training and test session. (*Left*) Training task: participants were instructed to detect the threshold-level speed-up events on the single dot field. A correct response was followed by on-screen reward feedback in coherent motion blocks and neutral feedback in random motion blocks. (*Right)* Test task: participants were instructed to attend to a specific motion stimulus (i.e., either coherent or random throughout a block of trials) and detect the threshold-level speed-up events on the attended stimulus.

The stimuli were presented on a CRT monitor (resolution: 1,024 × 768, refresh rate: 60 Hz). Participants were stabilized with a chinrest and viewed the display from a distance of 91 cm in a dark room.

Design and procedure

Each participant completed two experimental sessions (training and test) on two consecutive days. We used a within-subject design for tasks in both sessions. During training, we manipulated a single factor of reward (i.e., high and low reward) for coherent stimulus, whereas during test, we independently manipulated two factors: physical salience (i.e., high and low contrast) and reward salience (i.e., high and low reward) of the coherent stimulus, producing four experimental conditions (Figure 1A).

Training session: The training session was used to establish direction-reward association as well as to calibrate overall performance. Coherent motion and random motion stimuli were presented in separate blocks. In the coherent motion blocks (Figure 1B), each trial started with a fixation-cross for 0.5 s, followed by a single dot field that moved in a coherent direction (i.e., up-left or up-right) for 3 s. At a random time in each trial (1–2.8 s after the stimulus onset), a brief speed-up (i.e., target) occurred and lasted for 0.2 s. Participants were instructed to respond to the target as soon as possible, by pressing “1” with their right hands. An intertrial interval of 1.5–2 s followed the stimulus offset. We used a single staircase, the best PEST (Parameter Estimation by Sequential Testing) as implemented in the Palamedes Toolbox (Prins & Kingdom, 2018), to control the magnitude of the speed-up such that accuracy was at ~80%. The speed-up threshold was used in the subsequent test session. Correct response was defined as a button press within 1.5 s after the onset of the speed-up. Immediately after a correct response, a feedback for high reward (+5 points) or low reward (+1 point) was presented at the center for 1.5 s. No feedback was presented following an incorrect response. For half of the participants, the up-left direction was associated with a high reward and the up-right direction was associated with a low reward; for the other half of the participants, this association was reversed. The reward association was probabilistic, such that for the high-reward associated direction, a large-reward feedback occurred on 80% of correct trials, while a small-reward feedback occurred on 20% of correct trials. For the low-reward associated direction, the contingency was reversed (80% small-reward feedback and 20% large-reward feedback on correct trials). The probabilistic reward schedule is set for two purposes. First, a probabilistic reward schedule is more effective for associative learning than a fully predictable schedule (Schultz, 2002). Second, it makes the reward-direction contingency less obvious to participants, who were not informed about the contingency (Della Libera & Chelazzi, 2009; Hickey et al., 2010; Anderson et al., 2011a, 2011b).

In the random-motion blocks, the trial sequence was the same as the coherent-motion blocks with three exceptions. First, the coherent motion was replaced with random motion. Second, the reward feedback following a correct response was replaced by a neutral feedback ("correct" for correct response and no feedback for incorrect response). Third, they were asked to respond to the speed-up by pressing "2" with their right hands. Different response keys were used to avoid response interference between two dot fields. The speed-up event had the same timing as that in the coherent dot field (see above). We used a separate staircase to obtain a speed-up threshold for the random motion stimulus at the same performance level as that for the coherent dot field (~80%).

For both the coherent- and random-motion blocks, the stimulus contrast in each trial was randomly selected from the three possible levels (high, medium, and low) with equal probability. Participants performed six coherent motion blocks (60 trials/block) and three random motion blocks (60 trials/block) to equate the number of trials for random, up-left, and up-right directions. This was set to minimize the differences of the selection history across stimuli during the training session.

Test session: In separate blocks, we instructed the participants to selectively attend to coherent or random dot field. Each trial started with a fixation display (0.5 s), followed by a stimulus display of two superimposed dot fields (3 s). One of the dot fields moved coherently (i.e., up-left or up-right), while the other dot field moved randomly (Figure 1C). The random dot field always had a medium contrast, whereas the coherent dot fields can be either high or low contrast. We presented the two dot fields in different contrasts to facilitate perceptual separation between the dot fields and selective attention to either single dot field. At a random time in each trial (1–2.8 s after the stimulus onset), a brief speed-up occurred and lasted for 0.2 s. The magnitudes of speed-up for both dot fields were determined from the training session (see above). The speed-ups in the attended dot field were present in 75% of trials. Participants were asked to respond to the speed-up occurring in the attended dot field, by pressing "1" for the attend-to-coherent and "2" for the attend-to-random condition. In the remaining trials, there was either no speed-up (12.5%) or a speed-up in the unattended dot field (12.5%), and participants were explicitly informed not to respond on these trials. No feedback was provided in the test session. The intertrial interval varied randomly from 1.5 to 2 s. Participants performed five blocks (64 trials/block) for each of the two attention conditions (attend coherent vs. attend random). Half of the participants were asked to attend the coherent motion in the first half of the session, then attend to the random motion. The order was reversed for the other half of the participants.

