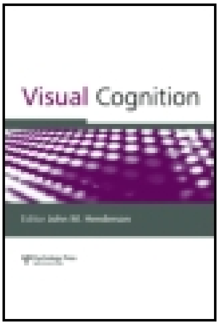

Visual Cognition
Publication details, including instructions for authors and subscription information:
http://www.tandfonline.com/loi/pvis20

Prevalence-based decisions undermine visual search

Jeremy D. Schwark [a], Justin MacDonald [a], Joshua Sandry [b] [c] & Igor Dolgov [a]

[a] Department of Psychology, New Mexico State University, Las Cruces, NM, USA

[b] Kessler Foundation Research Center, West Orange, NJ, USA

[c] Department of Physical Medicine and Rehabilitation, UMDNJ—New Jersey Medical School, Newark, NJ, USA

Published online: 02 Jul 2013.

To cite this article: Visual Cognition (2013): Prevalence-based decisions undermine visual search, Visual Cognition, DOI: 10.1080/13506285.2013.811135

To link to this article: http://dx.doi.org/10.1080/13506285.2013.811135

Visual Cognition, 2013
http://dx.doi.org/10.1080/13506285.2013.811135

Prevalence-based decisions undermine visual search

Jeremy D. Schwark[1], Justin MacDonald[1], Joshua Sandry[2,3], and Igor Dolgov[1]

[1]Department of Psychology, New Mexico State University, Las Cruces, NM, USA
[2]Kessler Foundation Research Center, West Orange, NJ, USA
[3]Department of Physical Medicine and Rehabilitation, UMDNJ—New Jersey Medical School, Newark, NJ, USA

In visual search, observers make decisions about the presence or absence of a target based on their perception of a target during search. The present study investigated whether decisions can be based on observers' expectation rather than perception of a target. In Experiment 1, participants were allowed to make target-present responses by clicking on the target or, if the target was not perceived, a target-present button. Participants used the target-present button option more frequently in difficult search trials and when target prevalence was high. Experiment 2 and 3 employed a difficult search task that encouraged the use of prevalence-based decisions. Target presence was reported faster when target prevalence was high, indicating that decisions were, in part, cognitive, and not strictly perceptual. A similar pattern of responses were made even when no targets appeared in the search (Experiment 3). The implication of these prevalence-based decisions for visual search models is discussed.

Keywords: Visual search; Prevalence; Low prevalence effect; Decision theory; Signal detection; Perception.

Please address all correspondence to Jeremy Schwark, Department of Psychology, MSC 3452, New Mexico State University, PO Box 30001, Las Cruces, NM 88003-8001, USA. E-mail: jschwark@nmsu.edu.

JDS was supported by the Howard Hughes Medical Institute's Scientific Teaching Program, under Award No. 52006932. JS was supported by the National Science Foundation through the Graduate STEM Fellows in K-12 Education (GK-12) Program, under Grant No. DGE-0947465. The authors wish to thank Dr. Charles Folk, Dr. Harris Schwark, and three anonymous reviewers for comments on an earlier draft, and members of the PACMANe lab for their assistance in collecting data.

The way in which observers make decisions about the presence or absence of a target during visual search is a topic central to visual perception and cognition research. In some ways, visual search tasks can be interpreted as a two-alternative forced choice (2AFC) task because the observer is forced to select one of two options: target-present or target-absent. Diffusion theory (Ratcliff, 1978) has been applied to many 2AFC tasks and has successfully modelled decisions in memory (Ratcliff, 1978), go/no-go tasks (Gomez, Ratcliff, & Perea, 2007), and risk assessment (Johnson & Busemeyer, 2005), as well as in tasks such as perceptual discrimination (Ratcliff & Rouder, 1998), detection (Smith, 1995), and estimation (Leite & Ratcliff, 2011). According to diffusion theory, information accumulates towards one of two decision thresholds which, once crossed, elicit the decision. One advantage of diffusion theory over a standard perceptual theory, signal detection theory (SDT; Green & Swets, 1966), is that it accounts for reaction times (Ratcliff, 2001).

