Spring 2021

Learned but not distracting: low-value stimuli and value-driven attentional capture

John Albanese
john.albanese@trincoll.edu

TRINITY COLLEGE

LEARNED BUT NOT DISTRACTING: LOW-VALUE STIMULI AND VALUE-DRIVEN ATTENTIONAL CAPTURE

BY

John S. Albanese

A THESIS SUBMITTED TO
THE FACULTY OF THE NEUROSCIENCE PROGRAM
IN CANDIDACY FOR THE BACCALAUREATE DEGREE
WITH HONORS IN NEUROSCIENCE

NEUROSCIENCE PROGRAM

HARTFORD, CONNECTICUT
May 16, 2021

Learned but not distracting:
low-value stimuli and value-driven attentional capture

BY

John S. Albanese

Honors Thesis Committee

Approved:

____
Michael Grubb, Thesis Advisor

____
Molly Helt, Thesis Committee

____
Sarah Raskin, Director, Neuroscience Program

Date: ____

Introduction

Background on Attention

With countless stimuli continuously bombarding us in our environments, what determines how we allocate our limited attention? We are constantly being overwhelmed with information, not all of which is important, so we must devise ways to prioritize certain stimuli while ignoring others, not allowing them to reach our conscious attention. Traditionally, attention is categorized according to a dichotomy, which consists of top-down attention versus bottom-up attention (Carrasco, 2011). Top-down attention is voluntary and involves the selective processing of stimuli that are relevant to one's goals. On the other hand, bottom-up attention is driven by the salience of stimuli; it is involuntary and goal-irrelevant, involving the reflexive allocation of attention. For example, when searching for your yellow car in a crowded parking lot, you would allocate top-down attention to search for the color yellow, and you would not attend to cars of any other color. However, if a car's headlights began flashing near you, this physically salient stimulus would suddenly and briefly capture your attention according to a bottom-up mechanism. Though these flashing headlights are irrelevant to your goal of finding your yellow car, this information is distracting and automatically captures attention, though briefly.

The neural mechanisms that are implicated in top-down and bottom-up attention are complex. Bottom-up attention has an earlier time course than does top-down attention (Connor, Egeth, & Yantis, 2004). Part of this difference in time course is due to the specific neural mechanisms, as top-down attention has been argued to utilize primarily feedback mechanisms, while bottom-up attention relies mainly on feedforward mechanisms (Pinto et al., 2013; Theeuwes, 2010). In order to describe the mechanisms associated with these types of attention, “feature maps” have been used, into which processed visual features are separated (Wolfe, 1994; Katsuki & Constantinidis, 2012). These feature maps represent basic stimulus components, including color and orientation. These feature maps are then combined to form a saliency map. The superior colliculus is an important brain structure in salience determination (Veale, Hafed & Yoshida, 2017; White et al., 2017). Feature and saliency maps are mostly concerned with bottom-up attention, which is reliant largely, but not entirely, on feedforward processes, contributing to a faster onset as compared to top-down attention (Khorsand, Moore & Soltani, 2015; Pinto et al., 2013).

Top-down and bottom-up attention do not rely on entirely different mechanisms, though. Top-down and bottom-up attention interact in order to guide attention, so a proposed “priority map” has been used to account for the combination of factors that are top-down and bottom-up which drive attention (Bisley and Goldberg 2010; Serences and Yantis 2006). By utilizing this concept of a priority map, the portion of the map with highest activation can be denoted as the area to which attention is projected (Koch and Ullman, 1985). In both top-down and bottom-up attention, the dorsolateral prefrontal cortex and the posterior parietal cortex are believed to be essential (Katsuki & Constantinidis, 2012; Arcizet et al., 2011; Constantinidis and Steinmetz, 2005; Gottlieb et al., 1998; Kusunoki et al., 2000). Furthermore, with these same brain areas being implicated in both kinds of attention, top-down and bottom-up attention should not be viewed as two entirely separate processes, since they are interconnected in complex ways (Katsuki & Constantinidis, 2012). Top-down and bottom-up attention rely on the coactivation of the same network of parietal and prefrontal cortical areas, which include the lateral intraparietal cortex and the frontal eye field (Paneri & Gregoriou, 2017; Buschman & Miller, 2007). The priority map receives input from stimuli in the environment driven by both modes of attention, and whichever stimulus elicits the greatest activity in the priority map is the one that reaches attention.

This dichotomy of attention assumes a simple split of stimuli into one of these two categories (top-down or bottom-up). However, stimuli cannot always be categorized neatly according to this dichotomy, as there are many situations in which this dichotomy fails (Awh et al., 2012). One of these instances considers the persistent effects of reward histories, which can be developed following the presentation of items associated with reward and which have the capacity to influence attention in subsequent tasks in a manner that is neither top-down nor bottom-up exclusively (Yantis et al., 2012). This phenomenon, value-driven attentional capture, is subsequently described in greater detail.

Background on Value-Driven Attentional Capture

Let us reconsider the example of searching for a specific car in a busy parking lot. Imagine now that you see your friend in the parking lot, who cannot find her red car. She offers you $100 to find her red car. Therefore, you utilize top-down, goal-directed attention to select for the color red, ignoring cars of all other colors. Eventually, you find her car, and she rewards you the $100 for accomplishing the task. Then, you see another friend in the parking lot, who cannot find his minivan. You offer to help and begin utilizing top-down attention to select for minivans only, ignoring sports cars, pickup trucks, and other cars in the lot. Now, the color red is no longer relevant to your task. However, you find yourself becoming distracted by red cars in the lot, since your previous task involved you selecting for the color red. Because of this distraction by red cars, you take longer to find your friend’s minivan. Since your task is now to search for your friend’s minivan, the color red is no longer task-relevant, nor does it have features that would make it physically salient. So, how do we explain this attentional capture by red cars when searching for minivans?

When completing tasks that involve stimuli with reward contingencies, it is beneficial for the observer to allocate attention to the rewarded stimuli. Moreover, the observer seeks to maximize reward, so voluntarily allocating attention to rewarded stimuli would increase the likelihood of the observer maximizing the possible reward gained from an experiment. However, if a once rewarded stimulus was presented again in a later task, one in which this stimulus was now solely a distractor, the observer may become distracted by this stimulus, due to the development of reward associations in the previous task, during which the observer benefitted from attending to the stimulus that had a certain reward contingency. In an unrewarded subsequent task, the attentional capture that may occur has been described as value-driven attentional capture (VDAC), a phenomenon in which stimuli that lack physical salience are rendered in a color that once signaled reward and are now capable of slowing responses and capturing eye movements, though now lacking the reward contingency that was once present (Anderson et al., 2011).

Typical VDAC Methodology & Results

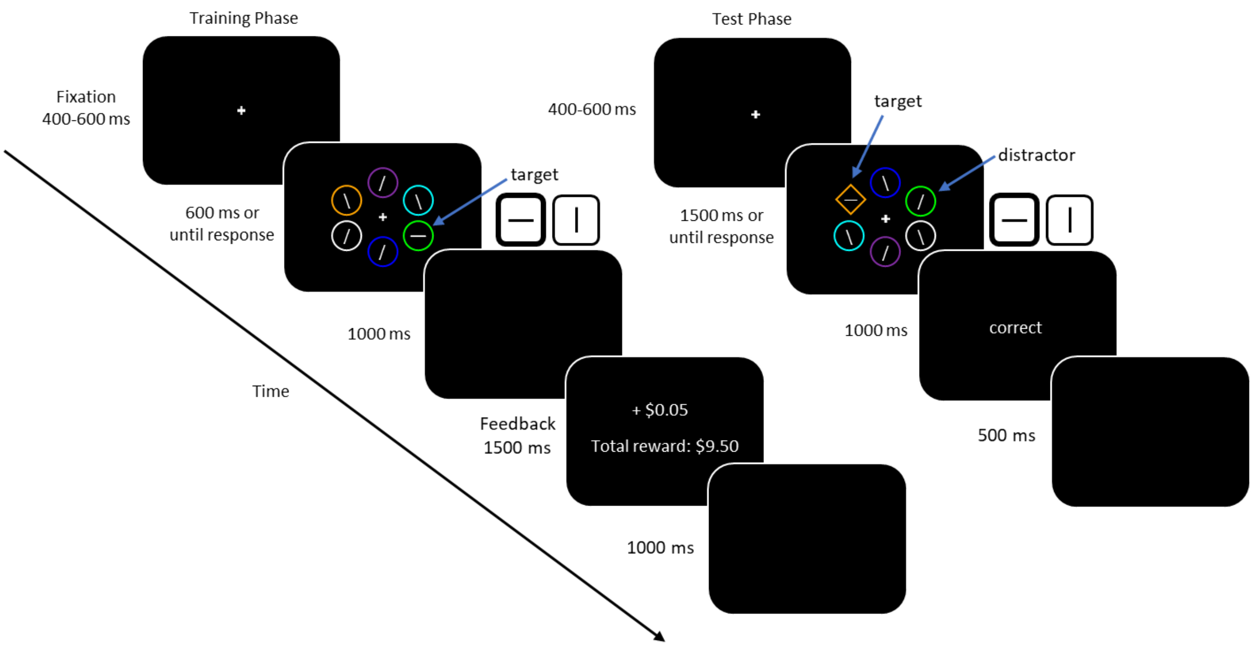

Figure 1. Trial sequence in the typical VDAC training and test phases, as proposed by Anderson and colleagues (2011).

