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The Role of Selection History in Low-Prevalence Visual Search

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by

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Dedicated to my parents, Linda Darlene Smith and Kenneth Smith, who always encouraged me to value learning, taught me I could do anything I set my mind to, and gave me the tools to pursue my education to the highest level.

ABSTRACT OF THE DISSERTATION

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The low prevalence effect (LPE), the tendency for observers to be more likely to miss rare targets than frequent targets, is a robust error and is difficult to reduce. The LPE is an obstacle in a variety of real-world search tasks in which targets are rare, including baggage screening and some medical imaging. The LPE is thought to occur because when an observer searches for a low-prevalence target, over time, the observer may become both more willing to indicate a target is not there and more likely to end the search early. The present experiments employ three selection history effects, including manipulating reward history, action history, and the availability of items in working memory, in order to learn more about the mechanisms behind the LPE, leading to a better understanding of low-prevalence search and possibly reducing the effect. In the reward history task, participants completed a training phase in which a specific feature was rewarded. Then, they completed a search task in which no reward was presented, and the LPE was measured. In the action history task, participants made simple actions or withheld responses as a prime was presented and then completed a search task. In the working memory task, participants held a target in working memory and completed a search task. The availability of low-prevalence targets in working memory reduced the LPE, but action history and reward history did not affect the LPE. The results from these experiments suggest that direct priming of

targets is the best way to reduce the LPE, and indirect priming of targets is not as effective. These experiments present the first evidence that selection history affects low-prevalence visual search. Theoretically, this informs both our understanding of visual search at a range of prevalence levels and our understanding of the mechanisms behind the LPE. Practically, these findings may contribute to methods that reduce the LPE in real-world search tasks.

Chapter 1: Introduction

Each and every day, people search for objects in their environment. On any given morning, you may look for a particular shirt in your closet, your toothbrush in the medicine cabinet, and your car keys. These are just a few of many searches that a person might complete on a daily basis. In psychology, this fundamental activity is called visual search, and it is often studied by presenting observers with a display of many shapes or objects and asking them to find a particular target shape or object.

Although visual search has long been a topic of interest, only recently has prevalence rate – the proportion of trials on which a target is presented – been considered. In many traditional visual search experiments, target prevalence is established at 50%; a target is present on half of the trials and absent on the other half. However, in many real-life searches, target prevalence is much lower than 50%. For example, weapons are low-prevalence targets in baggage screening, motorcycles are less common on the roads than cars, and the rate of cancer in routine mammography screenings is approximately 0.3% (Gur et al., 2003).

The *low-prevalence effect* (LPE) is a robust result in visual search in which low-prevalence targets (targets presented on only a small proportion of trials) are frequently missed (e.g., Wolfe et al., 2005). Wolfe et al. (2005) varied prevalence rates in visual search tasks and found that observers tend to miss rare targets frequently. Generally, the miss rate in low-prevalence visual search is higher than in medium- or high-prevalence visual search. Understanding why rare targets are missed at higher rates than frequent targets will provide insight into visual search processes more generally. Additionally, understanding what factors influence the magnitude of the LPE will inform us about attentional selection in general.

Further, given that missing rare targets can have serious consequences in real-world low-prevalence searches, understanding the LPE has many practical implications.

There are multiple influences that contribute to the allocation of attentional resources in visual search. Research on visual search has shown that goals, salience, and selection history each play a role in attentional allocation (Awh et al., 2010). Goals are voluntary and are related to the objective of the search task. For example, searching for a red car in a parking lot would result in the allocation of attention to red objects in the search scene. Salience plays a role as well; attention is involuntarily deployed to stimuli that are noticeable due to a unique or prominent feature. For example, a red car among many green cars would capture attention. Recently, selection history also has been identified as a factor that plays a role in the deployment of attention in visual search. For example, a red car might attract attention if red cars have recently been attended. Selection history considers the role of recent attentional allocation in the deployment of current attention and is distinct from goals and salience. Each of these influences – goals, salience, and selection history – play a role in attentional allocation.

Although the roles of goals and salience have been examined in low-prevalence visual search, influences of selection history on low-prevalence search have not been studied. The present dissertation seeks to determine the influence of different selection history effects on low-prevalence visual search.

1.1 The Basic Pattern of the LPE

In their seminal study, Wolfe et al. (2005) employed an artificial baggage screening task in which participants searched for tools amongst common distractors found in luggage. Wolfe et al. manipulated set size to obtain displays of three, six, twelve, or eighteen objects. They also manipulated target prevalence between-participants to be 1%, 10%, or 50%, meaning that a tool, the target, was presented in only the specified percentage of trials. Wolfe et al. found miss rates of 30%, 16%, and 7%, respectively, showing that less frequent targets were more likely to be missed. This was a clear demonstration that observers have difficulty finding rare targets, and the use of a baggage screening task showed that the LPE occurs in simulated real-world low-prevalence searches.

In addition to miss errors, Wolfe et al. (2005) also examined response times (RTs). They found that participants in the low-prevalence condition tended to make correct "absent" responses faster than participants in the high-prevalence condition, which indicated that search was terminated more quickly at low-prevalence rates. This pattern of increased miss rates and shorter target-absent RTs characterizes the LPE.

The LPE occurs across a variety of situations and stimuli. As previously mentioned, the LPE appears in simulated baggage screening tasks (e.g., Mitroff & Biggs, 2014; Wolfe et al., 2005). It also occurs in medical imaging (e.g., Ethell & Manning, 2001; Kundel, 1982), simulated driving tasks (Beanland et al., 2014), haptic search (Ishibashi et al., 2012), face matching (Papesh & Goldinger, 2014; Papesh et al., 2018), "pop-out" search (Rich et al., 2008), and with simple letters (Rich et al., 2008). The occurrence of the LPE in a wide range of situations is one illustration of the robustness of the effect.

1.2 Causes of the LPE

Many mechanisms for the LPE have been proposed, including motor errors, early search termination, perceptual errors, and criterion shifts. One of the first explanations for the LPE was that motor errors are responsible for the effect. Fleck and Mitroff (2007) proposed that the LPE only occurred because observers became accustomed to making the same "target absent" response repeatedly in low-prevalence search. Thus, it seemed that the LPE could essentially be explained by a speed-accuracy tradeoff; subjects respond quickly with the prepotent motor response, and even if they see the target, they may be in the process of executing a response and unable to change the response during the movement execution. Fleck and Mitroff found that when observers were permitted to correct their responses, miss rates were reduced for the low-prevalence condition. They took this as evidence that observers often see targets, but they quickly respond “target absent” and are not able to override the prepotent response. However, many studies after Fleck and Mitroff have found the LPE still exists even when the opportunity to correct a response is incorporated (e.g., Kunar et al., 2010; Kunar et al., 2017; Peltier & Becker, 2016; Russell & Kunar, 2012; Van Wert et al., 2009). Thus, motor errors do not fully explain the LPE, and they are likely not an issue in real-world low-prevalence searches given that there are opportunities to correct motor errors in such searches. However, motor errors likely do exacerbate the LPE in experimental low-prevalence visual search paradigms, so it is important to recognize the role of motor errors and allow for correction of them in experimental tasks or use methods that reduce motor errors. For example, one method to reduce motor errors in experimental paradigms is to include a high-prevalence target in the search task in addition to the low-prevalence target, thereby bringing overall target presence to 50%, eliminating the tendency to make a prepotent response, and allowing for a within-subjects comparison of high- and low-prevalence targets. This was the method used in the present experiments.

Another possible reason for the LPE is that target-absent search is too brief (Wolfe et al., 2005), given the pattern of reduced target-absent RTs in low-prevalence search conditions. For example, Wolfe et al. (2005) found that target-absent responses were faster than target-present responses in the 1% prevalence condition even though typical visual search paradigms with 50% target prevalence result in target-absent responses that are slower than target-present responses.

This is because when a target is present, it may be found before the entire display is evaluated. When the target is absent, observers tend to spend longer searching in order to evaluate more items in the display, resulting in longer target-absent RTs. Interestingly, Wolfe et al. found that this did not occur in low-prevalence conditions and the effect was actually reversed, with low-prevalence search resulting in faster target-absent than target-present RTs. If early search termination is responsible for the LPE, ensuring that observers do not respond too early would eliminate the error. However, neither issuing "speeding tickets" for fast responses (Wolfe et al., 2007), nor ensuring that observers fixate each object and do not terminate search early (Hout et al., 2015) eliminates the LPE. Therefore, although search is terminated early in most low-prevalence visual search experiments, early termination does not fully explain the LPE.

Another possibility for why the LPE occurs is that observers may see targets but fail to recognize them as targets, which are mistakes called perceptual errors (Horowitz, 2017). Evidence that perceptual errors occur comes from eye-tracking data from Peltier and Becker (2016) in addition to data from Hout et al. (2015), who implemented an experimental paradigm in which participants saw a stream of several objects in the center of the screen in rapid succession. In both of these tasks, the LPE occurred even when observers fixated the targets. Given that measures were taken to reduce motor errors, these patterns of results indicate that perceptual errors must contribute to the effect; observers look at targets but do not identify them as such. It is hypothesized that this occurs because high-prevalence targets have more robust mental representations than low-prevalence targets. These target templates and mental representations are enhanced each time a participant finds a target, which happens more frequently when the target is high-prevalence (Hout et al., 2015).

A final potential cause of the LPE is a criterion shift (Wolfe et al., 2007). A criterion shift is indicated by a decreased threshold for responding “absent.” Observers tend to shift criterion and become more willing to respond “absent” during low-prevalence search, which leads to elevated miss rates for rare targets (Wolfe et al., 2005; Wolfe & Van Wert, 2010). At low prevalence, the decision criterion shifts to be more conservative because observers attempt to balance the number of miss and false alarm errors (Wolfe et al., 2007). This bias in responding contributes to the LPE.

It is likely that the LPE is caused by a combination of mechanisms. Motor errors likely play a role in the LPE in experimental research, especially in experiments that do not control for them, and early search termination and criterion shifts may play a role in some cases. Finally, the finding that observers fixate targets but fail to recognize them indicates that perceptual errors are also involved.

1.3 The Multiple Decision/Dual-Threshold Model

The prevailing model of low-prevalence visual search is the multiple decision model (MDM), or dual-threshold model proposed by Wolfe and Van Wert (2010). According to the model, at any given moment in visual search (regardless of prevalence level), observers are faced with two decisions. One is a decision regarding whether the item that is currently being evaluated is a target. If the item is a target, a “target present” response is made. If the item is not a target, the next decision is whether to continue or stop searching. This process continues until a target is found or until the quitting threshold is reached.

As prevalence decreases, the process remains the same, but two aspects of the search change. First, the decision criterion shifts to be more conservative because observers attempt to balance the number of misses and false alarm errors (Wolfe et al., 2007): when targets are rare, observers shift their criterion to a more conservative level so that they do not make too many false alarms; the conservative criterion in turn results in an increase in misses. Indeed, when prevalence is varied systematically, the decision criterion changes along with prevalence (Wolfe & Van Wert, 2010).

The second part of the MDM that changes with prevalence is the quitting threshold. This is indicated by shorter target-absent response times at lower prevalence levels: when targets are rare, observers are quicker to make a target-absent decision, and quitting search early leads to more misses (Wolfe et al., 2005).

1.4 Reducing the LPE

Given that there exist critical real-world search tasks that involve low-prevalence targets, much research has focused on ways to reduce or eliminate the LPE because misses, especially those involving cancer or baggage screening, can have serious consequences. Several unsuccessful strategies have been used in an attempt to reduce the LPE, including encouraging observers to spend more time on search displays (Wolfe et al., 2007), dividing the display (either temporally or spatially) into smaller sections for evaluation (Kunar et al., 2010; Rich et al., 2008), ensuring fixation (Hout et al., 2015), adding pseudotargets (Wolfe et al., 2005), adding cues (Russell & Kunar, 2012), including reward payoffs (Navalpakkam et al., 2009; Pedersini et al., 2008), and working with another observer (Wolfe et al., 2007).

Although many interventions have been unsuccessful, there are some ways to reduce the error. The most effective method that has been discovered thus far was found by Wolfe et al. (2007; Exp. 7). They interspersed blocks of high-prevalence trials with feedback into a low-prevalence visual search task. The high-prevalence blocks with feedback served as a "retraining" for observers. Observers tended to rapidly shift decision criteria during the retraining blocks, thus reducing the LPE.

1.5 Visual Search and Selection History

According to Awh et al. (2012), there are three influences on visual search: physical salience (bottom-up influences), current goals (top-down influences), and selection history—the effect of recent searches on current search. As seen in Figure 1, it is theorized that each of these factors influences attentional selection, which is guided by an integrated priority map. An integrated priority map combines multiple selection influences working in parallel to guide attention (Wolfe et al., 1989). In the current model, the salience of visual features, the current goals of the observer, and the history of previous selections simultaneously guide attention. For example, while at the grocery store, you may be looking for carrots, so this goal guides your attention to orange objects. However, a salient object like a "SALE" sign may simultaneously compete for your attention. Further, you may notice your neighbor is in the same area of the store, and since that person has been relevant to you in the past, your attention may be guided towards that neighbor more strongly than it would be to other people. All of these aspects are weighed and combined within the integrated priority map to influence attentional guidance.

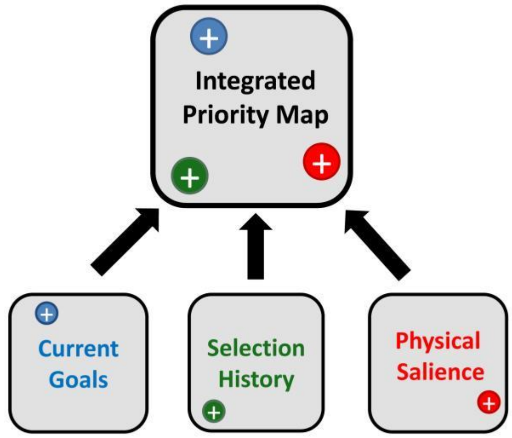

Figure 1. This model asserts that the allocation of attentional resources depends on current goals, selection history, and physical salience (from Awh et al., 2012).

Selection history biases are a broad class of influences on attention that are unrelated to goals or physical salience of a stimulus (Awh et al., 2012). For example, searching for a vertical line is easier after just having found a vertical line because attention has been recently deployed to that feature, so vertical lines have been primed for selection (Wolfe et al., 2003). Likewise, and relevant for low-prevalence search scenarios, searching for a knife in a baggage screening task might be easier after having recently found a knife because features associated with knives have been primed for selection as well. If the features have not been recently selected, which is often the case in low-prevalence visual search because targets are rare, that could contribute to the LPE.