Diffusion models have not been able to fully model visual search behaviour, particularly when observer behaviour changes as a result of target prevalence (how often the target is present). Wolfe and Van Wert (2010) found that the diffusion model properly predicted a quickening of target-absent responses when target prevalence was low. When target prevalence was high, the model predicted faster target-present responses, but this was not observed (Wolfe & Van Wert, 2010). Indeed, diffusion models arguably fail because visual search is not a simple 2AFC cognitive task, but a much more complex combination of perceptual and cognitive decisions. Therefore, increasing the prevalence of a target does not increase the speed at which a target can be perceived.

These ideas led Wolfe and Van Wert (2010) to propose a new model, the multiple-decision model, which takes into account both the perceptual and cognitive factors in visual search. The model asserts that observers search through a visual field of distractors for potential targets that fall above a decision criterion (determined using the decision mechanism from SDT). This process is a perceptual one, whereby target-present responses are only made if an object is perceived to be a target. While the search is ongoing, a quitting signal accumulates towards a threshold. If a target has not been identified by the time the quitting signal reaches threshold, the observer returns a target-absent response and the search is terminated. This quitting threshold is a cognitive threshold set by the observer which determines how long to search (Chun & Wolfe, 1996) and is presumed to be influenced by target prevalence (Wolfe & Van Wert, 2010). Importantly, this model and others (Wolfe, 2007) assume all target-present responses are a result of target perception, and all early search terminations lead to target-absent responses.

LOW PREVALENCE EFFECT

Wolfe and Van Wert's (2010) multiple-decision model accurately predicts operator behaviour in low prevalence visual search tasks where miss rates are high, termed the low prevalence (LP) effect (Wolfe, Horowitz, & Kenner, 2005). Studies of the LP effect have shown that target prevalence influences observers' perception and subsequent behaviour in search tasks, such that observers terminate their searches prematurely with target-absent responses under conditions of low target prevalence, resulting in an increased proportion of misses (Kunar, Rich, & Wolfe, 2010; Wolfe et al., 2007).

According to SDT, estimates of target prevalence are used when observers are setting their decision criteria, but do not influence an observer's sensitivity to the target (Schwark, Sandry, MacDonald, & Dolgov, 2012; Wolfe et al., 2007). This criterion shift impacts search times and appears to be due to the observer's attempt to equate the number of false alarms and misses that they commit (Schwark et al., 2012; Wolfe et al., 2007; Wolfe & Van Wert, 2010). Low target prevalence results in a more conservative decision criterion and shorter search times since there is little need to search extensively for a target that is unlikely to be present. As a result, observers are more likely to make target-absent responses. The link between criteria shifts and shorter search times is predicted by the multiple-decision model and has been observed in previous research (Rich et al., 2008; Schwark, Sandry, & Dolgov, 2013; Wolfe et al., 2005, 2007; Wolfe & Van Wert, 2010).

Some attempts have been made to reduce miss errors associated with the LP effect. In one such attempt, observers were allowed to change answers shortly after making their decision. This correctable search eliminated the LP effect (Fleck & Mitroff, 2007). However, another study using the same correctable search paradigm with a more challenging search task still found a pronounced LP effect (Van Wert, Horowitz, & Wolfe, 2009), suggesting that correctable search only amends motor errors associated with low prevalence in simple search tasks, but does not address perceptual or cognitive causes in more difficult tasks (Russell & Kunar, 2012). Further attempts to reduce the miss rate in low prevalence focused on repairing deficits of the search task itself, such as encouraging observers to search longer before making target-absent responses, but were unsuccessful (Wolfe et al., 2007).

