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# THE INFLUENCE OF CLUTTER ON TARGET PREVALENCE AND DECISION MAKING DURING VISUAL SEARCH

A Thesis

Submitted to the Graduate Faculty of the
Louisiana State University and
Agricultural and Mechanical College
in partial fulfillment of the
requirements for the degree of
Master of Arts

in

The Department of Psychology

by
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A.A., St. Louis Community College, 2016
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May 2022

## Table of Contents

## Abstract

Participants are sensitive to target prevalence effects in visual search. Low prevalence of targets leads to increased miss rates and shorter response times, and high prevalence of targets leads to increased false alarm rates and longer response times. These effects have been explained using the Multiple-Decision Model (MDM), in which two decisions impact performance during serial visual search. The first decision is whether an inspected item is a target. The second decision is whether the search should be ended with a target-absent response. Target prevalence influences these decisions, evidenced by changes in miss rate, false alarm rate, and response time. These decisions can likely be further affected by the number of target decisions that need to be made and the crowding present for each decision. Experiment 1 examined the effect of the number of target decisions to be made, by varying set size, on the target prevalence effect. Experiment 2 examined the effects of the number of decisions and crowding on the target prevalence effect by manipulating the amount of clutter in aeronautical search displays. Varying set size altered participants' quitting thresholds, and varying clutter altered participants' quitting thresholds and 2AFC decision-making starting points. In Experiment 1, the shift in participants' quitting thresholds in response to set size interacted with the target prevalence effect to alter participants' response times. In Experiment 2, the shift in quitting threshold and 2AFC decision-making starting point in response to clutter interacted with target prevalence to alter participants' response times and miss rates. These results suggest that the target prevalence effect can vary depending on the types of attention used. Additionally, this suggests that we can reasonably predict how participants will interact with a visual search display using the MDM model.

# Introduction

Visual search is a process used every day to find targets of interest among distracting items in various environments. The probability of items being found, and the complexity of environments being searched are important for visual search performance (Treisman & Gelade, 1980; Wolfe, Cave, & Franzel, 1989; Wolfe & Gray, 2007). For example, if a toothbrush is most often found in the bathroom and rarely in the kitchen, for a given instance when the toothbrush is present in both environments, you are more likely to be successful at finding the toothbrush in the bathroom and to miss finding it in the kitchen. In addition, searching for the toothbrush becomes more difficult if either environment is cluttered (i.e., there are many distracting items in the environment; Beck, Lohrenz & Trafton, 2010; Beck, Trenchard, van Lamsweerde, Goldstein, & Lohrenz, 2012; Rosenholtz, Li, Mansfield, & Jin, 2005; Rosenholtz, Li, & Nakano, 2007). The amount of clutter in an environment may impact decision processes during visual search that are also affected by target prevalence. Therefore, the amount of clutter in an environment could influence the effect of target prevalence on search performance.

Visual search often requires a serial process of attending to different aspects of the environment one after the other until the target is identified (Treisman & Gelade, 1980; Wolfe et al., 1989). A parallel process is used to determine the next best place to direct attention for the serial process of attending to and identifying an item as either a target or a distractor. Serial visual search occurs when a target is not salient enough to capture attention at the parallel processing stage. Response time increases as a function of the number of items that must be attended in a serial search before the target is attended and identified (Wolfe & Gray, 2007). Therefore, response time increases as a function of set size or clutter, where set size is the number of distracting items that are present in a display where these items are easily countable, and clutter is a way of quantifying the amount of distracting information in more complex scenes (Beck et al., 2010; Beck et al., 2012; Rosenholtz et al., 2005; Rosenholtz et al., 2007).

Performance on visual search tasks that require serial processing is impacted by participants' expectations and experiences with the task. For example, in a visual search that requires indicating if a target is present or absent in each search array, the frequency that a target is present across many trials, also known as target prevalence, impacts visual search performance (Wolfe et al., 2007; Wolfe, Horowitz, & Kenner, 2005). Low target prevalence leads to higher miss rates, and high target prevalence leads to higher false alarm rates and longer response times (Menneer, Donnelly, Godwin, & Cave, 2010; Wolfe et al., 2005; Wolfe et al., 2007). The influence of target prevalence can be explained by a decision-making model that accounts for a change in expectation based on previous experiences (Peltier & Becker, 2016; Wolfe & Van Wert, 2010). Our study aimed to determine if this decision-making model can also help explain how set size and clutter might influence the target prevalence effect. Due to the effect target prevalence has on serial search and the role of decision-making during search in this effect, a visual search task that varies the difficulty of serial search (i.e., small and large set sizes and low and high clutter) should further elucidate the role of decision-making in the target prevalence effect.

**Prevalence of Targets in Visual Search**

The prevalence of a target impacts visual search performance. In a typical target prevalence study, the probability of a target appearing on any given trial is manipulated. In low prevalence conditions, the target may appear on only 1-10 percent of trials (Peltier & Becker, 2016; Wolfe et al., 2005). In high prevalence conditions, the target may be present on up to 90 percent of trials or more (Peltier & Becker, 2016; Wolfe & Van Wert, 2010). Additionally, the prevalence effect has been found across many studies using different types of stimuli. Some studies have used baggage screening tasks to emulate real-world search (Ishibashi, Kita, & Wolfe, 2012; Wolfe et al., 2007; Wolfe et al., 2005; Wolfe & Van Wert, 2010), whereas other studies have used simplistic stimuli such as rotated Ts and offset Ls (Godwin et al., 2016; Peltier & Becker, 2016). The prevalence effects are similar with these varied stimuli, providing evidence for the robust influence the target prevalence effect has on participants across varied visual search tasks.

Typically, the target prevalence effect is categorized by three behavioral outcomes: a high miss rate at low target prevalence, a high false alarm rate at high target prevalence, and longer response times for high-prevalence target absent trials. When targets appear infrequently, they are often missed when they do appear, leading to high miss rates (Wolfe et al., 2007; Wolfe et al., 2005). When targets appear frequently, it is more likely that a participant will respond that a target is present on a trial with no target, leading to higher false alarms rates (Menneer et al., 2010; Peltier & Becker, 2016; Wolfe & Van Wert, 2010). Response times are mainly influenced by target prevalence in target-absent trials (Peltier & Becker, 2016; Wolfe & Van Wert, 2010). For example, when a target is not present in a high target prevalence trial, participants search longer before quitting, leading to longer response times than the low prevalence condition (Peltier & Becker, 2016; Wolfe & Van Wert, 2010). These results are evidence for target prevalence affecting visual search.

The effect target prevalence has on visual search performance is likely due to participants' sensitivity to targets on previous trials within a visual search task. Participants are sensitive to the prevalence effect over a large set of trials rather than a small subset of trials (Ishibashi et al., 2012). This sensitivity to target prevalence over time provides evidence for a shift in participants' expectations of whether a target will be present based on past experiences. Furthermore, high target prevalence trials have been inserted into an overall low target prevalence task to shift participants' expectations back to where they were before they encountered low target prevalence (Wolfe et al., 2007). This sensitivity to target prevalence is based on participants shifting their decision-making criteria in response to cumulative and recent experiences in the visual search task.

## Decision Making in Visual Search

Visual search decision-making models can help explain visual search performance. One model, called the Just Say No decision model, demonstrates how serial search for a target can result in preattentive processing of the probability that an item is a target (Chun & Wolfe, 1996). In this model, items on the display are selected for further inspection via the parallel processing stage. Each item is examined serially in decreasing order of the probability of the item being a target until a quitting threshold is reached. The quitting threshold is automatically set by the participant and is adaptive to allow for performance to be high while maintaining a desired level of speed (Chun & Wolfe, 1996). Therefore, this model predicts a speed/accuracy tradeoff. However, a speed/accuracy tradeoff cannot explain the slowed response times found with high target prevalence (Wolfe & Van Wert, 2010). When targets are expected to be absent, as in the low prevalence condition, response times are sped up. When targets are expected to be present, as in the high prevalence condition, response times are slowed down. Slowing down in response to high target prevalence indicates that participants are not always speeding up when they can predict the answer, which would be true if there was a speed/accuracy tradeoff (Wolfe & Van Wert, 2010). Therefore, a new decision-making model was required to accurately account for what is happening when participants make decisions based on their expectation towards whether a target is present.

The Multiple-Decision Model (MDM; Wolfe & Van Wert, 2010) is based on two decisions during serial search: deciding if the item being inspected is a target and deciding when to quit searching. The first decision of whether an item is a target is based on a two-alternative forced-choice (2AFC; Wolfe & Van Wert, 2010). If the item is a target, this results in a "yes" decision, while if not, a "no" decision is produced. Wolfe and Van Wert (2010) suggest that this 2AFC decision is modeled by signal detection theory. The second decision of the MDM involves deciding when to respond "no, a target is not present" based on a diffusion towards a quitting threshold, that once hit, results in trial termination. The MDM suggests that this quitting threshold can move up or down dependent on participants' expectations (Wolfe & Van Wert, 2010). This shift in the quitting threshold can explain the target prevalence results found previously. The quitting threshold moves down in response to low prevalence, resulting in faster response times, and moves up for high prevalence, resulting in longer response times. In the current study, we will use the MDM to understand the mechanisms involved with serial visual search and the influence target prevalence has on visual search performance.

Additional research to test the MDM suggests that the 2AFC decision is best represented as a drift-diffusion process (i.e., deciding based on a noisy accumulation of information towards a response with a variable starting point; see Figure 1) rather than by signal detection theory (Peltier & Becker, 2016). One study examined eye movements in a visual search task with varying target prevalence (10%, 50%, and 90%; Peltier & Becker, 2016). This study found that when targets were inspected during low prevalence trials, they were more likely to be misidentified, providing evidence for a shift in decision criteria based on prevalence (Peltier &

Becker, 2016). Furthermore, the authors found dwell times (the length of time spent looking at an item before shifting attention to another item) varied between target prevalence. For example, decreasing target prevalence resulted in longer target decisions (evidenced by longer dwell times on targets) and shorter distractor decisions (evidenced by shorter dwell times on distractors), suggesting that decision time varies based on the prevalence of targets. This finding supports a drift-diffusion account of the decision-making criterion shift proposed by the MDM, instead of a strictly 2AFC decision modeled by signal detection theory initially proposed by the MDM (Peltier & Becker, 2016; Wolfe & Van Wert, 2010). This drift-diffusion process of decision making, along with an adaptive quitting threshold of the MDM, can help to explain the findings of the target prevalence effect and provide a foundation for understanding how varying serial visual search might impact participants decision-making processes (Peltier & Becker, 2016; Wolfe & Van Wert, 2010).

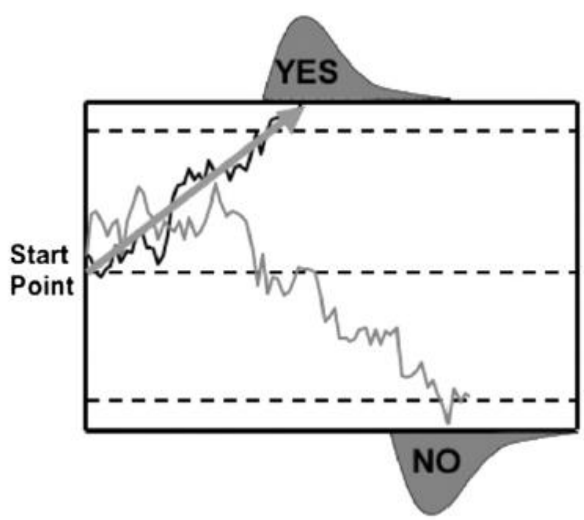


Figure 1. Drift Diffusion Model adaptation from Wolfe and Van Wert (2010) relating to a two-alternative forced choice (2AFC) task. Information begins accumulating from a starting point and can only generate one response (here it is “yes”) depending on which boundary is reached first. A shift in starting point reflects participants' willingness to respond, either moving up, resulting in quicker “yes” responses or moving down, resulting in quicker “no” responses.