Both goals and salience have been shown to play a role in low-prevalence searches, but selection history has not been studied, perhaps because selection history is a relatively new category considered in attentional allocation, or perhaps because its necessity in models of attentional allocation has been debated (e.g., Egeth, 2018). Regarding salience, targets that are more salient tend to be missed less frequently in low-prevalence searches (e.g., Beanland et al., 2014; Biggs et al., 2014). Beanland et al. (2014) investigated low-prevalence visual search using a simulated driving task. They found that vehicles were detected at farther distances when they were high prevalence compared to when they were low prevalence. They also found that salience mattered in this task, as observers were quicker to find salient vehicles. Biggs et al. (2014) found that salience plays a role in target detection by studying data from the *Airport Scanner* game. They examined the proportion of variance explained by several factors, including target frequency and salience, and found that although target frequency plays a bigger role than salience, salience still explains a significant proportion of the variance in search performance.

In addition to the bottom-up influence of salience, goals and top-down factors affect whether observers responded “present” or “absent” when search is terminated early (Peltier & Becker, 2017a). Peltier and Becker (2017a) terminated a subset of trials after participants made a set number of visual fixations. This resulted in the requirement to make a guess based on prevalence rates rather than evidence accumulation. The participants’ goal was to reduce the number of errors; thus, they made educated guesses based on prevalence rates.

Although physical salience and observer goals are known to play a role in low-prevalence search, selection history has not been studied. Awh et al. (2012) provide examples of selection history effects that have been examined at more typical prevalence rates, including *reward history*, *priming-of-pop-out*, and availability of items in working memory. Reward history, the effect of prior reward, is known to influence later search by biasing the orienting of attention towards previously rewarded features (Nakayama & Martini, 2011). Another selection history effect is called priming-of-pop-out (Maljkovic & Nakayama, 1994). Priming-of-pop-out is the general finding that observers are faster to find a target if it shares features with a previous target. For example, observers are faster to identify a color singleton (a unique color among uniformly colored targets) when the color of that singleton stays consistent from trial-to-trial compared to when it changes. Thus, selecting a specific target or target feature on one trial may bias attention towards that target or those features on a subsequent trial. This may be especially important in a low-prevalence search task because if features of a low-prevalence target, like color, have been previously relevant or attended, that may aid detection of a low-prevalence target. Further, frequent targets are more likely to be encoded into working memory, even when observers are unaware of target likelihood (Umemoto et al., 2010). Thus, it seems that low-prevalence targets would be less available in working memory, which may contribute to the LPE. Given these influences of selection history on search at more typical prevalence rates, selection history is likely important in low-prevalence search as well.

1.6 How the LPE is Related to Selection History

It is possible that the LPE may be driven, at least in part, by a reduction in selection history effects. Selection history effects occur when past selection episodes carry over into current trials, resulting in changes in attentional orienting (Awh et al., 2012). It has been asserted that frequent selection of a target results in higher levels of attentional allocation towards a frequent target because features of the frequent target are primed for selection (Awh et al., 2012). Given that low-prevalence targets are not selected frequently, less priming occurs and fewer attentional resources are allocated towards them, resulting in more misses.

Frequent targets are more likely to be encoded into working memory, even when observers are unaware of target likelihood (Umemoto et al., 2010). This may be especially relevant to low-prevalence search. Low prevalence targets may not be as available in working memory as more common targets are, especially when there are many search targets and the relative prevalence of some is low. For example, if observers are searching for hair dryers, water bottles, and explosives, the features related to hair dryers and water bottles may be more available in working memory given that those items are more common, which may enhance detection of those targets. Indeed, it has been shown that items in working memory are easier to find in visual search (Dowd & Mitroff, 2013). Because features related to explosives would be less available in working memory, explosives may be harder to detect. In sum, frequent targets are more available in working memory (Umemoto et al., 2010), and targets in working memory are easier to find in visual search (Dowd & Mitroff, 2013), so priming low-prevalence targets and features to make them available in working memory should reduce the LPE.

Individual differences work by Peltier and Becker (2017b) further indicates that working memory may be involved in the LPE. They found, via eye-tracking, that higher working memory capacity is related to fewer perceptual identification errors in low-prevalence search, errors in which participants fixated a target but did not identify it as such. This could be because those with higher working memory capacity are better at holding representations of targets in working memory and therefore commit fewer perceptual identification errors.

Further evidence that selection history may play a role in the LPE comes from an experiment showing that the LPE was exacerbated when a low-prevalence target was presented in an unexpected color (Russell & Kunar, 2012). Low-prevalence targets that are repeatedly found in a consistent color may be easier to find than those presented in an unexpected color because features of the target that have been previously selected, including color, are easier to find in subsequent trials than rare or new features. These findings provide further support for the possibility that selection history may be involved in the LPE.

In low-prevalence visual search, low-prevalence targets are, by definition, uncommon, so observers see the low-prevalence targets less often. Godwin et al. (2016) conducted an experiment similar to the experiment by Russell and Kunar (2012) in which target color was manipulated. Observers searched for a target letter among other-letter distractors. For some observers, the target letter was always the same color, but for other observers, the target color alternated. Godwin et al. found that the LPE occurred in both conditions, but the magnitude of the LPE was greater in the alternating color condition, which indicates that selection history plays a role in the LPE: less experience with the target results in more misses.

Importantly, additional support for the role of selection history comes from a method that has been previously shown to reduce the LPE. Interleaving high-prevalence blocks with blocks of low-prevalence search, as in Wolfe et al. (2007, Exp. 7), was a manipulation intended to shift an observer's criterion, but it could be considered a manipulation of selection history, although it was not explicitly identified as such. In high-prevalence blocks, observers saw and selected targets that were rare in low-prevalence blocks, which in turn made them better at detecting the targets when they were low-prevalence. Presumably, selecting features associated with the low-prevalence targets more often in the high-prevalence blocks resulted in priming that made those features more accessible, and attention was allocated to those features in the subsequent low-prevalence blocks, thus eliminating the LPE. Notably, this manipulation was not a manipulation of salience or top-down goals but of selection history, indicating that other manipulations of selection history could be promising methods of reducing the LPE.

The current dissertation seeks to employ known selection history effects in a low-prevalence visual search task. These selection history manipulations may enhance the representation of low-prevalence features and make them more available for selection. Enhanced representation would reduce the likelihood that participants make a perceptual error, an error in which a target is seen but not identified as a target. The present experiments will inform the current understanding of attentional allocation and visual search at a range of prevalence levels, and they will help us learn how salience, goals, and selection history guide attentional allocation at extreme prevalence levels. Further, there could be practical applications for real-world search tasks, including baggage screening and radiology, given that targets are often low prevalence in those scenarios.

Chapter 2: The Present Experiments

Reward history, action history, and availability of items in working memory are all selection history effects that are known to influence visual search at typical prevalence levels. Reward history effects are characterized by attentional orienting to previously rewarded stimuli even when those previously rewarded stimuli are not currently rewarded (e.g, Anderson et al., 2011a; Anderson et al., 2011b; Hickey et al., 2010a; Hickey et al., 2010b; Nakayama & Martini, 2011). Action history effects occur when simple actions towards objects with certain features lead to the allocation of attention toward those features in subsequent search (e.g., Buttaccio & Hahn, 2011; Weidler & Abrams, 2014; Weidler & Abrams, 2016). Finally, the presence of items in working memory can influence search; attention is guided toward items that are more available in working memory (Umemoto et al., 2010). In the present dissertation, each of these selection history effects will be applied to a low-prevalence visual search scenario.

Although reward history, action history, and presence of items in working memory can all be considered selection history effects, it is possible that they operate via distinct mechanisms. Another possibility is that reward history and action history influence search via working memory (i.e., reward and action make features more available in working memory). Whether these effects operate via distinct mechanisms or all operate via working memory, it is possible that they may have varied influences or strengths of influence on the LPE; results could vary in direction or magnitude. Recent research and reviews of the selection history literature have indeed posited that there are various mechanisms behind selection history. For example, Kim and Anderson (2019) have identified two distinct selection history processes that occur for reward history-related effects, associative learning and instrumental conditioning, showing that a common mechanism does not underlie all selection history effects. Expanding beyond reward history-related effects, Wolfe (2019) hypothesized, in a review of attentional orienting, that feature priming and knowledge of the world are additional selection history processes. Given these distinct mechanisms, it is reasonable to explore various selection history effects in order to determine if they have differential effects on the LPE.

2.1 General Methods

In each of the present experiments, the same basic low prevalence visual search task was used. As seen in Figure 2, participants searched for a red L or a green T in a search array of T/L combination symbols of various colors. All segments of the Ts, Ls, and T/L combination symbols were the same length. Stimuli like these have been used in visual search tasks, including low-prevalence visual search tasks (e.g., Godwin et al., 2016; Godwin et al., 2015; Rich et al., 2008). On half of the trials, there was no target present. On 45% of trials one of the targets, either a red L or a green T (counterbalanced across participants), was presented. This was the high-prevalence target. On 5% of trials, the other target (either the red L or green T, whichever was not the high-prevalence target) was presented. This was the low-prevalence target. Participants searched the displays and responded “present” or “absent” via keyboard responses.

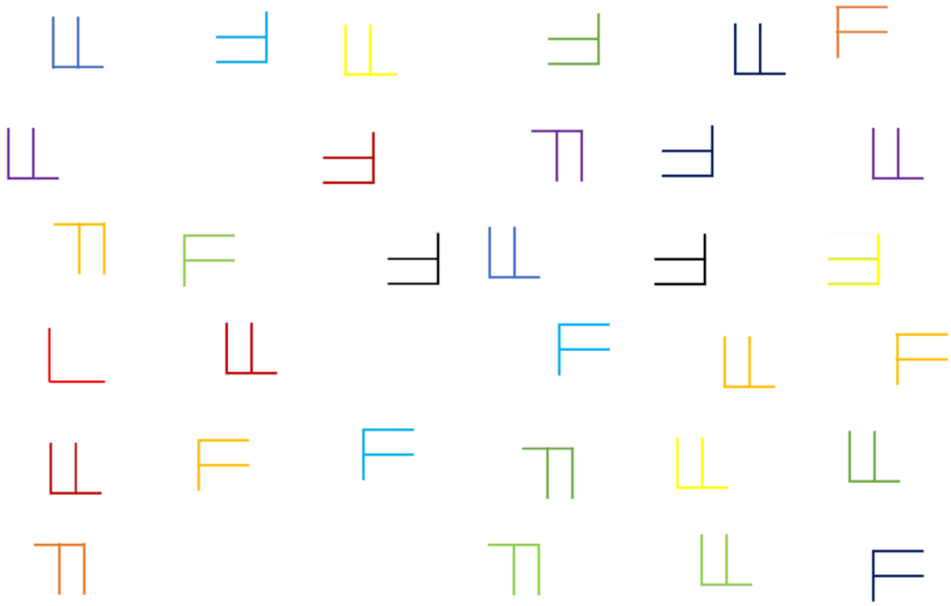

Figure 2. Basic display for low-prevalence visual search task.

Although these stimuli are not complex stimuli like those encountered in real-world low-prevalence search scenarios such as baggage and cancer screening, they were used in the following experiments for a few reasons. First, reward history effects and action effects have not been demonstrated using complex stimuli, such as x-ray baggage scans. Given that the success of these experiments depends upon the success of reward and action history manipulations, simple stimuli were chosen. If these manipulations do affect low-prevalence visual search, further research could employ more complex stimuli to generalize the findings to real-world search tasks.

Chapter 3: Experiment 1

3.1 Introduction

Reward history is known to influence later search by biasing attentional orienting towards previously rewarded features (Nakayama & Martini, 2011). This can even be involuntary (Anderson et al. 2011a; Anderson et al., 2011b; Hickey et al., 2010a; Hickey et al., 2010b) and occurs whether or not participants are aware of the award contingencies (Bourgeois et al., 2016). In Hickey et al. (2010a), observers searched for a shape singleton (a unique shape among an array of uniform shapes) and were told to ignore irrelevant color singletons. However, sometimes the color singletons were the same color as a stimulus that had previously been associated with high reward and sometimes they were not. When the color singletons were the same color as the previous high-value stimuli, they were more distracting than when they were a different color. This occurred even though color was irrelevant and the goal was to ignore distractors and identify the unique shape, showing that reward history can involuntarily guide attention during visual search.

Hickey et al. (2010a) found that, although targets become associated with reward in training phases, the deployment of attention to previously rewarded objects endures for trials that occur much later in the sequence, indicating that the effects of reward endure. Reward history is considered a type of selection history because the past experience of reward biases subsequent attention to a previously rewarded feature, and the bias is often contrary to the goals of the task and cannot be explained by salience (Awh et al., 2012; Theeuwes, 2018; Theeuwes, 2019). There is evidence that reward history effects may occur early in visual processing; Theeuwes and Belopolsky (2012) found that previously highly rewarded stimuli capture attention as evidenced by eye-movement patterns directed towards the high-reward stimuli. It is also known that stimulus salience has effects early in visual processing (Jonides, 1981). Given that salient objects are detected more easily even when they are low-prevalence (Biggs et al., 2014), associating stimuli with high-reward may create a selection history effect with an outcome that would be similar to increasing salience and reduce the LPE.

In Experiment 1, reward history was manipulated by introducing a training phase in which targets were associated with high- or low-reward. Observers then completed a search task without reward, and the effect of prevalence was examined.

3.2 Method

3.2.1 Participants

A power analysis based on the effect size from previous research on reward history in our lab (*d* = .44; Suh & Abrams, 2020) suggested that 10 participants should be run in each condition. Because this experiment was conducted online, this number was doubled in each of four groups (to counterbalance high-reward and high-prevalence colors) so that 20 useable participants were run in each counterbalancing condition for a total of 80 usable participants, according to requirements outlined in the Results section. Data were collected from 106 participants in order to obtain 80 usable participants. Participants received course credit in addition to a monetary reward up to $7.20 based on performance in the training phase.

3.2.2 Procedure

At the beginning of the experiment, participants were asked to calibrate the size of the objects on screen by matching an on-screen image, adjustable via keyboard controls, to an object of known size (a credit card). They were also presented with instructions to begin the experiment.

Training phase. The sequence of events for the training phase can be seen in Figure 3. The training phase was modeled according to Anderson et al. (2011b). During the training phase, observers saw a black fixation cross (2.3° x 2.3°) presented in the center of the screen for 600 ms. Then, six colored circles (2.3° in diameter; cyan, yellow, orange, magenta, purple, and red or green) appeared at 5° of eccentricity in a search display that was presented for 1500 ms or until response. Observers were told to search for red and green circles (the targets), exactly one of which was presented on every trial. Inside the target, a line segment (1.5° x .5°) was oriented either horizontally or vertically, and inside each of the non-targets (the remaining circles), a line segment was tilted at 45° to the left or to the right. Participants identified and indicated via a key press the orientation of the line segment within the red or green circle. After their response, a 500 ms interval in which nothing was visible on screen occurred before a feedback display informed participants of the reward earned on the trial, as well as total reward accumulated through that point. The display indicating the reward appeared for 1500 ms, followed by a 500 ms intertrial interval.