The most successful remedies for the LP effect involve changing the observer's perception of target prevalence. For example, observers that received accuracy feedback only during bursts of high target prevalence trials inserted into a low prevalence search were able to detect more targets during the low prevalence trials (Wolfe et al., 2007). This feedback presumably led observers to (falsely) believe that the overall prevalence of the target was higher. False feedback can also mediate the LP effect (Schwark et al., 2012). When observers were falsely informed that their miss rates were higher than was actually the case, they were able to shift their criteria to more optimal levels and find more targets. Both of these results indicate that implicit feedback (identification of the target; Wolfe et al., 2007) and explicit feedback (provided after each trial; Schwark et al., 2012) are used by observers to estimate target prevalence.

Models of visual search assume that decisions related to target presence or absence are based on a perceptual search. That is, an observer reports target-present when the target is perceived and target-absent when it is not. However, the inability to ameliorate the LP effect without changing the observer's perception of the target prevalence may suggest otherwise. Specifically, the fast dismissal of a low prevalence trial with a target-absent response indicates that observers are not gathering as much perceptual evidence before making a target-absent response. This is also supported by the shallow search slopes observed in low prevalence searches and their interaction with steeper search slopes in high prevalence (Rich et al., 2008), indicating that the reduction of perceptual information needed to elicit a response is additive with each item in the search, resulting in larger differences in search time between low and high prevalence search as set size increases.

Although all target-absent decisions in visual search are cognitive choices to stop searching (Chun & Wolfe, 1996), here we distinguish between two different types of decisions: search-based decisions, which result after a perceptual search for the target is completed, and what we term prevalence-based decisions, which are cognitive decisions made primarily from an assumption about target presence based on the statistical evidence of target prevalence gathered while performing the task. In prevalence-based decisions, knowledge of target prevalence reduces the amount of perceptual evidence needed, allowing the decision to be made before a thorough perceptual search has occurred, much like the multiple-decision model predicts. The key difference between prevalence-based decisions and decision behaviour predicted by the multiple-decisions model is that prevalence-based decisions would not only be made under low target prevalence, but under high target prevalence they would similarly reduce the amount of perceptual evidence needed to make a target-present response.

Prevalence-based decisions would offer a number of potential advantages over search-based decisions. They would be particularly accurate when target prevalence is very high or very low (it is easier to accurately predict outcomes that are extremely likely or extremely unlikely). For example, if the target is extremely rare, a decision based on target prevalence would yield a target-absent response and be correct most of the time. In high prevalence, these decisions could be used to overcome the inability to find a target, such that a target-present response could be given even if the observer failed to immediately locate it. Additionally, decisions could be made before sufficient evidence had accumulated for or against the presence of a target. Thus, less energy would be spent in challenging target search conditions. Decisions could be made quickly and efficiently while maintaining relatively high accuracy. Perhaps the biggest advantage is that the accuracy of prevalence-based decisions would be independent of task (i.e., perceptual) difficulty, so observers could maintain high overall accuracy even in tasks that are perceptually demanding.

The questions we address here are whether prevalence-based decisions are a distinct type of visual search decision and whether they help explain prevalence effects. It seems unlikely that observers would ever only use prevalence-based decisions because visual search is, by its very nature, a perceptual task. However, as described earlier, there are a number of potential advantages of using prevalence-based decisions. Indeed, previous results from research on low prevalence might reflect the presence of prevalence-based decisions due to the shortened target-absent response times, indicating that less evidence is needed to rule out the presence of a target. However, we suggest that prevalence-based decisions should also be present under conditions of high prevalence, and that they offer benefits under high prevalence as well as low prevalence.

Prevalence-based decisions under high prevalence would result in target-present decisions being made without perceiving the target. These decisions could theoretically be made faster than the minimum time required to perceive a target since they could be made before definitive evidence of a target's presence is gathered. That is, target-present responses could be given before enough time has elapsed to perceive the target. This behaviour would be distinct from search-based decisions, in which target-present responses would not be made as quickly. Although shortened response times have not been seen in previous studies using high target prevalence (Wolfe & Van Wert, 2010), this could have been due to the nature of the task, which involved searching through realistic x-ray images of luggage that contained three, six, 12, or 18 objects. This task required relatively short search times to successfully identify a target (< 2 s) and yielded high overall accuracy (approximately 97%). Under these conditions, the targets may have been perceived quickly enough to eliminate the appeal of using prevalence-based decisions.