Shifts within the MDM related to participants’ quitting thresholds and decision-making starting points have been used to explain target prevalence effects in the past (Peltier & Becker, 2016; Wolfe & Van Wert, 2010). In response to low target prevalence, the MDM prediction is that the 2AFC decision-making starting point shifts closer to the "no" decision, resulting in a quicker "no" decision and a longer "yes" decision for every item inspected (Peltier & Becker, 2016). Additionally, the quitting threshold moves down, such that less accumulation of information is needed to reach the threshold, in response to the probability that a target is not likely to be present on any given trial within a low target prevalence condition (Peltier & Becker, 2016; Wolfe & Van Wert, 2010). These shifts for participants’ decision-making starting points and quitting thresholds result in the high miss rate and quick response times found with low target prevalence. When the decision-making starting point and quitting threshold shift in response to low target prevalence, participants quit search sooner and expect a target to be absent, resulting in quicker "no" distractor decisions, even if a target is present on a trial (Peltier & Becker, 2016; Wolfe et al., 2007; Wolfe et al., 2005).

According to the MDM, high target prevalence leads to a 2AFC decision-making starting point that is shifted closer to the "yes" decision and a quitting threshold that is shifted upward. These shifts result in shorter "yes" target decisions and longer "no" distractor decisions and decrease the likelihood that a participant will quit searching before finding a target. Based on this, it is expected that participants will exhibit longer response times in response to high target prevalence, as they are making longer distractor ("no") decisions and are less likely to give up (Peltier & Becker, 2016). Additionally, the high false alarm rate can be attributed to the 2AFC decision-making starting point shifting closer to the "yes" decision, as it is easier for participants to make a "yes" response, even in response to a distractor, resulting in a false alarm (Peltier &

Becker, 2016). Additional support for these predictions is found with further analysis from eye-tracking data, where it can be seen when participants misidentify either a target or distractor (Peltier & Becker, 2016).

Examining the types of miss trials has provided additional information about how participants' decision-making starting point and quitting thresholds are influenced by target prevalence. Identification errors (i.e., a target has been fixated but reported as absent) make up fewer of the misses at both high and low prevalence than selection errors (i.e., when a target is never fixated and reported as absent; Peltier & Becker, 2016). Identification errors can provide a measure of the decision-making starting point, as they indicate that an incorrect 2AFC decision has been made. In contrast, selection errors are a measure of the quitting threshold, as participants quit before identifying the target. Identification errors are highest in response to low prevalence, suggesting the decision starting point shifts closer to the "no" response, such that it is easier to misidentify a target as a distractor (Peltier & Becker, 2016). Selection errors are also highest for low prevalence. The quitting threshold is lowered in response to low target prevalence, leading to quicker trial termination. However, the quitting threshold is heightened for high target prevalence, indicating that participants search longer before responding target-absent (Peltier & Becker, 2016). The MDM's ability to flexibly respond to participants' expectations and experiences allows it to predict how participants will shift their decision-making starting points and quitting thresholds to perform various visual search tasks (i.e., varying set size, clutter, and target prevalence).

## Clutter in Visual Search

The MDM has not yet been used to explore the impact image clutter has on visual search performance even though clutter varies the difficulty of visual search and likely influences the decision-making starting point and quitting thresholds of participants. As clutter increases in a display, visual search performance is affected negatively (Beck et al., 2010; Beck et al., 2012). This negative effect on visual search performance is due to the amount of variable visual information within the display leading to increased perceptual difficulty when identifying a target (Lohrenz, Trafton, Beck, & Gendron, 2009; Rosenholtz et al., 2005; Rosenholtz et al., 2007). The variable visual information within a display refers to the set size, or the number of searchable items in a display, and other aspects of the scene that lead to increased perceptual difficulty, such as color and luminance contrast along with the shape and line orientation of items within the display (Lohrenz et al., 2009; Rosenholtz et al., 2005; Rosenholtz et al., 2007). While in traditional visual search tasks where arrays of distinct, non-overlapping objects are used and easy to count (set size), clutter is generally applied to complex and real-world images where the number of distracting elements in the search array is harder to quantify.

Clutter helps quantify set size in complex images and other elements that add perceptual difficulty, like color and luminance contrast, that make it more difficult to search a display as clutter increases (Rosenholtz et al., 2005). The feature congestion theory suggests that clutter can be thought of as congestion of an image, in that it would be hard to add a new salient item onto the image if it is highly cluttered or "congested" (Rosenholtz et al., 2005). A different model called the color-clustering clutter model (C3 model) suggests that clutter is based on an interaction between global saliency and color density (Lohrenz et al., 2009). The C3 model compares pixel clusters within an image to measure clutter based on the color density and saliency between these pixel clusters. When there is low color density and high saliency, this results in a high clutter measure for an image. In contrast, high color density and low saliency result in a low clutter measure for an image (Lohrenz et al., 2009). Both the feature congestion and C3 model clutter measures had relatively similar and high success rates when correlated with subjective ratings of clutter (Lohrenz et al., 2009; Rosenholtz et al., 2005). Based on these clutter accounts, we proceed with the notion that high clutter occurs when multiple items are presented on a display and that large degrees of variation between items lead to increased perceptual difficulty as these factors increase. Additionally, we will use the Feature Congestion model to measure clutter levels in our study, as this model and the C3 model accurately accounted for clutter levels within images in the past (Lohrenz et al., 2009; Rosenholtz et al., 2005).

Clutter impacts the number of target decisions that need to be made during visual search (attention for recognition) and the amount of crowding present for each decision (attention against competition; Beck et al., 2010; Reddy & VanRullen, 2007). Attention for recognition refers to the shifting of attention from item to item that is necessary to recognize targets and distractors in a display. Attention for recognition is needed more as the number of items to shift attention between increases, as it does with a larger set size and higher levels of clutter (Beck et al., 2010; Reddy & VanRullen, 2007). Attention against competition refers to the need to inhibit information surrounding an item to prevent interference with identifying a target. Attention against competition is needed more as the clutter surrounding the item to be identified increases (Beck et al., 2010; Reddy & VanRullen, 2007). The effects of clutter on these different needs for attention can help us understand how clutter might influence participants' 2AFC decision-making starting points and quitting thresholds to impact visual search performance.

Based on what is known about clutter and how the MDM has a variable decision-making starting point and quitting threshold, we can predict how clutter and set size will influence participants. Clutter and set size will likely impact the quitting threshold because they both impact the number of items to be attended (attention for recognition). Clutter, but not necessarily set size, should impact the 2AFC decision-making starting point because of the added perceptual difficulty in identifying elements of a cluttered display (attention against competition). Specifically, in response to high clutter or large set size, the quitting threshold should move up, with the opposite being true for low clutter and a small set size. In response to more items/information being displayed, participants will need to search longer to identify if a target is present. Additionally, the 2AFC decision-making starting point should lower towards the "no, not a target" decision boundary for clutter but should not be affected by set size. Lowering towards this "no, not a target" boundary is due to clutter adding perceptual difficulty to the display and crowding around items. Thus, the 2AFC decision-making starting point should lower towards the "no, not a target" boundary further for high clutter than low clutter, due to high clutter adding more information and perceptual difficulty to the display compared to low clutter. Participants should be making longer target decisions due to this perceptual difficulty and crowding that increases as clutter increases. However, the 2AFC decision-making starting point for set size should remain relatively unaffected due to needing no attention against competition, allowing participants to make an easier decision compared to clutter, as each item is easily dissociable and identifiable.

Based on the MDM’s predictions and previous research on target prevalence, the MDM can help predict how set size and clutter will influence the target prevalence effect. Low target prevalence has been shown to move the 2AFC decision-making starting point closer to the "no" decision boundary and lower the quitting threshold (Peltier & Becker, 2016; Wolfe & Van Wert, 2010). To expand on this knowledge, we examined if manipulating the amount of information to search through (attention for recognition) influences the target prevalence effect. To test this, we varied set size in Experiment 1 and clutter in Experiment 2 to measure how the number of items to search through in a display influences the target prevalence effect. Further, clutter also impacts the perceptual difficulty of identifying an item as a target (attention against competition). By comparing the effects of set size and clutter on the target prevalence effect, we can begin to isolate the effects of attention against competition versus attention for recognition. Therefore, we tested how clutter in real-world map images (Lohrenz et al., 2009) influences the target prevalence effect in Experiment 2. Because a large set size and high clutter increase the number of items and information in the display presented and high clutter increases perceptual difficulty (Rosenholtz et al., 2005; Rosenholtz et al., 2007), we predicted that both set size and clutter should influence the quitting threshold effect of target prevalence, but only clutter should impact the 2AFC decision-making starting point effect of target prevalence.

# Experiment 1

Experiment 1 examined how set size affects the target prevalence effect within the MDM framework. Set size has previously been examined with the prevalence effect, specifically with simplistic stimuli, such as Ts and Ls (Cheng & Rich, 2018; Peltier & Becker, 2016). However, this has mainly been used to find other effects, such as when misses increase after detecting one target when multiple targets are present on a given trial (subsequent search misses; Cheng & Rich, 2018). Studies with varied set sizes also examined different aspects of the prevalence effect, such as how single and dual-target search is affected by prevalence (Cheng & Rich, 2018). Additionally, target prevalence studies that have varied set size did not include very large set sizes that may be needed to test the effects we are interested in here (i.e., set size typically being set to around 25 in higher cases; Fleck, Samei & Mitroff, 2010; Peltier & Becker, 2016). Thus, we manipulated set size to determine how the target prevalence effect in single target serial visual search is impacted by the presence of a high number of distractors versus a low number of distractors. We hypothesized that set size would influence the target prevalence effect. We further hypothesized that set size would mainly affect participants' quitting thresholds to interact with the target prevalence effect. Only affecting participants' quitting thresholds is due to a change in set size altering the amount of information to search through (attention for recognition) but not the perceptual difficulty in deciding whether an item is a target or not (attention against competition).

## 2AFC Decision Making Starting Point

Set size is not likely to alter the 2AFC decision-making starting point due to the items on the display being spaced out and easily discernable. Therefore, the 2AFC decision-making starting point is likely to be altered only by target prevalence. The dependent variables used to measure the decision-making starting point are the false alarm and miss rates. Previously low target prevalence has increased the miss rate by lowering participants' 2AFC decision-making starting point closer to the "no, not a target" boundary (Peltier & Becker, 2016). Set size should not alter the target prevalence effect in this case, such that low target prevalence will still increase the miss rate for participants. As for the false alarm rate, high target prevalence should increase the false alarm rate based on participants' 2AFC decision-making starting points rising towards the "yes, item is a target" boundary (Peltier & Becker, 2016). Again, set size should not interact with this target prevalence effect due to not altering participants' 2AFC decision-making starting point.

**Quitting Threshold**

Set size is likely to influence the quitting threshold for participants. Participants will make more attention shifts with more items to search through, raising the quitting threshold and searching longer. Searching longer should lead to longer response times in the large set size condition. Previously low target prevalence has lowered the quitting threshold of participants, leading to shorter response times on target absent trials compared to high target prevalence (Peltier & Becker, 2016; Wolfe & Van Wert, 2010). Set size should alter this effect for low target prevalence, making participants have shorter response times with a small set size and longer response times with a large set size on target absent trials. In response to a small set size, participants' quitting threshold should be lower, leading to these shorter response times. The quitting threshold should rise with a large set size, making participants search longer in response to more items on the screen. Previously high target prevalence has heightened the quitting threshold of participants, leading to longer response times on target absent trials compared to low target prevalence (Peltier & Becker, 2016; Wolfe & Van Wert, 2010). Set size should alter this effect, making participants have shorter response times with a small set size and longer response times with a large set size on target absent trials. By set size influencing the quitting thresholds of participants, this should alter how strongly the target prevalence effect can alter participants quitting thresholds. This influencing of quitting thresholds by both set size and target prevalence could lead to them interacting to alter the response times of individuals. This interaction would be due to a small set size lowering the quitting threshold making the difference between prevalence conditions for response times with a small set size smaller than the difference for a large set size across prevalence conditions. This interaction would provide evidence that set size does influence the target prevalence effect by altering participants quitting thresholds, making participants at times act in contrast to how the target prevalence effect influences the quitting threshold within the MDM (i.e., small set size lowers the quitting threshold, while high target prevalence raises it).