Anderson and colleagues (2011) presented the foundational methodology for studying and measuring VDAC. Their methods include a visual search task utilizing a training phase and a test phase (Figure 1). During the VDAC training phase, observers are presented with a search array, and their task is to search for a color-defined target (red or green). One of these colors is a predictor of high reward while the other is a predictor of low reward. Observers are not explicitly informed of these reward contingencies and are only instructed to indicate the orientation of a line contained within the red or green shape. The colors red and green are never presented on the same trial. As observers proceed through this training phase, they use provided reward feedback to associate each target color with either high or low reward. The typical VDAC test phase tasks observers with searching for a shape-defined target (e.g. a circle among diamonds or a diamond among circles) and indicating the orientation of a line contained within the shape singleton in the search array. In the test phase, color is completely irrelevant; however, on half of the trials, one of the distractor shapes in the search array is rendered in one of the target-defining colors from the training phase, either the color that predicted high reward or the color that predicted low reward.

When quantifying VDAC, changes in response time (RT) are typically used. Traditionally, mean RT is found for each condition. When the previously high-value distractor color is present in the test phase, it is common to find slowed orientation judgements compared to when the low-value distractor color is present and compared to when neither distractor color is present (Anderson & Halpern, 2017, Exp 1, Reanalysis of Anderson et al. 2011b). When considering these results within the context of the traditional dichotomy of attention, we encounter one of the many circumstances under which this dichotomy fails. For test phase trials on which one of the training phase target colors is present, the traditional dichotomy of attention would assume no reason to prioritize the stimulus whose color was previously rewarded. From the viewpoint of the dichotomy, these previously rewarded colors are no longer task-relevant, nor are they physically salient, thereby predicting no reason that they should capture attention when presented in the test phase. However, a multitude of experimental evidence conflicts with the predictions of the traditional dichotomy, thereby demonstrating its inadequacy (Anderson et al., 2011; Anderson et al., 2016; Jiao et al., 2015; Anderson & Yantis, 2013; Anderson & Halpern 2017).

Neural Basis of VDAC

When stimuli that were previously associated with high reward are presented, stronger neural responses result. Specifically, stronger responses evoked by visual stimuli are observed in ventral visual cortex and caudate tail (Anderson, Laurent & Yantis, 2014; Anderson et al., 2016; Donohue et al, 2016; Yamamoto, Kim & Hikosaka, 2013). Additional research has shown stronger responses in the early visual cortex (MacLean & Giesbrecht, 2015; Serences, 2008). Anderson (2019) mentions two different mechanisms through which previously rewarded stimuli can elicit attentional capture on a neural level. The first mechanism involves an increase in response in the visual perceptual system, which also includes feature-selective responses in early visual cortex and possibly in object-selective cortex (MacLean & Giesbrecht, 2015; Serences, 2008; Hickey & Peelen, 2015; Hickey, Kaiser & Peelen, 2015). The signals produced by previously rewarded stimuli impact the priority map in the parietal cortex. Anderson (2019) discusses how previously rewarded stimuli follow trends similar to bottom-up attentional capture, in that processing occurs earlier in the visual system and relies heavily on feedforward mechanisms. This serves as an explanation for how previously rewarded stimuli could obtain priority over more slowly processed top-down stimuli. The second mechanism that Anderson (2019) mentions has to do with the caudate tail, which influences reflexive eye movements. This mechanism would permit information that is reward-associated to yield higher priority in the parietal cortex and could help explain situations where priority is given to reward-associated stimuli over those which are processed in either a top-down or bottom-up manner.

In a study by Anderson, Laurent, and Yantis (2014), the authors demonstrate that cortical structures including the extrastriate cortex for both the left and right visual field shows increased activation when a previously valued distractor is present in the test phase versus when it is absent. Also, the authors discuss subcortical structures that show increased activation when previously valued distractors are present, and these structures include the caudate tail, primarily. Anderson and colleagues (2016) demonstrate a correlation between value-based distraction and distractor-evoked dopamine response. Moreover, this dopamine release occurs in the right posterior caudate, right posterior, putamen, and right anterior caudate. Since reward is no longer associated with the stimuli in the test phase, when dopaminergic release was measured in this experiment, distraction by previously rewarded stimuli may be due to dopaminergic reward-prediction errors, since dopamine is mistakenly released in response to stimuli that are no longer associated with reward.

Controversy in the Literature Regarding VDAC

While learned reward is commonly attributed to driving distraction in the test phase, there is an alternate explanation in the literature for the capture effects that occur in the test phase. Some studies offer an explanation for the VDAC effects that focuses on selection history, not reward learning, driving attentional capture in the test phase (Grubb & Li, 2018; Sha & Jiang, 2016). Consistently deploying attention to some stimulus feature can result in the development of a selection history, which can engender lasting attentional biases, even when the stimulus feature is no longer relevant to the present task (Awh et al., 2012). In the traditional VDAC paradigm, observers must find target-defined colors in a search array before indicating the orientation of the line contained within the shape. Could it be the case that selection histories, rather than reward histories, drive attentional capture in the VDAC test phase?

Figure 2. *Different types of training phase feedback.* **A.** Example of reward feedback for a correct trial in training, which is used during the typical VDAC training phase. **B.** Example of accuracy-based feedback on a correct trial, which could be used during a training phase where reward has been removed.

If selection history drives attentional capture, then the slowed RTs in the test phase when a previous target color was presented should still be observed in the absence of reward in the training phase. To test this experimentally, rather than giving observers a high or low reward for correct judgements, observers can be provided accuracy-based feedback only. Furthermore, as opposed to reward feedback which notifies the observer of reward gained on each trial and total accrued reward, accuracy-based feedback only informs observers whether they made a correct determination on each training phase trial (Figure 2). Some research has demonstrated the ability to elicit capture effects by former targets in the test phase by merely using accuracy-based feedback in the training phase, as opposed to reward feedback (Sha & Jiang, 2016; Grubb & Li, 2018).

In their 2018 publication, Grubb and Li investigate the selection history versus reward history debate by completing experiments that elicited capture in the test phase after using accuracy-based feedback in the training phase. In the background study to their Registered Report (*Attention, Perception, & Psychophysics,* 2013), Grubb and Li utilize a modified version of the short-training VDAC paradigm proposed by Anderson and colleagues (2011, Exp. 3). These modifications include adding a group of observers who only received correct/incorrect feedback during training and utilizing visual instead of auditory feedback. In this background experiment, they found that RTs in the test phase slow when the training phase target is present as a distractor in the test phase. Interestingly, this modulation of RT occurred for each of the groups, including that which only received accuracy-based feedback.

In the preregistered study, Grubb and Li explore a possible difference in methodology that could have accounted for accuracy-based feedback still resulting in capture in test in their background study but not in Anderson and Halpern (2017), in which the authors found that accuracy-based feedback was not sufficient to create capture effects. This methodological difference had to do with the type of accuracy-based feedback in the training phase. Anderson and Halpern (2017, Exp. 2A) only inform observers of responses that were either incorrect or too slow. They do not inform observers of correct responses, thereby not providing positive feedback. Grubb and Li also mention two studies from Anderson, Laurent, and Yantis (2012; 2014), both of which signal accurate responses by withholding negative feedback in training, a scenario which consistently failed to elicit capture in test. Grubb and Li, on the other hand, explicitly display "correct" when observers made the right judgement in training, as their feedback consisted of "correct," "incorrect," or "too slow."

In order to investigate whether the withholding of negative feedback influences the occurrence of capture in test, Grubb and Li include two accuracy-based feedback groups in their preregistered study, one that received identical feedback to that in the background study and one that only received "incorrect" or "too slow," thereby having correct responses indicated by the withholding of negative feedback. Grubb and Li replicate the finding that capture occurs in the test phase just by using accuracy-based feedback in training. However, the authors find no evidence that capture was reliant on the presentation of positive feedback in the training phase, as the "correct"-delivered and "correct"-withheld groups both showed capture in the test phase. Therefore, Grubb and Li present further evidence that accuracy-based feedback in training is capable of engendering capture in the test phase.

On the other hand, there is also a significant body of research that has demonstrated that accuracy-based feedback is not sufficient to create capture effects, with Anderson and colleagues at the forefront of these studies (Anderson, Laurent & Yantis, 2011, 2012, 2014; Anderson & Yantis, 2012; Anderson & Halpern, 2017). This conflicting literature on the reward dependence of capture effects in the test phase invokes the need for a more in-depth analysis of the methodological minutia of the training phase which could give rise to these conflicting results.

The potential role of selection history has been debated, though a clear consensus on its role has yet to be determined. Anderson and Halpern (2017) mention that greater magnitude of attentional capture by the previously high-reward color as compared to capture by the previously low-reward color must be due to the difference in learned value, since these colors possess the same histories as targets and are of the same physical salience. Therefore, other than for reward learning, this argument assumes no reason for capture to be greater when one of these colors is presented in the test phase over the other. Le Pelley and colleagues (2016) also support the hypothesis that selection does not have a major role in determining capture effects, since they propose that selection history is equated for the high-value and low-value colors. Moreover, in training, it is equally likely that the high-value or low-value color will appear on any given trial, and as long as any other differences are controlled for, Le Pelley and colleagues (2016), like Anderson and Halpern (2017), argue that the only factor that could be contributing to capture differences in the test phase is the difference in value of the two colors in training. However, upon further investigation of the training phase, this explanation is called into question.