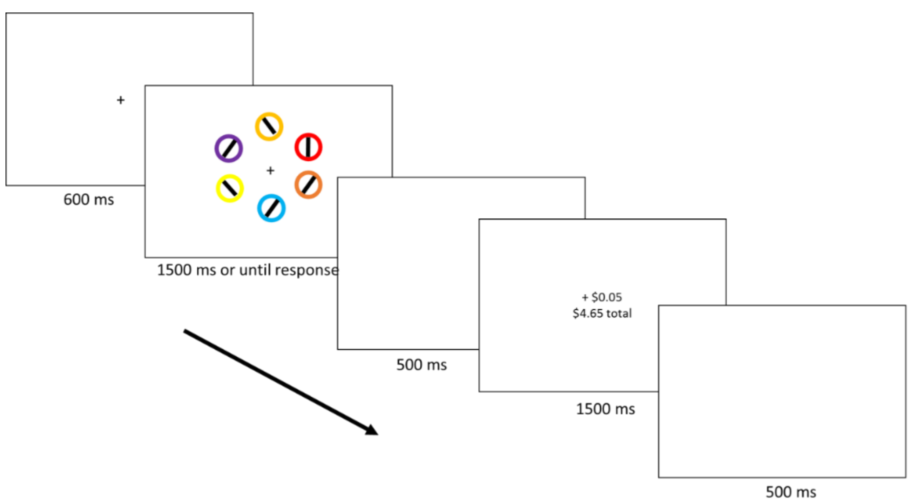

Figure 3. Sequence of events for the training phase in Experiment 1. Figure is not to scale.

One target (red circle for half the participants, green circle for the rest) was associated with a high probability (P = 0.8) of a high reward (5¢) and a low probability (P = 0.2) of a low reward (1¢); for the other target, this mapping was reversed. Therefore, one of the colors was associated with a high value and the other was associated with a low, but still positive, value. Participants were not informed of this reward contingency but learned it over the course of 240 trials (e.g., Anderson et al., 2011b, Experiment 3). There were five distractors presented on each trial, and they each appeared randomly at one of the six preset locations from trial-to-trial.

Search phase. After the training phase was completed, participants were instructed to complete a search phase for which they would receive no reward. The search phase comprised 300 trials. The sequence of events for the search phase can be seen in Figure 4. Participants searched for red L's and green T's in a search array containing 32 objects. On *target present* trials, there were 31 rotated T/L combination symbols of varying colors and one target, a red L or green T. On *target absent* trials, there were 32 rotated T/L combination symbols. The set size of 32 has been used in previous research on low-prevalence visual search (e.g., Hout et al., 2015). Each trial began with the presentation of a fixation cross (2.3° x 2.3°) for 500 ms. Next, the search display was presented for 10 s or until a response was made. Participants made a spacebar press to indicate they were finished searching. They then responded using the "f" and "j" keys, indicating present or absent.

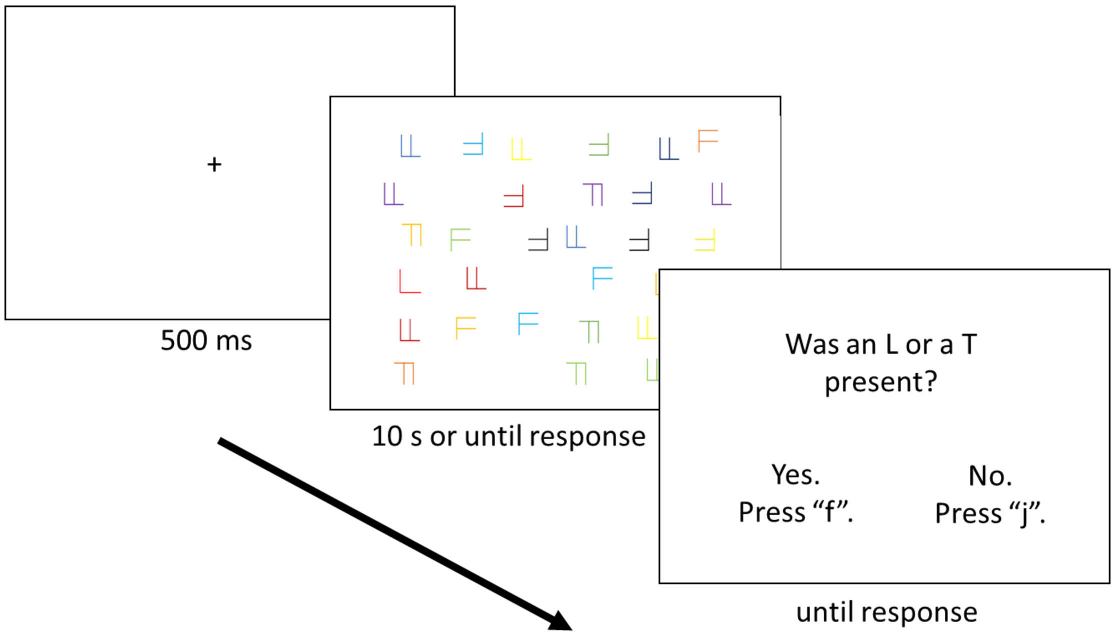

Figure 4. Sequence of events for the visual search phase in Experiment 1.

3.2.3 Design

In the training phase, participants completed 20 practice trials followed by four blocks of 60 trials for a total of 240 trials. On half of the trials, participants saw the high-value color and on the other half, they saw the low-value color. The identity of the high-value and low-value color was counterbalanced across participants.

In the search phase, participants completed 12 practice trials followed by three blocks of 100 trials for a total of 300 search trials. On half of the search trials, no target was presented. On the other half of the trials, there was a target present, but one of those targets was presented on a total of 45% of the trials (the high-prevalence target) while the other target was presented on 5% of the trials (the low-prevalence target). The identity of the high- and low-prevalence targets was counterbalanced across participants. Importantly, for half of the participants, the high-prevalence target was presented in the low-reward color from the training phase, and the low-prevalence target was presented in the high-reward color from the training phase. For the other participants, the opposite mapping was used.

3.3 Results

3.3.1 Inclusion Criteria

Data were analyzed from 80 useable participants. A useable participant was defined as: following directions (including changing the size of the stimuli to the appropriate size on their monitor and pressing the spacebar to end the search on the majority of trials rather than letting the 10 s allocated for the search to expire), responding with at least 80% accuracy in both the high-value and low-value conditions in the training phase, and responding with at least 90% accuracy on the target absent conditions in the search phase. Nineteen participants were eliminated due to not following instructions, five due to low accuracy in the training phase, and two due to low accuracy on target absent trials in the search phase. These criteria were chosen because not following instructions could indicate not taking the experiment seriously and if stimuli were not sized appropriately, it is possible that some would not appear on the screen, resulting in higher miss rates in the search phase. Low accuracy in the training phase would result in the reward manipulation not being effective, and high error rates on target absent trials (responding present when there was no target present) could indicate random responding or a lack of understanding of the task.

3.3.2 Training Phase

Error rates and response times (RTs) for correct trials were calculated for the low-value and high-value colors. There was no significant difference between RTs for the high-value (M = 686 ms, SD = 83 ms) and low-value (M = 693 ms, SD = 85 ms) colors, $t(79) = 1.43$, $p = .16$. Likewise, there was no significant difference between accuracy on the high-value color (M =.96, *SD* = .03) and low-value color trials (*M* = .95, *SD* = .04), *t*(79) = 1.04, *p* = .30. These results indicate that, overall, there was no significant difference between the high- and low-value colors during the training phase. Although effects often occur in the search phase even when there is no difference in the training phase (e.g., Anderson et al., 2011b), differences in the training phase would indicate that the training was effective.

It is possible that the training phase overall may not show differences yet there may be differences in later blocks of training. In order to examine the trends throughout the training phase, a 4 (training block: 1-4) x 2 (condition: low-value, high-value) repeated measures analysis of variance (ANOVA) was conducted. It revealed a main effect of block $F(3, 237) = 39.95$, $p < .001$, $\eta_p^2 = .33$, such that later blocks were faster than earlier blocks. There was no main effect of reward, $F(1, 79) = 1.99$, $p = .16$, nor an interaction, $F < 1$. A paired samples t-test on the final training block revealed that there was a marginally significant difference between the low-value and high-value colors, $t(79) = 1.83$, $p = .07$, $d = .20$, indicating that the high-value color (*M* = 654, *SD* = 92) was associated with numerically faster responses than the low-value color (*M* = 664, *SD* = 91) in the final training block, but this did not reach statistical significance. Taken together, these analyses show that the value manipulation may have been weaker than expected, even in the final 60 trials of training.

3.3.3 Search Phase

Error rates. The main variable of interest for the search phase was error rates, which can be seen in Figure 5. All of these errors were misses because they were incorrect responses when a target was present (i.e., the participant indicated absent when a target was indeed present). A 2 (between-subjects training-test combination: low-prevalence-high-value color, high-prevalence-low-value color vs. low-prevalence-low-value color, high-prevalence-high-value color) x 2 (condition: low-prevalence, high-prevalence) mixed ANOVA revealed a main effect of prevalence, $F(1, 78) = 68.06$, $p < .001$, $\eta_p^2 = .47$, in which error rates for low-prevalence trials ($M = .24$, $SD = .21$) were higher than error rates for high-prevalence trials ($M = .05$, $SD = .05$). This reveals the typical low-prevalence effect. There was no main effect of training-test combination nor an interaction (Fs < 1), indicating that reward did not influence the LPE.

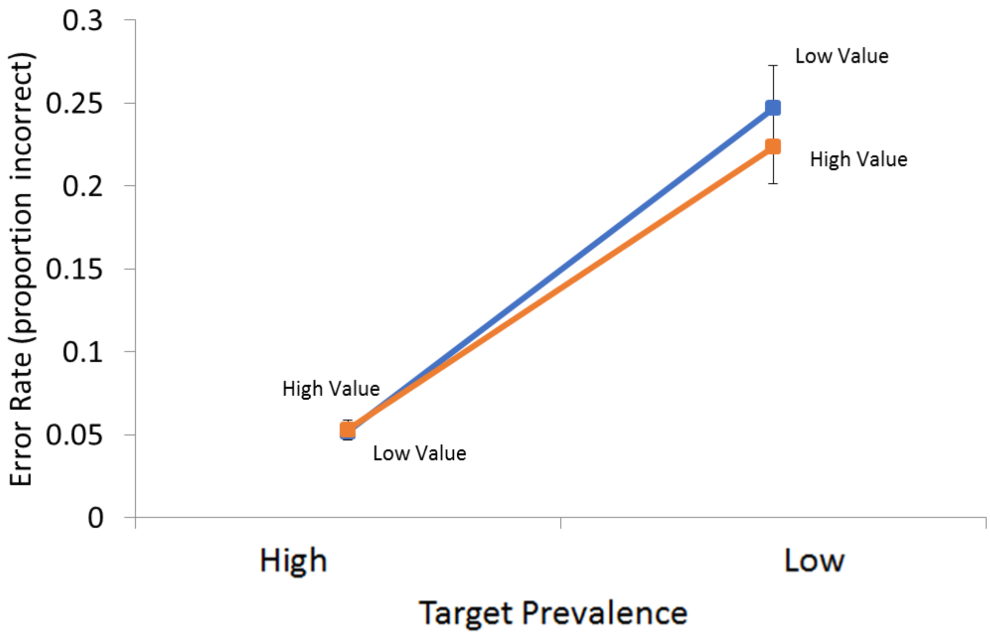

Figure 5. Error rates for Experiment 1. Particpants received a *low-value, high prevalence/high-value, low-prevalence* pairing or a *high-value, high-prevalence/low-value, low-prevalence* pairing; thus, the low-prevalence target was either previously highly or lowly rewarded. There was a main effect of prevalence, but no main effect of training-test combination, nor an interaction. However, the trend is in the direction such that when the low-prevalence color matched the high-value color, error rates were reduced compared to when the low-prevalence color matched the low-value color. Error bars indicate standard error of the mean.

Although the interaction was not significant, the results did follow the expected pattern such that when the low-prevalence color matched the high-value color, error rates were reduced in comparison to when the low-prevalence color matched the low-value color. Overall, the proportion of error was .18 higher for low-prevalence than high-prevalence trials. To calculate the magnitude of difference for the training-test combinations, the difference between the means for the condition pairings were computed. The difference was smaller for the low-prevalence, high-value combination (M = .17, SD = .18) than the low-prevalence, low-value combination (M = .20, SD = .21). Although this difference was not significant, $t(78) = .55$, $p = .58$, it suggests that associating the low-prevalence color with reward does lead to a small reduction in miss rates for low-prevalence targets.

In order to determine how much credence can be put into the interpretation of the direction of the effects, a Bayesian mixed factor ANOVA was conducted. The Bayes factor indicated that the data were best represented under a model that included the factor of prevalence. The Bayes factor was $1.18*10^{11}$, indicating decisive evidence for this model compared to the null model.

However, given that the effect of prevalence has long been established, a null model that incorporated the factor of prevalence was examined. Under this condition, the data were best represented under the null model which incorporated the factor of prevalence. The null model was 15.54 times more likely than the model that included the interaction, indicating strong evidence for the null model. This suggests that little weight should be put on the directionality of the effects, given the strong evidence that prevalence is the only effect needed to support the data.

For completeness, error rates for target absent trials were examined. Target absent trials would be expected to have a low error rate because an error on a target absent trial would be a false alarm, indicating a target was present when there was not actually one there. Because the targets were simple letters, participants should not indicate they see a target when a target is not actually there. Target absent trials (M = .01, SD = .01) were indeed more accurate than low-prevalence trials, $t(79) = 9.59$, $p < .001$, $d = 1.07$, and high-prevalence trials, $t(79) = 8.75$, $p < .001$, $d = .98$, showing that participants made few false alarm responses.

Response times. Response times for target present trials were also examined (see Figure 6). A 2 (between-subjects training-test combination: low-prevalence-high-value color, high-prevalence-low-value color vs. low-prevalence-low-value color, high-prevalence-high-value color) x 2 (condition: low-prevalence, high-prevalence) mixed ANOVA revealed a main effect of prevalence, $F(1, 78) = 69.19$, $p < .001$, $\eta_p^2 = .47$, in which RTs for low-prevalence trials (M = 1620 ms, SD = 545 ms) were slower than RTs for high-prevalence trials (M = 1130 ms, SD = 267 ms). There was no main effect of training-test combination, $F(1, 78) = 2.28$, $p = .14$, nor an interaction, $F(1, 78) = 1.75$, $p = .19$. Because the low-prevalence-high-value color, high-prevalence-low-value color condition was both (numerically but not significantly) faster and more accurate than the high-prevalence-high-value, low-prevalence, low-value, a speed-accuracy tradeoff does not seem to be at play.