## Methods

### Participants

One hundred seventy-five participants (*M* = 20.49, *SD* = 2.29, 139 women) were recruited from undergraduate Psychology classes at Louisiana State University. All participants received course credit for participating and had normal or corrected-to-normal vision. Data from 21 participants were excluded overall. Fourteen participants' data were excluded for having over a quarter of their trials resulting in responses within 200ms. Three participants' data were excluded for having accuracy three standard deviations away from their group mean. Two participants' data were excluded for being collected after all participants were gathered to fill the required number of participants needed and were excluded solely for being the most recent participants. One participant's data was excluded for participating in the study twice by mistake (only the second time was excluded from analysis). Another participant's data was excluded for only ever responding with "target absent." After exclusion, there were 154 participants included in the data analysis, with 77 participants in each group (*M* = 20.55, *SD* = 2.28, 123 women). The number of participants needed was determined by estimating a small to moderate effect size ($\eta_p^2$ = 0.08) for the interaction between target prevalence and set size. Based on achieving this level of power, g*Power suggested we needed 154 participants to achieve a power of 0.95 (alpha = 0.05), with 77 participants in each group.

**Design**

This study employed a 2 x 2 mixed design with the prevalence of targets (low vs. high) as a between-subjects variable and set size (small vs. large) as a within-subjects variable.

**Stimuli and Apparatus**

Experiment 1 used stimuli similar to previous prevalence effect research (Cheng & Rich, 2018; Godwin et al., 2016; Peltier & Becker, 2016). The search arrays contained rotated Ts and rotated offset Ls (Ts and Ls could be rotated left, right, right-side up, or upside-down) for the targets and distractors, respectively. The arrays were made using python code that randomly placed one T (26x26 pixels) and the remaining number of Ls (26x26 pixels) within an 8x8 grid for a large set size. For the small set size, items were placed using the inner 4x4 grid within the 8x8 grid to place the 10 items for a small set size. Placing the Ts and Ls within the smaller 4x4 grid allowed the visual angle to be the same, keeping the spacing and items' size the same between the small and large set size conditions (see Figure 2). The placement of each stimulus could be anywhere within the chosen square from the grid, which jittered the placement of each stimulus to reduce any order in the display. The study was run online using the program lab.js to program the study (Henninger, Shevchenko, Mertens, Kieslich, & Hilbig, 2019) and OpenLab

(Shevchenko, n.d.) to host the experiment and store participant data. The set sizes used were small, with 10 items on the screen and large, with 40 items on the screen (see Figure 2).

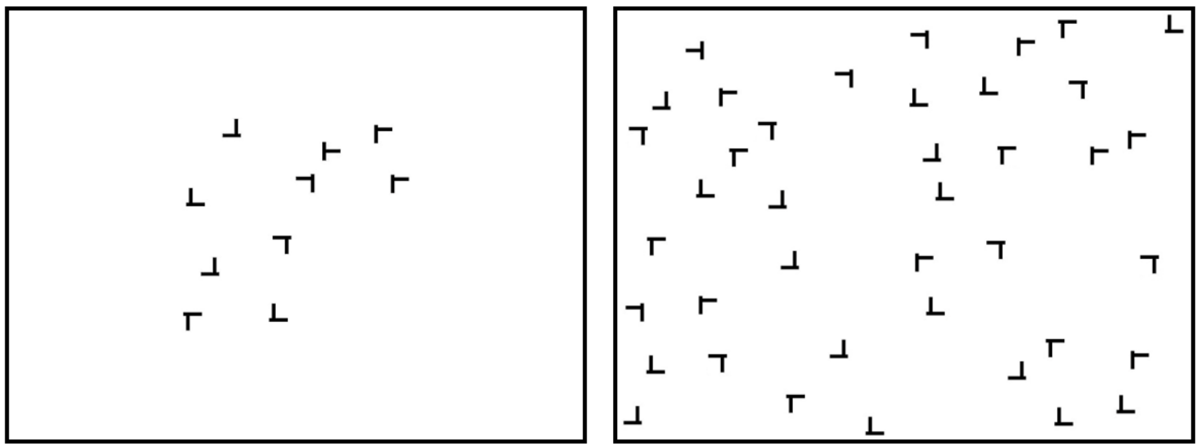

Figure 2. Image depicting a sample display with a set size of 10 items on the left and a sample display with a set size of 40 on the right. The target, a rotated T, is in the top middle amongst offset L's in the small set size image. The target, a rotated T, is in the top left amongst offset L's in the large set size condition.

**Procedure**

Participants performed 260 trials. The first 60 trials were used to ensure that participants adjusted to the prevalence effect (either high or low), as previous research has found that it takes around 48 trials to elicit the effect (Ishibashi et al., 2012). The last 200 trials were used to examine the effects of prevalence and set size on visual search. Half of the trials were a small set size (10 items), and half were a large set size (40 items), with predetermined arrays that would be randomly selected before each trial. For the low prevalence condition, a target was present on 10% of the trials, while the high prevalence condition had a target present on 90% of the trials. Twenty trials out of the 200 trials had a target present for the low prevalence condition, and 180 out of 200 trials had a target present for the high prevalence condition. Additionally, the target-absent and target-present trials were divided in half for the small and large set size conditions to ensure both set size conditions were presented equally for both prevalence conditions. To ensure that participants were exposed to these trials evenly across the experiment, there were five blocks of 40 trials with the target-present trials evenly divided amongst them. For the low prevalence condition, this meant that within the five blocks, each block had four target-present trials. For the high prevalence condition, each block had 36 target-present trials. There was only ever one target present on any given trial. If a target was present, the participants responded by pressing the "s" key with their left index finger, and if a target was absent, they responded by pressing the "k" key with their right index finger. This response/key mapping was counterbalanced across participants. Participants had one minute to respond to whether a target was absent or present. If participants did not respond within one minute, the trial was counted as a timeout.

## Results

### Overall Accuracy and Timeouts

The overall accuracy was 79.57% (*SD* = 14.49%) for the high prevalence condition and 93.92% (*SD* = 9.98) for the low prevalence condition. No participants were removed from analysis for having an excess of timeouts. Across all trials from the 154 participants included in the analysis, 27 trials resulted in a timeout, with 16 of those trials coming from participants in the low prevalence condition.

### Miss Rate

The miss rate analysis only included target present trials and was examined in a 2 (target prevalence: low & high) x 2 (set size: small & large) mixed ANOVA. There was a significant main effect of set size, $F(1, 152) = 181.72$, $p < .001$, $\eta_p^2 = .55$, due to a higher miss rate on target present trials for the large set size condition (*M* = 44.68%, *SD* = 25.32%) than for the small set size (*M* = 26.20%, *SD* = 24.08%). There was also a main effect of target prevalence, $F(1, 152) = 76.1$, $p < .001$, $\eta_p^2 = .33$, due to a higher miss rate on target present trials for low prevalence (*M*

= 48.08%, *SD* = 26.30%) than for high prevalence (*M* = 21.91%, *SD* = 19.24%). There was no significant interaction, $F(1, 152) = 0.05$, $p = .829$, $\eta_p^2 = .00$ (see Figure 3).

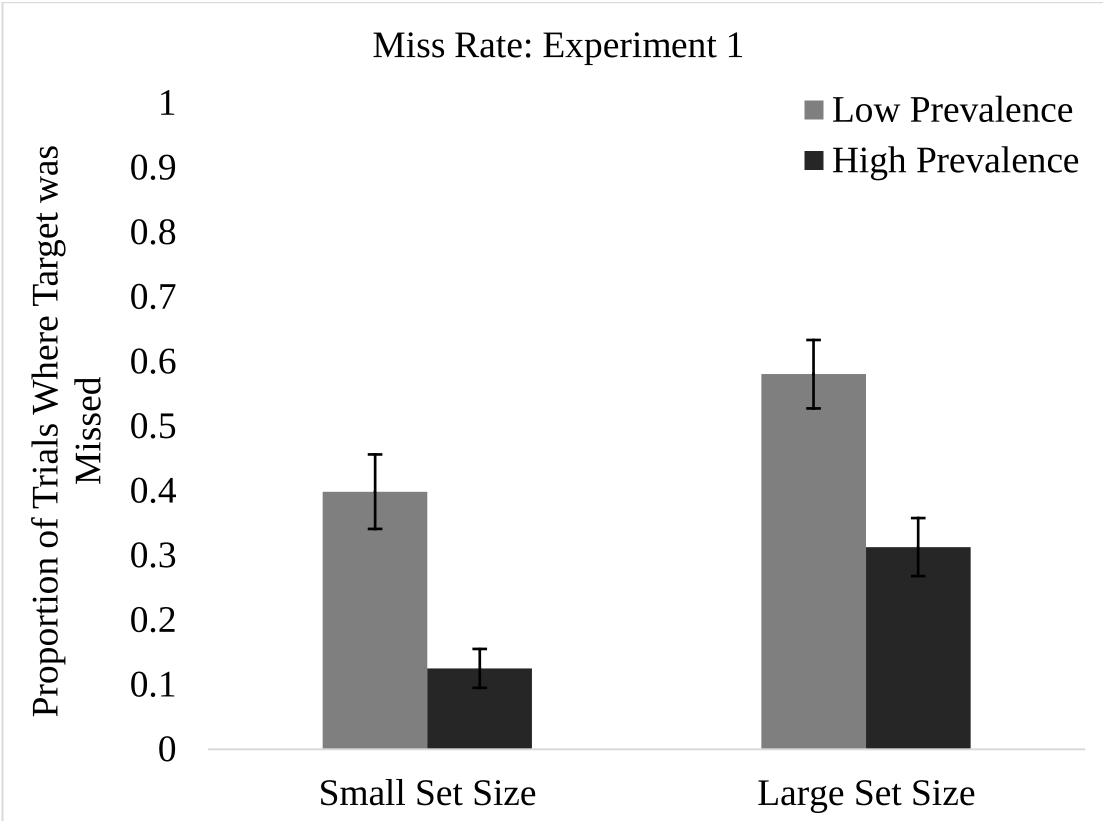


Figure 3. Miss rate for target present trials in Experiment 1. Error bars represent 95% confidence intervals.

**False Alarm Rate**

The false alarm rate analysis only included target absent trials and was examined in a 2 (target prevalence: low & high) x 2 (set size: small & large) mixed ANOVA. There was a significant main effect of set size, $F(1, 152) = 7.15$, $p = .008$, $\eta_p^2 = .05$, due to a higher false alarm rate on target absent trials for the large set size (*M* = 4.83%, *SD* = 13.01%) than for the small set size condition (*M* = 2.73%, *SD* = 7.70%). There was also a main effect of target prevalence, $F(1, 152) = 12.3$, $p < .001$, $\eta_p^2 = .08$, due to a higher false alarm rate on target absent trials for high prevalence (*M* = 6.36%, *SD* = 14.23%) than for low prevalence (*M* = 0.99%, *SD* =

3.37%). Additionally, there was no significant interaction, $F(1, 152) = 3.89$, $p = .0502$, $\eta_p^2 = .03$ (see Figure 4).