Data analysis

To assess the effects of reward and physical salience, we calculated participants' detection performance in each attention condition (i.e., attend-to-coherent or attend-to-random motion stimulus) during the test session. Hit trials were defined as responses made within 0.2–1.5 s after the onset of a speed-up target, while false alarm trials referred to any response made on target-absent trials or trials with the speed-up in unattended dot field. Task performance was measured as the difference between hit and false alarm rates (all of the reported results remained essentially the same if we used the signal detection d' as the dependent variable). Then, we sorted the data from each attention condition into four experimental conditions (Reward × Physical Salience) and entered into a two-way repeated-measures ANOVA. Separate two-way ANOVAs were performed instead of a single three-way ANOVA, because the dependent measure was different: in the attend-to-coherent condition, we measured detection performance on the coherent stimulus where a performance benefit was expected for reward and physical salience, whereas in the attend-to-random condition, we measured detection performance on the random stimulus, where a performance impairment was expected. To confirm that any effects observed in the test session were not specific to the particular choice of response window, we also used an individual-based approach that defined the response window based on each participant's response time (RT) distribution. In this approach, we first excluded all responses shorter than 0.1 s after target onset. Then we chose the response window range that corresponded to 0.1% and 99% of the RT distribution. Similar patterns of results were obtained when using this individually adjusted approach for valid responses. For the sake of brevity, we only report results from the standard analysis above.

As a complementary analysis to the standard null-hypothesis significance test (NHST) above, we also conducted parallel Bayesian analyses, which are particularly useful in evaluating the strength of evidence for the interaction or the lack thereof between reward and physical salience. We performed Bayesian repeated-measures ANOVA using JASP (JASP Team, 2017). For data from each attention condition, we specified the factors of reward and physical salience as nuisance variables, and constructed two models: a null model and an interaction model. The null model contained subject-related effect and separate main effects of reward and salience; whereas the interaction model contained all factors of the null model, plus an interaction term between reward and salience. By comparing the Bayes factors of the interaction model against the null model, we can quantify the evidence for the interaction (or the lack thereof) between reward and physical salience.

Results and discussion

In the training session, participants' overall accuracy was 77.6% ($SD = 12.9\%$) for the coherent dot field condition. We compared RT between high reward-associated and low reward-associated motion directions, and found no significant differences: paired t test, $t(21) = 0.30$, $p = 0.769$. The effect of reward on training performance has exhibited large variance across studies using similar associative learning paradigms (Chelazzi et al., 2014; Gong, Yang, & Li, 2016; Gong, Jia, & Li, 2017; Sha & Jiang, 2016; Rajsic, Perera, & Pratt, 2017). The participants' overall performance in the random dot field condition was 75.3% ($SD = 11.2\%$). The obtained speed-up threshold by the end of training was not significantly different between the coherent (0.95° ± 0.42°/s) and random dot field (1.03° ± 0.49°/s) conditions; $t(21) = -1.0$, $p = 0.329$. Although we did not observe the effect of reward for the coherent motion condition during training, the results in the test session confirmed that participants indeed acquired reward-motion association.

For the test session data, participants' overall detection accuracy were comparable between attend-to-coherent and attend-to-random conditions; 72% vs. 76.3%, $t(21) = -1.09$, $p = 0.288$, suggesting task difficulty was similar between two attention conditions. We excluded a small proportion of trials with multiple responses (0.4 ± 0.8%), and separately measured detection performance for two attention conditions, using the difference between hit and false alarm rates (Figure 2A and B). A two-way repeated-measures ANOVA (Reward × Physical Salience) in the attend-to-coherent condition showed a significant main effect of reward, $F(1, 21) = 12.32$, $p = 0.002$, $\eta_p^2 = 0.37$, and physical salience, $F(1, 21) = 7.91$, $p = 0.010$, $\eta_p^2 = 0.27$. There was no interaction between the two factors, $F(1, 21) = 1.18$, $p = 0.289$, $\eta_p^2 = 0.05$. Thus, when attending the coherent dot field, both high reward and high physical salience could enhance detection performance, regardless of the level of the other factor. These results indicated an independent contribution of these two factors to attentional priority, when previously rewarded stimulus was linked to the target. In addition, these results also validated the effectiveness of our manipulation of reward and physical salience by demonstrating that both had an effect on performance.

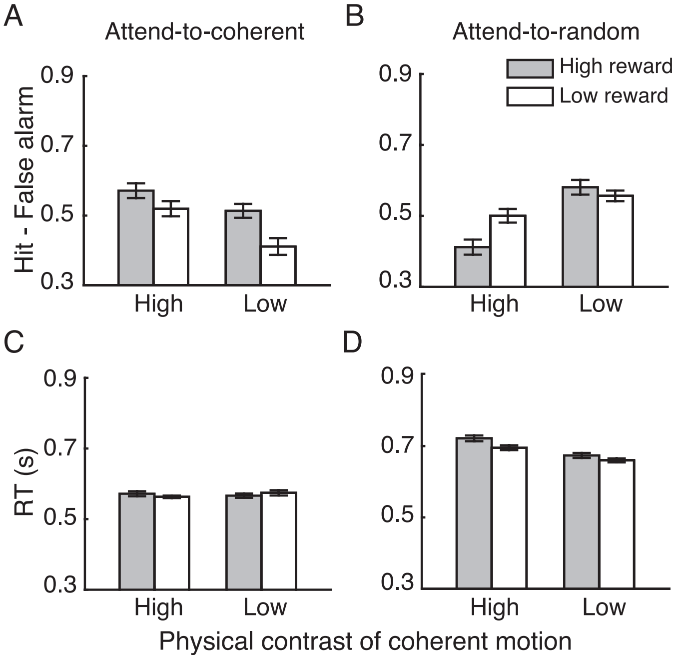

Figure 2. Results from Experiment 1. (A, C) Detection performance (hit–false alarm and RT) in attend-to-coherent dot field condition. (B, D) Detection performance (hit–false alarm and RT) in attend-to-random dot field condition. Error bar are within-subject standard errors (*SEM*), as suggested by Cousineau (2005).