Although the interaction was not significant, the results did indicate a numerical, but not significant, benefit of reward. When the low-prevalence color matched the high-value color, response times were faster in comparison to when the low-prevalence color matched the low-value color. Overall, the response time was 490 ms slower for low-prevalence than high-prevalence trials. To calculate the magnitude of RT difference for the training-test combinations, the difference between the means for the condition pairings were computed. The difference was smaller for the low-prevalence, high-value combination (M = 401, SD = 447) than the low-prevalence, low-value combination (M = 579, SD = 597). Although this difference was not significant, $t(78) = 1.51$, $p = .14$, it suggests that associating the low-prevalence color with high value does lead to slightly faster responses for low-prevalence targets than associating a low-prevalence color with a low value.

Figure 6. Pattern of RT results for target present trials in Experiment 1. There was a main effect of prevalence, but no main effect of training-test combination, nor an interaction. Error bars indicate standard error of the mean.

In order to determine how much credence can be put into the interpretation of the direction of the RT effects, a Bayesian mixed factor ANOVA was conducted. The Bayes factor indicates that the data were best represented under a model that included the factor of prevalence. The Bayes factor was $5.02*10^{10}$, indicating decisive evidence for this model compared to the null model.

However, given the established effect of prevalence, a null model that incorporated the factor of prevalence was examined. Under this condition, the data were best represented under the null model that included the factor of prevalence. The null model was 3.39 times more likely than the model that included the interaction, suggesting substantial evidence for the null model. This indicates that little weight should be put on the directionality of the RT effects, given the evidence that prevalence is the only effect needed to support the data.

To ensure that the response time patterns were consistent with other visual search research in which overall target prevalence is not considered low (e.g., 50% overall prevalence, as in the present experiment), it was confirmed that RTs for absent trials (M = 2697 ms, SD = 829 ms) were slower than RTs for low-prevalence trials, $t(79) = 12.09$, $p < .001$, $d = 1.35$, and high-prevalence trials, $t(79) = 20.49$, $p < .001$, $d = 2.29$. Notably, this does not follow the pattern of Wolfe et al. (2005) in which overall target prevalence was low (e.g., 10% or 1%), resulting in faster target-absent responses, because overall target prevalence was 50% in the present experiment.

3.3.4 Exploratory Analyses

For both speed and accuracy, the effects of reward history on low-prevalence search were in the predicted direction, but neither reached significance. Therefore, a combined speed-accuracy measure was computed and used in analyses to determine whether reward affected the LPE when the two dependent variables were combined. The combined speed-accuracy measure was based on a balanced integration score (BIS) devised by Liesefeld et al. (2014). The BIS integrates speed and accuracy with equal weights and decreases the likelihood of interpreting spurious effects that are driven by speed-accuracy tradeoffs (Liesefeld & Janczyk, 2019). The BIS is computed by standardizing RTs and percent correct (1 - error rate) for each condition of interest using the overall means and standard deviations for speed and accuracy for all conditions. Then, standardized RT is subtracted from standardized accuracy. This gives an integrated measure of task performance. A participant who performs with average speed and accuracy would receive a BIS score of 0 on a condition (0 on accuracy – 0 on RT). If they were more accurate and faster by 1 standard deviation on a condition, they would receive a BIS score of 2 (1 on accuracy – -1 on RT). A participant who is slower and less accurate by 1 standard deviation would receive a BIS score of -2 (-1 on accuracy – 1 on RT). Someone who is trading speed for accuracy would receive a 0 if they were 1 standard deviation faster and 1 standard deviation less accurate (-1 on accuracy – -1 on RT) or 1 standard deviation slower and 1 standard deviation more accurate (1 on accuracy – 1 on RT). Thus, negative scores indicate poor performance, and positive scores indicate strong performance.

To analyze these data, BIS scores were calculated for low- and high-prevalence targets. A 2 (between-subjects training-test combination: low-prevalence-high-value color, high-prevalence-low-value color vs. low-prevalence-low-value color, high-prevalence-high-value color) x 2 (condition: low-prevalence, high-prevalence) mixed ANOVA on BIS scores revealed a main effect of prevalence, $F(1, 78) = 77.94$, $p < .001$, $\eta_p^2 = .50$, in which BIS scores for low-prevalence trials ($M = -5.64$, $SD = 7.21$) were lower than BIS scores for high-prevalence trials ($M = 1.18$, $SD = 1.64$). This indicates, consistent with previous analyses, that participants performed better on high-prevalence than low-prevalence trials. No other effects were significant (Fs < 1), indicating that reward history did not influence search performance. Thus, BIS was not used in any further exploratory analyses, and the following analyses focus only on accuracy or response time independently.

In another set of analyses, differences in error rates and response times for the two targets (the red L and green T) were examined. Interestingly, there was a statistically significant difference in error rates between the green T ($M = .18$, $SD = .14$) and red L targets ($M = .11$, SD

= .14), $t(79) = 2.57$, $p = .012$. Participants were less likely to find green T's compared to red L's. They were also slower to find green T's ($M = 1515$ ms, $SD = 470$ ms) than red L's ($M = 1235$ ms, $SD = 479$ ms), $t(79) = 3.75$, $p < .001$.

In order to separate the effect of color from effects of interest, the dataset was split based on the identity of the low-prevalence target, leaving a dataset of 40 participants who had the red L as the low-prevalence target, and a dataset of 40 participants who had the green T as the low-prevalence target.

For the participants with a red L as the low-prevalence target, a 2 (between-subjects training-test combination: low-prevalence-high-value color, high-prevalence-low-value color vs. low-prevalence-low-value color, high-prevalence-high-value color) x 2 (condition: low-prevalence, high-prevalence) mixed ANOVA on error rates revealed no main effect of prevalence, $F(1, 38) = 1.30$, $p = .26$, no main effect of training-test combination, $F(1, 38) = 1.66$, $p = .21$, and no interaction ($F < 1$).

For the participants with a green T as the low-prevalence target, a 2 (between-subjects training-test combination: low-prevalence-high-value color, high-prevalence-low-value color vs. low-prevalence-low-value color, high-prevalence-high-value color) x 2 (condition: low-prevalence, high-prevalence) mixed ANOVA on error rates revealed a marginal effect of prevalence, $F(1, 38) = 3.97$, $p = .05$, no main effect of training-test combination, $F(1, 38) = 1.18$, $p = .28$, nor an interaction ($F < 1$).

This set of results indicates that a dataset of 40 participants does not provide enough power to detect a result as strong as the LPE, which is typically a robust effect, in an online setting. The effect was nearly present for participants who had the green T as the low-prevalence target, but it did not reach statistical significance.

Examining response times, for participants with a red L as the low-prevalence target, a 2 (between-subjects training-test combination: low-prevalence-high-value color, high-prevalence-low-value color vs. low-prevalence-low-value color, high-prevalence-high-value color) x 2 (condition: low-prevalence, high-prevalence) mixed ANOVA on response times revealed a main effect of prevalence, $F(1, 38) = 10.94$, $p = .002$. RTs for high-prevalence trials (the green T; M = 1298 ms, SD = 242 ms) were faster than RTs for low-prevalence trials (the red L; M = 1508 ms, SD = 534 ms). There was no main effect of training-test combination and no interaction (Fs< 1).

For participants with a green T as the low-prevalence target, a 2 (between-subjects training-test combination: low-prevalence-high-value color, high-prevalence-low-value color vs. low-prevalence-low-value color, high-prevalence-high-value color) x 2 (condition: low-prevalence, high-prevalence) mixed ANOVA on response times revealed a main effect of prevalence, $F(1, 38) = 98.43$, $p < .001$. RTs for high-prevalence trials (the red L; M = 963 ms, SD = 169 ms) were faster than RTs for low-prevalence trials (the green T; M = 1733 ms, SD = 540 ms). There was no main effect of training-test combination, $F(1, 38) = 2.54$, $p = .12$, and no interaction, $F(1, 38) = 2.91$, $p = .10$.

The RT results were consistent across target condition. Participants were faster to find high-prevalence targets compared to low-prevalence targets regardless of the identity of the targets.

It is possible that the value manipulation was not strong enough to induce an effect that would influence low-prevalence visual search. In order to examine this possibility, participants who were faster on high-value than low-value trials in the final block of training were analyzed separately. This yielded a set of 51 participants. It is important to note that, although these participants showed a numerical effect of training, they may not have truly been influenced by the value manipulation; about half of participants would be expected to show an effect in this direction due to noise. Nonetheless, this analysis was conducted in order to thoroughly examine the data. A 2 (between-subjects training-test combination: low-prevalence-high-value color, high-prevalence-low-value color vs. low-prevalence-low-value color, high-prevalence-high-value color) x 2 (condition: low-prevalence, high-prevalence) mixed ANOVA on error rates revealed a main effect of prevalence, $F(1, 49) = 39.54$, $p < .001$, $\eta_p^2 = .45$, in which error rates for low-prevalence trials ($M = .22$, $SD = .20$) were higher than error rates for high-prevalence trials ($M = .05$, $SD = .05$). This reveals the typical low-prevalence effect. There was no main effect of training-test combination nor an interaction (Fs < 1), indicating that even when the training manipulation was effective, there was no effect on the LPE. The same pattern of results occurred for response times. There was a main effect of prevalence, $F(1, 49) = 46.19$, $p < .001$, $\eta_p^2 = .49$, in which RTs for low-prevalence trials ($M = 1562$, $SD = 469$) were slower than RTs for high-prevalence trials ($M = 1122$, $SD = 259$), but there was no main effect of training-test combination nor an interaction (Fs < 1).

Another way of determining if the LPE was affected for participants for whom training was effective is by including only participants who were faster overall on high-value training trials compared to low-value training trials (rather than just block 4). This yielded a sample of 44 participants. The same caveat applies here: some participants would show numerical differences in this direction due to noise rather than a true effect of reward. A 2 (between-subjects training-test combination: low-prevalence-high-value color, high-prevalence-low-value color vs. low-prevalence-low-value color, high-prevalence-high-value color) x 2 (condition: low-prevalence, high-prevalence) mixed ANOVA on error rates revealed a main effect of prevalence, $F(1, 42) = 35.31$, $p < .001$, $\eta_p^2 = .46$, in which error rates for low-prevalence trials ($M = .24$, SD

= .21) were higher than error rates for high-prevalence trials (*M* = .06, *SD* = .05). This reveals the typical low-prevalence effect. There was no main effect of training-test combination nor an interaction (*F*s < 1), indicating that even when the training manipulation was effective as defined by this relatively conservative criterion, there was no effect on the LPE. The same pattern of results occurred for response times. There was a main effect of prevalence, $F(1, 42) = 42.23$, $p < .001$, $\eta_p^2 = .50$, in which RTs for low-prevalence trials (*M* = 1616, *SD* = 478) were slower than RTs for high-prevalence trials (*M* = 1139, *SD* = 262), but there was no main effect of training-test combination nor an interaction (*F*s < 1).

3.4 Discussion

Results from Experiment 1 suggest that reward does not strongly alter the low-prevalence effect. Although the results, that a previously rewarded target reduced errors in the low-prevalence condition, were in the expected direction, they did not reach significance for either accuracy or RT.

One possible explanation for the lack of an effect is that the value manipulation in the training phase was not strong enough to induce an effect. Notably, there was no significant difference in RTs for the low- and high-value colors in training, even in the final 60 training trials, indicating that the reward manipulation may not have been strong enough to induce an effect in the search phase.

Interestingly, the LPE did not appear when each of the two low-prevalence targets were considered individually, indicating that more than 40 participants may be needed to find the LPE in an online experiment, perhaps because of increased variability in numerous aspects of the setting, including features of the stimuli, the responses, and the potential distractions in the environment. Another possibility is that, due to the factors listed above, an online experiment may have resulted in more errors overall, including in the high-prevalence trials, than an in-lab experiment would have. This increased variability in error rates may have made the detection of an effect more difficult. Previous experiments have shown the LPE with just 10 participants (e.g., Rich et al., 2008, Exp. 1). Perhaps conducting the experiment in a more controlled environment would decrease variability and produce the expected pattern of results with this number of participants.

Chapter 4: Experiment 2

4.1 Introduction

Action history is known to influence visual search. Making a simple action biases visual attention to items that share properties of the object towards which the simple action was made (e.g., Buttaccio & Hahn, 2011; Weidler & Abrams, 2014; Weidler & Abrams, 2016). For example, making a simple spacebar press when a blue object is presented biases subsequent visual search towards blue objects. This bias towards blue objects in a subsequent search does not occur after merely viewing a blue object. This effect has been shown to occur with features other than color as well. For example, objects that match the shape of an acted-upon prime are prioritized in search (Wang et al., 2021).

The action effect is a robust effect that occurs regardless of conscious awareness (Suh & Abrams, 2018), influences eye movements (Weidler et al., 2018), and influences pop-out search (Weidler & Abrams, 2016). A few mechanisms for the effect have been proposed, including event files and repetition priming (Weidler & Abrams, 2014). Event files are temporary links between actions, perceptual events, and contexts in which tasks are performed (Hommel, 2004). In the action effect, an action and the acted-upon object may become temporarily bound, affecting attentional allocation during search (Weidler & Abrams, 2014). Alternatively, repetition priming has been posited as a possibility because, in repetition priming, attention is allocated to a previously relevant feature (Kristjánsson & Campana, 2010). Each of these mechanisms highlights the importance of selection history in the action effect; the previous experience of linking an action to a feature biases subsequent search.

Another mechanism by which prior action could influence the LPE is via preattentive processing. It has been shown that action history influences preattentive processing (Weidler et al., 2018), and thus might have an effect on low-prevalence search similar to increasing the salience of an item (Jonides, 1981). If this is the case, making an action towards an object that shares properties with a low-prevalence target before search should reduce the LPE. In the current study, observers made actions and completed visual search trials, and the effects of action and prevalence were examined.

4.2 Method

4.2.1 Participants

Although previous research on the action effect (e.g., Weidler & Abrams, 2014) has used a sample size of 12 to 24 participants, including the extra factor of prevalence meant that more participants would be needed. Therefore, 60 Washington University students participated in this 30-minute lab-based experiment in exchange for course credit.