Addressing the Inconsistencies in VDAC Studies

Prioritization of Training Phase Targets. While it is certainly true that there is equal probability of the high- or low-reward color appearing on any given trial of a typical VDAC training phase, observers may not prioritize each of these colors equally in training. Differences in prioritization could thereby lead to differences in selection history for each color. Observers' motivation in the training phase should be to obtain maximum reward, and in order to do this, preallocating attention to the high-value color once the observers learn the reward contingencies may be a beneficial strategy to accrue maximum reward (Grubb & Li, 2018). Once observers learn the reward contingencies of the training phase colors, they could deploy feature-based attention (FBA) voluntarily towards the high-value color prior to each trial, so as to ensure they do not miss trials on which a high-reward color is present. Feature-based attention is attention that is selectively allocated to visual features, including object color, and can enhance these features (Carrasco, 2011). If observers deploy FBA towards the high-value color in training, they are developing stronger selection biases for the high-value color than for the low-value color. This strategy to preallocate FBA to the high-value color may also be a beneficial strategy given the strict time constraints of the typical training phase, as mentioned by Grubb and Li (2018). When shown the search array in training, observers are given a strict window of time during which they must make a response (600 ms in Anderson et al., 2011, Exp 1; 800 ms in Anderson et al., 2011, Exp 3 and in Anderson & Halpern, 2017, Exp 1). With such limited time to make a response, a reward-maximization strategy may be beneficial to ensure that observers miss as few trials where the high-value color is present as possible. In order to confidently decipher the causes of capture in the test phase, a more comprehensive understanding of the types of attention deployed in the training phase is required.

The Importance of the Low-Value Color. As mentioned, typical VDAC test phase results include capture by the high-value color when presented as a distractor in the test phase. However, there have been studies that have used versions of the paradigm proposed by Anderson and colleagues (2011) that have consistently failed to demonstrate capture by the low-value color when presented in the test phase (see Anderson & Halpern, 2017, Exp 1). Moreover, in Anderson and Halpern (2017, Exp. 1), the authors showed nearly identical RTs for trials on which the previously low-value color was present and trials on which neither training phase color was present. This finding has not been of primary concern in the literature, though, because a difference in capture by the high-value color when presented in training has been interpreted as being the result of learned value in training (Anderson & Halpern, 2017; Jiao et al., 2015; Roper, Vecera & Vaidya, 2014). However, by bringing our attention back to the failure of the low-value color to elicit capture in the test phase, we may actually be surprised. Assuming that observers learn the reward contingencies for the high- and the low-value colors in training, why would the low-value color, when presented in the test phase, fail to modulate attention to any extent? In order to address this question, we might reconsider the workings of the training phase, specifically in terms of the development of reward associations for the low-value color.

There are a couple possible explanations for the lack of capture by the low-value training phase color when presented in the test phase. It could be the case that VDAC is truly dependent on the relative value for high-value color as compared to the low-value color. In the literature, some studies argue that the magnitude of reward modulates the amount of capture in the test phase (Failing & Theeuwes, 2018; Le Pelley et al., 2014). However, another explanation could be that people do not actually learn much about the reward contingencies for the low-value color in training. If this were the case, observers could potentially be over-attending to the high-value color and failing to actually learn about the low-value color. This over-attention to the high-value color could be a result of selection biases due to reward maximization strategies being employed by observers, which implies that it may be the case that selection biases are being developed for the high-value color in training, while the low-value reward contingency is not actually being learned.

Supplementing RT Analyses with Computational Modeling

When analyzing RT data, utilizing RT distributions are extremely useful(Hohle, 1965; Ratcliff, 1978). Moreover, merely using measures of central tendency, such as mean or median RT, can potentially cause important information about the distributions of RTs to be overlooked (Schmiedek et al., 2007; Heahtcote, Popiel & Mewhort, 1991). Therefore, it is beneficial to supplement traditional analyses using measures of central tendency with distributions that model RT data well. It has been shown that RT distributions are not Gaussian (normal) distributions, and instead, they are best represented by a mixture of a Gaussian distribution and an exponential distribution, termed an exponentially modified Gaussian distribution (ex-Gaussian, Luce, 1991; Whelan, 2008).

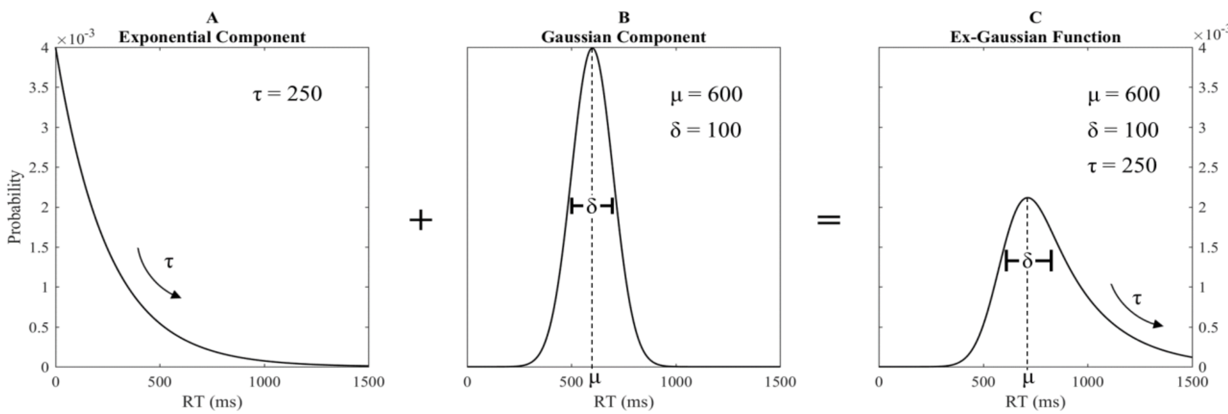

Figure 3. The ex-Gaussian function has both an exponential component and a Gaussian component. It can be described by three parameters (μ, δ, τ).

The ex-Gaussian distribution is useful because it can adequately be described by three parameters (Figure 3). These three parameters are mu (μ), the mean of the Gaussian component, sigma (δ), the standard deviation of the Gaussian component, and tau (τ), the mean of the exponential component. The Gaussian and exponential components of the distribution possess psychological meaning as well, which can be useful in characterizing RTs. The Gaussian component has been proposed to describe the transduction component, which consists of more automatic processes, including the time required by the sensory process and the time to physically make a motor response, while the exponential component has been proposed to describe decision-based processes, meaning the time required for the observer to make a decision about the stimuli (Hohle, 1965; Luce, 1991; Schmiedek et al., 2007; Lacouture & Cousineau, 2008). By fitting RT distributions with ex-Gaussian functions, there is more that could potentially be revealed about the underlying cognitive processes that yield the distribution of RTs.

In VDAC, these distributions of RTs are useful in helping to determine the underlying causes of capture in the test phase. Moreover, we can analyze potential differences in parameter values for each distribution of RTs (previously high-value color present, previously low-value color present, no training phase color present). Since mu is representative of the sensory component, a greater value for mu is indicative of a longer sensory process taking place. Therefore, when relating this to VDAC, we would expect a larger mu value when a training phase value-color is presented as a distractor in the test phase. When a previously valued distractor color is present in test, this color automatically captures attention, thereby causing a longer sensory process. Once the previously valued color grasps attention briefly, the sensory process must bring attention back to the task at hand. Due to attention reflexively being allocated to the training phase color, we would expect a greater mu value, due to the longer sensory process. Since tau represents the decision process, a greater value for tau would be indicative of a longer time needed to make a decision about the stimuli on the screen. We would not expect tau to differ when comparing the distributions in a typical VDAC experiment, since the attentional capture in VDAC is likely due to the reflexive allocation of attention to the previously valued color, a phenomenon that would likely be described by the mean of the Gaussian component (mu), which accounts for the more automatic processes.

The Present Study

In this study, we asked whether observers learned the reward contingencies for the low-value stimulus in a modified VDAC training phase. The modifications to the training phase sought to provide observers with an environment where reward alone drove attentional capture by eliminating benefits of adopting a reward maximization strategy as well as the creation of biased selection histories. We hypothesized that observers would develop reward associations for the low-value stimulus and show VDAC effects in the test phase. Since our modifications sought to limit confounding factors, we expected the magnitude of reward alone to drive attentional capture. The modified training phase consisted of two stimuli, and the task was to choose a stimulus (left or right) while using feedback to maximize reward. On each trial, a value stimulus (high or low) was paired with a "no-value" match. Following the modified training phase, observers completed a traditional VDAC test phase, which entailed indicating the orientation of a line contained within a unique shape. In the test phase, color was completely irrelevant. To analyze the test phase data, we completed a traditional response time analysis utilizing the mean and completed a computational modeling analysis to confirm the reliability of the results.

As a preview of our results, observers learned the reward contingencies in training; however, there was no significant difference in learning between the high-value and low-value stimuli. In the test phase, RTs slowed when the high-value training phase color was present relative to when the low-value training phase color was present. However, the low-value training phase color did not slow RTs relative to when neither training phase value color was present. Fitting these data with ex-Gaussian distributions confirmed the results from the RT analyses and further revealed the complexities of the psychological mechanisms resulting in these capture effects.