CURRENT STUDY

The current study was designed to investigate prevalence-based decisions in visual search. The goal of Experiment 1 was to identify prevalence-based decisions in high prevalence search by employing a task of varying difficulty in which participants could respond by clicking on the target, clicking on a target-absent button, or clicking on a target-present button. Experiment 2 and 3 sought to examine these decisions in a visual search task that was likely too challenging to be completed perceptually.

EXPERIMENT 1

In Experiment 1, participants completed a simple visual search task in which they had to determine whether the letter X was present in a random array of letters. Critically, participants were told to click on the X when they saw it. If they did not see it, they could click on either a target-absent (TA) button or a target-present (TP) button. The TP button represented a prevalence-based decision: a way to terminate the search without perceiving the target, but still making a target-present response. Additionally, all trials in the search task were classified as easy, moderate, or hard depending on how many distractor letters appeared in the image.

Experiment 1 was designed to test several hypotheses. First, it was predicted that participants would use the TP button more often in harder trials and would use it more often in the high prevalence condition than a moderate prevalence (50%) condition, due to the relative advantages that prevalence-based decisions would have in difficult searches and the higher accuracy these decisions would maintain in high prevalence. Additionally, since prevalence-based decisions in high prevalence would result in frequent target-present responses, it was predicted that accuracy decrements due to trial difficulty in high prevalence would result from a diminished correct rejection rate (caused by incorrectly responding target-present) rather than a diminished hit rate. Finally, it was predicted that prevalence-based decisions would be made with less perceptual information, resulting in these responses being made before an exhaustive search was performed. This should result in TP button responses being made faster than TA button responses even though both button presses terminated the search before target perception.

Method

Participants. Forty undergraduate students (27 female, 13 male) from New Mexico State University participated in the experiment for partial course credit. The mean age was 20.2 years ($SD = 5.1$) and all participants reported normal or corrected-to-normal vision.

Materials. The experiment was conducted using E-Prime 2.0 on a computer with a 21-inch monitor, with a resolution of 1920×1080 pixels and a refresh rate of 65 Hz, which was set at a distance of approximately 22 inches from the participant. Each stimulus consisted of randomly placed capital letters set in a 900×600 pixel area (Figure 1). The number of letters in each stimulus was increased to make the target less salient, increasing the difficulty (Nothdurft, 2006). Easy stimuli contained an average of 50 letters (uniformly distributed from 25–75 letters), moderate stimuli contained an average of 150 letters

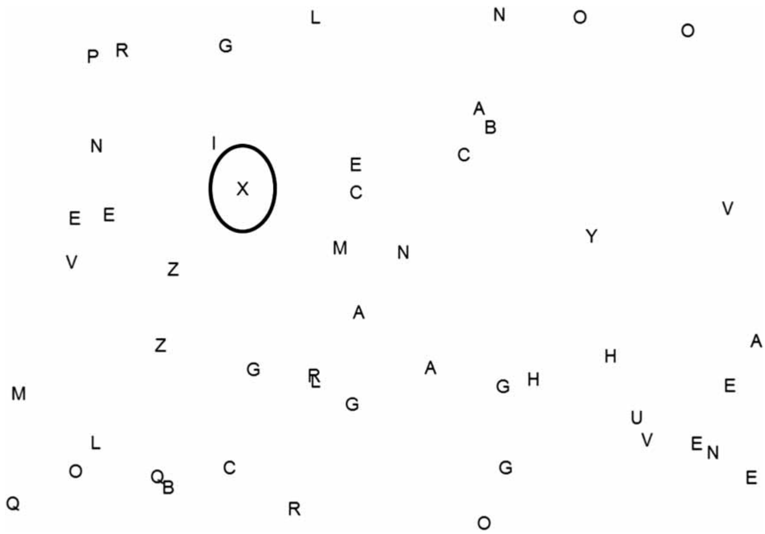

Figure 1. Sample target-present stimulus (easy difficulty) used in Experiment 1. Target letter X is circled for readers' ease.