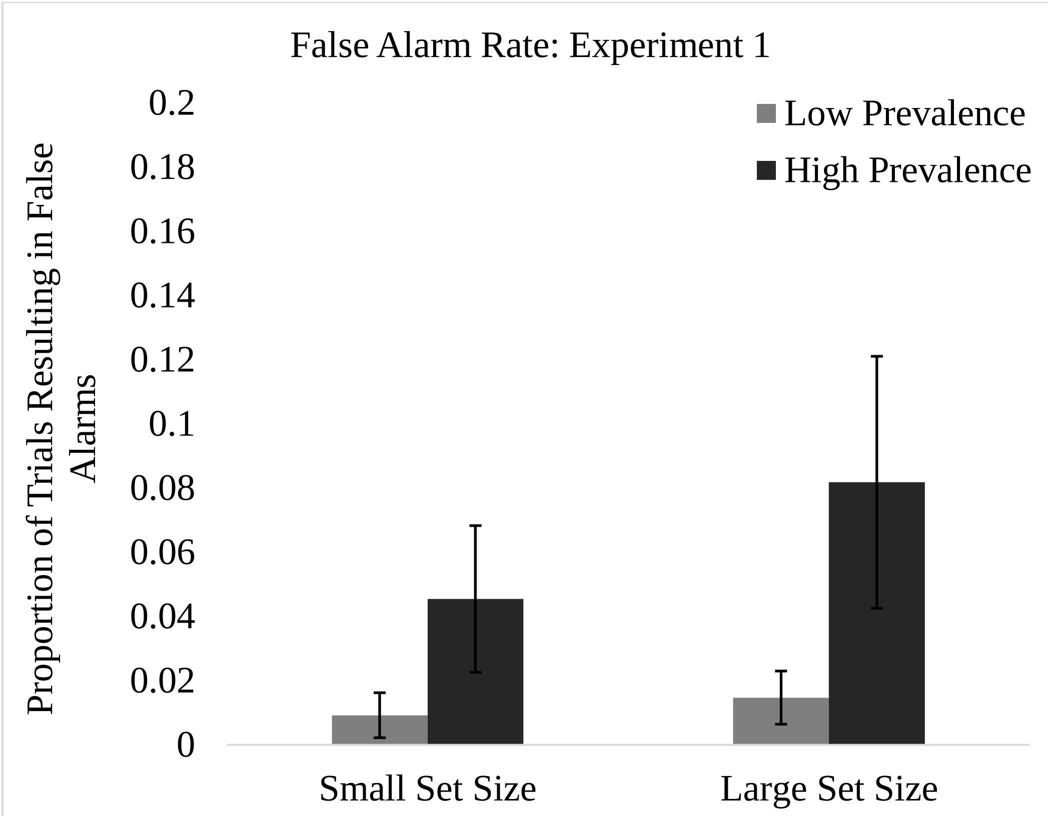


Figure 4. False alarm rate (identifying a target when there is none) for target absent trials in Experiment 1. Error bars represent 95% confidence intervals.

**Response Time**

For response time, only correct trials were included in the analysis, as past research has done (Peltier & Becker, 2016). We examined response time in a 2 (target prevalence: low & high) x 2 (set size: small & large) x 2 (target presence: present & absent) mixed ANOVA. We observed significant main effects of target prevalence, $F(1, 152) = 13.7$, $p < .001$, $\eta_p^2 = .08$, set size, $F(1, 152) = 408.2$, $p < .001$, $\eta_p^2 = .73$, and target presence, $F(1, 152) = 132.1$, $p < .001$, $\eta_p^2 = .47$. We also observed a significant two-way interaction between set size and target prevalence, $F(1, 152) = 14.2$, $p < .001$, $\eta_p^2 = .09$, between target presence and target prevalence, $F(1, 152) =$

52.2, $p < .001$, $\eta_p^2 = .26$, and between set size and target presence, $F(1, 152) = 58.6$, $p < .001$, $\eta_p^2 = .28$. We also observed a significant three-way interaction between set size, target presence and target prevalence, $F(1, 152) = 12.2$, $p < .001$, $\eta_p^2 = .07$.

A 2 x 2 mixed ANOVA was ran to compare set sizes between prevalence conditions on target absent trials. We observed significant main effects of set size $F(1, 152) = 308.6$, $p < .001$, $\eta_p^2 = .67$, and target prevalence $F(1, 152) = 28.9$, $p < .001$, $\eta_p^2 = .16$, and a significant interaction between set size and target prevalence $F(1, 152) = 18.1$, $p < .001$, $\eta_p^2 = .11$. To follow up on this significant interaction, pairwise comparisons were performed. For the high prevalence condition, target absent trials with a large set size ($M$ = 12,175.68ms, $SD$ = 6,759.68ms) had significantly longer response times compared to small set size trials ($M$ = 4,523.89ms, $SD$ = 1,723.18ms), $t(76) = 12.34$, $p < .001$, $d = 1.41$, 95% CI [1.09, 1.72]. For the low prevalence condition, large set size trials ($M$ = 7,702.71ms, $SD$ = 4,033.73ms) had significantly longer response times than small set size trials ($M$ = 3,031.99ms, $SD$ = 1,242.78ms), $t(76) = 14.23$, $p < .001$, $d = 1.62$, 95% CI [1.28, 1.96]. For a small set size, the high prevalence group ($M$ = 4,523.89ms, $SD$ = 1,723.18ms) had significantly longer response times compared to the low prevalence group ($M$ = 3,031.99ms, $SD$ = 1,254.19ms), $t(152) = 6.14$, $p < .001$, $d = 0.99$, 95% CI [0.64, 1.34]. For a large set size, the high prevalence group ($M$ = 12,175.68ms, $SD$ = 6,759.68ms) had significantly longer response times than the low prevalence group ($M$ = 7,702.71ms, $SD$ = 4,019.96ms), $t(152) = 4.99$, $p < .001$, $d = 0.80$, 95% CI [0.46, 1.14] (see Figure 5).

A 2 x 2 mixed ANOVA was ran to compare set sizes between prevalence conditions on target present trials. We observed a significant main effect of set size, $F(1, 148) = 342.73$, $p < .001$, $\eta_p^2 = .70$, but not of target prevalence, $F(1, 148) = 2.81$, $p = .096$, $\eta_p^2 = .02$, nor a significant interaction between set size and target prevalence, $F(1, 148) = 1.56$, $p = .214$, $\eta_p^2 = .01$.

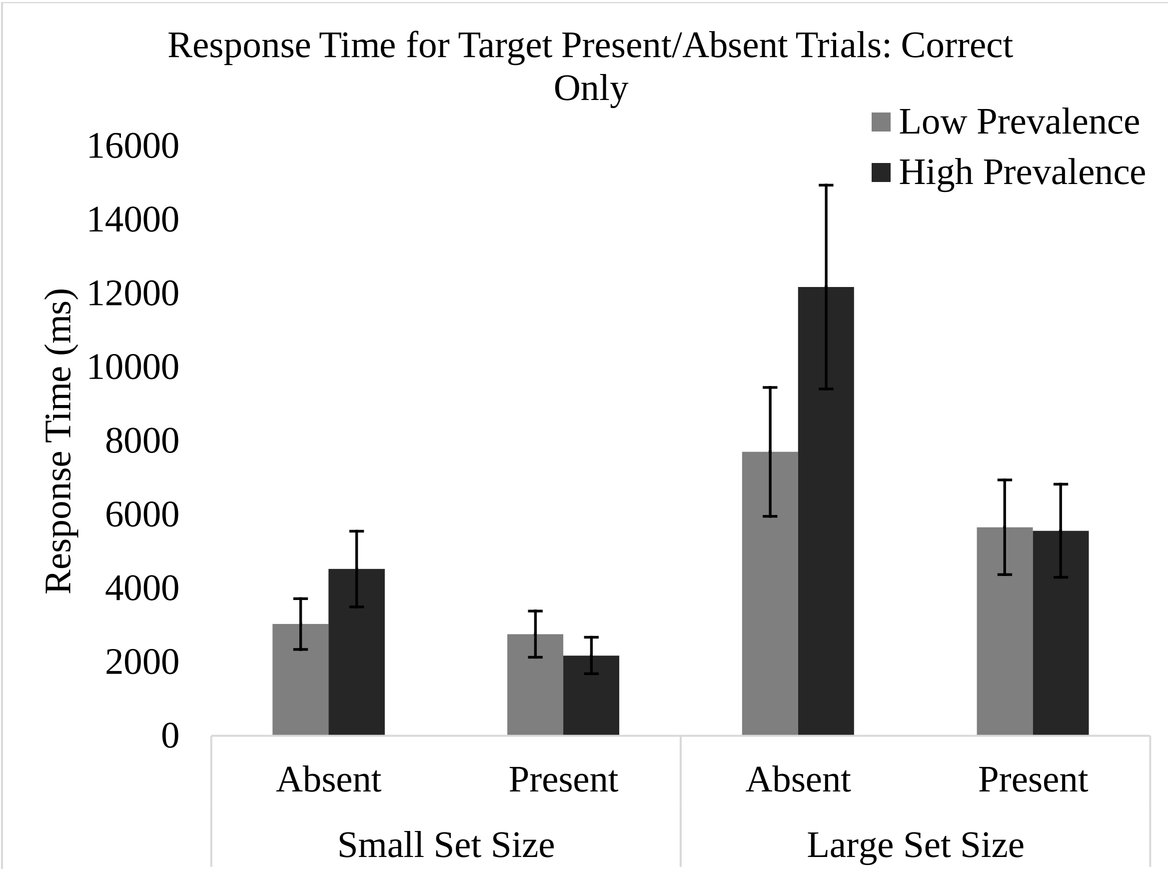


Figure 5. Response time results on target present and absent trials based on the set size (small: 10 items vs. large: 40 items) and prevalence of targets (low: 10% of trials vs. high: 90% of trials). Error bars represent 95% confidence intervals.

**Discussion**

Experiment 1 demonstrated that the target prevalence effect is affected by set size, influencing participants within the MDM framework. Specifically, set size altered participants' quitting thresholds to influence the target prevalence effect. In past research, low target prevalence resulted in shorter response times on target absent trials by lowering participants' quitting thresholds compared to high target prevalence, where the reverse was found (Peltier & Becker, 2016; Wolfe & Van Wert, 2010). We replicated the target prevalence effect in

Experiment 1 for response times. In response to low target prevalence, participants had shorter response times on target absent trials than high target prevalence. For the response time analysis, the difference between prevalence conditions with a small set size had a larger effect size than for a large set size. A larger effect size for the small set size condition between prevalence conditions suggests a small set size influenced the target prevalence effect more than a large set size. This larger effect size would suggest that a small set size lowered the quitting threshold further than low target prevalence does alone, leading to a larger target prevalence effect than for a large set size. This smaller effect size for a large set size further suggests that in response to a large set size, participants were searching longer, leading to longer response times but greater variability in how long participants would search. The increased variability with a large set size could be due to participants searching longer but at times giving up early based on the increase in items on the display, making search more difficult.

Further evidence that participants varied in how they responded to set size is the increased miss rate for a large set size. Even though participants searched longer, evidenced by the increased response times for a large set size, they were still likely to give up before finding the target in response to more items on the screen. Therefore, in response to set size, participants are updating their quitting thresholds, and this effect is more consistent and stronger at interacting with the target prevalence effect in response to a small set size. A small set size led to participants lowering their quitting thresholds, evidenced by shorter response times and a larger effect size than a large set size. Set size’s ability to alter the target prevalence effect was only evident for response time. Thus, set size likely only influenced participants’ quitting thresholds and not their 2AFC decision-making starting points, as we predicted.

When looking at the miss rate analysis, it seems unlikely that set size influenced participants' 2AFC decision-making starting points. In previous research, low target prevalence influenced participants' 2AFC decision-making starting points to lower them towards the "no, not a target" boundary, increasing the miss rate compared to high target prevalence, where the reverse was found (Peltier & Becker, 2016). We replicated the target prevalence effect for the miss rate, where participants had a higher miss rate in response to low target prevalence. Set size did not interact with the target prevalence effect for the miss rate, keeping the results in line with previous research (Peltier & Becker, 2016; Wolfe et al., 2005; Wolfe & Van Wert, 2010). In response to a large set size, participants searched longer but had an increased miss rate. Searching longer but having an increased miss rate was likely due to needing to search through more items on the display rather than a shift in the 2AFC decision-making starting point. Participants were unlikely to find the target before giving up search due to searching through more items, even in response to an increased quitting threshold. This increased miss rate for a large set size did not interact with the target prevalence effect. No interaction between set size and target prevalence speaks to set size's inability to shift the decision-making starting point for participants enough to alter target prevalence.