Methods

Observers and Procedure

22 adults (aged 18-24, 13F) participated in the experiment for monetary compensation. All had normal color vision and provided written informed consent before participating; experimental procedures were approved by the Institutional Review Board at Trinity College. Each observer completed a single experimental session, consisting of a training phase and a test phase. At the end of the session, observers were paid according to their cumulative reward earnings from the training phase (mean earnings, $10.41) as well as an additional $5 from the test phase.

Apparatus

The experiment was programmed in PsychoPy (Peirce, 2007) and run on a 3.0GHz Dual-Core Intel Core i7 Mac Mini; stimuli were displayed on 27.0" LED-Lit Dell Gaming Monitor (model: S2716DG). Participants were seated in a darkened experimental testing room approximately 96 cm from the monitor. Responses were collected with a Logitech F310 gaming controller.

Training Phase

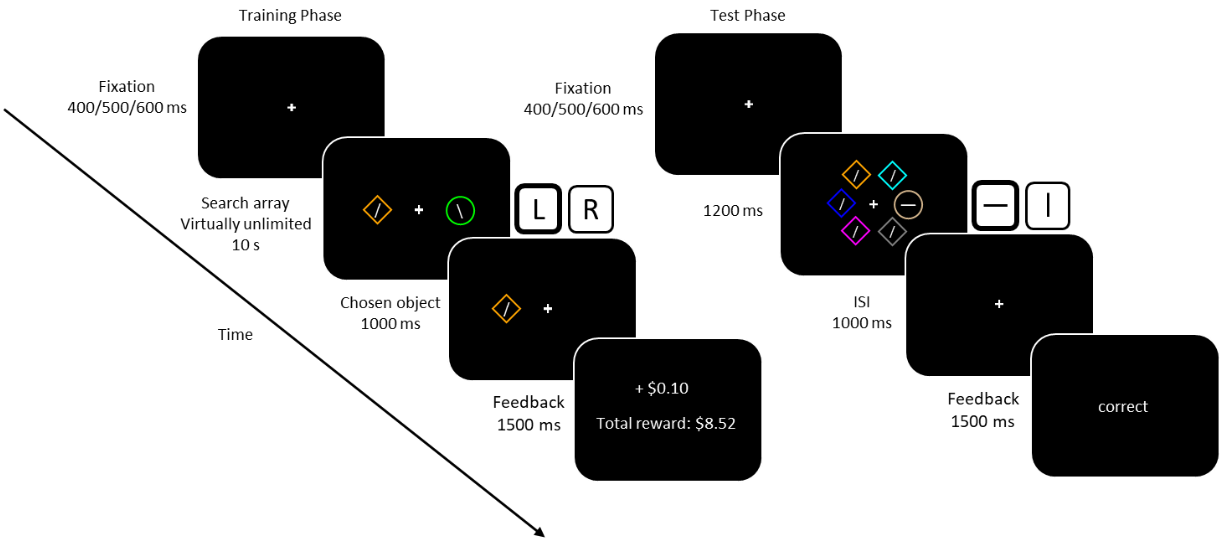

Figure 4. Trial sequences for the training and test phases. See text for details.

Modifications Overview

We addressed this selection history versus reward history debate by modifying the traditional VDAC training phase in a number of ways. In typical studies using the traditional VDAC paradigm, the training phase consisted of six shapes in the search array. Instead, we presented two shapes in the training phase search array on each trial. We also modified the task. Observers no longer were instructed to search for red or green and instead were instructed to use feedback to maximize reward. Limiting the search array to two shapes and modifying the instructions allowed us to determine potential reward learning for each value color individually. Also, by increasing the response window significantly, we eliminated the time constraints of typical VDAC training phases, thereby minimizing the incentive to adopt a reward maximization strategy because of strict time constraints. These modifications were designed to decrease the benefit of preallocating FBA to the high-reward color, which is crucial in limiting selection history effects. By not specifically instructing observers to search for red or green, they would not as easily be able to utilize FBA.

Methodological Details

A randomly selected period of fixation (400, 500, or 600 ms) began each trial, followed by the presentation of a visual search array. Participants had a virtually unlimited response window (10 seconds). The search array consisted of two stimuli, one which was a diamond and the other a circle (radius, 1.15 DVA), both presented on the horizontal meridian, one to the left and one to the right of a central fixation cross (eccentricity, 5 DVA). The diamond was sized to match the area of the circle. One of these stimuli contained a line oriented 45 degrees clockwise of vertical, and the other stimulus contained a line oriented 45 degrees counterclockwise of vertical. The stimuli never contained the same internal line orientation, and the orientation was randomly selected on each trial. Prior to the training phase, two pairs of colors were randomly chosen from a set of ten colors (red, lime, blue, yellow, magenta, cyan, white, gray, orange, tan). One pair of colors consisted of a high-value color and a “no-value” match; the other pair consisted of a low-value color and a different “no-value” match. Therefore, each stimulus had three distinct features on each trial (shape, color, and internal line orientation).

On each trial, one pair of colors was presented, either the high-value color and its “no-value” match or the low-value color and its “no-value match.” On every trial, the shape and internal line orientation for each of the colors in the pair was randomly chosen, so that there was one square and one diamond present, as well as one CW internal line and one CCW internal line. Prior to the commencement of the training phase, observers were instructed to “use the feedback to learn which object will give the highest reward on each trial.” Importantly, observers were not told that color was the reward-defining feature. Observers selected either the stimulus on the left or the right by pressing one of two buttons on a gaming controller (two-alternative forced-choice task). Throughout training, observers needed to learn that color was the relevant feature, so that they could maximize reward. All stimuli appeared against a black background.

Following a response, the chosen object alone remained present for 1000 ms. Choosing a high-value color yielded high reward ($0.10) with probability 0.8, low reward ($0.02) with probability 0.1, or no reward with probability 0.1. Choosing a low-value color yielded low reward ($0.02) with probability 0.8, high reward ($0.10) with probability 0.1, or no reward with probability 0.1. Finally, choosing the “no-value” match for either value color yielded no reward with probability 0.8, low reward ($0.02) with probability 0.1, or high reward ($0.10) with probability 0.1. After each trial, observers were shown their reward for the current trial, displayed above the total accrued reward. If no response was made before the deadline, the words “too slow” were displayed. There was a 1000 ms break between trials.

Test Phase

The experimental design of the test phase was a direct replication of that in Grubb and Li (2018), which itself was a replication of the “short-training” paradigm proposed by Anderson and colleagues (2011, Exp. 3). The sizes of the shapes in the test phase were identical to those used in the training phase. Prior to completion of the test phase, observers completed two blocks of practice trials, with each block containing 10 trials. A random period of fixation was once again presented to begin each trial. Following the fixation period, the search array appeared for 1200 ms. The visual search array consisted of six differently colored items positioned at the vertices of an imaginary hexagon encompassing a central fixation point, but the target was now defined as the unique shape: a diamond among five circles, or a circle among five diamonds. However, on half of the trials, one of these six distractor shapes was rendered in a color that matched a training phase color, either the color that predicted high-value reward or the color that predicted low-value reward. The high-value training phase color was present on a quarter of the total test phase trials and likewise for the low-value training phase color. The high-value and low-value training phase colors were never present on the same trial.

In the other half of the trials, none of the distractor shapes were rendered in a color that matched a training phase value color. Additionally, the "no-value" match colors never appeared in the test phase, not as distractors and not as targets. In all trials, the target itself was never the high-value or low-value training phase color, and the target appeared equally often at each of the six possible locations. On trials when a training phase value color was not present, the six objects were rendered in the remaining six colors from the above list once the training phase high-value and low-value colors and their "no-value" matches were excluded. On trials with a training phase value color present, the colors of remaining five distractors were randomly chosen from this list of six colors without replacement. When a training phase value color was present, it appeared equally often at each of the five remaining non-target locations. Observers were told that color was irrelevant, and they were instructed to "respond as quickly as possible while minimizing errors." The task was to report the orientation (horizontal or vertical) of a line contained inside the target (the unique shape), using one of two buttons on the gaming controller. The five distractors all contained an internal line that was oriented 45 degrees clockwise or counterclockwise of vertical. An interstimulus interval (ISI) of 1000 ms followed the presentation of the search array. After the ISI, accuracy-based feedback appeared on the screen for 1500 ms. Feedback consisting of "correct," "incorrect," and "too slow" was displayed for accurate responses, inaccurate responses, and missed response deadlines, respectively. All stimuli appeared against a black background.

RT Analyses

In line with convention (e.g., Anderson et al., 2011; Anderson & Halpern, 2017), the dependent variable for all RT-based analyses was mean RT for correct trials only; individual distributions were first trimmed to remove responses occurring 3 standard deviations above or below the condition mean.

Training Phase

We determined the proportion of trials on which a value stimulus was selected during the training phase in an attempt to show learning taking place. Also, we determined the proportion of trials on which the high-value stimulus was selected compared to the proportion of trials on which the low-value stimulus was selected. We compared the proportion of trials on which the different stimuli were selected utilizing paired t-tests to determine the learning of reward contingencies.

Test Phase

In the test phase, we determined the mean RTs for trials on which a previously valued stimulus was presented as a distractor and for trials on which no previously valued distractor was present. We compared these mean RTs utilizing paired t-tests to determine any differences in capture brought about by the distractors rendered in a previously valued color.