We applied another ANOVA to performance data in the attend-to-random condition and found a significant main effect of physical salience, $F(1, 21) = 23.61$, $p < 0.001$, $\eta_p^2 = 0.53$, suggesting a larger interference on performance when the coherent dot field was at high contrast than at low contrast. Critically, instead of a main effect of reward, $F(1, 21) = 1.67$, $p = 0.211$, $\eta_p^2 = 0.07$, we found a significant reward by salience interaction, $F(1, 21) = 9.85$, $p = 0.005$, $\eta_p^2 = 0.32$. Simple effect analysis revealed that reward interfered with performance only when the coherent dot field was at high contrast, $F(1, 21) = 7.03$, $p = 0.015$, $\eta_p^2 = 0.25$, but not when the coherent dot field was at low contrast, $F(1, 21) = 0.76$, $p = 0.393$, $\eta_p^2 = 0.03$. The physical salience effect was present regardless of reward condition: high reward, $F(1, 21) = 24.84$, $p < 0.001$, $\eta_p^2 = 0.54$; low reward, $F(1, 21) = 5.56$, $p = 0.028$, $\eta_p^2 = 0.21$. Therefore, unlike the observed independence between reward and physical salience in the attend-to-coherent condition, the results under attend-to-random condition suggest that reward interacted with physical salience when they served as the distractor.

To further confirm the distinct patterns of influence from reward and physical salience between the two attention conditions (attend-to-coherent vs. attend-to-random), we used Bayesian model comparison to evaluate the evidence for an independent versus an interaction effect between these two factors (see Methods for details). We found that the null model was preferred to the interaction model by a Bayes factor of 2.3 in the attend-to-coherent condition, whereas the interaction model outperformed the null model by a Bayes factor of 3.84 in the attend-to-random condition. These results suggest an additive model is more likely for the attend-to-coherent condition, whereas an interaction model is more likely for attend-to-random condition, consistent with the results from conventional ANOVA.

To rule out alternative accounts of the accuracy effects, such as speed-accuracy trade-off and reward-induced arousal effects, we examined RTs on correct trials and performed repeated-measures ANOVA (Figure 2C and 2D). The speed-accuracy trade-off hypothesis predicts opposite patterns of results to the detection accuracy, while the arousal hypothesis predicts faster RTs for high reward than low reward-associated directions in both attention conditions. However, we found no significant effects in attend-to-coherent condition (all $ps > 0.11$), whereas in the attend-to-random condition, we found main effects of reward, $F(1, 21) = 7.02$, $p = 0.015$, $\eta_p^2 = 0.25$, and physical salience, $F(1, 21) = 23.55$, $p < 0.001$, $\eta_p^2 = 0.53$, that were opposite to the prediction of speed-accuracy trade-off and arousal effect (the two-factor interaction was nonsignificant, $p = 0.424$).

The data from Experiment 1 showed that both reward and physical salience contributed to feature-based attentional priority. In contrast to previous studies that did not require feature-based selection (e.g., Hickey et al., 2010; Failing et al., 2015; Le Pelley et al., 2015), the present task required participants to select specific features based on a preset attentional template (i.e., coherent or random motion). Our results revealed independent effects of reward and physical salience when they worked in congruence with the attentional template, whereas reward interacted with physical salience when they worked in opposition to the attentional template. These findings suggest that the allocation of goal-directed attention modulates the interaction pattern between reward and physical salience during feature-based selection.

Experiment 2

The results in Experiment 1 showed the interaction between reward and physical salience when the reward-associated stimulus served as the distractor, which is inconsistent with previous suggestions of independent contributions from physical salience and reward to attentional priority (Failing et al., 2015; Le Pelley et al., 2015). However, before we attribute the interaction effect to feature-based attention, an alternative possibility is that in the attend-to-random condition, participants could prepare a strong attentional template for the random dot field, which may override reward-driven attentional priority when the reward-associated stimulus was of low physical salience. To address whether the modulation of goal-directed attention by reward and physical salience relied on the preparation, here we instructed participants to distribute attention to both the coherent and random dot fields. During the task, a speed-up event occurred equally often in both dot fields, and participants needed to report the identity of the dot field (i.e., coherent or random) containing the target. Under this setup, preparatory attention was identical to both dot fields before the speed-up event, but the onset of speed-up should orient feature-specific attention towards one of the dot fields, in order to correctly perform the identification task. Therefore, if the interaction effect relied on preparation, we would expect only independent effects between reward and physical salience in this experiment. However, if the interaction effect was due to feature-specific attention, we would observe similar pattern of results as those in Experiment 1.

Methods

Participants

Twenty-two individuals (13 women, 9 men; mean age = 20.9) participated in the experiment (the same number of subjects as in Experiment 1). All had normal or corrected-to-normal vision and were right-handed. They were undergraduate and graduate students at Michigan State University. Participants were paid for their participation at $10/hr with an extra bonus of up to $10 based on their performance during the training session. Participants gave informed consent according to the study protocol approved by the Institutional Review Board at Michigan State University.

Stimuli, design, and procedure

The stimuli and procedure were identical to Experiment 1 with the following changes. The main change from Experiment 1 was that participants needed to discriminate speed-up events on either dot field, which increased overall task difficulty. We thus increased the converging accuracy of the staircase (85%) during the training session, and increased the duration of motion stimuli to 6.1 s. We also added a practice block for participants to familiarize with the test task of attending to two superimposed stimuli (data from this block were not used for subsequent analyses).