(125–175 letters), and hard stimuli contained an average of 300 letters (275–325 letters). The slight randomization in the number of letters was used to reduce the saliency between stimuli difficulties. The letters were presented in black 16 point Arial font on a white background and were permitted to overlap. A single letter X was present in target-present stimuli while no letter X was present in target-absent stimuli.

Procedure. Participants were told that they would search for the letter X in a series of images and, if they saw the target, they should click on it. If participants did not see the X, they were instructed to click a TA or TP button, located below the stimulus, to indicate their answer. The first screen on each trial displayed a fixation cross (500 ms) followed by the stimulus display and then a feedback screen (1500 ms), which indicated whether their decision was correct or incorrect. Clicking on the target, a distractor letter (which was recorded as an inaccurate target click response), or either of the response buttons would terminate the stimulus display and advance participants to the next trial. Participants were informed that clicking on the X would always yield a correct answer, even if it overlapped with other letters. The mouse cursor appeared in the centre of the screen with each stimulus onset and they had as much time as needed to respond. No explicit instructions were given regarding target prevalence.

A scoring system identical to those used in previous studies (Schwark et al., 2012; Wolfe et al., 2007) was used to discourage misses and imitate an applied visual search task in which misses are critically damaging. Points were awarded for hits (+25) and correct rejections (+5); points were lost for false alarms (−75) and misses (−150). Additionally, participants received + 5 bonus points for correctly clicking on the target instead of using the TP button, in order to encourage target identification clicks. This point system was updated and displayed on each feedback screen. Participants were informed of the point system ahead of time and told they should try to achieve the highest point total possible.

Participants completed 20 practice trials followed by 200 experimental trials at either 50% prevalence ($n = 18$) or 96% prevalence ($n = 22$), randomly assigned between participants. Each participant completed 100 easy trials, 50 moderate trials, and 50 hard trials, which were randomly intermixed. More instances of the easy trial type were presented in order to encourage searching. Each participant's target prevalence condition was maintained equally through each difficulty type. An optional break was provided after 100 experimental trials were completed. The experiment lasted approximately 1 hour and accuracy, response type (target click or button click), and response time (RT) measures were collected and used as the dependent variables in the following analyses.

Results

The large majority of participants followed the experimental protocol correctly. Three participants were removed from analyses for primarily using the TP button to identify the target (~91% of their target-present responses in easy trials were made with the TP button as compared to ~1% from the remaining participants). One participant was removed for search accuracy exceeding 2.5 standard deviations below the average, leaving 36 participants remaining in the analyses. All trials, regardless of accuracy, were included in analyses.

Analyses using SDT measures could not be performed due to the infrequent occurrence of false alarms in easy trials. Averaging performance across difficulty levels would be inappropriate as SDT measures are sensitive to task difficulty.

TP button responses. A 2 × 3 (Prevalence × Trial difficulty) mixed ANOVA performed on the number of TP button responses revealed a significant main effect of prevalence, $F(1, 34) = 6.71$, $p = .01$, $\eta_p^2 = .17$, a significant main effect of trial difficulty, $F(2, 68) = 37.30$, $p < .001$, $\eta_p^2 = .52$, and a significant interaction between the two, $F(2, 68) = 7.03$, $p = .002$, $\eta_p^2 = .17$ (Figure 2). Participants made more TP button responses in the 96% prevalence condition than the 50% prevalence condition and the number of TP button responses increased as trial difficulty increased. Simple effects were