Computational Model

To supplement the traditional RT analyses with an alternate approach that utilizes the entire distributions of RTs, we fit the response time distributions with computational models. Specifically, we utilized the ex- Gaussian function to model the distributions. With the computational tools written in MATLAB source code provided by Lacouture and Cousineau (2008), we used maximum likelihood estimation to determine the parameters mu, sigma, and tau for each distribution (previously high-value distractor present, previously low-value distractor present, and no previously valued distractor present). Once we determined these parameters for each distribution, we were able to calculate the mean of each distribution ($\bar{x} = \mu + \tau$). By comparing the means of the distributions utilizing paired t-tests, we were able to supplement our RT analyses. Furthermore, the distributions also allowed us to analyze potential differences in specific parameters. We completed paired t-tests to potentially determine differences in specific parameters by distribution, which would reveal more specific insight into the specific components of RT modulation occurring in the test phase.

Recoverability Procedure

In order to assess the reliability of our findings using the ex-Gaussian distributions, we completed a parameter recovery exercise. To begin, we determined the minimum and maximum values that we observed in our experimental participants for each parameter. Using the ranges for each parameter, we determined ten values for each parameter that were equally spaced beginning with the minimum value and ending with the maximum value. Furthermore, by utilizing all possible combinations of these parameter values, we were able to obtain 1000 different combinations. Then, for each of these 1000 sets of parameter values, we generated 240 random trials of simulated data. We were then able to complete our original model-based analysis on this extensive new data set. Once we determined the parameters from this simulated data, we were able to determine whether we successfully recovered the original parameters. The ideal results for this procedure would be a tight correlation between the parameters from the true experiment and the simulated parameters (Wilson & Collins, 2019).

Results

Response Time Analyses

Training Phase

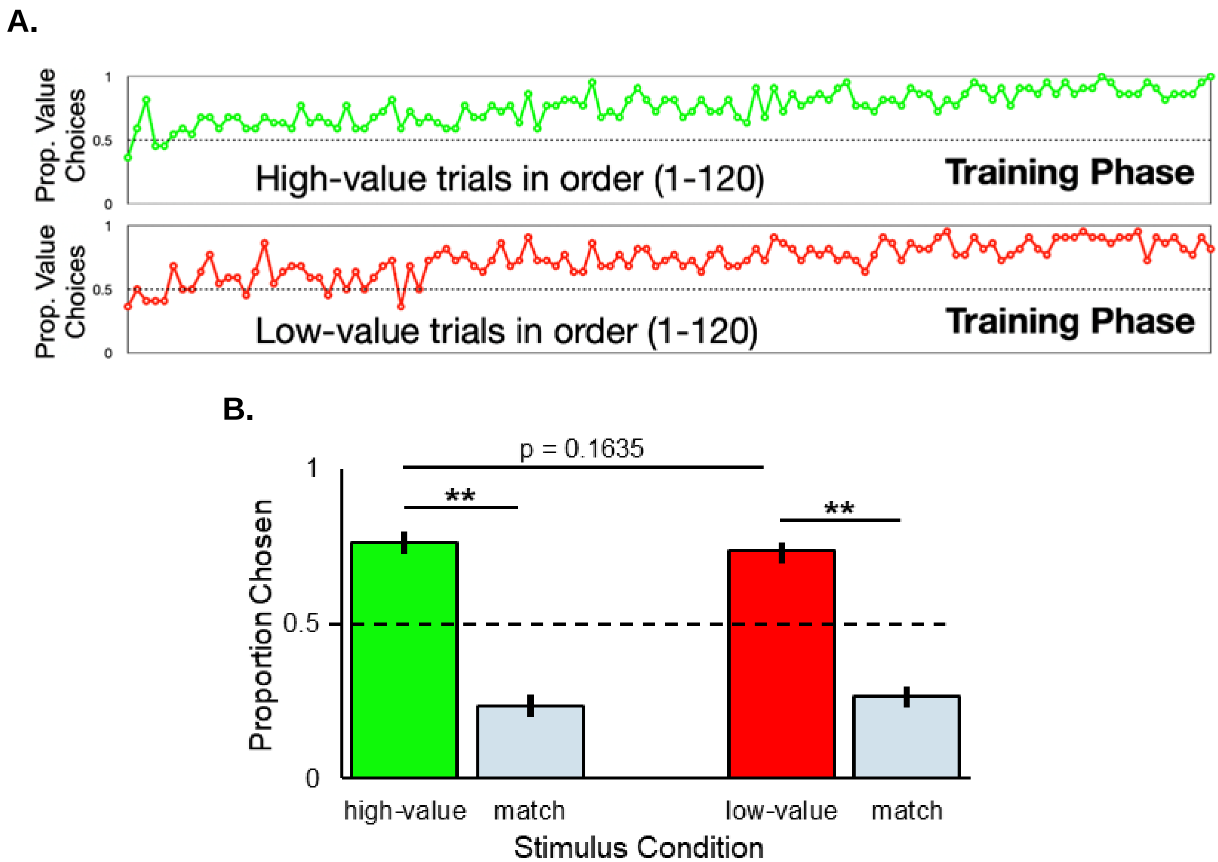

Figure 5. *Results from the training phase data.* **A.** Scatterplot displaying proportion of participants choosing each value stimulus over time, showing learning for each value stimulus. **B.** Bar graph displaying the proportion of high-value and low-value stimulus choices in comparison to each "no-value" match, averaged across participants.

As the training phase trials progressed, observers demonstrated learning of the value stimuli. Figure 5A demonstrates the overall trend of learning that occurred, as the proportion of observers choosing the value stimulus increased across trials. For both the high- and low-value conditions, the proportion of value choices began around chance (0.5), meaning that observers were guessing a stimulus. However, as the trials progressed, observers showed learning for each value stimulus, as the proportion of value choices increased over time. A single factor ANOVA revealed that learning of the value stimuli impacted observers' decisions, as they selected the value stimuli more often than chance would predict (ANOVA, F=28.61, p<0.0001). To determine if learning occurred for both the high-value and low-value conditions separately, paired-sample t-tests were completed for each value condition, and the results are displayed in Table 1. These analyses revealed that participants chose both the high-value stimulus and the low-value stimulus significantly more often than chance. However, learning did not significantly differ for the high-value condition compared to the low-value condition.

Table 1. Summary of t-tests comparing proportion of trials on which the value stimuli were chosen.

	High vs. Chance	Low vs. Chance	High vs. Low
t-statistic	7.28	7.91	1.00
df	21	21	21
p-value	<0.0001	<0.0001	0.1635
mean within-participant different	0.263	0.233	0.031

Test Phase

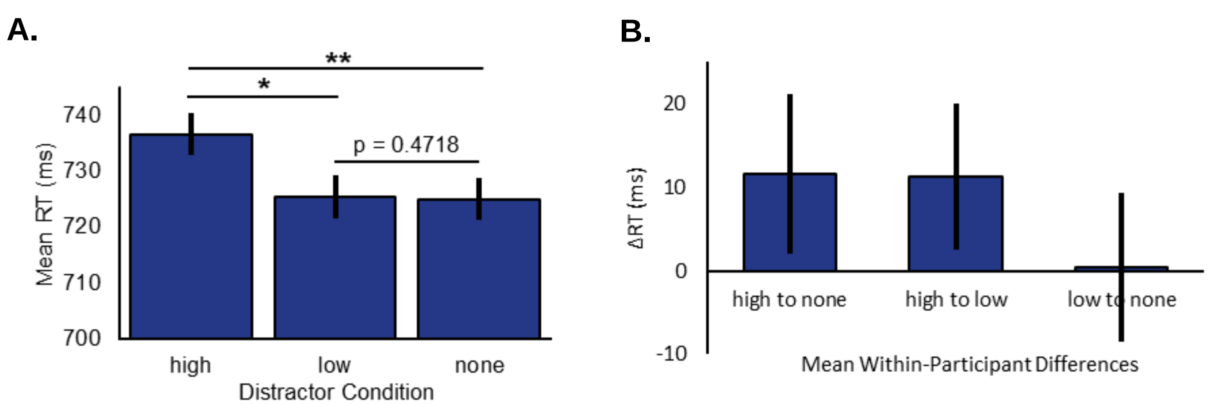

Figure 6. *Results from the test phase data.* **A.** Bar graph displaying the mean RTs in each condition. **B.** Bar graph displaying the mean, within-participant differences in RT.

In the test phase, RTs slowed when the high-value training phase color was present as a distractor relative to when neither training phase color was present (one-tailed, paired t-test, $t(21)=2.5380$, $p=0.0096$). Further analysis revealed that RTs slowed significantly when the high-value training phase color was present relative to when the low-value training phase color was present (one-tailed, paired t-test, $t(21)= 1.9169$, $p= 0.0345$). This was not the case for the low-value training phase color, when present, relative to when neither training phase color was present. The low-value training phase color did not slow RTs relative to when neither training phase value color was present (one-tailed, paired t-test, $t(21)=0.0715$, $p=0.4718$). Figure 6 displays this RT modulation by the high-value distractor when present, while the mean RTs for the low and none condition are nearly identical. Analysis of error rates confirmed that these changes in response time were not the result of simple speed-accuracy tradeoffs (see Table 2). There were no significant differences in accuracy when comparing any of the distributions (high-value vs. none: paired t-test, $t(21)= -0.7160$, $p= 0.2409$; high-value vs. low-value: paired t-test: $t(21)= -0.9925$, $p=0.1661$; low-value vs. none: paired t-test: $t(21)= 0.6526$, $p=0.2605$).