In brief, each trial contained a brief speed-up, which occurred at a random time (1.5–5.7 s after the stimulus onset) and lasted for 0.3 s. During training of coherent motion stimuli, correct response was followed by an immediate reward feedback with the same probabilistic reward schedule. We made identical changes to random motion condition, except that reward feedback was replaced with neutral feedback. Participants performed eight blocks of coherent condition (30 trials/block) and four blocks of random condition (30 trials/block). In the test session, we presented superimposed dot fields with the same parameters inherited from the training session. Due to the temporal uncertainty of speed-ups and restricted window of valid responses (0.2–1.5 s), a strategy of only attending to one dot field would be ineffective. To ensure that participants' responses reflected the processing of speed-ups on specific stimulus, we instructed them to respond which of the dot fields contained the speed-up by pressing "1" to indicate coherent and "2" to indicate random, using the index and middle finger of their right hands. Participants were informed that speed-up could occur equally likely in both dot fields. Participants performed a practice block and 11 test blocks trials (32 trials/block).

Data analysis

To assess the effects of reward and physical salience, we calculated participants' discrimination performance during the test session. Correct identification of a target (i.e., speed-up) was defined as appropriate key press responses within 0.2–1.5 s after the onset of speed-up. Key presses that fell outside this time window were taken as invalid responses. We classified the trials into two types of target conditions, depending on which dot field the target had appeared (i.e., target-in-coherent or target-in-random motion stimulus). Then, we sorted the data from each target condition into four experimental conditions (Reward × Physical Salience). To confirm that any effects observed in the test session were not specific to the particular choice of response window, we also used the individual-based approach that defined the response window based on each participant's response time (RT) distribution as in Experiment 1. Again, similar patterns of result were obtained when using this individually adjusted approach for defining valid responses. Thus, we only report the results from the standard analysis below.

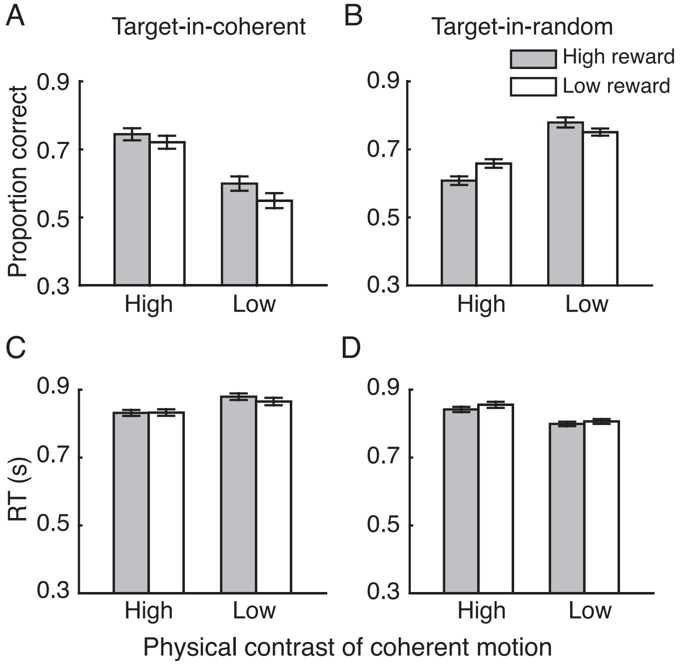

Figure 3. Results from Experiment 2. (A, C) Discrimination accuracy and RT in target-in-coherent dot field condition. (B, D) Discrimination accuracy and RT in target-in-random dot field condition. Error bar are within-subject standard errors (*SEM*).

Results and discussion

In the training session, participants' overall performance was 86.6% ($SD = 5.3\%$) and 84.9% ($SD = 7.9\%$) for the coherent and random dot field condition, respectively. The obtained speed-up threshold by the end of training was significantly lower for coherent (1.02 ± 0.37°/s) than random dot field (1.21 ± 0.46°/s) condition, $t(21) = -2.60$, $p = 0.0169$. We further compared RT between high and low rewarded motion directions, and did not find a significant difference: paired t test, $t(21) = -0.14$, $p = 0.886$.

Overall accuracy in the test session was 67.5% ($SD = 13.9\%$), after excluding a small proportion of trials that contained multiple responses (3.2 ± 3.1%). Accuracy in the target-in-coherent and target-in-random condition was similar (65.4% vs. 69.9%, $t(21) = -0.99$, $p = 0.333$, indicating comparable task difficulty in two target conditions. We separately calculated the discrimination accuracy under conditions of target-in-coherent and target-in-random dot field (Figure 3A and 3B). A two-way repeated-measures ANOVA (Reward × Physical Salience) on the accuracy from target-in-coherent dot field revealed a significant main effect of reward, $F(1, 21) = 5.16$, $p = 0.034$, $\eta_p^2 = 0.20$, and physical salience, $F(1, 21) = 23.36$, $p < 0.001$, $\eta_p^2 = 0.53$. The interaction effect between two factors was not significant, $F(1, 21) = 0.65$, $p = 0.430$, $\eta_p^2 = 0.03$. The repeated-measures ANOVAs on the discrimination accuracy from target-in-random dot field revealed a significant main effect of physical salience, $F(1, 21) = 48.98$, $p < 0.001$, $\eta_p^2 = 0.70$, and a significant interaction between reward and physical salience, $F(1, 21) = 13.58$, $p = 0.001$, $\eta_p^2 = 0.39$. We did not find a main effect of reward, $F(1, 21) = 0.68$, $p = 0.419$, $\eta_p^2 = 0.03$. Further simple effect analysis showed a reward-driven interference effect only when the coherent dot field was at high contrast, $F(1, 21) = 9.02$, $p = 0.007$, $\eta_p^2 = 0.30$, but not when the coherent dot field was at low contrast, $F(1, 21) = 2.61$, $p = 0.121$, $\eta_p^2 = 0.11$. The influence of physical salience was significant at both levels of reward condition ($p < 0.001$).