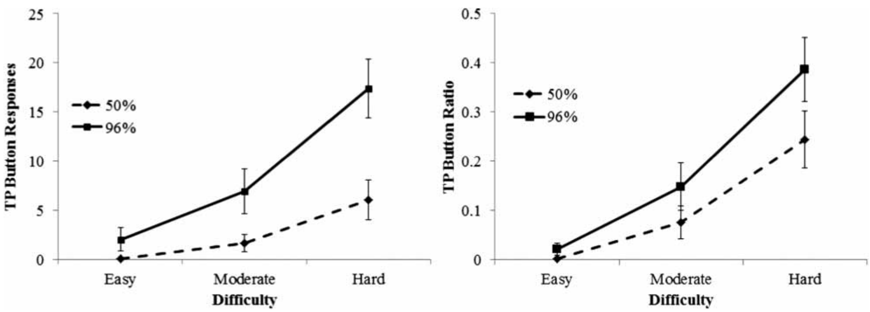

Figure 2. Analyses on number of TP button responses (left) and ratio of TP button responses (right) on prevalence and trial difficulty in Experiment 1. Overall trends show increased TP button use in hard trials, especially in the 96% prevalence condition. Error bars represent standard error of the mean.

determined using pairwise comparisons[1] and revealed that the number of TP button responses increased to a greater extent across difficulty levels in the 96% than the 50% condition. That is, a marginal difference was found between the 96% and 50% conditions in the easy trials, $t(34) = 1.45$, $p = .16$, and moderate trials, $t(34) = 1.96$, $p = .06$, and a significant difference was found in the hard trials, $t(34) = 2.97$, $p = .005$, $d = 1.02$. The same ANOVA performed on the ratio of TP button responses (TP button responses / [target click + TP button responses]) trended in the same direction, with a marginal main effect of prevalence, $F(1, 34) = 2.42$, $p = .13$, $\eta_p^2 = .07$, and significant main effect of trial difficulty, $F(2, 68) = 43.27$, $p < .001$, $\eta_p^2 = .56$. While the interaction failed to reach significance, $F(2, 68) = 1.69$, $p = .19$, $\eta_p^2 = .05$, a similar trend to that observed in the TP button response analysis was seen in the interaction (Figure 3). Overall, the results of the TP button behaviour support the hypotheses that target-present prevalence-based decisions occur more frequently in harder trials and under high prevalence.

Accuracy. A $2 \times 2 \times 3$ (Prevalence $\times$ Trial type $\times$ Trial difficulty) mixed ANOVA was performed with accuracy as the dependent variable. The inclusion of trial type (target-present or target-absent) was used to differentially investigate correct rejection[2] and hit rate. Results revealed a significant interaction between all three factors, $F(2, 68) = 23.33$, $p < .001$, $\eta_p^2 = .41$ (Figure 4). This three-way interaction was further investigated

[1] All post hoc probabilities were corrected using Sidak adjustments.

[2] It should be noted that correct rejection rates in the 96% condition could only be calculated based on four target-absent trials in the easy condition and two target-absent trials in both the moderate and hard conditions. Standard error of the means for these correct rejection rates were 0.03 (easy), 0.06 (moderate), and 0.09 (hard).

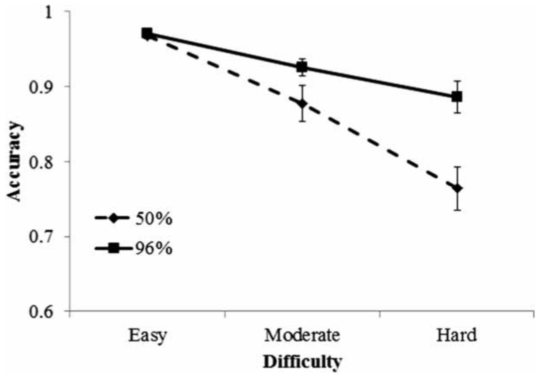

Figure 3. Significant interaction between prevalence and trial difficulty on overall accuracy in Experiment 1. Accuracy was higher in the 96% condition and dropped off to a greater extent due to difficulty in the 50% condition. Error bars represent standard error of the mean.