Table 2. Summary of test phase statistics, depending on the presence of the previously valued color.

Training Phase Value Color	RT (ms)		% Correct	
	Mean	*SD*	Mean	*SD*
High	736.6	41.8	91.1	76.1
Low	725.4	40.9	92.3	53.7
Neither	725.0	44.6	91.8	52.0

Computational Model

Using the ex-Gaussian distributions, we computed the means of each distribution (Table 3). The results of the computational model confirmed the results from the response time analyses. We determined the means of the distributions by summing mu and tau ($\bar{x} = \mu + \tau$). When comparing the mean of the distribution for the data when the high-value training phase color was present to that when no training phase distractor was present and to that when the low-value training phase distractor was present, the high-value distribution had a significantly greater mean (Table 3). Again, there was no significant difference between the mean of the distribution when the low-value training phase color was present as compared to the distribution when no training phase color was present (Table 3).

Table 3. Summary of t-tests comparing the means of the distributions.

	High vs. None	High vs. Low	Low vs. None
t-statistic	1.9269	1.9514	-0.4169
df	21	21	21
p-value	0.0338	0.0322	0.6595
mean within-participant difference	8.8663	11.2838	-2.4175

To investigate the potential impact of a change in mu or tau, we completed paired t-tests comparing mu and tau values for each distribution. We found a significant difference in mu when comparing mu from the high-value distribution to mu from the distribution for trials when neither previously valued distractor was present (Table 4). However, this was the only significant difference found when searching for differences in individual parameters.

Table 4. Summary of t-tests investigating potential differences in mu or tau between distributions.

	High vs. None		High vs. Low		Low vs. None	
	Mu	Tau	Mu	Tau	Mu	Tau
t-statistic	1.1477	-0.6192	1.9098	-1.0633	-0.8031	0.4933
df	21	21	21	21	21	21
p-value	0.1320	0.5425	0.0350	0.2997	0.7846	0.6269
mean within-participant difference	20.8457	-11.9795	28.2540	-16.9702	-7.4082	4.9907

Recoverability Procedure

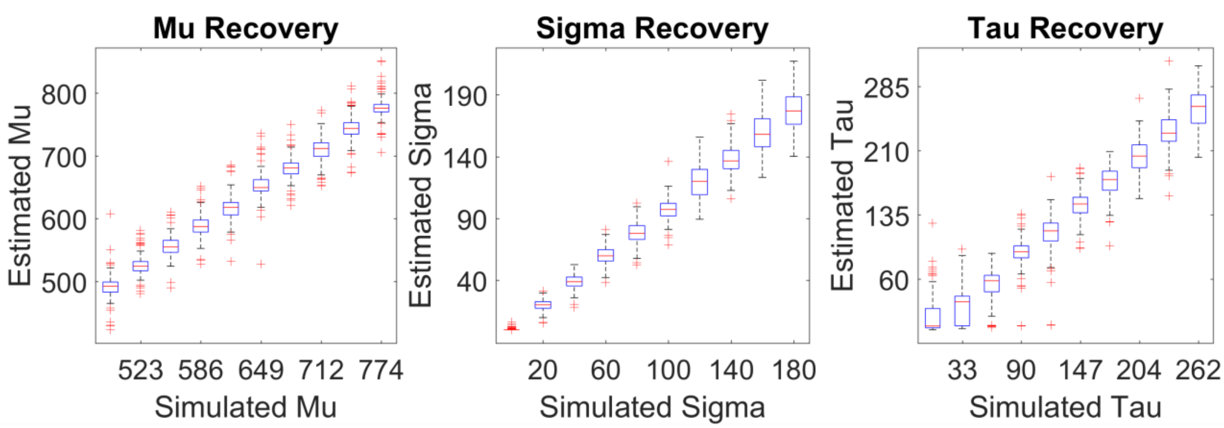

Figure 7. Parameter recovery for mu, sigma, and tau.

After determining the range for each parameter in our experiment (mu: 491.52 ms – 774.42 ms; sigma: 2.29E-10 ms – 179.76 ms ; tau: 4.15 ms – 261.58 ms), we divided these values into ten equal steps. These steps served as the simulated values for each parameter, derived from the parameter values obtained in our experiment. The recoverability procedure revealed a near linear relationship for each parameter in Figure 7. Each box plot that represents a simulated value is composed of 100 estimated values. Another representation of the relationship between fit and simulated parameter values is demonstrated in Table 5, which presents the values obtained from our range of parameters as well as the median estimated values.

Table 5. Summary of median simulated parameter values for every fit value used for mu, sigma, and tau.

mu		sigma		tau	
simulated	estimated	simulated	estimated	simulated	estimated
491.52	492.29	2.29E-10	1.45E-07	4.15	4.84
522.95	524.03	19.97	20.19	32.75	33.29
554.38	554.66	39.95	38.84	61.36	57.79
585.82	587.23	59.92	59.74	89.96	91.78
617.25	617.80	79.89	78.01	118.56	116.22
648.69	649.37	99.86	97.21	147.17	147.67
680.12	680.49	119.84	120.02	175.77	176.09
711.55	711.73	139.81	136.54	204.37	203.68
742.99	743.36	159.78	158.05	232.97	230.51
774.42	775.59	179.76	176.93	261.58	261.75

Discussion

Limitation due to COVID-19

Before we begin our discussion of the results, we acknowledge that a major limitation to the present study is that we are only analyzing data from 22 participants. Our initial intention was to replicate this experiment with slight modifications on a significantly larger dataset; however, restrictions on in-person experiments due to COVID-19 made this replication intent impossible. Therefore, we remain cognizant of this limitation and are cautious when interpreting our data.

Methodological Modifications

Our modifications to the training phase sought to provide an environment where observers could learn reward contingencies, while limiting other confounding factors.

Presentation of the search array for ten seconds eliminated any time constraints that could have potentially incited observers to use some kind of reward maximization strategy, as discussed by Grubb and Li (2018). Furthermore, it would not have benefited observers to preallocate attention to the high-value color in our training phase, due to the lack of a time constraint. In our training phase, observers did not know prior to the experiment what feature of the stimuli would yield reward. Moreover, the content of our instructions was another instrumental difference in our training phase as compared to others typically used in VDAC experiments. By only instructing observers to use feedback to maximize reward, we incited observers to determine the reward contingencies on their own, assuming their strategy was to maximize total accrued reward. We attempted to decrease their potential use of FBA, since we did not bias them to searching for two specific colors before the commencement of the experiment.

Once observers learned that color was the reward predicting feature in training, they would not have benefitted from adopting a reward maximization strategy that involved the preallocation of attention to the high-value color. Moreover, since we did not restrain the training phase temporally, observers could be searching for either color once they made reward associations, since there was an equal likelihood that the high- or low-value color would appear in training. Adopting a reward maximization strategy similar to the one described by Grubb and Li (2018) would not have necessarily harmed observers in our training phase, but it certainly would not have benefitted them, and for that reason we can do not expect them to have used this type of strategy.

Learning in the Training Phase

In our analysis of data from the training phase, we found that observers learned the value for both the high-value and low-value colors. VDAC studies in the literature typically have explicit directions to search for red or green in training (Anderson & Halpern, 2017, Exp 1, Reanalysis of Anderson et al., 2011b; Roper, Vecera, & Vaidya, 2014). These studies demonstrate learning of the reward contingencies for the high-value color by demonstrating capture by the high-value color in the test phase. However, they are unable to explicitly demonstrate learning of the low-value color in training, since the low-value color does not have any capture effects in the test phase. Furthermore, our ability to demonstrate learning of the low-value color in training is a crucial result when considering outcomes in the test phase of typical VDAC studies.

We also determined that learning for the high-value color as compared to the low-value color was not significantly different. This is an important result, because our data imply that observers learn the high-value color and the low-value color equally well. However, we remain cautious when interpreting this result. While we can be confident that observers learn the reward contingencies for both the high- and low-value colors in training, we remain open to the possibility of a difference in learning for the high-value color as compared to the low-value color. With more data, could a difference in learning have emerged? Future research is needed to investigate this possibility.

We can now revisit one of the possibilities mentioned prior when analyzing the Anderson and Halpern (2017, Exp 1) study. In this study, the authors found that RTs for trials on which the previously low-value training phase color was preset were nearly identical to RTs for trials on which no training phase color was present. One of the possibilities for these identical RTs is that observers do not learn much about the reward contingencies for the low-value color. However, we have demonstrated that this is not the case, as observers do learn the reward contingencies for the low-value color.

Demonstrating learning for the low-value stimulus in training is novel in the literature. Given that the reward associations were made for the low-value stimulus, we expected the low-value color to modulate attention in the test phase. Capture effects by the high-value color in test are explained by many as occurring due to reward learning (Anderson, Laurent & Yantis, 2011, 2012, 2014; Anderson & Yantis, 2012; Anderson & Halpern, 2017). If learning for the high-value color and low-value color is equal, the low-value color should modulate attention in the test phase significantly if capture truly is dependent on persistent reward histories. Ruling out this possibility based on the data from our study is an important step to understanding how capture effects are created in the test phase.