We also evaluated the distinct patterns of interaction between reward and physical salience in the two target conditions (target-in-coherent vs. target-in-random) using Bayesian model comparisons, similar to Experiment 1. In line with the results from conventional ANOVAs, the null model was preferred to the interaction model by a Bayes factor of 3.12 in the target-in-coherent condition, whereas the interaction model outperformed the null model by a Bayes factor of 4.81 in the target-in-random condition.

We used two-way repeated-measures ANOVAs on RTs to confirm that the observed effects on accuracy were not due to a speed-accuracy trade-off or reward-related arousal effects. (Figure 3C and 3D). We found a significant main effect of physical salience for both target-in-coherent, $F(1, 21) = 10.18$, $p = 0.004$, $\eta_p^2 = 0.33$, and target-to-random dot fields, $F(1, 21) = 27.76$, $p < 0.001$, $\eta_p^2 = 0.57$, which were exactly opposite to the predicted results of speed-accuracy trade-off. None of the other effects reached significance level (all $ps > 0.3$), also excluding possible contributions from reward-related arousal effects.

Here we again found that reward differentially interacted with physical salience (for targets appearing in the coherent vs. random dot field), when preparatory attention was not linked to a particular feature. Our manipulation of attending to both dot fields should weaken the influence of preparatory attention, as supported by previous studies employing multiple attentional templates (Houtkamp & Roelfsema, 2008; Stroud, Menneer, Cave, Donnelly, & Rayner, 2011; Liu, Becker, & Jigo, 2013; Liu & Jigo, 2017). However, top-down biasing to a particular feature in this task could be triggered by the speed-up event, which is analogous to a reactive mechanism of cognitive control, where task goals are activated by transient events as needed, rather than sustained in a preparatory state (Braver, 2012). This top-down, feature-specific selection is necessary because the task required the identification of the specific dot field that contained the speed-up target, which could not be accomplished by the detection of speed change alone. Therefore, goal-directed, feature-specific attention that was reactively deployed could still modulate the interaction between reward and physical salience. Experiment 2 replicates and extends Experiment 1 by demonstrating the robustness of the differential interaction effect of reward and physical salience.

General discussion

Learned reward association was proposed to modulate the attentional priority map, which controls the allocation of spatial attention (Chelazzi et al., 2014). The present study shows that such modulation extends to feature-based priority when orienting of spatial attention was not feasible. Our findings showed that reward facilitated attentional selection independent of physical salience when the reward-associated stimulus contained the target. Participants were better at identifying the speed-ups in coherent dot field for high reward-associated than low reward-associated direction, both when the coherent dot field was of high and low contrast. However, reward interfered with attentional selection dependent on physical salience when reward-associated stimulus served as the distractor. In this case, the identification of the speed-up in random dot field was more disrupted by high reward-associated than low reward-associated direction only when the coherent dot field was of high contrast. These results were obtained in two experiments that varied preparatory attention, confirming that the feature-specific attention determines how reward interacts with physical salience during attentional selection.

Based on the pattern of results from previous studies (Kiss et al., 2009; Raymond & O'Brien, 2009; Kristjánsson et al., 2010; Lee & Shomstein, 2014), one might infer that reward and physical salience independently contribute to attentional priority when the rewarded item contained the target. However, we note that physical salience was not directly manipulated in these studies. Our study directly tested this inference and showed comparable effect of reward on target selection at both high and low levels of physical salience. These results also demonstrated the effectiveness of reward-motion association at both levels of physical salience, ruling out the possibility that features with low physical salience lack the ability to gain reward association during training in the current study (c.f., Wang, Yu, & Zhao, 2013). Different from previous studies, we found an interaction of reward and physical salience when the rewarded item was the distractor. On the one hand, our finding that reward-associated, physically salient distractor competed for priority even when top-down attention was directed to another feature, is consistent with previous findings that reward-associated distractor can break into the focus of spatial attention (Munneke, Belopolsky, &

Theeuwes, 2016; Wang, Li, Zhou, & Theeuwes, 2018). On the other hand, the absence of reward effect when the distractor was of low physical salience is in apparent contradiction to previous findings that have shown spatial capture effects by reward-associated distractors regardless of physical salience (Hickey et al., 2010; Anderson et al., 2011b; Failing et al., 2015; Le Pelley et al., 2015). We believe there are three potential explanations for this apparent discrepancy. First, while previous studies mostly focused on how reward shapes spatial attention, our study emphasized how well the reward-associated feature was processed without spatial selection. The control of spatial attention might rely on different mechanisms than those for feature-based attention (Giesbrecht, Woldorff, Song, & Mangun, 2003; Greenberg, Esterman, Wilson, Serences, & Yantis, 2010; Liu & Hou, 2013). Second and related, the reward-driven attentional capture effects were generally found in singleton search task (e.g., search for a unique shape while reward-associated color served as distractors), in which participants likely adopted a search strategy that relies on the feature-level contrast among stimuli (i.e., singleton search mode). Thus, a task that requires attention to a specific feature value (i.e., feature search mode) may change the interaction between reward and physical salience, as different search modes are known to differentially modulate the influence of physical salience (Bacon & Egeth, 1994; Lamy & Egeth, 2003). Although our experiments were not designed to manipulate search modes, our task shares some formal similarity with the feature-search mode in that it required participants to select a specific feature (either coherent or random motion). Third, the manipulation of physical salience by means of feature singleton (e.g., diamond among circles) was only qualitative, which did not permit systematic examination of the effects of reward and physical salience. Thus, it is possible that more quantitative measurements would also reveal differential interactions effects between reward and physical salience in paradigms eliciting spatial capture.

Our findings suggest that when reward and physical salience are integrated to influence attentional priority, whether they act independently or interactively was contingent on feature-specific selection. What could be the underlying mechanism for such differential interaction patterns between reward and physical salience? Here we consider two potential mechanisms that can account for our findings.