4.2.2 Procedure

The sequence of events for Experiment 2 can be seen in Figure 7. The basic action task was identical to the one used in previous research examining the effect of action on visual search (Weidler & Abrams, 2014, Exp. 3). Participants viewed a black fixation cross (3° x 3°) for 500 ms. Next, participants saw the word "GO" or "NO" (3° height) for 500 ms followed by another fixation cross for 130 ms. Trials on which participants saw the word "GO" are referred to as go trials, and trials on which they saw the word "NO" are referred to as no-go trials. After seeing the word "GO" or "NO", a prime (a red or green circle; 6° x 6°) appeared for 750 ms or until participants made a response. Participants made a speeded spacebar press for go trials and withheld responses for no-go trials. They then once again saw a fixation cross for 500 ms.

Finally, participants were presented with a search display of 32 items, identical to those used in Experiment 1, and their task was to search for a red L or a green T. Participants made a spacebar press to indicate they were finished searching. They then responded whether a target was "present" or "absent" using the "f" and "j" keys. The display was presented for 10 s or until a response was made. Importantly, when a target was present, the color of the target was either congruent or incongruent with the prime; for example, a red prime followed by a green T in the search display was classified as incongruent, but a red prime followed by a red L was classified as congruent.

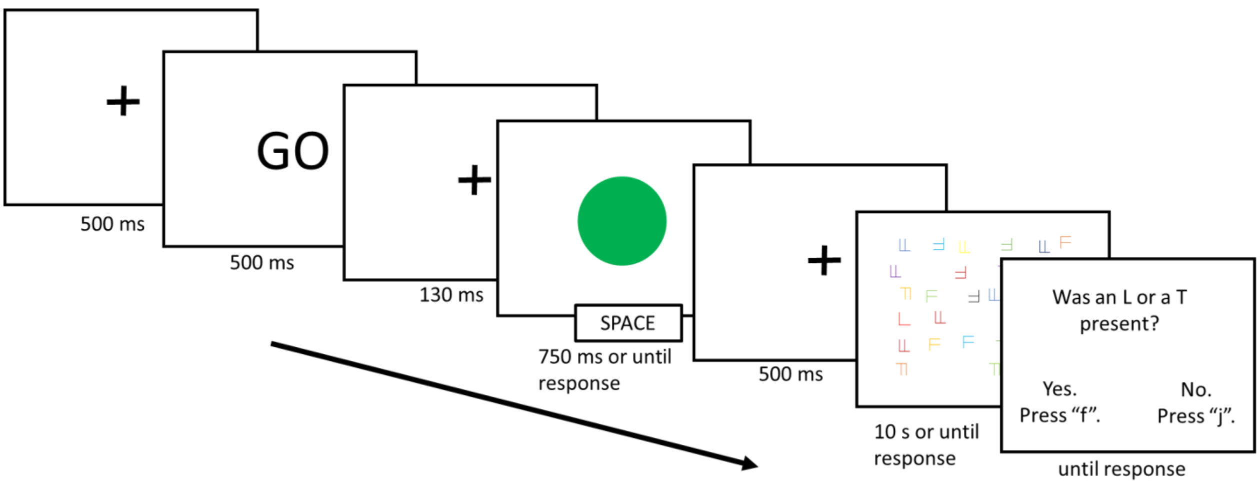

Figure **7**. Sequence of events for Experiment 2.

4.2.3 Design

Participants completed 400 experimental trials. Half of the trials were go trials and half were no-go trials, with the red and green prime colors presented equally often in each half. Within each of these go/no-go and color combinations, no target was presented on half of the trials. On the other half of the trials, a target was presented, with one of the two targets presented on 45% of the trials (the high-prevalence target) while the other was presented on 5% of the trials (the low-prevalence target). The identity of the high- and low-prevalence targets was counterbalanced across participants.

4.3 Results

Error rates. Trials in which an action error (a spacebar press on a no-go trial or a lack of a spacebar response on a go trial) was made and trials in which no response was made in the search task were eliminated from analyses (2.1% of trials). As seen in Figure 8, a 2 (action condition: go vs. no-go) x 2 (congruency: congruent vs. incongruent) x 2 (prevalence: high-prevalence vs. low-prevalence) repeated measures ANOVA on error rates revealed a main effect of prevalence in which error rates for low-prevalence trials (*M* =.17, *SD* =.18) were higher than error rates for high-prevalence trials (*M* =.03, *SD* =.02), *F*(1, 59) = 40.43, *p* < .001, η_p^2 = .41. No other main effects or interactions were significant (action x congruency, *F*(1, 59) = 1.42, *p*=.24; action x congruency x prevalence, *F*(1,59) = 1.15, *p* = .29; all other *F*s < 1). It is not atypical for an action effect to appear only in RTs and not in error rates (e.g., Weidler & Abrams, 2014), but importantly, there was no action effect present in either error rates or responses times (as indicated below) for this experiment, which limits the conclusions that can be drawn about the effect of action on low-prevalence visual search.

For completeness, error rates for target absent trials were examined. Target absent trials (*M* = .01, *SD* = .01) were indeed more correct than low-prevalence trials, *t*(59) = 7.23, *p* < .001, *d* = .93, and high-prevalence trials, *t*(59) = 5.73, *p* < .001, *d* = .74, showing that participants made few false alarm responses.

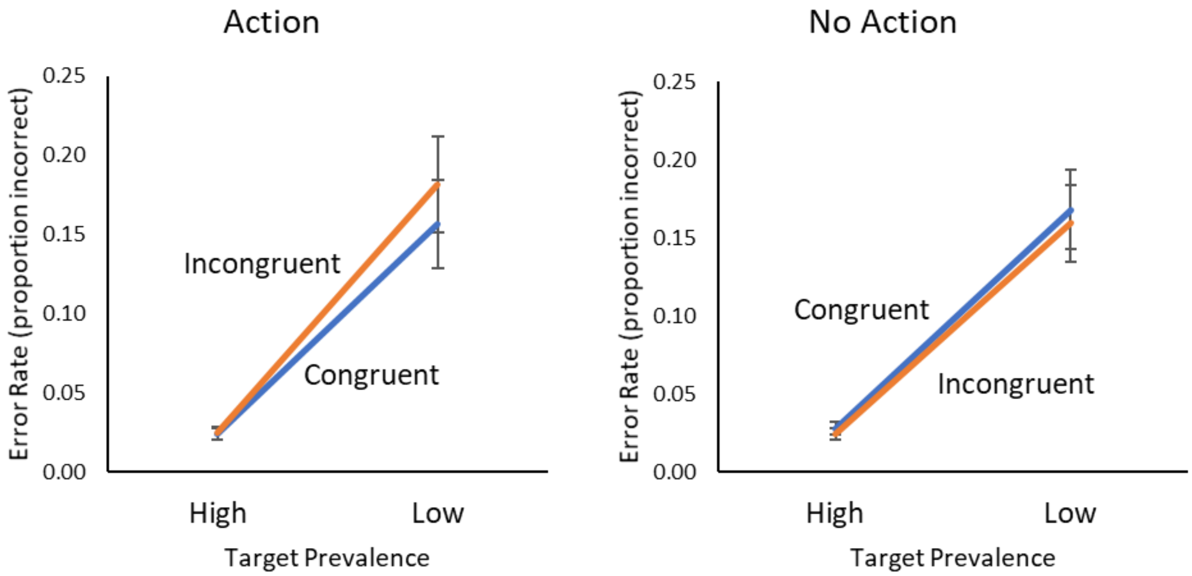

Figure 8. Error rates from Experiment 2. There was a main effect of prevalence, but no other effects were significant. Error bars indicate standard errors of the mean.

Response times. Results are displayed in Figure 9. Trials in which an action error or search error were made were eliminated from analyses (4.4% of trials). A 2 (action condition: go vs. no-go) x 2 (congruency: congruent vs. incongruent) x 2 (prevalence: high-prevalence vs. low-prevalence) repeated measures ANOVA on response times revealed a main effect of prevalence in which response times for low-prevalence trials (M = 1678, SD = 358) were slower than response times for high-prevalence trials (M = 1191, SD = 277), $F(1, 58) = 114.55$, $p < .001$, $\eta_p^2 = .66$. (Degrees of freedom differed in response time data compared to accuracy data because one participant had no response time data for incongruent low-prevalence go trials, indicating that they let the 10 s limit for search time run out on these particular trials.) No other main effects or interactions were significant (congruency x prevalence, $F(1,58) = 1.58$, $p = .21$, all other Fs < 1). Importantly, there was no action effect present in response times for this experiment. Typically, the action effect appears in the response time data (e.g., Weidler &

Abrams, 2014). The lack of an action effect limits the conclusions that can be drawn about the effect of action on low-prevalence visual search.

For completeness, response times for target absent trials were examined. Target absent trials (M = 2881, SD = 677) were slower than low-prevalence trials, $t(59) = 17.45$, $p < .001$, d = 2.25, and high-prevalence trials, $t(59) = 23.49$, $p < .001$, $d = 3.03$, showing that participants did indeed spend longer on target-absent trials than target-present trials.

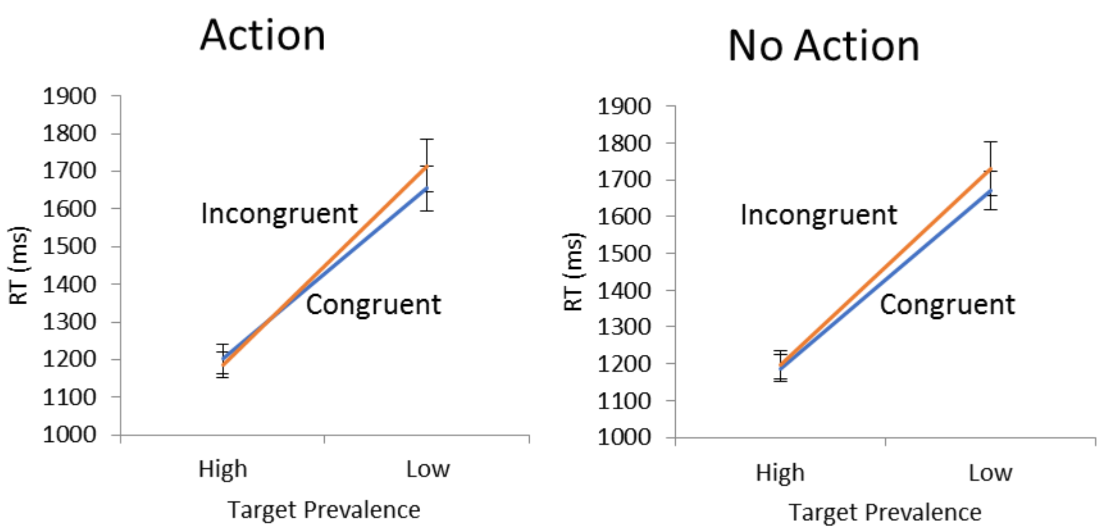

Figure 9. Response time results for Experiment 2. There was a main effect of prevalence in which low-prevalence trials were slower than high-prevalence trials, but no other effects were significant. Error bars indicate standard errors of the mean.

Exploratory Analyses. Although the overall data did not show an action effect, some participants did exhibit an action effect; therefore, their data was analyzed separately. An action effect was defined as the difference in response times between incongruent and congruent trials being greater for the go trials than the no-go trials. This was the case for 30 out of the 60 participants. Importantly, this analysis should be qualified by noting that some participants would show a numerical action effect due to noise rather than a true action effect. Thus, it cannot be confirmed that all of the participants included in this analysis were influenced by action, but this analysis was conducted to ensure thorough inspection of the data.

For the 30 out of 60 participants who exhibited an action effect, a 2 (action condition: go vs. no-go) x 2 (congruency: congruent vs. incongruent) x 2 (prevalence: high-prevalence vs. low-prevalence) repeated measures ANOVA on response times revealed a main effect of prevalence in which response times for low-prevalence trials (M = 1662, SD = 448) were slower than response times for high-prevalence trials (M = 1155, SD = 259), $F(1, 28) = 48.72$, $p < .001$, $\eta_p^2 = .64$. Additionally, the action effect was confirmed by an action x congruency interaction, $F(1, 28) = 5.998$, $p = .02$, $\eta_p^2 = .18$. No other effects were significant (Fs < 1).

After confirming that the action effect occurred in RTs for this subset of participants, a 2 (action condition: go vs. no-go) x 2 (congruency: congruent vs. incongruent) x 2 (prevalence: high-prevalence vs. low-prevalence) ANOVA on accuracy in the search task was conducted to determine if the action effect affected the low-prevalence effect. Only the main effect of prevalence was significant, $F(1, 29) = 19.51$, $p < .001$, $\eta_p^2 = .40$. Error rates for low-prevalence trials (M = .14, SD = .19) were higher than error rates for high-prevalence trials (M = .02, SD = .03). No other main effects or interactions were significant (congruency, $F(1, 29) = 2.96$, $p = .10$; congruency x prevalence, $F(1, 29) = 3.34$, $p = .08$; all other Fs < 1). The marginal congruency x prevalence effect indicates that low-prevalence error rates were lower when the prime was congruent with the search target. Importantly, there were no effects involving action. These results indicate that even when participants exhibited an action effect, there was no effect on the LPE.

4.4 Discussion

In this experiment, there was no effect of action history on low-prevalence search errors. The lack of an action effect (the tendency for participants to find targets more quickly after making an action towards an object that shares properties with that target) in this paradigm limits the conclusions that can be drawn about the effect of action on low-prevalence search. Importantly, the low-prevalence effect was still present in both the action and no action conditions. There are several differences between the search task in the present experiment and previous research, which could explain the lack of an action effect. These differences and further implications are explored in the General Discussion.

Chapter 5: Experiment 3

5.1 Introduction

Working memory and visual search are interconnected (Luria & Vogel, 2011). Working memory is especially relied upon when search is difficult, and it is necessary both for identifying targets and rejecting distractors (Luria & Vogel, 2011). When a target is maintained in working memory, it can be easily accessed, and its representation can be easily updated if needed (Umemoto et al., 2010). Further, working memory can aid in selection of relevant items because when a target or set of targets is maintained in working memory, irrelevant items consume less capacity (Vogel et al., 2005).

Additionally, availability of items in working memory may help explain why the low-prevalence effect occurs. Frequent targets are more likely to be encoded into working memory (Umemoto et al., 2010); therefore, low-prevalence targets may not be as available in working memory as more common targets, especially when there are many search targets and the relative prevalence of some is low. For example, if observers are searching for hair dryers, water bottles, and explosives, the features related to hair dryers and water bottles may be more available in working memory given that those items are more common, which may enhance detection of those features and make features related to explosives harder to detect.

Flexible resource models of working memory assert that there is a pool of resources that can be allocated across items such that prioritized items can receive greater attention (e.g., Alvarez & Cavanagh, 2004). Thus, if specific targets are prioritized in working memory, they may be more easily found in a search task. Indeed, targets in working memory are easier to find in visual search (Dowd & Mitroff, 2013). This would be especially important in low-prevalence visual search because if low-prevalence items could be maintained in working memory, those items may be more easily found, and the low-prevalence effect could be reduced.