Modulation in the Test Phase

Interestingly, we did not find capture effects by the previously low-value training phase color in the test phase. The previously high-value training phase color, when presented as a distractor in the test phase, modulated attention. This modulation of attention by the high-value color, but not by the low value color has been displayed by experiments completing versions of the standard VDAC paradigm (see Anderson & Halpern, 2017, Exp 1, Reanalysis of Anderson et al. 2011b). However, our study demonstrated learning of the value of the low-value color in training. So, why did the low-value color from training fail to show capture effects in the test phase when presented? This question points to the complexity of the VDAC training phase.

The attentional capture effects are likely not due to selection history alone or reward learning alone. Further examination of the different mechanisms at play resulting in capture or the lack thereof must be a task of future research. How selection history effects manifest themselves in terms of influencing attentional capture can blur the lines between selection history and reward history effects. Moreover, a sense of accomplishment due to positive performance on a task can be accompanied by reinforced sensory processes resulting in bias towards a specific stimulus feature such as the high-value color in training. This feature of perceptual learning has been investigated for the ability of certain stimulus features to invoke this internal reward signaling (Watanabe & Sasaki, 2015; Kim & Anderson, 2019). Though our feedback in the training phase presented the reward gained on that trial and the total accrued reward and did not include accuracy-based feedback including "correct or "incorrect," the sense of accomplishment from reward gain on a particular trial could have invoked internal reward signaling for the successful completion of the task along with external reward signaling for the specific monetary gain. If this were the case, it could have been the case that associations to the high-value color were greater than those to the low-value color in training since the internal reward signaling would have been greater when $0.10 was gained as opposed to when $0.02 was gained. This could have resulted in the reward learning for the low-value stimulus in training, but the subsequent failure to modulate attention in test. This explanation that relative value influences the magnitude of capture in the test phase is one of the possibilities proposed prior when attempting to explain the nearly identical capture effects for trials on which the previously low-value training phase color was present and the trials on which no training phase color was present in Anderson and Halpern (2017, Exp 1).

To address this possibility, an interesting modification could be made to our experiment in an attempt to equate this potential difference in prioritization. This modification involves dividing the training phase trials into blocks. One group of participants would undergo the training phase as one block which consists of trials containing only the low-value color and its "no-value" match followed by trials consisting of solely the high-value color and its "no-value" match. Another group would complete these same training phase blocks, but in the reverse order.

Finally, the third group, a control group, would complete this training phase in an identical manner as the one from this experiment with trials interspersed. Breaking the training phase into blocks would allow observers to explicitly focus on learning the rules independently of one another, for those in the two experimental groups. By learning the reward predictor, independent of whether it is high or low, subsequently searching for that reward predictor on every trial would certainly prevent observers from prioritizing one color over another or from preallocating attention to one color over the other once the reward contingencies are learned, since the focus of the block is entirely on one color, as opposed to two colors of different value predictions. Furthermore, observers could learn the reward-predictor in the specific block and search for that specific reward-predictor on every trial. When completing the block containing the low-value color, observers' strategy should be to always attend to the low-value color once it is learned, since there will be no threat of the high-value color appearing on any trial in the block. This strategic presentation of trials in the training phase could result in stronger associations made for the low-value stimulus.

By then having observers complete an identical test phase, the previously low-value training phase color could potentially have capture effects when compared to trials on which no training phase color was present. It has been demonstrated that the magnitude of reward associated with the distractor previously impacts the extent of capture that occurs (Failing & Theeuwes, 2018; Le Pelley et al., 2014). Therefore, it could be the case that the low-value color, when presented as a distractor in test, captures attention compared to baseline, but does so to an extent less than the high-value color is able. Such an experiment would more thoroughly investigate the possibility that VDAC effects are dependent on relative reward magnitude. These types of methodological minutia are crucial to understanding the learning that takes place in the typical VDAC paradigms. Our experiment begins to unravel the complexities of the training phase; however, further investigation is certainly needed.

Ex-Gaussian Function

Confirmation and Extension of Results

The distributions we modeled using the ex-Gaussian function supported the traditional RT analyses we completed. The mean of the distribution for trials on which the previously high-value training phase color was present was significantly greater than the mean of the distribution both for trials on which the previously low-value training phase color was present and for trials on which neither training phase color was present. However, the mean of the distribution for trials on which the low-value training phase color was present was not significantly different from the distribution for trials when neither training phase color was present. Therefore, we can have a greater degree of confidence in our results from the traditional RT analyses.

We also utilized the RT distributions to address a different possibility, which sought to understand whether the specific parameter values differed for the different distributions. We found that mu was significantly greater for the high-value distractor present distribution compared to the low-value distractor present condition. A greater value for mu translates to the mean of the Gaussian component being greater. This implies that when the previously high-value distractor was present, the sensory process required more time. This interpretation would account for the previously high-value distractor capturing attention and resulting in a longer sensory process since the observers' attentional systems have to refocus attention after being distracted by the previously high-value distractor before allowing the observer to make a decision about the search array. However, we will not over-interpret this significant value of mu. We did not find any other significant differences in parameter values among the distributions. While it may be the case that mu is significantly greater for the high-value distractor condition, we would have expected this to hold true when comparing the high-value distractor condition to the “no-value” distractor condition as well, which was not the case in our experiment. Additional and more extensive research on VDAC utilizing the ex-Gaussian function to try to understand the psychological underpinnings of these RTs is needed.

Recoverability Procedure

Based on the parameter recovery exercise, we confirmed that our results from the computational model were reliable. As displayed by the tight correlation between the estimated parameters and the simulated parameters in Figure 7, we were able to recover the parameters successfully. This exercise was very important, since we are now able to have confidence that the data we fit with the ex-Gaussian function provided meaningful parameter values.

Future Directions

Recent research has demonstrated differences in capture effects on an individual basis, suggesting differences in capture based on the specific observer. Much of this research has focused on the impact of depressive symptoms on capture affects due to reward learning (Anderson et al., 2017; Anderson et al., 2014). Moreover, these studies demonstrate that the magnitude of attentional capture by previously rewarded stimuli is sharply decreased in those who demonstrate symptoms of depression. Therefore, depressive symptoms may be an important factor to consider when participants complete studies on VDAC. One study by Marchner and Preuschhof (2018) screened participants for acute depressive symptoms prior to administration of the VDAC experiment, since they considered the potential impact of depressive symptoms on the magnitude of capture effects. This consideration is especially important when measuring VDAC effects, and more research regarding depressive effects on capture may reveal the importance of considering these effects in future experiments.

We have only begun to scratch the surface on the complex happenings of the learning that takes place in the VDAC training phase. Importantly, this study has shown that observers do learn the reward contingencies for the low-value color. However, by no means does this study reveal the specific mechanisms of attentional capture in the test phase. We encourage future investigation into the workings of the training phase and broad consideration of all the possible factors that could impact capture in the test phase, from the selection history versus reward history problem to the potential impact of individual differences on capture effects.

Acknowledgements

Thank you to my advisor, Professor Michael Grubb, for his guidance and support. Throughout the past four years, Professor Grubb has taught me numerous lab techniques, including coding for experimental procedures as well as data analyses. Most importantly, Professor Grubb has provided encouragement and given me confidence in my skills as a researcher. I would also like to thank Elena Bernewitz ’21 who helped extensively with this project and Jacob Deck ’24 who provided his assistance with data analysis. Additionally, thank you to Professor Molly Helt for being my second reader. Finally, I would like to thank the Trinity College Department of Psychology and Neuroscience Program for making research opportunities readily available for students as undergraduates and for providing support in my research and studies.

References

Anderson, B. A. (2019). Neurobiology of value-driven attention. *Current Opinion in Psychology*, *29*, 27–33. https://doi.org/10.1016/j.copsyc.2018.11.004

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., Kuwabara, H., Wong, D. F., Gean, E. G., Rahmim, A., Brašić, J. R., George, N., Frolov, B., Courtney, S. M., & Yantis, S. (2016). The Role of Dopamine in Value-Based Attentional Orienting. *Current Biology*, *26*(4), 550–555. https://doi.org/10.1016/j.cub.2015.12.062

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

Anderson, B. A., Laurent, P. A., & Yantis, S. (2012). Generalization of value-based attentional priority. *Visual Cognition*, *20*(6), 647–658. https://doi.org/10.1080/13506285.2012.679711

Anderson, B. A., Laurent, P. A., & Yantis, S. (2014). Value-driven attentional priority signals in human basal ganglia and visual cortex. *Brain Research*, *1587*, 88–96. https://doi.org/10.1016/j.brainres.2014.08.062

Anderson, B. A., Leal, S. L., Hall, M. G., Yassa, M. A., & Yantis, S. (2014). The attribution of value-based attentional priority in individuals with depressive symptoms. *Cognitive, Affective, & Behavioral Neuroscience*, *14*(4), 1221–1227. https://doi.org/10.3758/s13415-014-0301-z

Anderson, B. A., & Yantis, S. (2012). Value-driven attentional and oculomotor capture during goal-directed, unconstrained viewing. *Attention, Perception, & Psychophysics*, *74*(8), 1644–1653. https://doi.org/10.3758/s13414-012-0348-2

Anderson, B. A., & Yantis, S. (2013). Persistence of value-driven attentional capture. *Journal of Experimental Psychology. Human Perception and Performance*, *39*(1), 6–9. https://doi.org/10.1037/a0030860