Our false alarm rate analysis results further suggest that set size did not alter participants' 2AFC decision-making starting point. In previous research, high target prevalence influenced participants' 2AFC decision-making starting points to shift upward towards the "yes, item is a target" boundary, increasing the false alarm rate compared to low target prevalence, where the reverse was found (Peltier & Becker, 2016). We replicated the target prevalence effect for the false alarm rate, where participants had a higher false alarm rate in response to high target prevalence. Set size did not interact with the target prevalence effect for the false alarm rate, even though it was trending toward significance. However, based on this being only for the false alarm rate and likely being due to a floor effect in response to low target prevalence, this suggests that set size did not influence the 2AFC decision-making starting point. The trend toward significance for the interaction between set size and target prevalence likely speaks to the ability set size has to influence the quitting threshold rather than the 2AFC decision-making starting point. High target prevalence increases the 2AFC decision-making starting point towards the "yes, item is a target" boundary, and a large set size could increase the false alarm rate by having participants search longer, making it more likely they make a potential mistake. Further evidence to suggest there was no change in the 2AFC decision-making starting point is that our results fell in line with previous prevalence research (Peltier & Becker, 2016; Wolfe et al., 2005; Wolfe & Van Wert, 2010).

Using the MDM, we predicted that set size would influence participants' quitting thresholds based on changes in the amount of information present on the screen (attention for recognition). Set size did alter participants' quitting thresholds, and this led to a small set size increasing the target prevalence effect in some cases by lowering the quitting threshold for participants. Even though a small set size led to a larger effect size, a large set size did seem to alter participants quitting thresholds as well, raising them compared to a small set size. A large set size led to longer response times and an increased miss and false alarm rate compared to a small set size. However, it could be expected that participants might have a lower miss rate in response to a heightened quitting threshold, but this was not observed. Not having a lower miss rate speaks to how strong the prevalence effect is at shifting the decision-making starting point for participants. In response to low target prevalence, participants searched longer in response to a large set size but still assumed a target was not present, leading to a lower 2AFC decision-making starting point shifted towards the "no, not a target" boundary and more misses. Overall, set size worked to influence the miss rate and false alarm rate of participants but did not interact with the target prevalence effect for these measures, suggesting that set size mainly influences the quitting thresholds of participants by increasing the attention for recognition needed as the number of items on the screen increases. Therefore, clutter, which is more complex than set size alone, should require both attention for recognition and attention against competition and might influence participants' decision-making starting points and quitting thresholds further than set size to further interact with the target prevalence effect.

# Experiment 2

Experiment 2 examined how clutter affects the target prevalence effect within the MDM framework. Clutter not only influences the number of items to be inspected (attention for recognition) as set size does but also impacts the perceptual difficulty of identifying items (attention against competition; Lohrenz et al., 2009; Rosenholtz et al., 2005; Rosenholtz et al., 2007). This perceptual difficulty created by adding details to an image (i.e., curved lines, color, etc.) can increase search difficulty (Lohrenz et al., 2009; Rosenholtz et al., 2005; Rosenholtz et al., 2007). Therefore, we predicted the 2AFC decision-making starting point should be shifted by clutter due to an increase in information presented on the screen. Thus, changes in clutter should impact the 2AFC decision-making starting point influencing both the false alarm rate and miss rate because each decision becomes more difficult as clutter increases. Additionally, as with set size in Experiment 1, based on the information on the screen increasing as clutter increases, the quitting threshold should also be influenced by clutter.

**2AFC Decision Making Starting Point**

Clutter should influence participants' 2AFC decision-making starting point due to clutter adding perceptual difficulty due to increased variations in features, such as color and luminance contrast (Lohrenz et al., 2009; Rosenholtz et al., 2005; Rosenholtz et al., 2007). This added perceptual difficulty will make each 2AFC decision participants make more challenging as there is competing information that interferes with their ability to identify a target (attention against competition). The 2AFC decision-making starting point should lower as clutter increases based on this increased perceptual difficulty as clutter increases. The dependent variables used to measure the decision-making starting point are the false alarm and miss rates.

In response to low clutter, where the 2AFC decision-making starting point should not lower as much as high clutter, the target prevalence effect should be weaker, leading to a smaller difference between low and high target prevalence for low clutter. In previous research, low target prevalence lowered the 2AFC decision-making starting point towards the "no, not a target" boundary, increasing the miss rate and lowering the false alarm rate, with the opposite being found for high target prevalence (Peltier & Becker, 2016). Low clutter should decrease this target prevalence effect due to the 2AFC decision-making starting point lowering towards the "no, not a target" boundary. This shift down for the 2AFC decision-making starting point towards the "no, not a target" boundary for participants should make the miss rate between high and low target prevalence more similar. This increased similarity would be due to an increased miss rate for high target prevalence based on this shift downward in the 2AFC decision-making starting point for low clutter. Additionally, the false alarm rate should be similar between prevalence conditions for low clutter based on a lowered 2AFC decision-making starting point, making the high target prevalence condition less likely to have an increased false alarm rate. Weakening the target prevalence effect should lead to an interaction between target prevalence and clutter for the false alarm and miss rates, where low clutter should decrease the target prevalence effect, and high clutter should increase it.

In response to high clutter, where the 2AFC decision-making starting point should lower more than low clutter, the target prevalence effect should be stronger, leading to a larger difference between low and high target prevalence for high clutter. In previous research, low target prevalence lowered the 2AFC decision-making starting point towards the "no, not a target" boundary, increasing the miss rate and lowering the false alarm rate, with the opposite being found for high target prevalence (Peltier & Becker, 2016). High clutter should increase this target prevalence effect due to the 2AFC decision-making starting point lowering towards the “no, not a target” boundary further than with low clutter. This shift further down for the 2AFC decision-making starting point towards the “no, not a target” boundary for participants should make the difference in miss rate between high and low target prevalence more pronounced. This difference would be due to an increased miss rate for low target prevalence based on this shift downward in the 2AFC decision-making starting point for both high clutter and low target prevalence, leading to the largest miss rate with this condition. Additionally, the false alarm rate should be different between prevalence conditions for high clutter based on a lowered 2AFC decision-making starting point, making the low target prevalence condition likely to have a decreased false alarm rate. Strengthening the target prevalence effect should lead to an interaction between target prevalence and clutter for the false alarm and miss rates, where high clutter should increase the target prevalence effect, and low clutter should decrease it.

**Quitting Threshold**

Clutter should influence participants’ quitting thresholds due to clutter increasing the information to search through as clutter increases (Lohrenz et al., 2009; Rosenholtz et al., 2005; Rosenholtz et al., 2007). This added information will make participants make more attention shifts to recognize the target (attention for recognition). Therefore, the quitting threshold should rise as clutter increases based on this increase in information as clutter increases. The dependent variable used to measure the quitting threshold is response time.

In response to low clutter, where the quitting threshold should lower in response to less information being in the search array, the target prevalence effect should be weaker, leading to a smaller difference between low and high target prevalence for low clutter. In previous research, low target prevalence lowered the quitting threshold, leading to shorter response times, with the opposite being found for high target prevalence (Peltier & Becker, 2016; Wolfe & Van Wert, 2010). Low clutter should decrease this target prevalence effect due to the lowering of the quitting threshold. This shift down for the quitting threshold for participants should make the response times between high and low target prevalence more similar. This increased similarity would be due to a shortened response time for high target prevalence due to the shift downward for the quitting threshold in response to low clutter. Weakening the target prevalence effect should lead to an interaction between target prevalence and clutter for response time, where low clutter should decrease the target prevalence effect, and high clutter should increase it.

In response to high clutter, where the quitting threshold should rise in response to more information in the search array, the target prevalence effect should be stronger, leading to a larger difference between low and high target prevalence for high clutter. In previous research, low target prevalence lowered the quitting threshold, leading to shorter response times, with the opposite being found for high target prevalence (Peltier & Becker, 2016; Wolfe & Van Wert, 2010). High clutter should increase this target prevalence effect due to the quitting threshold rising. This rise in quitting threshold for participants should make the difference in response times between low and high target prevalence more pronounced. This difference would be due to longer response times for high target prevalence based on a raised quitting threshold from both high clutter and high target prevalence, leading to the longest response times with this condition. Strengthening the target prevalence effect should lead to an interaction between target prevalence and clutter for response time, where high clutter would increase the target prevalence effect, and low clutter should decrease it.

## Methods

### Participants

One hundred seventy-eight participants (*M* = 20.71, *SD* = 4.09, 128 women) were recruited from undergraduate Psychology classes at Louisiana State University. All participants received course credit for participating and had normal or corrected-to-normal vision. Data from 24 participants were excluded overall. Fourteen participants' data were excluded for having over a quarter of their trials with responses within 200ms. One participant's data was excluded for only ever responding with target absent. One participant's data was excluded for having an average response time below 200ms. Eight participants' data were excluded for being collected after all participants were gathered to fill the required number of participants needed and were excluded solely for being the most recent participants. This left 154 participants included in the data analysis, with 77 participants in the high prevalence group and 77 participants in the low prevalence group (*M* = 20.75, *SD* = 4.25, 112 women). The number of participants needed was determined by estimating a small to moderate effect size ($\eta_p^2$ = 0.08) for the interaction between prevalence and clutter. Based on achieving this level of power, g*Power suggested we needed 154 participants to achieve a power of 0.95 (alpha = 0.05), with 77 participants in each group.

### Design

This study employed a 2 x 2 mixed design with the prevalence of targets (low vs. high) being a between-subjects variable and level of clutter (low vs. high) being a within-subjects variable.

### Stimuli and Apparatus

This study used map stimuli from Beck et al. (2012) and created new maps. For target-present trials, a single bump elevation marker was added to the maps as the target (see Figure 6), with 25% of targets placed in each quadrant for both low and high clutter conditions. Additional map stimuli were used to have enough to cover the necessary number of trials. These additional map stimuli were found online and cropped to match stimuli used from Beck et al. The clutter ratings of each additional map stimuli were calculated from the Feature Congestion model of clutter and placed into either high or low clutter based on the ratings obtained with ratings lower than 11 being low clutter and higher than 11 being high clutter (Rosenholtz et al., 2005). Based on having 220 trials with 60 trials used to set up the prevalence effect, we needed 80 images for both low (see Figure 7) and high (see Figure 8) clutter conditions. Having this many map images allowed each map to be used once for all 160 trials. We also used 60 different map stimuli for the practice trials to ensure no overlap between the maps used for the practice trials and those used for analysis. The study was run online using the program lab.js to program the study (Henninger et al., 2019) and OpenLab (Shevchenko, n.d.) to host the experiment and store participant data.


Figure 6. Example of target for clutter condition. The target is always a single bump elevation marker placed on the image.

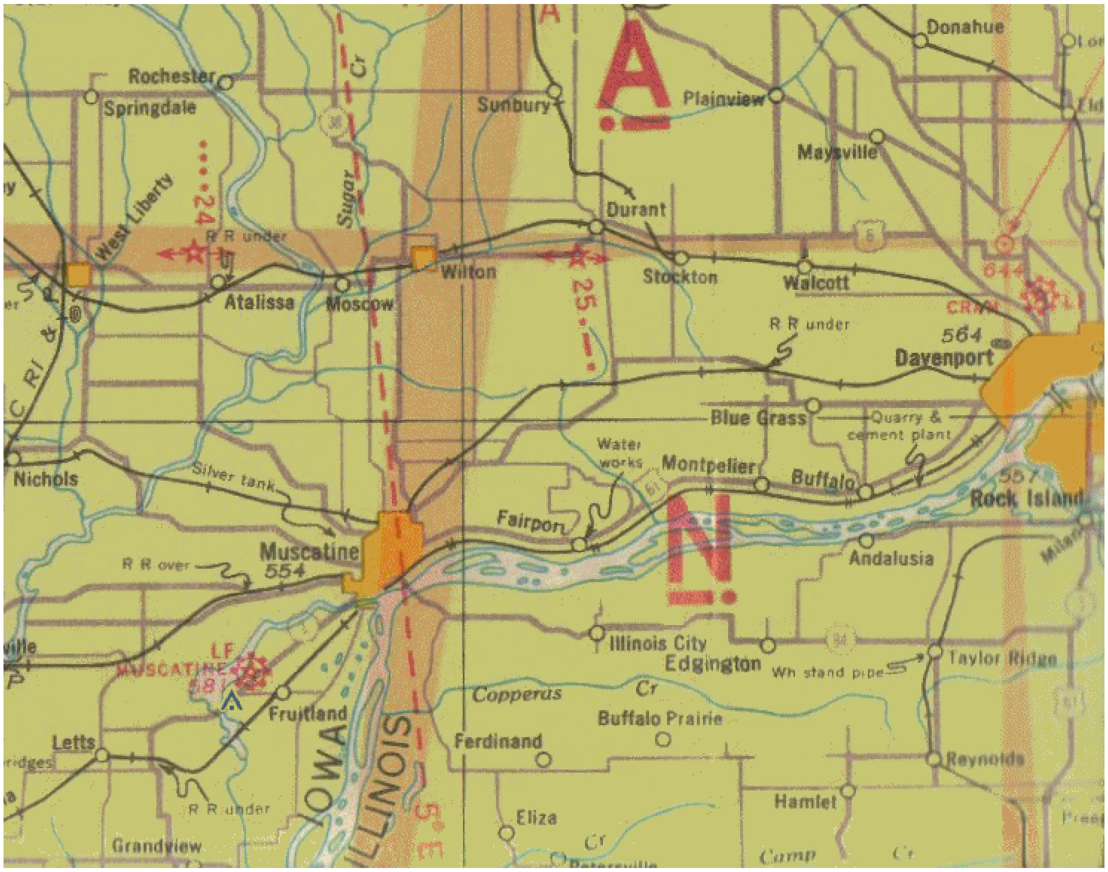


Figure 7. Example image for low clutter condition. The target, a single bump elevation marker can be seen in the bottom left corner.