The present experiment manipulated the availability of the low-prevalence targets in working memory, and the effect on the LPE was examined, providing insight into the effect of another selection history manipulation in low-prevalence visual search. It was hypothesized that if low-prevalence targets could be made more available in working memory, the LPE could be reduced.

5.2 Method

5.2.1 Participants

A power analysis suggested a sample size of 24 participants, but to ensure an adequate sample, the sample size was increased to 40. Forty-five Washington University students completed the one-hour experiment in exchange for course credit. Twenty-three completed the experiment in the lab, but two participants were eliminated due to not completing the experiment in the allotted amount of time. Twenty-two completed the experiment online, but three participants were eliminated due to total accuracy falling below 75%. Thus, the total number of participants included in analyses was 40.

5.2.2 Procedure

The sequence of events for Experiment 3 can be seen in Figure 10. At the beginning of the experiment, participants were told to search for red L's and green T's on each trial. They were also told that they would hear a prompt before each trial (either "remember T" or "remember L") that they should hold in memory but that the prompt they would hear would be unrelated to whether any particular target would be presented. Each trial began with the presentation of a fixation cross for 500 ms. The participants then heard "Remember L" or

“Remember T” through headphones. This method of presenting a target in order to manipulate presence in working memory has been previously shown to be effective (e.g., Kim & Cho, 2016). Next, participants saw a search display with 32 items and responded with a spacebar press to indicate they were finished searching. They then responded whether a target was “present” or “absent” using the “f” and “j” keys. The display was presented for 10 s or until a response was made. If the prompt was the same as the target in the search task, the trial was considered congruent. If the prompt was different from the target in the search task, the trial was considered incongruent. On 20% of trials, after reporting the target, participants were asked whether they were remembering the L or the T by making a key press. This was to ensure that they were holding the instructed item in memory.

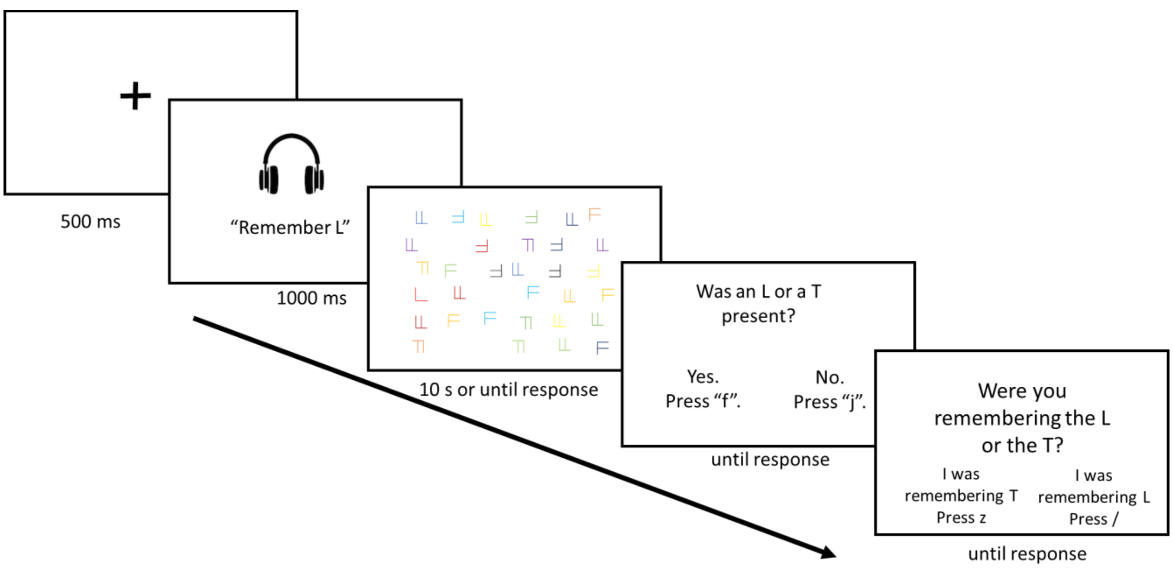

Figure 10. Sequence of events for Experiment 3. On 20% of trials, participants were asked if they were remembering T or L, but on 80% of trials they were not. Participants did not see the image of the headphones or the words “Remember L” or “Remember T” but instead were presented a blank screen while the audio played.

5.2.3 Design

Participants completed 400 search trials in the online version and 480 in the in-person version. This difference in number of trials was due to the increased time to load and familiarize oneself with the task in the online version and to be sure all participants completed the task in under 1 hour. On half of the search trials, no target was presented. On the other half of the trials, there was a target present, but one of those targets was presented on a total of 45% of the trials (the high-prevalence target) while the other target was presented on 5% of the trials (the low-prevalence target). The identity of the high- and low-prevalence targets was counterbalanced across participants.

Participants completed a block of 16 practice trials and were probed for their memory prompt on 50% of the trials. Thereafter, the percentage of trials on which participants were probed was lowered to 20%.

5.3 Results

Trials with incorrect responses to the probe question and trials in which no response was made on a search trial were eliminated from analyses. This resulted in the elimination of .5% of trials, indicating that participants were very good at holding the probe in memory, and they were likely performing the memory task throughout the experiment since they did not know on which trials they would be probed.

Error rates. Error rates can be seen in Figure 11. A 2 (within-subjects memory prompt congruency: congruent vs. incongruent) x 2 (within-subjects target prevalence: high-prevalence vs. low-prevalence) x 2 (between-subjects setting: in-person vs. online) mixed ANOVA on error rates was conducted. The between-subjects factor of setting was included in order to determine if the pattern of the effect differed based on whether participants completed the experiment in the lab or online. The ANOVA revealed a main effect of prevalence in which error rates for low-prevalence trials (M = .11, SD = .16) were higher than error rates for high-prevalence trials (M = .03, SD = .06), $F(1, 38) = 31.36$, $p < .001$, $\eta_p^2 = .44$. There was also a main effect of congruency in which error rates for incongruent trials (M = .05, SD = .09) were higher than error rates for congruent trials (M =.03, SD =.05), $F(1, 38) = 6.93$, $p = .01$, $\eta_p^2 = .15$. Critically, there was a prevalence x congruency interaction, indicating the low-prevalence effect (the increased errors on low prevalence compared to high prevalence trials) was smaller when the target was congruent with the memory prompt, $F(1, 38) = 4.17$, $p = .048$, $\eta_p^2 = .10$. There were no significant effects or interactions involving setting (in-person vs. online; main effect of setting, $F(1,38) = 3.84$, $p = .06$, prevalence x setting, $F(1,38) = 2.48$, $p = .12$, all other Fs < 1), indicating the pattern of results did not differ significantly based on whether the participants completed the experiment in the lab or online.

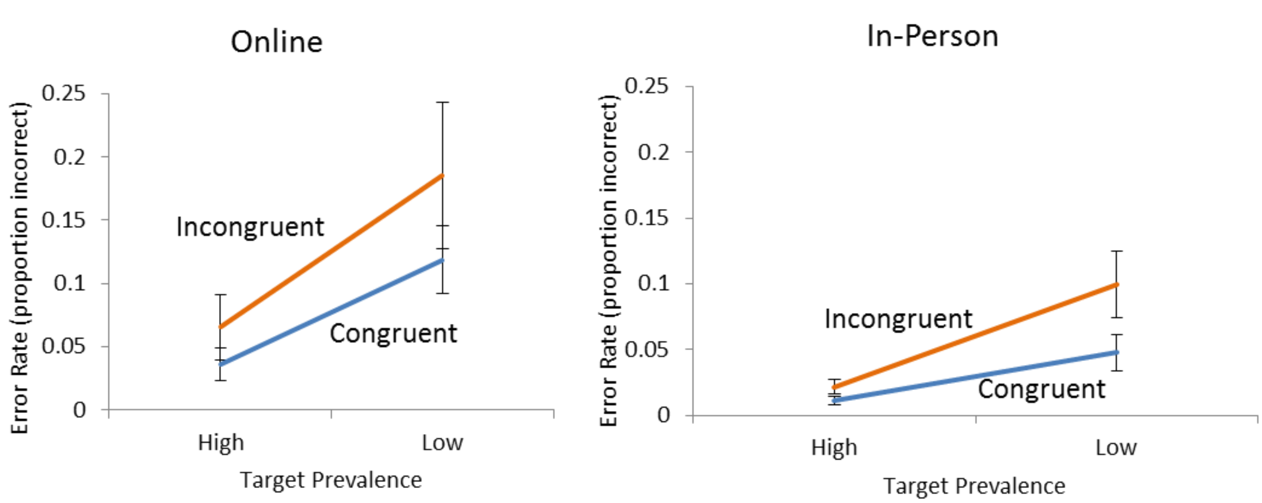

Figure 11. Error rates from Experiment 3. The interaction indicates that the low-prevalence effect was reduced when a prime congruent with the low-prevalence target was remembered. Error bars indicate standard error of the mean.

For completeness, error rates for target absent trials were examined. Target absent trials (M = .01, SD = .02) were more correct than low-prevalence trials, $t(39) = 5.37$, $p < .001$, $d = .85$, and high-prevalence trials, $t(39) = 3.36$, $p = .002$, $d = .53$, showing that participants made few false alarm responses.

Response times. Reaction time results from Experiment 3 can be seen in Figure 12. A 2 (within-subjects prompt congruency: congruent vs. incongruent) x 2 (within-subjects target prevalence: high-prevalence vs. low-prevalence) x 2 (between-subjects setting: in-person vs. online) mixed ANOVA on response times revealed a main effect of prevalence in which response times for low-prevalence trials (M = 1699, SD = 620) were slower than response times for high-prevalence trials (M = 1228, SD = 411), $F(1, 38) = 44.82$, $p < .001$, $\eta_p^2 = .54$. There was also a main effect of congruency in which incongruent trials (M = 1328, SD = 457) were slower than congruent trials (M = 1222, SD = 406), $F(1, 38) = 9.27$, $p < .01$, $\eta_p^2 = .19$. There was no prevalence x congruency interaction. There was, however, a prevalence x congruency x setting interaction, $F(1, 38) = 5.181$, $p = .03$, $\eta_p^2 = .12$. This interaction showed that low-prevalence trials had similar response times in the online setting regardless of whether the prompt was congruent or incongruent, while low-prevalence prompt-congruent trials were faster than low-prevalence prompt-incongruent trials in the in-person setting. No other effects or interactions involving setting were significant (prompt congruency x setting, $F(1,38) = 1.43$, p = .24, all other Fs < 1).

It does appear that there may have been a speed accuracy tradeoff for the participants in the online condition because they were slower in the low-prevalence congruent condition but also very accurate in that condition. However, the working memory manipulation may have caused this effect, and the main goal in reducing the LPE is to reduce error rates. A slowing of response times would not be a concern.

For completeness, response times for target absent trials were examined. Target absent trials (M = 2945, SD = 964) were slower than low-prevalence trials, $t(39) = 13.27$, $p < .001$, d = 2.10, and high-prevalence trials, $t(39) = 13.12$, $p < .001$, d = 2.07, showing that participants did spend longer on target-absent trials than target-present trials.

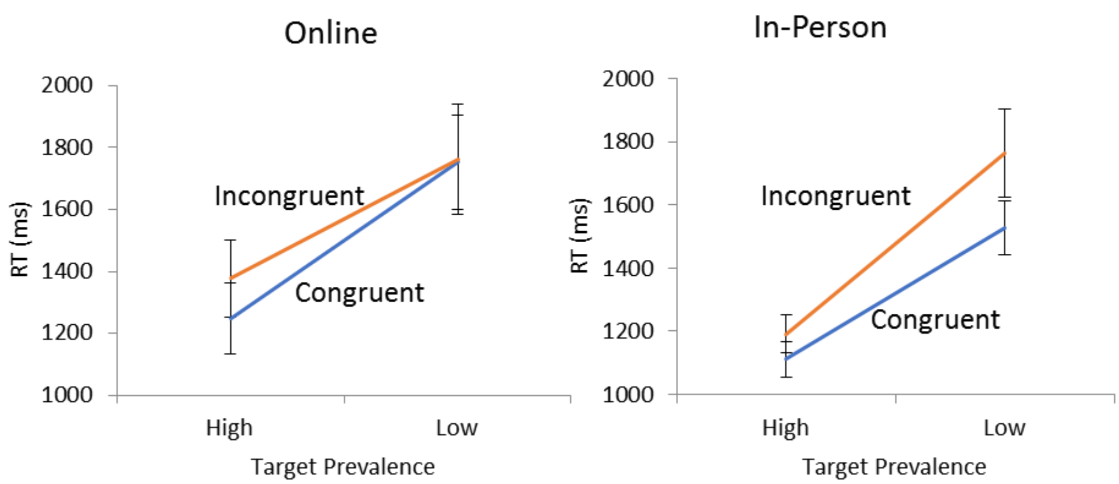

Figure 12. Response time results from Experiment 3. Error bars indicate standard error of the mean.

In order to examine individual differences in the low-prevalence effect, response times, and memory prompt errors, a low-prevalence index score was computed. This score was computed as the difference between the proportion incorrect on low-prevalence and high-prevalence trials; thus, a positive score indicated that a participant exhibited the low-prevalence effect, and a negative score indicated the opposite. Pearson's correlations between the low-prevalence index score and mean response time and memory probe accuracy were computed. As seen in Figure 13, there was a significant correlation between the low-prevalence index and proportion of probe errors, *r*(38) = .62, *p* <.001, 95% CI [.39, .78]. This correlation indicates that the better participants performed on the memory task, the smaller the low-prevalence effect, showing that successfully maintaining an item in working memory reduces the LPE. The low-prevalence index was not significantly related to mean RT (*r*(38) = -.23, *p* = .16), nor was mean RT related to memory probe errors (*r*(38) = .01, *p* = .95).