One possible mechanism relates to the proposal that the attentional system integrates separate sources of priority, namely task goal, physical salience, and reward history (Awh et al., 2012). Although this influential model did not explicitly specify whether such integration reflects independent or interactive contributions from these sources, as discussed earlier, previous findings favor the interpretation that reward contributes to attentional priority independently from other factors (Hickey et al., 2010; Anderson et al., 2011b; Failing et al., 2015; Le Pelley et al., 2015). However, our findings are incompatible with such a strict independent interpretation and call for a refinement of the model. One possibility is that attentional priority is derived by summing the three sources of influence and can only guide selection after exceeding a threshold level of activation. Under this account, when the reward-associated stimuli contained the target, the summed influence from all three sources may be sufficient to surpass the threshold, resulting in independence between reward and physical salience. In contrast, when the reward-associated stimuli served as the distractor, the lack of input from task goal might require a certain level of physical salience in combination with reward to exceed the threshold, resulting in an interactive pattern.

Alternatively, reward could exert its effect via modulations of task goal and physical salience in separate pathways, rather than directly influences priority. In the first pathway, reward contributes to attentional priority by flexibly adjusting goal-directed attention. In the second pathway, reward influences priority by modulating the strength of sensory representation. When the reward-associated stimuli contained the target, it will modulate attention priority via the first pathway, which is separate from physical salience, thus giving rise to independent effects. Conversely, when the reward-associated stimuli served as the distractor, reward modulation will go through the second pathway, which includes physical salience, and thus leading to interactive effects. Although this interpretation deviates from the original model (Awh, et al., 2012), the idea of separate pathways has received some support from previous neurophysiological studies (e.g., the first pathway: Small et al., 2005; Mohanty, Gitelman, Small, & Mesulam, 2008; the second pathway: Shuler & Bear, 2006; Serences, 2008; Stănior, van der Togt, Pennartz, & Roelfsema, 2013). While both mechanisms can account for our behavioral data, they are speculative and deserve further investigations.

A remaining question concerns whether the observed reward effects can be attributed to selection history without reward association. One the one hand, reward-associated stimulus was found to elicit quantitatively similar attentional capture effect as previous selected target during training (Sha & Jiang, 2016). On the other hand, reward association and selection history have also been shown to have distinct effects (Anderson & Halpern, 2017; Anderson, Chiu, DiBartolo, & Leal, 2017). The present study minimized the contribution of selection history in the first place, not only by adopting equivalent training for the coherent and random motion stimuli, but also de-emphasizing explicit selection during training because participants were presented with one stimulus at a time and responded to the change of speed. These results were aligned with the notion that reward-based learning is different from pure selection biases to previous target (Anderson et al., 2017).

The present study provided novel findings for reward-driven priority during feature-based selection, extending prior studies that predominantly focused on location-based priority (Hickey et al., 2010; Anderson et al., 2011b; Chelazzi et al., 2014). Specifically, we found that reward differentially interacts with physical salience, depending on the allocation of feature-based attention. Our novel findings provide new insights on how different sources of selection biases interact during feature-based attention, which could be accommodated by two potential mechanisms.

Keywords: reward history, *physical salience*, *feature-based selection*, *attentional priority*

Acknowledgments

We thank Eric Chantland and Andrew Becker for their assistance in data collection. We also thank Dr. Susan Ravizza and Dr. Mark Becker for their comments on an earlier draft of the manuscript. The authors declare no competing financial interests. This work is supported by a grant from the National Institutes of Health (R01EY022727).

Commercial relationships: none.

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References

Anderson, B. A. (2013). A value-driven mechanism of attentional selection. *Journal of Vision*, *13*(3):7, 1–16, https://doi.org/10.1167/13.3.7. [PubMed] [Article]

Anderson, B. A. (2016). The attention habit: How reward learning shapes attentional selection. *Annals of the New York Academy of Sciences*, *1369*(1), 24–39. https://doi.org/10.1111/nyas.12957.

Anderson, B. A., Chiu, M., DiBartolo, M. M., & Leal, S. L. (2017). On the distinction between value-driven attention and selection history: Evidence from individuals with depressive symptoms. *Psychonomic Bulletin & Review*, *24*(5), 1636–1642, https://doi.org/10.3758/s13423-017-1240-9.

Anderson, B. A., & Halpern, M. (2017). On the value-dependence of value-driven attentional capture. *Attention, Perception, & Psychophysics*, *79*(4), 1001–1011, https://doi.org/10.3758/s13414-017-1289-6.

Anderson, B. A., Laurent, P. A., & Yantis, S. (2011a). Learned value magnifies salience-based attentional capture. *PLoS One*, *6*(11): e27926, https://doi.org/10.1371/journal.pone.0027926.

Anderson, B. A., Laurent, P., & Yantis, S. (2011b). Value-driven attentional capture. *Proceedings of the National Academy of Sciences, USA*, *108*(25), 10367–10371, https://doi.org/10.1073/pnas.1104047108.

Awh, E., Belopolsky, A. V., & Theeuwes, J. (2012). Top-down versus bottom-up attentional control: A failed theoretical dichotomy. *Trends in Cognitive Sciences*, *16*(8), 437–443, https://doi.org/10.1016/j.tics.2012.06.010.

Bacon, W. F., & Egeth, H. E. (1994). Overriding stimulus-driven attentional capture. *Perception & Psychophysics*, *55*(5), 485–496, https://doi.org/10.3758/BF03205306.

Braver, T. S. (2012). The variable nature of cognitive control: A dual mechanisms framework. *Trends in Cognitive Sciences*, *16*(2), 106–113, https://doi.org/10.1016/j.tics.2011.12.010.