Figure 8. Example image for high clutter condition. The target, a single bump elevation marker can be seen in the bottom right corner.

***Creating new maps*.** For the creation of new maps, the overall RGB values of each map previously used in Beck et al. (2012) were calculated as well as the RGB values of the marker placed on the map. We calculated these values because Beck et al. used the CIE de2000 color difference formula to ensure that targets were different enough from the background to be noticeable but not so salient as to grab attention immediately through the parallel process used in visual search. Once the RGB values of the background and target were calculated, a difference score was obtained for each image and then averaged to get one value for each RGB value. The map stimuli gathered online were then averaged for their RGB values, and the RGB values gathered from the difference scores of the previous stimuli were used to change the color of the new target placed on the new map stimuli. By using these calculated RGB values this ensured that the RGB values of the targets, like in Beck et al., were different enough from the background to be noticeable but not so salient as to capture attention through early visual search processes. Additionally, we used python to code randomly place the target in one of the four quadrants of the new maps an equal number of times across images, and then targets were adjusted by hand on the maps to ensure they were not obstructed by background information.

**Procedure**

The procedure for Experiment 2 closely followed that of Experiment 1. Participants performed 220 trials within a predetermined target prevalence (either high or low). Having this many trials allowed us to use 160 trials to examine the effect clutter has on target prevalence during visual search, while the initial 60 trials were used as a practice block to set up the prevalence effect. On each trial, an image with either a low or high level of clutter was presented. The order of the maps was randomized. For low prevalence, a target was present on 10% of trials, while high prevalence had a target present on 90% of trials. This meant that 16 trials had a target present out of the 160 trials for the low prevalence condition, while the high prevalence condition had 144 trials with a target present. To ensure that participants were exposed to these trials evenly overall, there were four blocks of 40 trials with the target-present trials evenly divided amongst them. For the low prevalence trials, this meant that within the four blocks, each block had four target-present trials, and for the high prevalence trials, each block had 36 target-present trials within them. Additionally, there was only ever one target present on any given trial. If a target was present, the participant responded by pressing the “s” key, whereas if a target was absent, they responded by pressing the “k” key. This key mapping was counterbalanced across participants.

Participants had 3 minutes to respond whether a target was absent or present. This length of time ensured that participants did not feel rushed to respond, leading to an increased error rate. Past research had an elevated rate of timeouts when the length of time was set to 1 minute (Beck et al., 2012), but the target was always present, meaning that by adding target-absent trials, we require a longer timeout. Thus, a rate of time longer than 1 minute should ensure that time is less of a factor in influencing participants. If participants do not respond within the three minutes, the trial will be counted as a timeout.

# Results

## Overall Accuracy and Timeouts

The overall accuracy was 60.73% (*SD* = 17.53%) for the high prevalence condition and 84.68% (*SD* = 16.89%) for the low prevalence condition. No participants were removed from analysis for having an excess of timeouts. Of the 154 participants included in the analysis, seven trials resulted in a timeout, with five of those trials coming from participants in the high prevalence condition.

## Miss Rate

The miss rate analysis only included target present trials and was examined in a 2 (target prevalence: low & high) x 2 (clutter: low & high) mixed ANOVA. There was a significant main effect of clutter, $F(1, 152) = 331.93$, $p < .001$, $\eta_p^2 = .69$ and target prevalence, $F(1, 152) = 24.91$, $p < .001$, $\eta_p^2 = .14$. There was a significant interaction, $F(1, 152) = 25.19$, $p < .001$, $\eta_p^2 = .14$. Following up these significant main effects and interaction independent samples t-tests were run for the between subjects' condition of target prevalence and paired samples t-tests were run for the within subjects' condition of clutter. Independent samples t-tests revealed that between the high and low prevalence conditions, miss rate was not significantly different for the low clutter condition, with the high prevalence condition (*M* = 28.34%, *SD* = 18.02%) having no difference in miss rate compared to the low prevalence condition (*M* = 33.44, *SD* = 16.90%), $t(152) = 1.81$, $p = .072$, $d = 0.29$, 95% CI [-0.61, 0.03]. For high clutter, the high prevalence condition (*M* = 50.83%, *SD* = 20.27%) had a significantly smaller miss rate than the low prevalence condition (*M* = 73.05%, *SD* = 24.08%), $t(152) = 6.19$, $p < .001$, $d = 1.00$, 95% CI [0.64, 1.35]. Paired samples t-tests revealed that clutter within the high prevalence condition was significantly different, with low clutter (*M* = 28.34%, *SD* = 18.02%) having a significantly smaller miss rate than high clutter (*M* = 50.83%, *SD* = 20.27%), $t(77) = 12.65$, $p < .001$, $d = 1.44$, 95% CI [1.12, 1.76]. For low prevalence, again a significant difference was found, such that low clutter (*M* = 33.44%, *SD* = 16.90%) had a significantly smaller miss rate than high clutter (*M* = 73.05%, *SD* = 24.08%), $t(77) = 13.62$, $p < .001$, $d = 1.55$, 95% CI [1.22, 1.88] (see Figure 9).

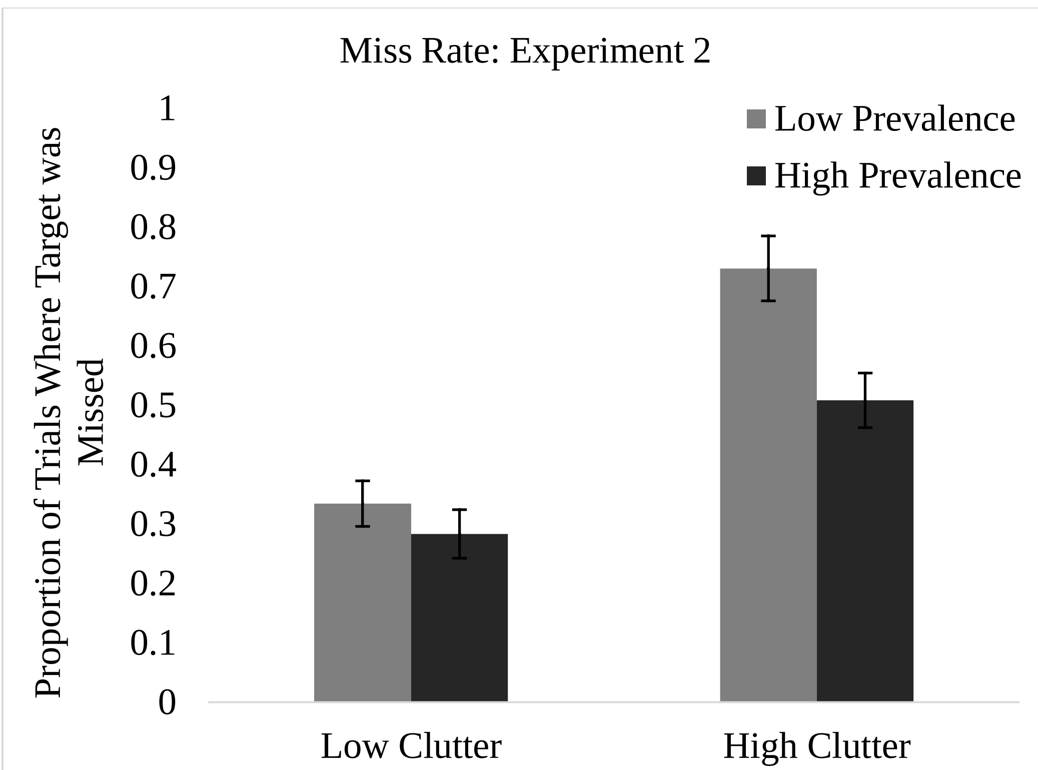


Figure 9. Miss rate for target present trials in Experiment 2. Error bars represent 95% confidence intervals.

**False Alarm Rate**

The false alarm rate analysis only included target absent trials was examined in a 2 (target prevalence: low & high) x 2 (clutter: low & high) mixed ANOVA. There was a significant main effect of clutter, $F(1, 152) = 7.363$, $p = .007$, $\eta_p^2 = .05$, due to a higher false alarm rate for high clutter ($M = 12.05\%$, $SD = 20.53\%$) than for low clutter ($M = 9.92\%$, $SD = 20.84\%$). There was no significant main effect of target prevalence, $F(1, 152) = 0.034$, $p = .854$, $\eta_p^2 = .0002$. Additionally, there was no significant interaction, $F(1, 152) = 0.0004$, $p = .984$, $\eta_p^2 = .00$ (see Figure 10).

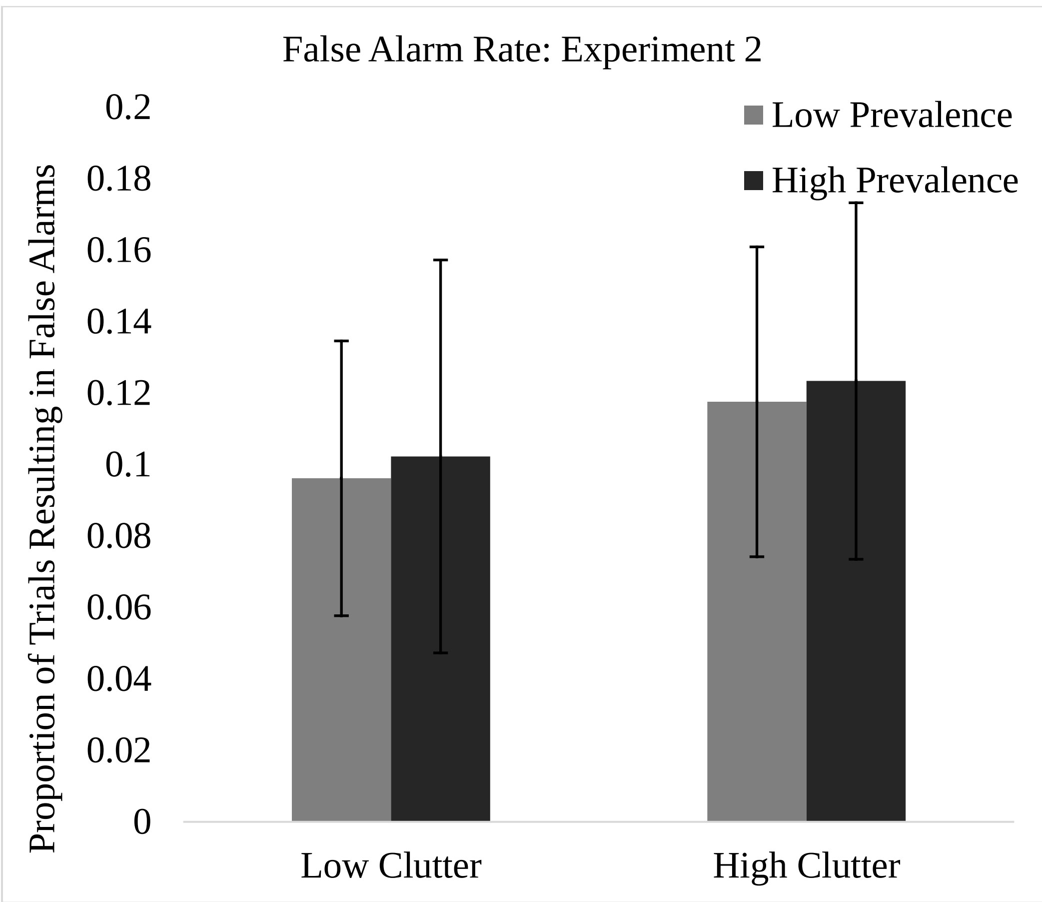


Figure 10. False alarm rate for target absent trials in Experiment 2. Error bars represent 95% confidence intervals.