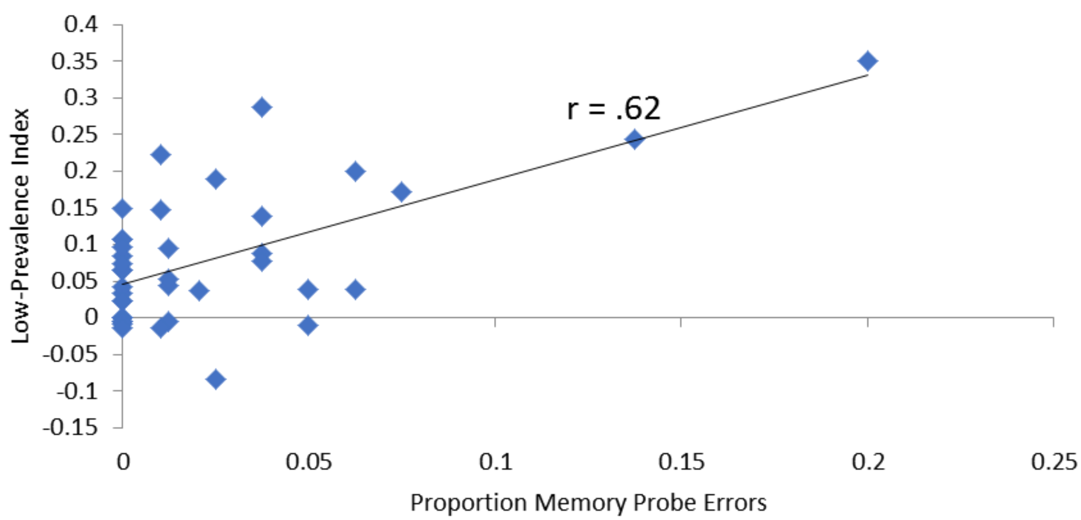

Figure 13. Correlation between proportion memory probe errors and the low-prevalence index, which is computed as the difference between proportion of errors on low-prevalence trials and proportion of errors on high-prevalence trials. Participants with a stronger low-prevalence effect were also more likely to misremember the memory probe.

Examining Figure 13, it appears as if there are two data points that may be driving the correlation. After eliminating these two points, the correlation remains significant, *r*(36) = .33, *p* = .04, 95% CI [.01, .59].

5.4 Discussion

In this experiment, holding a target in memory reduced the low prevalence effect. These results indicate that working memory plays a role in the identification of low-prevalence targets. Perhaps maintaining an item in working memory enhances mental representation of that item, which is known to be important in visual search tasks (e.g., Hout et al., 2015; Umemoto et al., 2010). These results provide insight into the LPE and will be examined further in the General Discussion.

Chapter 6: General Discussion

6.1 Summary of Results

The present experiments examined the effect of selection history on the low-prevalence effect. Experiment 1 examined the role of reward history, Experiment 2 examined the effect of action history, and Experiment 3 examined the effect of holding an item in working memory. Considering these three experiments together, there is some evidence that selection history plays a role in reducing the LPE. The strongest effect was holding an item in working memory. The effect of reward history was in the expected direction, but did not reach significance, possibly because of the lack of a reward effect found in training. Additionally, there was no action effect in the action history experiment, and, thus, no effect of action history on the LPE.

6.1.1 The LPE and Reward History

In Experiment 1, the effect of reward history on the LPE was examined. Previous research indicated that a color that was highly rewarded during a training phase captured attention and was more distracting in a subsequent search (Anderson et al., 2011b). The aim was to use this effect to determine the influence of selection history on the LPE and possibly reduce the effect. Although the expected results in error rates were not found, the changes for both error rates and response times were in the expected direction.

Notably, associating high-reward with a low-prevalence target resulted in a numerical decrease in error rates and response times for low-prevalence targets in a visual search task in comparison with associating low-prevalence targets with a low, but still positive, reward. Thus, a high-value reward seemed to speed search and reduce error rates, even though the effect did not reach significance.

Because miss rates of low-prevalence targets characterize the LPE, error rates were the main variable of interest, but there were changes in response times such that low-prevalence targets presented in colors that were highly rewarded in training were found more quickly than those that were associated with low reward. This indicates that the effect of reward was split between accuracy and response times in Experiment 1. Perhaps if the effects on response time could be eliminated by ensuring participants spend equal amounts of time on each display, the effects would only show up in error rates and the LPE could be reduced.

Importantly, there was no evidence from the training phase that the training was effective in inducing prioritization of highly rewarded colors. The response times for the high-reward and low-reward colors were statistically similar, even when looking at the pattern across blocks. A difference in the final block of training would have shown that participants prioritized the high-reward color and low-reward color differently. Because no difference appeared in training, it cannot be known whether training was effective. Notably, it is possible that reward-related effects appear in search even when there is no clear evidence that training was effective in inducing reward-related prioritization (e.g., Anderson et al., 2011a), but a difference in the training phase would be a clear indication of effectiveness. Even if the training was effective, it may not have been effective enough to produce changes in a difficult search, such as the one in the present experiments. Incorporating more training trials may be a way to enhance the efficacy of reward training.

Additionally, there were a few key differences between the task in Experiment 1 and previous research, which may explain the lack of effect in the present task. Although the present training task was identical to Anderson et al. (2011b), the present search task was more complex. In the Anderson et al. search task, participants were instructed to indicate the direction of a line within a shape singleton in an array of six shapes. In the present task, participants evaluated 32 items rather than 6. Indeed, it is known that set size does influence the effect of salient items on search such that when there are many heterogenous distractors in a display, even an otherwise salient item may not capture attention (Theeuwes, 2004). Thus, even if reward increased the salience of the low-prevalence target, the target may be harder to find in the presence of the many heterogenous distractors. Further, in Anderson et al., a shape singleton was always present, thus a target line was always evaluated. In the present task, a target appeared on only 50% of trials. Additionally, although the high-reward color attracted attention in the Anderson et al. (2011b) paradigm, the goal in their experiment was not to find one of the previously rewarded colors but rather to find a shape singleton, and the previously rewarded colors were never the target. In Experiment 1 of the present study, participants' goal was to find a target displayed in the previously rewarded color, which was another key difference from Anderson et al. Finally, the shapes in Anderson et al. were similar in the training and test phases. In the present experiment, the training and test phase targets differed in size, and letters rather than shapes were used in the test phase. Perhaps in future research, the training and search stimuli could match more closely. These differences in the search task may have contributed to the lack of an effect of reward in Experiment 1.

Despite these differences, the effects were in the expected direction, and perhaps in a lab setting where participants progress is monitored and they cannot be distracted by uncontrolled environmental stimuli or electronic devices, results would be stronger or significant. Notably, the LPE is usually an easy effect to find, but in this experiment, it was not present when the dataset was divided in half, indicating that even a very strong effect was weakened with online data collection.

6.1.2 The LPE and Action History

Experiment 2 examined the effect of action history on the LPE. Previous research indicated that making a space bar press (in comparison to merely viewing a colored circle) when a colored circle was presented biased attention towards targets presented in that color (Weidler & Abrams, 2014). The hope was that employing the action effect in a low-prevalence search experiment would reduce or eliminate the LPE. Unfortunately, this did not happen in Experiment 2.

For both error rates and response times in Experiment 2, there was a main effect of prevalence that indicated low-prevalence targets were missed at higher rates and found more slowly than high-prevalence targets. Importantly, there was no action effect in the present experiment, which would have been indicated by an action x congruency interaction such that an action facilitated search on congruent trials in comparison to incongruent trials.

However, a subset of participants did exhibit the action effect (30 out of 60 participants). In order to determine if the action effect did have an influence on low-prevalence search, the analyses were run with only this subset of participants. Still, no effect of action on the LPE was found. Therefore, it seems that action does not affect the LPE. It is important to acknowledge that 30 participants may be underpowered to find an effect, but there was no trend that indicated action affects the LPE, even for participants who exhibited an action effect.

There were a few key differences between the present task and previous research that could have contributed to the lack of an action effect and, therefore, a lack of an effect on the LPE. Although the action task was the same as in previous experiments on the action effect (e.g., Weidler & Abrams, 2014; Weidler et al., 2018), the search targets in Experiment 2 differed from the search targets in previous work. In previous work, the search targets were identical in shape to the prime, but in Experiment 2 of the present research, the search targets were letters and the primes were circles. A future extension of this work may incorporate target letters as primes so that the primes and targets match. Although the action effect has been found with picture-word pairs, indicating the prime and target do not need to be identical for the effect to occur (Weidler & Abrams, 2018), another key difference was that there was always a search target that corresponded to the prime in the Weidler and Abrams experiments. Here, no target was present on 50% of trials. Further, Weidler and Abrams had just two objects in the search task, whereas the present experiment's search phase had 32 objects. As mentioned previously, the number of heterogeneous distractors in a display influences target detection, even when a target is salient (Theeuwes, 2004). Perhaps the action effect is not strong enough to bias attention when a target's presence is uncertain or when there are numerous distractors in a display, which could be a reason that no action effect was found and, therefore, no effect on the LPE was found.

6.1.3 The LPE and Working Memory

The strongest evidence of a selection history effect on the LPE comes from Experiment 3, which examined the effect of holding an item in working memory. There was a reduction in the LPE when participants held the low-prevalence target in working memory. This indicates that attentional orienting changes merely by remembering an item, and that item can be presented auditorily rather than visually. Importantly, these results show that working memory plays a critical role in low-prevalence visual search.

In Experiment 3, even though the memory prompt was not predictive of the target, it may be argued that participants treated the prompt as predictive, producing the pattern of results that was found. For example, perhaps prompts were noticeable because they were presented on each trial, but the instructions at the beginning of the experiment telling participants that the prompts were not predictive of the target were less noticeable because they only occurred once. Although it is the case that congruent prompts aided search for both high- and low-prevalence targets in comparison to incongruent prompts, this difference was exacerbated for low-prevalence targets; even if participants treated the prompt as predictive, it benefited search for low-prevalence targets more than for high-prevalence targets. On the other hand, the very low error rates on incongruent trials (5%) suggests that participants did not treat the prompt as predictive; they found targets that differed from the prompt the vast majority of instances those incongruencies occurred. Further, although the prompts on each trial were more noticeable than the instructions at the beginning of the experiment, participants would frequently recognize that the prompt and target were not necessarily congruent because they consistently found the targets even when maintaining an inconsistent prompt in memory. For example, participants could hear “remember L” as the prompt, find a T in the search phase, and correctly identify that they were remembering the L when asked. These inconsistencies would not go unnoticed for the duration of the experiment. Further support comes from the fact that most prompts were inconsistent; there was no target presented on 50% of trials, and the prompt was incongruent with the target on 25% of trials. Therefore, only 25% of trials had a prompt that matched the target in the search phase. Thus, it would be impossible for participants to treat the prompt as predictive, despite its salience, while effectively completing the experiment.

The rationale behind manipulating selection history to reduce the LPE relies on priming rare targets or features for selection. Interestingly, prompting participants to remember a target is the most direct way (of the three methods examined) to prime a target for selection. This manipulation essentially inserts a target into working memory. In visual search, low-prevalence targets are not primed for selection as easily as high-prevalence targets; observers see high-prevalence targets with greater frequency and those items are therefore more available in working memory (e.g., Umemoto et al., 2010). Experiment 3 indicates that inserting an item in working memory via an auditory prompt can aid in identification of low-prevalence targets in a search task.

Further, Hout et al. (2015) assert that perceptual errors in low-prevalence search occur because high-prevalence targets have more robust mental representations than low-prevalence targets and that target templates and mental representations are enhanced each time a participant finds a target. These auditory prompts may prime mental representations of a target at the beginning of a search, thereby enhancing its representation in working memory and aiding search.

In the present manipulation, the maintenance of an item in working memory was meant to assist in identification of targets, and, as discussed previously, it is thought that priming rare targets or features for selection may help observers identify those targets. These two factors may be interrelated, or they may have independently influenced the results. Specifically, it may be the case that maintaining a low-prevalence target in working memory assists with identification of that target. Alternatively, it may be that the memory prompts served to prime targets on each trial and assist in identification of targets regardless of their prevalence. If this were the case, it may explain the overall low error rates in this experiment compared to Experiments 1 and 2. The condition with the highest error rate in Experiment 3 had an error rate of .14, whereas the highest error rate was .25 in Experiment 1 and .19 in Experiment 2. Regardless of the mechanism or selectivity on the low-prevalence targets, this working memory manipulation and ones like it may be effective in reducing the LPE. Future studies may attempt to distinguish between these two possible mechanisms.

In sum, these findings are theoretically informative because they tell us that at least one selection history effect can be used to reduce the LPE. These findings also show that working memory is involved in the LPE; holding an item in working memory facilitates the identification of low-prevalence targets. Implications for mechanisms that cause the LPE in addition to models that explain the LPE will be examined in the next section.

Practically, these findings are informative because they could be used in real-world low-prevalence searches to reduce the LPE. For example, if a baggage screener or radiologist were to hold a critical item in working memory, that may facilitate identification of rare but important targets. Of course, these findings are only an initial indication of the way working memory could be employed in low-prevalence search tasks. Further research would need to examine if holding multiple items in working memory facilitates low-prevalence search and if this method could be transferred to real-world scenarios in which targets vary greatly.

6.2 Implications

6.2.1 Mechanisms of the LPE

Of the multiple possible mechanisms for the LPE that have been proposed – motor errors, early search termination, perceptual errors, and criterion shifts – the present experiments help eliminate some possibilities.

It seems unlikely that motor errors are responsible for the LPE given that the effect occurred even when methodological changes were incorporated to reduce motor errors. In the present experiments, participants pressed the spacebar when they finished searching. Then, they selected an option of present or absent. Due to this two-part response, motor errors are quite unlikely. For example, even if participants found a target while carrying out a spacebar response to terminate search, they would be able to indicate that the target was present; a spacebar press did not lock a participant into a particular answer. Additionally, there was no prepotent “present” or “absent” response. Because targets were present 50% of the time, participants would not possess a motor bias to preferentially respond to one or the other. In experiments in which overall target prevalence is very low (e.g., 1%-10%), participants often develop a strong motor bias to respond “absent” since that is the correct motor response on most trials. Because the LPE was found in the present experiments despite the methodological considerations incorporated to reduce motor errors, these findings contribute additional evidence to previous research that has eliminated the possibility of motor errors as a sole cause of the LPE (e.g., Kunar et al., 2010; Kunar et al., 2017; Peltier & Becker, 2016; Russell & Kunar, 2012; Van Wert et al., 2009).

Additionally, early search termination seems unlikely to be the sole cause of the LPE. In experiments in which the overall target prevalence is low, participants exhibit reduced target-absent RTs, with target-absent responses sometimes faster than target-present responses (e.g., Wolfe et al., 2005). In the present experiments, overall target prevalence was 50%; thus, there was an equal probability that a target would be present or absent, so early termination of search did not occur; rather, target-absent responses were significantly slower than low- or high-prevalence target-present responses.

The present experiments provide some evidence that perceptual errors cause, at least in part, the LPE. Perceptual errors occur when observers see targets but fail to recognize them as targets (Horowitz, 2017), which may occur because of less robust mental representations of low-prevalence targets (Hout et al., 2015). The present experiments attempted to enhance the mental representations of features of such targets. This was done with success in the case of Experiment 3, where observers were told to remember a specific target while completing a search trial. Thus, it seems likely that perceptual errors account for some proportion of low-prevalence search misses because when mental representations were enhanced, misses decreased.