Chelazzi, L., Eštočinová, J., Calletti, R., Lo Gerfo, E., Sani, I., Della Libera, C., & Santandrea, E. (2014). Altering spatial priority maps via reward-based learning. *The Journal of Neuroscience*, *34*(25), 8594–8604, https://doi.org/10.1523/JNEUROSCI.0277-14.2014.

Chelazzi, L., Perlato, A., Santandrea, E., & Della Libera, C. (2013). Rewards teach visual selective attention. *Vision Research*, *85*, 58–62, https://doi.org/10.1016/j.visres.2012.12.005.

Connor, C. E., Egeth, H. E., & Yantis, S. (2004). Visual attention: Bottom-up versus top-down. *Current Biology*, *14*(19), R850–R852, https://doi.org/10.1016/j.cub.2004.09.041.

Corbetta, M., & Shulman, G. L. (2002). Control of goal-directed and stimulus-driven attention in the brain. *Nature Reviews Neuroscience*, *3*(3), 201–215, https://doi.org/10.1038/nrn755.

Cousineau, D. (2005). Confidence intervals in within-subject designs: A simpler solution to Loftus and Masson's method. *Tutorials in Quantitatve Methods for Psychology*, *1*(1), 42–45.

Della Libera, C., & Chelazzi, L. (2009). Learning to attend and to ignore is a matter of gains and losses. *Psychological Science*, *20*(6), 778–784, https://doi.org/ 10.1111/j.1467-9280.2009.02360.x.

Desimone, R., & Duncan, J. (1995). Neural mechanisms of selective visual attention. *Annual Review of Neuroscience*, *18*(1), 193–222, https://doi.org/10.1146/annurev.ne.18.030195.001205.

Failing, M., Nissens, T., Pearson, D., Le Pelley, M., & Theeuwes, J. (2015). Oculomotor capture by stimuli that signal the availability of reward. *Journal of Neurophysiology*, *114*(4), 2316–2327, https://doi.org/10.1152/jn.00441.2015.

Failing, M., & Theeuwes, J. (2017). Selection history: How reward modulates selectivity of visual attention. *Psychonomic Bulletin & Review*, *25*(2), 514–538, https://doi.org/10.3758/s13423-017-1380-y.

Faul, F., Erdfelder, E., Lang, A. G., & Buchner, A. (2007). G*Power 3: A flexible statistical power analysis program for the social, behavioral, and biomedical sciences. *Behavior Research Methods*, *39*(2), 175–191, https://doi.org/10.3758/BF03193146.

Greenberg, A. S., Esterman, M., Wilson, D., Serences, J. T., & Yantis, S. (2010). Control of spatial and feature-based attention in frontoparietal cortex. *Journal of Neuroscience*, *30*(43), 14330–14339, https://doi.org/10.1523/JNEUROSCI.4248-09.2010.

Giesbrecht, B., Woldorff, M. G., Song, A. W., & Mangun, G. R. (2003). Neural mechanisms of top-down control during spatial and feature attention. *Neuroimage*, *19*(3), 496–512, https://doi.org/10.1016/S1053-8119(03)00162-9.

Gong, M., Jia, K., & Li, S. (2017). Perceptual competition promotes suppression of reward salience in behavioral selection and neural representation. *The Journal of Neuroscience*, *37*(26), 6242–6252, https://doi.org/10.1523/JNEUROSCI.0217-17.2017.

Gong, M., & Li, S. (2014). Learned reward association improves visual working memory. *Journal of Experimental Psychology: Human Perception and Performance*, *40*(2), 841–856, https://doi.org/10.1037/a0035131.

Gong, M., Yang, F., & Li, S. (2016). Reward association facilitates distractor suppression in human visual search. *European Journal of Neuroscience*, *43*(7), 942–953, https://doi.org/10.1111/ejn.13174.

Hickey, C., Chelazzi, L., & Theeuwes, J. (2010). Reward changes salience in human vision via the anterior cingulate. *The Journal of Neuroscience*, *30*(33), 11096–11103, https://doi.org/10.1523/JNEUROSCI.1026-10.2010.

Hickey, C., & Peelen, M. V. (2015). Neural mechanisms of incentive salience in naturalistic human vision. *Neuron*, *85*(3), 512–518, https://doi.org/10.1016/j.neuron.2014.12.049.

Houtkamp, R., & Roelfsema, P. R. (2009). Matching of visual input to only one item at any one time. *Psychological Research PRPF*, *73*(3), 317–326, https://doi.org/10.1007/s00426-008-0157-3.

JASP Team (2017). JASP (Version 0.8.6) [Computer software]. Amsterdam, The Netherlands: University of Amsterdam.

Kastner, S., & Ungerleider, L. G. (2000). Mechanisms of visual attention in the human cortex. *Annual Review of Neuroscience*, *23*(1), 315–341, https://doi.org/10.1146/annurev.neuro.23.1.315.

Kiss, M., Driver, J., & Eimer, M. (2009). Reward priority of visual target singletons modulates event-related potential signatures of attentional selection. *Psychological Science*, *20*(2), 245–251, https://doi.org/10.1111/j.1467-9280.2009.02281.x.

Kristjánsson, Á., Sigurjónsdóttir, Ó., & Driver, J. (2010). Fortune and reversals of fortune in visual search: Reward contingencies for pop-out targets affect search efficiency and target repetition effects. *Attention, Perception, and Psychophysics*, *72*(5), 1229–1236, https://doi.org/10.3758/APP.72.5.1229.

Lamy, D., & Egeth, H. E. (2003). Attentional capture in singleton-detection and feature-search modes. *Journal of Experimental Psychology: Human Perception and Performance*, *29*(5), 1003–1020, https://doi.org/10.1037/0096-1523.29.5.1003.