using a pair of 2 × 3 (Trial type × Trial difficulty) repeated-measures ANOVAs performed on accuracy in the 50% and 96% conditions. Main effects of trial type, $F(1, 15) = 16.60$, $p = .001$, $\eta_p^2 = .53$, and $F(1, 19) = 28.40$, $p < .001$, $\eta_p^2 = .60$, and main effects of trial difficulty, $F(2, 30) = 41.31$, $p < .001$, $\eta_p^2 = .73$, and $F(2, 38) = 46.58$, $p < .001$, $\eta_p^2 = .71$, were significant for both analyses in the 50% and 96% condition, respectively. The interaction reached statistical significance in the 96% condition, $F(2, 38) = 27.83$, $p < .001$, $\eta_p^2 = .59$, but was only marginally significant in the 50% condition, $F(2, 30) = 2.76$, $p = .08$. This indicates that decrements in accuracy due to difficulty in the 96% condition were driven by reduced correct rejection rates while hit rates remained high, supporting the hypothesis. In the

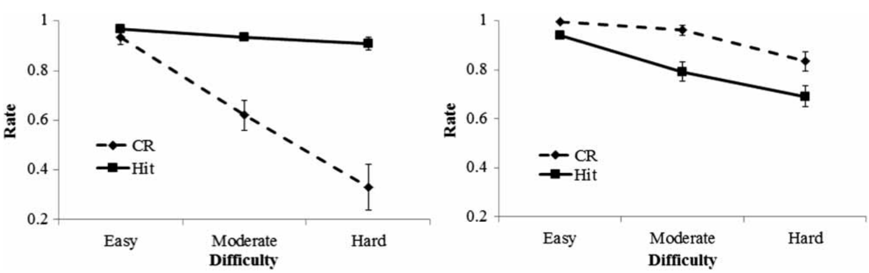

Figure 4. Follow-up analysis on accuracy between trial type (target-absent or target-present) and trial difficulty in the 96% condition (left) and 50% condition (right) in Experiment 1. Both main effects in each condition were significant, but the interaction was marginal in the 50% and significant in 96% condition. Correct rejection (CR) rate contributed largely to the decrement in accuracy due to difficulty in the 96% condition, whereas both hit and CR rate contributed more equivalently in the 50% condition. Also of importance is the reversal in the relationship between hit and CR rate in the two conditions. Error bars represent standard error of the mean.

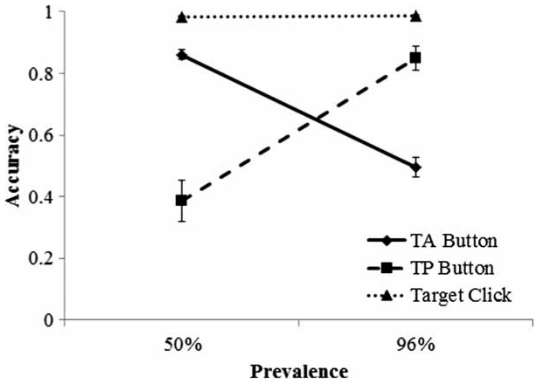

Figure 5. Analysis on accuracy between prevalence and response type in Experiment 1 revealing a significant interaction. Accuracy for target click responses was near ceiling in both conditions, whereas TP button responses were more accurate in the 96% than 50% condition and vice versa for TA button responses. Error bars represent standard error of the mean.

50% condition, the marginal interaction indicates hit and correct rejection rates more equally contributed to decreased accuracy due to difficulty. Overall, hit rates were higher than correction rejection rates in the 96% condition, but the opposite was true in the 50% condition. Thus, framing these results in terms of error rates, participants were more likely to commit false alarms in the 96% condition than the 50% condition.