A final potential cause of the LPE is a criterion shift (Wolfe et al., 2007). Observers tend to shift their criterion and become more willing to respond “absent” during low-prevalence search, leading to increased miss rates for rare targets (Wolfe et al., 2005; Wolfe & Van Wert, 2010). It is possible that this mechanism remains at play in low-prevalence visual search. Although target presence was maintained at 50% in the present experiments, it has been suggested that each target has a criterion for detection (Godwin et al., 2010). If this is the case, participants could selectively shift the decision criterion for one target but not the other. This possibility will be examined further in the next section.

The present experiments focused on reducing perceptual errors rather than shifting observers’ criteria. Perhaps more effective ways of reducing the LPE may combine manipulations aimed at reducing perceptual errors, like the ones in the present experiments, with manipulations aimed at shifting observers’ criteria, such as incorporating high-prevalence blocks as a form of retraining (e.g., Wolfe et al., 2007, Exp. 7).

6.2.2 Implications for the Multiple Decision Model

The multiple decision model asserts that at any given moment in visual search (regardless of prevalence level), observers are faced with two decisions: determine whether the item that is currently being evaluated is a target and to continue or stop searching (Wolfe & Van Wert, 2010). This process continues until a target is found or until the quitting threshold is reached. In low-prevalence searches, the decision criterion shifts to be more conservative, and the quitting threshold is reduced (Wolfe & Van Wert, 2010).

As mentioned previously, the present experiments did not attempt to manipulate criterion, but attempts were made to ensure that the quitting threshold was not reached too quickly. Because overall target prevalence was 50%, participants were equally likely to be presented or not presented with a target. Thus, participants would not have a bias to quickly respond absent, as they would in search tasks in which overall prevalence is low. In support of this, target absent response times were slower than target-present response times in all of the present experiments.

Although it is possible that the quitting threshold was selectively reduced for low-prevalence targets, that does not seem to be the case due to the response time patterns for low-prevalence targets. Across the three experiments, response times were consistently slower for low-prevalence than high-prevalence trials, and target-absent trials were slower than each of those. This is consistent with previous research that has maintained overall target prevalence at 50% (e.g., Hout et al., 2015). It does not seem that a decreased quitting threshold explains the LPE when overall prevalence is maintained at 50%. Additionally, participants were actually slower to find the low-prevalence than high-prevalence items, indicating they spent longer on low-prevalence search displays.

The pattern of RTs in these experiments as well as others that maintain overall target prevalence at 50% (e.g., Hout et al., 2015) indicate that, in addition to higher miss rates for low-prevalence targets, the LPE may manifest as slower RTs for low-prevalence targets. This would indicate that low-prevalence search may be even more difficult than previously recognized; participants are slower to find low-prevalence items yet still miss them more frequently than high-prevalence items.

Although a possible explanation for the slower low-prevalence responses is that observers first search for the high-prevalence target and then search for the low-prevalence target if the high-prevalence target is not found, previous research examining eye-movement data indicates that this is not the case (Hout et al., 2015). Rather, it is likely that participants either simultaneously search for targets or rapidly switch back and forth between targets (Hout et al., 2015).

Another possible explanation for slower low-prevalence responses is that, as discussed previously, observers may hold an individual criterion for each target (Godwin et al., 2010). Godwin et al. describe how an individual criterion for each target would explain the pattern of RTs in which low-prevalence targets are detected more slowly than high-prevalence targets when overall target prevalence is maintained at 50%. They explain that a more conservative criterion would require more time for evidence accumulation in order to justify identification of low-prevalence targets compared to high-prevalence targets, thus making observers slower to respond "present" to low-prevalence targets than high-prevalence targets.

The results in the present experiments are consistent with the idea that each target may have an individual criterion under the MDM. This would explain both accuracy and RT results for low-prevalence targets. However, the present results are not consistent with the reduced quitting threshold in the MDM because participants exhibited the LPE even when they spent longer on target-absent trials.

6.2.3 The LPE and Selection History

The present experiments sought to inform our understanding of the influence of selection history on the LPE. As discussed previously, selection history effects occur when past selection episodes carry over into current trials, resulting in changes in attentional orienting (Awh et al., 2012). Because low-prevalence items are less frequently selected simply because they are presented less often, there may be less priming of those features and, therefore, more misses.

Additionally, frequent targets are more likely to be encoded into working memory (Umemoto et al., 2010). Because low-prevalence targets are, by definition, infrequent, they may not be as available in working memory as more common targets are. Indeed, it is known that items held in working memory are easier to find in visual search (Dowd & Mitroff, 2013).

The three manipulations used in the present experiments were meant to prime low-prevalence features for selection and, thus, make a target or feature more available in working memory. Herein may lie the reason that Experiment 3 was more effective than Experiments 1 and 2 in reducing the LPE: In Experiments 1 and 2, the goal was to make target features available in working memory by associating them with reward or action; however, this is an indirect way of making the features available in working memory. Experiment 3 was the most effective and, notably, the most direct way of making a target available in working memory.

Another important aspect to note is that in Experiments 1 and 2, reward and action were meant to enhance the features of color. In Experiment 3, participants were told to remember a specific target rather than a color. Again, this is a much more direct and complete way of making a target available in working memory.

Additionally, the similarities of the target colors to some of the distractors may have weakened the effects of color in Experiments 1 and 2. In the present experiments, there were shades of red and green that did not match the target colors, but were nonetheless variations in shade from those basic colors. Those distractors were used to avoid the possibility of pop-out in search by having one unique target color and many repeated distractor colors. Although the target color was unique and matched exactly the color of the primed colors, having distractors in different shades of the same color may have dissipated effects of color. Because these distractors appeared on each trial, even the target absent trials, participants may have put less importance on color, given that the presence of a green or red object was not unique to target-present trials.

6.2.4 Limitations for Reward and Action History

As mentioned previously, transferring effects like reward history and action history to the LPE is difficult for a number of reasons, including increased complexity of the search task in comparison to search tasks used in previous research. The lack of reward and action effects in Experiments 1 and 2 suggest that these selection history effects may only be influential in limited situations, such as the paradigms examined in past research, and they may not be present or apparent in paradigms that differ in substantial ways from those previously examined.

Despite this, it may be interesting to simplify the methods used in the present experiments to more closely parallel the paradigms in which reward history and action history effects have been found. Specifically, reward and action history could be used to prime targets rather than features. For example, if the exact targets (the Ts and Ls) could be made valuable rather than a color being made valuable, or an action could be made when a target letter is presented rather than when a colored circle is presented, these effects could possibly be made stronger. These methods would be more similar to typical reward history and action history paradigms because close perceptual matches of targets would be associated with reward or action. Therefore, they may be more effective ways of inserting targets rather than target features into working memory. In turn, this may enhance their representations, thereby reducing the LPE.

Unlike in Experiment 3, participants may have perceived the reward and action history experiments to have two separate tasks. In the reward history experiment, the tasks were separated into two phases of the experiment, and in the action history experiment, there was a unique action task and search task on each trial. This differs from Experiment 3 in that participants were only asked about the memory task on 20% of trials, and the memory task was clearly related to the search task; participants were asked to find Ts and Ls and remember Ts and Ls. This difference may have influenced the effect on low-prevalence search. For Experiments 1 and 2, participants may have seen the tasks as separate and attempted to complete them independently, whereas participants could have intentionally used the prompts to their advantage in Experiment 3. This may also help to explain why an effect was found in Experiment 3 but not in Experiments 1 and 2.

6.2.5 Implications for Selection History

These experiments explored the effect of a previously unexamined aspect of attentional allocation, selection history, on the LPE. The effects of goals and salience on the LPE are known (e.g., Beanland et al., 2014; Biggs et al., 2014, Peltier & Becker, 2017a), but no prior research had been done to explore the effect of selection history. The three selection history effects examined here have all been studied at more typical prevalence rates (Anderson et al., 2011b; Weidler & Abrams, 2014; Umemoto et al., 2010), but the current research extended these findings by examining these effects at low target prevalence.

Through examining each of these mechanisms and finding varied effects on the LPE, it is important to recognize the possibility that these selection history effects may stem from different mechanisms. Specifically, one of the mechanisms posited for reward history includes automatic processing via reward centers in the brain (Anderson, 2016). Meanwhile, event files and repetition priming have been explored as possible mechanisms underlying the action effect (Weidler & Abrams, 2014). Working memory is thought to enhance search because maintenance of a target allows easier access to and better representation of the target (Umemoto et al., 2010) and because when a target is maintained in working memory, irrelevant items consume less capacity (Vogel et al., 2005).

Although each of these effects has different mechanisms, each is related to selection history. Despite this commonality, it is not surprising that each of these effects, due to the varied mechanisms behind them, has different influences on the LPE. This provides yet another possible reason for why there was an effect in Experiment 3 but not in Experiments 1 or 2. Of course, other possibilities discussed previously may have contributed to the lack of effects in Experiments 1 and 2, but there are theoretical reasons that explain why some selection history effects may influence the LPE while others do not.

Kim and Anderson (2019) have parsed selection history into two distinct processes rather than a single mechanism. They assert that associative learning and instrumental conditioning are two independent components of selection history. In their experiments, they instructed participants to look away from various targets. In one experiment, successfully executing this eye movement for a certain target color was rewarded, and in a subsequent block, the valuable color associated with that target captured attention. In another experiment, the same stimuli were used, and no reward was involved. Here, participants more frequently looked away from one color compared to another, and in a subsequent block, they were slower to attend to that color. In these experiments, looking away from a target produced two opposite effects; thus, both value and oculomotor habits guided attention. These two effects indicate distinct components of selection history.

In addition to the two components suggested by Kim and Anderson (2019), Wolfe (2019) suggested third and fourth components, feature priming and knowledge of the world, in a review of selection history and attentional orienting. Feature priming occurs when a previously attended feature, like color, captures attention in a subsequent trial. Finally, knowledge of the world influences attention because we know some objects would not be found, or would be unlikely to be found, in some locations. For example, you would not look for your phone on the ceiling because it is physically impossible for it to be there, and you would not look for it in the fridge because it would be unlikely for it to be there.

The three present experiments relied on these four selection history mechanisms to various extents. Reward history would be most related to an associative learning mechanism because an association is created between value and a stimulus. Action history and availability of items in working memory would be related to feature priming. Action history primes features via the guidance of attention to a previously prioritized feature, and maintaining a feature or target in working memory makes the feature or target available and primes it for selection.

Despite the three present manipulations all being related to selection history, the results may have varied because the three effects are rooted in distinct selection history mechanisms. Perhaps only a subset of these four mechanisms is involved in the LPE. Further, the varied influences, and strengths of influences, of these effects on the LPE adds new evidence consistent with the assertion that distinct mechanisms underlie selection history.

It is worth pointing out that some researchers have questioned the characterization of selection history as being unique from other top-down influences on attention. Egeth (2018) argues that top-down influences are a wide category of effects that include selection history effects. He asserts that rather than including selection history as a third category affecting attentional allocation, top-down and bottom-up processes are sufficient; bottom-up processes should include all perceptual processes and top-down process should include all cognitive processes. Further, he explains that the division of processes could continue limitlessly and that dividing processes into top-down and bottom-up is a parsimonious way of explaining attentional allocation.

Theeuwes (2018; 2019) disagrees with Egeth (2018) and asserts that selection history differs from top-down goal-oriented processes because selection history effects are automatic in nature. In contrast, top-down effects are slow and effortful. Theeuwes argues that most effects are either related to salience and selection history and that top-down effects are the least frequent of the three. Regardless of the best fitting model of attentional allocation, it is clear that multiple effects guide attention, and the present results show the influence of these various effects, irrespective of the category to which they belong, on the LPE.

6.3 Limitations and Future Directions

There were a few limitations to the present study. Experiment 1 was originally intended to be run in the lab, but it had to be run online. In order to combat the increase in variability brought on by an online study, sample size was increased, but the strength of the effects, including the LPE, were reduced in this experiment. A similar situation was encountered in Experiment 3, but the setting factor was included in analyses and statistically significant results were still found.

Further, the effects of reward and action could be revisited with some modifications. Reward history would be interesting to revisit in a lab setting where greater control can be maintained. The results of Experiment 1 were in the expected direction, so perhaps reducing variability would produce statistically significant results. Additionally, the search targets themselves could be associated with reward in the training phase rather than only features of those targets, like color, being associated with reward. For action history, perhaps the action could be performed towards primes that match the potential targets; for example, one of the target letters could appear as the prime during the action task. It may also be worthwhile to reduce the number of items in the search display to more closely parallel previous conditions in which action and reward effects were found. Importantly, in order to expect a reduction in the LPE from any of these effects, the manipulations likely need to be stronger. It would be ideal to find an effect of reward in the training phase of a reward history experiment and necessary to find an action effect in an action history experiment.

In addition to reexamining these effects, further research could explore other selection history effects and how they influence the LPE. For example, Anderson and Kim (2019) and Wolfe (2019) have subdivided selection history into at least four categories. Only two of those four were explored here; thus, future experiments could examine instrumental conditioning and knowledge of the world. Indeed, knowledge of the world may be an extremely important selection history influence in real-world low-prevalence search. For example, a baggage screener may know that specific weapons may not appear in bags that are smaller than a certain size, and radiologists may know that certain cancers or lesions are more likely to be found in some areas than others.

Finally, the effect of holding an item in working memory on the LPE is theoretically informative and may be a promising avenue for future research. Theoretically, this informs an understanding of maintaining an item in working memory and its influence on the LPE. The present manipulation directly inserted a target into working memory rather than indirectly. Perhaps the most promising ways of influencing selection history is through manipulations that directly influence the contents of working memory. Importantly, the contents of working memory do not need to be predictive of the target. This means that observers could hold a low-prevalence target in working memory and simultaneously find another target or effectively end a search when a target is not present. Additionally, the present experiments inform knowledge regarding the multiple decision model of visual search and mechanisms that cause the LPE. A reduced quitting threshold is not necessary for the LPE to appear. Further, perceptual errors must be responsible for some errors underlying the LPE given that enhanced mental representations of targets helps reduce the LPE.

A practical extension of the Experiment 3 results would be to examine this effect in a variety of other real-world settings, including baggage screening. For example, if a baggage screener maintained the concept of weapon in working memory, perhaps that would increase the likelihood of finding low-prevalence weapons. These real-world applications are important areas for future investigation.

6.4 Conclusion

Across three experiments, there was varying support for selection history affecting the LPE. The strongest evidence came from Experiment 3, which examined the availability of a low-prevalence target in working memory. This is the first time the effect of selection history on the LPE has been examined. These results contribute to the current literature on the LPE by showing that, in addition to current goals and salience, selection history affects the LPE. Maintaining an item in working memory may help observers find low-prevalence targets with greater accuracy. Selection history effects and the LPE remain an area for future research, both for theoretical and practical reasons.

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