**Response Time**

For response time, only correct trials were included in the analysis, as past research has done (Peltier & Becker, 2016). We examined response time in a 2 (target prevalence: low & high) x 2 (clutter: low & high) x 2 (target presence: present & absent) mixed ANOVA. We observed a significant main effect of clutter, $F(1, 131) = 28.61$, $p < .001$, $\eta_p^2 = .18$, due to a longer response time for high clutter ($M$ = 14,459.82ms, $SD$ = 16,035.18ms) than low clutter ($M$ = 12,806.93ms, $SD$ = 11,234.16ms). There was a significant main effect of target presence, $F(1, 131) = 82.39$, $p < .001$, $\eta_p^2 = .39$, due to longer response times for target absent trials ($M$ = 13,638.81ms, $SD$ = 13,861.87ms) than target present trials ($M$ = 5,941.99ms, $SD$ = 5,296.67ms). Additionally, there was a significant main effect of target prevalence, $F(1, 131) = 6.89$, $p = .0097$, $\eta_p^2 = .05$, due to longer response times for high prevalence ($M$ = 17,366.26ms, $SD$ = 17,120.37ms) than low prevalence on target absent trials ($M$ = 10,008.19ms, $SD$ = 8,258.44ms). We also did not observe a significant two-way interaction between clutter and target prevalence, $F(1, 131) = 3.89$, $p = .051$, $\eta_p^2 = .03$, but we did observe a significant interaction between target presence and target prevalence, $F(1, 131) = 8.58$, $p = .004$, $\eta_p^2 = .06$. We also observed a significant two-way interaction between clutter and target presence, $F(1, 131) = 4.12$, $p = .044$, $\eta_p^2 = .03$. We did not observe a significant three-way interaction between clutter, target prevalence and target presence, $F(1, 131) = 1.45$, $p = .231$, $\eta_p^2 = .01$ (see Figure 11).

To look at how clutter affected the target prevalence effect, we ran a 2 x 2 ANOVA with target prevalence and clutter for target absent trials. Running this analysis for target absent trials is based on finding a significant difference for target presence and because target absent trials are directly relevant for the target prevalence effect. We observed a significant main effect of target prevalence, $F(1, 149) = 12.95$, $p < .001$, $\eta_p^2 = .08$ and clutter, $F(1, 149) = 9.05$, $p = .003$, $\eta_p^2 =$

.06. We also observed a significant interaction between target prevalence and clutter, $F(1, 149) = 6.72$, $p = .01$, $\eta_p^2 = .04$. We followed this up with paired samples t-tests to examine the differences within the prevalence conditions. For high prevalence, low clutter had significantly faster response times (*M* = 15,859.74ms, *SD* = 13,373.35ms) than high clutter (*M* = 19,226.34ms, *SD* = 20,218.61ms), $t(73) = 2.92$, $p = .0046$, $d = 0.34$, 95% CI [0.10, 0.57]. For low prevalence, low clutter response times (*M* = 9,882.67ms, *SD* = 7,721.77ms) did not significantly differ from high clutter response times (*M* = 10,133.70ms, *SD* = 8,811.55ms), $t(76) = 0.62$, $p = .539$, $d = .07$, 95% CI [0.15, 0.29]. Independent samples t-tests were run to test for differences between prevalence conditions. For low clutter, low prevalence trials (*M* = 9,882.67ms, *SD* = 7,721.77ms) had significantly faster response times than high prevalence (*M* = 15,849.74ms, *SD* = 13,373.35ms), $t(149) = 3.37$, $p < .001$, $d = 0.55$, 95% CI [0.22, 0.88]. For high clutter, low prevalence trials (*M* = 10,133.70ms, *SD* = 8,811.55ms) had significantly faster response times compared to high prevalence trials (*M* = 18,842.87ms, *SD* = 20,093.53ms), $t(151) = 3.48$, $p < .001$, $d = 0.56$, 95% CI [0.23, 0.89] (see Figure 11).

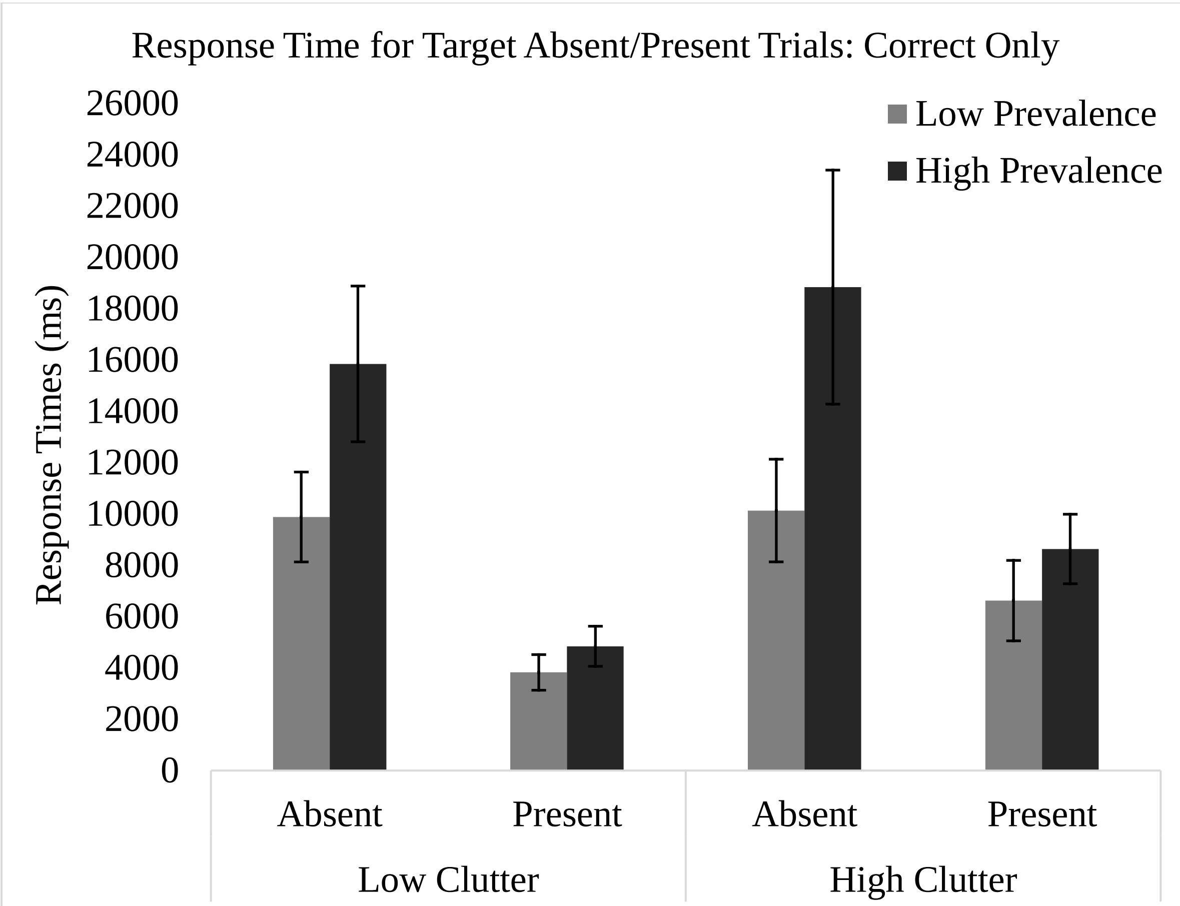


Figure 11. Response time on target present and absent trials based on the prevalence of targets (low: 10% of trials vs. high: 90% of trials) and clutter (low vs. high). Error bars represent 95% confidence intervals.

**Discussion**

Experiment 2 demonstrated that the target prevalence effect is affected by clutter, influencing participants within the MDM framework. Specifically, clutter altered participants' 2AFC decision-making starting points and quitting thresholds to influence the target prevalence effect. In past research, low target prevalence resulted in a higher miss rate, false alarm rate and shorter response times on target absent trials by lowering participants' 2AFC decision-making starting points and quitting thresholds, while the opposite was found for high target prevalence (Peltier & Becker, 2016; Wolfe & Van Wert, 2010). We replicated this target prevalence effect for the miss rate and response time analysis but not the false alarm rate analysis. Failing to replicate the target prevalence effect in Experiment 2 for the false alarm rate likely speaks to clutters ability to lower the 2AFC decision-making starting point of participants leading to no differences between conditions for the false alarm rate analysis. Therefore, evidence for this lowering of 2AFC decision-making starting points and quitting thresholds for clutter comes from the miss rate and response time analyses.

Our response time results suggest that clutter influenced the quitting threshold of participants and target prevalence. In previous research, low target prevalence made participants have shorter response times on target absent trials compared to high target prevalence, where the reverse was found (Peltier & Becker, 2016; Wolfe et al., 2005; Wolfe & Van Wert, 2010). We replicated this target prevalence effect for our response time data, where participants had shorter response times in response to low target prevalence than high target prevalence. Clutter altered this target prevalence effect, where in response to high clutter, participants had longer response times than low clutter. However, there was no difference in response time for low target prevalence between clutter conditions. No difference in response times for low target prevalence between clutter conditions suggests that when participants expect a target to be absent, they will not continue to search even when needing to make more attention shifts as the information on the screen increases (attention for recognition). Participants in the low target prevalence condition not increasing their quitting thresholds as the amount of information on the screen increases suggests that there may be a cap on the quitting threshold when participants expect a target to be absent. Evidence that there is only a cap on how high the quitting threshold will rise in response to the amount of information on the screen increasing is found with high target prevalence. In response to high target prevalence, participants expected a target to be present. Based on expecting a target to be present, participants searched longer when more information was presented on the screen, evidenced by longer response times in the high clutter condition than the low clutter condition for high target prevalence. This difference in response time data for high target prevalence suggests that clutter does shift the quitting threshold for participants, increasing it as the number of attention shifts that need to be made increases but that there is a cap to this when participants expect a target to be absent. This difference between prevalence conditions led to an interaction between clutter and target prevalence. Further evidence to support clutter altering the target prevalence is found with our miss rate analysis.

When looking at the miss rate analysis, clutter influenced participants' 2AFC decision-making starting points. In previous research, low target prevalence influenced participants' 2AFC decision-making starting points to lower them towards the "no, not a target" boundary, increasing the miss rate compared to high target prevalence, where the reverse was found (Peltier & Becker, 2016). We replicated the target prevalence effect in this case based on our main effect of target prevalence. In response to low target prevalence, participants had a higher miss rate than high target prevalence. Clutter did interact with the target prevalence effect for the miss rate, altering the target prevalence results from previous research (Peltier & Becker, 2016; Wolfe et al., 2005; Wolfe & Van Wert, 2010). In response to low clutter, participants had no difference in miss rate between prevalence conditions. No difference for the miss rate between prevalence conditions suggests that the target prevalence effect was not found for low clutter. Low clutter getting rid of the target prevalence effect is likely due to low clutter lowering the 2AFC decision-making starting point towards the "no, not a target" boundary, making participants in the high target prevalence condition have a higher miss rate leading to no difference between prevalence conditions. Even though high clutter should have lowered the 2AFC decision-making starting point further than low clutter, participants had longer response times in this condition which likely led to fewer misses for the high target prevalence condition leading to a larger difference between prevalence conditions for high clutter. A larger difference between prevalence conditions for the miss rate analysis in response to high clutter led to an interaction due to low clutter getting rid of the target prevalence effect. This interaction between clutter and target prevalence for the miss rate and elimination of the target prevalence effect for low clutter suggests that attention against competition strongly influences the target prevalence effect and participants' 2AFC decision-making starting points, which is further evidenced by our false alarm rate analysis.