Lee, J., & Shomstein, S. (2014). Reward-based transfer from bottom-up to top-down search tasks. *Psychological Science*, *25*(2), 466–475, https://doi.org/10.1177/0956797613509284.

Le Pelley, M. E., Mitchell, C. J., Beesley, T., George, D. N., & Wills, A. J. (2016). Attention and associative learning in humans: An integrative review. *Psychological Bulletin*, *142*(10), 1111–1140, https://doi.org/10.1037/bul0000064.

Le Pelley, M. E., Pearson, D., Griffiths, O., & Beesley, T. (2015). When goals conflict with values: Counterproductive attentional and oculomotor capture by reward-related stimuli. *Journal of Experimental Psychology: General*, *144*(1), 158–171, https://doi.org/10.1037/xge0000037.

Liu, T., Becker, M. W., & Jigo, M. (2013). Limited featured-based attention to multiple features. *Vision Research*, *85*, 36–44, https://doi.org/10.1016/j.visres.2012.09.001.

Liu, T., & Hou, Y. (2013). A hierarchy of attentional priority signals in human frontoparietal cortex. *Journal of Neuroscience*, *33*(42), 16606–16616, https://doi.org/10.1523/JNEUROSCI.1780-13.2013.

Liu, T., & Jigo, M. (2017). Limits in feature-based attention to multiple colors. *Attention, Perception, & Psychophysics*, *79*(8), 2327–2337, https://doi.org/10.3758/s13414-017-1390-x.

Mohanty, A., Gitelman, D. R., Small, D. M., & Mesulam, M. M. (2008). The spatial attention network interacts with limbic and monoaminergic systems to modulate motivation-induced attention shifts. *Cerebral Cortex*, *18*(11), 2604–2613, https://doi.org/10.1093/cercor/bhn021.

Munneke, J., Belopolsky, A. V., & Theeuwes, J. (2016). Distractors associated with reward break through the focus of attention. *Attention, Perception, & Psychophysics*, *78*(7), 2213–2225, https://doi.org/10.3758/s13414-016-1075-x.

Peck, C. J., Jangraw, D. C., Suzuki, M., Efem, R., & Gottlieb, J. (2009). Reward modulates attention independently of action value in posterior parietal cortex. *The Journal of Neuroscience*, *29*(36), 11182–11191, https://doi.org/10.1523/JNEUROSCI.1929-09.2009.

Posner, M. I., & Petersen, S. E. (1990). The attention system of the human brain. *Annual Review of Neuroscience*, *13*(1), 25–42, https://doi.org/10.1146/annurev.ne.13.030190.000325.

Prins, N., & Kingdom, F. A. A. (2018) Applying the model-comparison approach to test specific research hypotheses in psychophysical research using the Palamedes Toolbox. *Frontiers in Psychology*, *9*: 1250, https://doi.org/10.3389/fpsyg.2018.01250.

Rajsic, J., Perera, H., & Pratt, J. (2017). Learned value and object perception: Accelerated perception or biased decisions? *Attention, Perception, and Psychophysics*, *79*(2), 603–613, https://doi.org/10.3758/s13414-016-1242-0.

Raymond, J. E., & O'Brien, J. L. (2009). Selective visual attention and motivation: The consequences of value learning in an attentional blink task. *Psychological Science*, *20*(8), 981–988, https://doi.org/10.1111/j.1467-9280.2009.02391.x.

Schultz, W. (2002). Getting formal with dopamine and reward. *Neuron*, *36*(2), 241–263, https://doi.org/10.1016/S0896-6273(02)00967-4.

Serences, J. T. (2008). Value-based modulations in human visual cortex. *Neuron*, *60*(6), 1169–1181, https://doi.org/10.1016/j.neuron.2008.10.051.

Shuler, M. G., & Bear, M. F. (2006, March 17). Reward timing in the primary visual cortex. *Science*, *311*(5767), 1606–1609, https://doi.org/10.1126/science.1123513.

Sha, L. Z., & Jiang, Y. V. (2016). Components of reward-driven attentional capture. *Attention, Perception, and Psychophysics*, *78*(2), 403–414, https://doi.org/10.3758/s13414-015-1038-7.

Small, D. M., Gitelman, D., Simmons, K., Bloise, S. M., Parrish, T., & Mesulam, M. M. (2005). Monetary incentives enhance processing in brain regions mediating top-down control of attention. *Cerebral Cortex*, *15*(12), 1855–1865, https://doi.org/10.1093/cercor/bhi063.

Stroud, M. J., Menneer, T., Cave, K. R., Donnelly, N., & Rayner, K. (2011). Search for multiple targets of different colours: Misguided eye movements reveal a reduction of colour selectivity. *Applied Cognitive Psychology*, *25*(6), 971–982. http://doi.org/10.1002/acp.1790.

Stănişor, L., van der Togt, C., Pennartz, C. M., & Roelfsema, P. R. (2013). A unified selection signal for attention and reward in primary visual cortex. *Proceedings of the National Academy of Sciences, USA*, *110*(22), 9136–9141, https://doi.org/10.1073/pnas.1300117110.

Wang, L., Li, S., Zhou, X., & Theeuwes, J. (2018). Stimuli that signal the availability of reward break into attentional focus. *Vision Research*, *144*, 20–28, https://doi.org/10.1016/j.visres.2017.10.008.

Wang, L., Yu, H., & Zhou, X. (2013). Interaction between value and perceptual salience in value-driven attentional capture. *Journal of Vision*, *13*(3): 5, 1–13, https://doi.org/10.1167/13.3.5. [PubMed] [Article]