Arcizet, F., Mirpour, K., & Bisley, J. W. (2011). A Pure Salience Response in Posterior Parietal Cortex. *Cerebral Cortex (New York, NY)*, *21*(11), 2498–2506. https://doi.org/10.1093/cercor/bhr035

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

Bisley, J. W., & Goldberg, M. E. (2010). Attention, intention, and priority in the parietal lobe. *Annual Review of Neuroscience*, *33*, 1–21. https://doi.org/10.1146/annurev-neuro-060909-152823

Buschman, T. J., & Miller, E. K. (2007). Top-Down Versus Bottom-Up Control of Attention in the Prefrontal and Posterior Parietal Cortices. *Science*, *315*(5820), 1860–1862. https://doi.org/10.1126/science.1138071

Carrasco, M. (2011). Visual attention: The past 25 years. *Vision Research*, *51*(13), 1484–1525. https://doi.org/10.1016/j.visres.2011.04.012

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

Constantinidis, C., & Steinmetz, M. A. (2005). Posterior Parietal Cortex Automatically Encodes the Location of Salient Stimuli. *Journal of Neuroscience*, *25*(1), 233–238. https://doi.org/10.1523/JNEUROSCI.3379-04.2005

Donohue, S. E., Hopf, J.-M., Bartsch, M. V., Schoenfeld, M. A., Heinze, H.-J., & Woldorff, M. G. (2016). The Rapid Capture of Attention by Rewarded Objects. *Journal of Cognitive Neuroscience*, *28*(4), 529–541. https://doi.org/10.1162/jocn_a_00917

Failing, M., & Theeuwes, J. (2018). 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

Gottlieb, J. P., Kusunoki, M., & Goldberg, M. E. (1998). The representation of visual salience in monkey parietal cortex. *Nature*, *391*(6666), 481–484. https://doi.org/10.1038/35135

Grubb, M. A., & Li, Y. (2018). Assessing the role of accuracy-based feedback in value-driven attentional capture. *Attention, Perception, & Psychophysics*, *80*(4), 822–828. https://doi.org/10.3758/s13414-018-1494-y

Heathcote, A., Popiel, S. J., & Mewhort, D. J. (19910601). Analysis of response time distributions: An example using the Stroop task. *Psychological Bulletin*, *109*(2), 340. https://doi.org/10.1037/0033-2909.109.2.340

Hickey, C., Kaiser, D., & Peelen, M. V. (2015). Reward guides attention to object categories in real-world scenes. *Journal of Experimental Psychology. General*, *144*(2), 264–273. https://doi.org/10.1037/a0038627

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

Hohle, R. H. (19650101). Inferred components of reaction times as functions of foreperiod duration. *Journal of Experimental Psychology*, *69*(4), 382. https://doi.org/10.1037/h0021740

Jiao, J., Du, F., He, X., & Zhang, K. (2015). Social comparison modulates reward-driven attentional capture. *Psychonomic Bulletin & Review*, *22*(5), 1278–1284. https://doi.org/10.3758/s13423-015-0812-9

Katsuki, F., & Constantinidis, C. (2014). Bottom-Up and Top-Down Attention: Different Processes and Overlapping Neural Systems. *The Neuroscientist*, *20*(5), 509–521. https://doi.org/10.1177/1073858413514136

Khorsand, P., Moore, T., & Soltani, A. (2015). Combined contributions of feedforward and feedback inputs to bottom-up attention. *Frontiers in Psychology*, *6*. https://doi.org/10.3389/fpsyg.2015.00155

Kim, H., & Anderson, B. A. (2019). Dissociable neural mechanisms underlie value-driven and selection-driven attentional capture. *Brain Research*, *1708*, 109–115. https://doi.org/10.1016/j.brainres.2018.11.026

Koch, C., & Ullman, S. (1985). Shifts in selective visual attention: Towards the underlying neural circuitry. *Human Neurobiology*, *4*(4), 219–227.

Kusunoki, M., Gottlieb, J., & Goldberg, M. E. (2000). The lateral intraparietal area as a salience map: The representation of abrupt onset, stimulus motion, and task relevance. *Vision Research*, *40*(10–12), 1459–1468. https://doi.org/10.1016/s0042-6989(99)00212-6

Lacouture, Y., & Cousineau, D. (2008). How to use MATLAB to fit ex-Gaussian and other probability functions to a distribution of response times. *Tutorials in Quantitative Methods for Psychology*, *4*. https://doi.org/10.20982/tqmp.04.1.p035

Le Pelley, M. E., Mitchell, C. J., Beesley, T., George, D. N., & Wills, A. J. (20160808). Attention and associative learning in humans: An integrative review. *Psychological Bulletin*, *142*(10), 1111. https://doi.org/10.1037/bul0000064

Le Pelley, M. E., Pearson, D., Griffiths, O., & Beesley, T. (20141124). When goals conflict with values: Counterproductive attentional and oculomotor capture by reward-related stimuli. *Journal of Experimental Psychology: General*, *144*(1), 158. https://doi.org/10.1037/xge0000037

Luce, R. D. (1991). *Response Times: Their Role in Inferring Elementary Mental Organization*. Oxford University Press.

MacLean, M. H., & Giesbrecht, B. (2015). Neural evidence reveals the rapid effects of reward history on selective attention. *Brain Research*, *1606*, 86–94. https://doi.org/10.1016/j.brainres.2015.02.016

Marchner, J. R., & Preuschhof, C. (2018). Reward history but not search history explains value-driven attentional capture. *Attention, Perception, & Psychophysics*, *80*(6), 1436–1448. https://doi.org/10.3758/s13414-018-1513-z

Paneri, S., & Gregoriou, G. G. (2017). Top-Down Control of Visual Attention by the Prefrontal Cortex. Functional Specialization and Long-Range Interactions. *Frontiers in Neuroscience*, *11*. https://doi.org/10.3389/fnins.2017.00545

Pinto, Y., Leij, A. R. van der, Sligte, I. G., Lamme, V. A. F., & Scholte, H. S. (2013). Bottom-up and top-down attention are independent. *Journal of Vision*, *13*(3), 16–16. https://doi.org/10.1167/13.3.16

Ratcliff, R. (19780101). A theory of memory retrieval. *Psychological Review*, *85*(2), 59. https://doi.org/10.1037/0033-295X.85.2.59

Registered Reports and Replications in Attention, Perception, & Psychophysics. (2013). *Attention, Perception, & Psychophysics*, *75*(5), 781–783. https://doi.org/10.3758/s13414-013-0502-5

Roper, Z. J. J., Vecera, S. P., & Vaidya, J. G. (2014). Value-Driven Attentional Capture in Adolescence. *Psychological Science*, *25*(11), 1987–1993. https://doi.org/10.1177/0956797614545654

Schmiedek, F., Oberauer, K., Wilhelm, O., Süß, H.-M., & Wittmann, W. W. (2007). Individual differences in components of reaction time distributions and their relations to working memory and intelligence. *Journal of Experimental Psychology: General*, *136*(3), 414–429. https://doi.org/10.1037/0096-3445.136.3.414

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

Serences, J. T., & Yantis, S. (2006). Selective visual attention and perceptual coherence. *Trends in Cognitive Sciences*, *10*(1), 38–45. https://doi.org/10.1016/j.tics.2005.11.008

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

Theeuwes, J. (2010). Top–down and bottom–up control of visual selection. *Acta Psychologica*, *135*(2), 77–99. https://doi.org/10.1016/j.actpsy.2010.02.006

Veale, R., Hafed, Z. M., & Yoshida, M. (2017). How is visual salience computed in the brain? Insights from behaviour, neurobiology and modelling. *Philosophical Transactions of the Royal Society B: Biological Sciences*, *372*(1714), 20160113. https://doi.org/10.1098/rstb.2016.0113

Watanabe, T., & Sasaki, Y. (2015). Perceptual learning: Toward a comprehensive theory. *Annual Review of Psychology*, *66*, 197–221. https://doi.org/10.1146/annurev-psych-010814-015214

Whelan, R. (2008). Effective Analysis of Reaction Time Data. *The Psychological Record*, *58*(3), 475–482. https://doi.org/10.1007/BF03395630

White, B. J., Kan, J. Y., Levy, R., Itti, L., & Munoz, D. P. (2017). Superior colliculus encodes visual saliency before the primary visual cortex. *Proceedings of the National Academy of Sciences*, *114*(35), 9451–9456. https://doi.org/10.1073/pnas.1701003114

Wilson, R. C., & Collins, A. G. (n.d.). *Ten simple rules for the computational modeling of behavioral data*. 35.

Wolfe, J. M. (1994). Guided Search 2.0 A revised model of visual search. *Psychonomic Bulletin & Review*, *1*(2), 202–238. https://doi.org/10.3758/BF03200774

Yamamoto, S., Kim, H. F., & Hikosaka, O. (2013). Reward Value-Contingent Changes of Visual Responses in the Primate Caudate Tail Associated with a Visuomotor Skill. *Journal of Neuroscience*, *33*(27), 11227–11238. https://doi.org/10.1523/JNEUROSCI.0318-13.2013

Yantis, S., Anderson, B. A., Wampler, E. K., & Laurent, P. A. (2012). Reward and Attentional Control in Visual Search. In M. D. Dodd & J. H. Flowers (Eds.), *The Influence of Attention, Learning, and Motivation on Visual Search* (pp. 91–116). Springer. https://doi.org/10.1007/978-1-4614-4794-8_5