Our results for the false alarm rate analysis further suggest that clutter did alter participants' 2AFC decision-making starting point. In previous research, high target prevalence influenced participants' 2AFC decision-making starting points to shift upward towards the "yes, item is a target" boundary, increasing the false alarm rate compared to low target prevalence, where the reverse was found (Peltier & Becker, 2016). We did not replicate this target prevalence effect in Experiment 2. Clutter might have eliminated the target prevalence effect based on finding a significant main effect of clutter. Participants had a higher false alarm rate in response to high clutter than low clutter, but there was no main effect of target prevalence or interaction between clutter and target prevalence. This lack of a main effect of target prevalence and no interaction suggests that using clutter likely made the search too challenging for participants. We predicted that participants lowered their 2AFC decision-making starting points towards the "no, not a target" boundary as clutter increased, leading to no differences between target prevalence conditions for the false alarm rate analysis. The increase in false alarm rate for high clutter speaks to an increased search leading to more false alarms during visual search. The general increase in response times in Experiment 2 compared to Experiment 1 would also help explain an overall increase in false alarm rate between experiments. Additionally, the increased information and variation on the screen as clutter increases could make it more likely that something on the display could be mistaken as the target more easily, which could also lead to an increase in false alarm rate.

Using the MDM, we predicted that clutter would influence participants' 2AFC decision-making starting points and quitting thresholds based on changes in the amount of information present on the screen (attention for recognition), as well as crowding around items increasing the difficulty in identifying items in a cluttered display (attention against competition). This use of both types of attention was observed and led to high clutter increasing the target prevalence effect in some cases by lowering the 2AFC decision-making starting points towards the "no, not a target" boundary and raising participants' quitting thresholds. Additionally, our results suggest that low clutter got rid of the target prevalence effect in response to a lowered 2AFC decision-making starting point and lowered quitting threshold, making the miss rate between target prevalence conditions not significantly different. Together, these results suggest that clutter did alter the target prevalence effect by altering participants' 2AFC decision-making starting points and quitting thresholds. We suggest this ability of clutter to alter participants' decision-making criteria within the MDM framework is based on participants' use of attention for recognition and attention against competition influencing how long they are willing to search and how effective they are at making each decision.

## General Discussion

Our results showed the typical target prevalence results, where, as target prevalence decreased, response times and the false alarm rate decreased while misses increased. However, in Experiment 2, the false alarm rate had no difference between prevalence conditions, suggesting that we did not replicate the target prevalence effect in this case. This lack of finding the target prevalence effect was likely due to the increased search difficulty of using clutter, as no such findings were observed in Experiment 1. Additionally, this lack of finding the target prevalence effect is surprising but likely due to what we predicted within the MDM framework, that clutter should lower the 2AFC decision-making starting point for participants. This lowering of the 2AFC decision-making starting point led participants to respond similarly across prevalence conditions for the false alarm rate. Based on these behavioral results, we provide support for our predictions that set size and clutter influence the target prevalence effect within the MDM framework.

Our results showed that two different types of attention, attention for recognition and attention against competition, influence the target prevalence effect by shifting participants' decision criteria within the MDM framework. Attention for recognition refers to the number of attention shifts participants need to make to recognize items, and attention against competition refers to the attention needed to inhibit the information surrounding items to correctly identify them (Beck et al., 2010; Reddy & VanRullen, 2007). In Experiment 1, set size was used to only recruit attention for recognition due to every item in the display being separate and easily discernable, requiring little or no attention against competition. Requiring primarily attention for recognition led to set size altering the quitting thresholds of participants, where the quitting threshold rose as set size did based on needing to make more attention shifts in response to more items being on the display. The quitting threshold rising as set size did led to significant main effects for the miss rate, false alarm rate and response times in Experiment 1, where in response to a large set size the miss rate, false alarm rate and response times increased compared to a small set size. An increase in miss rate, false alarm rate and response times for a large set size is evidence for set size only increasing the quitting threshold of participants, as the results were in line with typical target prevalence results (Peltier & Becker, 2016; Wolfe et al., 2005; Wolfe & Van Wert, 2010). In Experiment 2, clutter was used, which recruited both attention for recognition and attention against competition, leading to the quitting threshold rising as clutter increased and a decrease in the 2AFC decision-making starting point towards the "no, not a target" boundary as clutter increased. By recruiting both types of attention, this led to significant main effects for the miss rate, false alarm rate and response times, as in Experiment 1, where in response to high clutter, the miss rate, false alarm rate and response times increased compared to low clutter. An increase in the miss rate, false alarm rate and response times is evidence that clutter influences participants' decision-making criteria within the MDM to affect the dependent variables directly relevant for the target prevalence effect, and in some cases, this led to an interaction for both set size and clutter with target prevalence.

In Experiment 1, we predicted that attention for recognition would be recruited based on using only set size and that this would interact with the target prevalence effect to alter participants' response times. Based on our results, set size did interact with target prevalence by altering participants' quitting thresholds. This interaction was brought about by a small set size influencing the target prevalence effect to lead to a larger target prevalence effect for a small set size than a large set size. In addition, a large set size did raise participants quitting thresholds leading to longer response times in response to a large set size. We observed no other interactions between set size and target prevalence, which suggests that set size did not influence the 2AFC decision-making starting point of participants, keeping the miss rate and false alarm rate in line with previous target prevalence research (Peltier & Becker, 2016; Wolfe et al., 2005; Wolfe & Van Wert, 2010). Overall, this suggests that set size only influenced the quitting threshold of participants, and more specifically, this suggests that attention for recognition alters the quitting threshold of participants. This effect of attention for recognition to alter the quitting threshold of participants was also observed in our second experiment, where we used clutter instead of set size, and it was again observed that attention for recognition alters the quitting threshold of participants.

In Experiment 2, we predicted that attention for recognition and attention against competition would be recruited by using clutter and that this would interact with the target prevalence effect to alter the miss rate, false alarm rate and response times of participants. Based on our results, clutter did interact with the target prevalence effect by altering both participants' 2AFC decision-making starting points and quitting thresholds. However, this interaction was not observed for the false alarm rate where no target prevalence effect was observed. Nevertheless, there was an interaction for the miss rate brought about by low clutter lowering the 2AFC decision-making starting point closer to the "no, not a target" decision boundary, which led to no difference between prevalence conditions for low clutter. In addition, there was an interaction for our response time data, where the quitting threshold rose in response to clutter increasing, except for low target prevalence, where participants had a cap on their quitting threshold in response to expecting a target to be absent. Overall, these results suggest that clutter influenced both the 2AFC decision-making starting points and quitting thresholds of participants to alter the target prevalence effect and, at times, eliminate it. Thus, the data from Experiments 1 and 2 show that attention for recognition and attention against competition alter participants' decision-making and influence the target prevalence effect.

Through two experiments, we found that attention for recognition and attention against competition alters the target prevalence effect and participants' decision-making. Attention for recognition alters how long participants will search based on the number of attention shifts participants need to make. However, attention for recognition might influence the target prevalence effect less than attention against competition. This line of thinking, that attention for recognition might influence the target prevalence effect less than attention against competition, is based on the shift in quitting threshold in response to set size, keeping the target prevalence effects in line with previous prevalence research (Peltier & Becker, 2016; Wolfe et al., 2005; Wolfe & Van Wert, 2010). In addition, attention for recognition did not influence the low target prevalence condition as strongly in Experiment 2, where there was no difference in response times between clutter levels.

In comparison, attention against competition seemed to eliminate the target prevalence effect at times. In Experiment 2, the miss rate was not different between prevalence conditions for low clutter, and there was no difference in false alarm rate. We attribute this elimination of the target prevalence effect to attention against competition used for clutter in Experiment 2, where the 2AFC decision-making starting point lowered towards the "no, not a target" boundary as clutter increased. The 2AFC decision-making starting point lowering brought the miss rate closer between prevalence conditions for low clutter and made the task too challenging to observe differences in the false alarm rate between prevalence conditions across both clutter levels. Thus, attention against competition seems to be more effective at interacting with the target prevalence effect, and future research should examine aspects of visual search that vary attention against competition to better understand how this type of attention can influence the target prevalence effect.

By being able to make predictions of how clutter and set size will influence the target prevalence effect, our experiments lend credence to the MDM and support the notion that the decision-making starting point and quitting threshold are both adaptive and based on a diffusion process that influence observers' decisions (Peltier & Becker, 2016; Wolfe & Van Wert, 2010). The MDM is a comprehensive and responsive model that accounts for participants taking in information during visual search to update expectations and perform per those expectations (Peltier & Becker, 2016; Wolfe & Van Wert, 2010). Based on participants updating their expectations in response to a visual search task, results in performance can vary per those expectations. Having a responsive model to visual search that updates based on past experiences is crucial, as a model better explains the prevalence effect with such a capacity. Our results show that participants also update their expectations in response to the types of attention they need to use. The attention needed to shift between items (attention for recognition) alters the quitting threshold of participants, and the attention needed to inhibit information from interfering with item processing (attention against competition) alters the 2AFC decision-making starting point. In sum, our results support the MDM based on how participants respond to different search displays and how their quitting thresholds and decision-making starting points update in response to previous experiences. By providing support for the MDM, future researchers can use the MDM to better understand how participants update their decision criteria to perform visual search tasks.

Past research has found that selection errors (i.e., errors related to the quitting threshold) make up most of the misses within target prevalence visual search tasks (Peltier & Becker, 2016). Therefore, one way to increase visual search performance would be to lower the number of selection errors participants make. Participants' quitting thresholds rose in response to a large set size in Experiment 1, making participants search longer but not better at making accurate target decisions. An increase in the quitting threshold might have reduced the number of selection errors participants made in Experiment 1, but only eye-tracking can confirm this. Compared to Experiment 2, Experiment 1 had significantly lower miss rates which likely speaks to the increased quitting threshold without increased perceptual difficulty. However, based on miss rates being in line with previous target prevalence research, it seems that an increased quitting threshold alone is not sufficient to reduce miss rates entirely. Additionally, an increased miss rate in Experiment 2 compared to Experiment 1 with an increased quitting threshold suggests that a lowered decision-making starting point might also increase selection errors. A lowered decision-making starting point means participants make quicker "no, not a target" decisions and thus more quickly accumulate information towards the quitting threshold. Therefore, with the quitting threshold raised and increased information on the display, a quicker accumulation of no responses might inflate the miss rate. This combination of a lowered decision-making starting point and heightened quitting threshold resulting in a high miss rate suggests that an increase to both might better serve to improve visual search performance. Future work should try to better isolate the influence each of these processes has on participants' visual search performance. For example, one way to better isolate these effects would be to raise participants' quitting thresholds without increasing the amount of information participants have to search through.

Future studies should also follow up on these results with additional measures showing set size and clutter's effect on the target prevalence effect. One measure should be eye-tracking, allowing researchers to tell when a target has been inspected. Additionally, eye tracking has been used to show the length of time participants take for target and distractor decisions (Peltier & Becker, 2016). This information is crucial for a more robust measure of participants' decision-making starting point and quitting threshold beyond simplistic behavioral data alone. Future studies should also examine the level of clutter throughout an image. Measuring global and local clutter (i.e., clutter directly around the target) would allow researchers to better understand how clutter influences participants' decision-making. Having a measure of both global and local clutter would further the implication of attention for recognition and attention against competition impacting visual search performance to better understand how these factors influence participants.

In conclusion, our results show that participants update their expectations within the MDM framework. Because participants are responsive to both prevalence and set size (attention for recognition)/clutter (attention for recognition & attention against competition), we have provided evidence that participants' quitting thresholds and decision-making starting points can be influenced based on their expectations and the types of attention used when interacting with a visual search task. Additionally, attention for recognition and attention against competition influence the target prevalence effect by altering the decision criteria within the MDM framework. Based on this, we provide support for the MDM framework and evidence that set size and clutter influence the target prevalence effect within this framework to impact visual search performance.

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## Vita

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