A 3 × 2 (Response type[3] × Prevalence) mixed ANOVA[4] performed on search accuracy was used to investigate how accurate participants were when making target clicks, TP button responses, or TA button responses. Results revealed a significant main effect of response type, $F(2, 58) = 57.76$, $p < .001$, $\eta_p^2 = .67$, no significant effect of prevalence condition, $p = .25$, and a significant interaction, $F(2, 58) = 62.45$, $p < .001$, $\eta_p^2 = .68$ (Figure 5). Not surprisingly, target click accuracy was near ceiling across both prevalence conditions ($M = 0.99$, $SD = 0.01$). Pairwise comparisons revealed that the interaction was driven by participants' accuracy when making TP and TA button responses. Target-absent button responses were more accurate than TP button responses in the 50% condition, $t(29) = 9.44$, $p < .001$, $d = 3.50$, but this relationship reversed in the 96% condition, $t(29) = 5.91$, $p < .001$,

[3] Trial difficulty could not be included as a factor with response type (TP click, TP button, or TA button response) in accuracy or RT due to few participants making TP button responses in easy trials. Including both factors would have excluded all but one participant in the 50% condition from analyses.

[4] Five participants could not be included in the analysis due to never making TP button responses, resulting in $n = 13$ in the 50% condition and $n = 18$ in the 96% condition included in the analysis.

$d = 2.20$, confirming the hypothesis that prevalence-based decisions could be made more accurately in high prevalence than moderate prevalence.

A 3 × 2 (Trial difficulty × Prevalence) mixed ANOVA performed on the accuracy of target clicks revealed a significant main effect of trial difficulty, $F(2,\ 68) = 15.90$, $p < .001$, $\eta_p^2 = .32$, indicating that target click accuracy decreased across difficulties. Click accuracy was extremely high in the easy ($M = 0.99$, $SD = 0.01$) and moderate trials ($M = 0.99$, $SD = 0.02$) and slightly decreased in the hard trials ($M = 0.93$, $SD = 0.10$). No significant effects of prevalence, $p = .93$, or the interaction, $p = .97$, were observed.

Response time. A 2 × 2 × 3 (Prevalence × Response type × Trial difficulty) mixed ANOVA[5] performed on RT revealed a significant interaction between all three factors, $F(2,\ 68) = 3.22$, $p = .047$, $\eta_p^2 = .09$. The three-way interaction was further investigated using a pair of 2 × 3 (Response type × Trial difficulty) repeated-measures ANOVAs performed on RT in the 50% and 96% conditions. Main effects of response type, $F(1,\ 15) = 217.78$, $p < .001$, $\eta_p^2 = .94$, and $F(1,\ 16) = 92.39$, $p < .001$, $\eta_p^2 = .85$, main effects of trial difficulty, $F(2,\ 30) = 78.27$, $p < .001$, $\eta_p^2 = .84$, and $F(2,\ 32) = 78.57$, $p < .001$, $\eta_p^2 = .83$, and the interactions, $F(2,\ 30) = 43.49$, $p < .001$, $\eta_p^2 = .74$, and $F(2,\ 32) = 30.63$, $p < .001$, $\eta_p^2 = .66$, were significant for both analyses in the 50% and 96% condition, respectively. Results in both the 50% and 96% conditions were similar, with target-present responses being made faster than target-absent responses, and participants responding slower as trial difficulty increased, especially when selecting the TA button.

A 3 × 2 (Response type × Prevalence) mixed ANOVA performed on RT revealed only a significant main effect of response type, $F(2,\ 58) = 41.48$, $p < .001$, $\eta_p^2 = .59$ (Figure 6). Pairwise comparisons found significant differences between all types of responses, with target clicks resulting in the fastest RTs, TA button RTs being made the slowest, and TP button RTs falling in the middle (all *p*s < .05), confirming the hypothesis that TP button response would be made faster than TA button responses. Similar to previous findings (Wolfe & Van Wert, 2010), TP responses did not speed up in the 96% condition as compared to the 50% condition ($p = .27$), but TA responses were significantly slower in the 96% condition, $t(34) = 2.38$, $p = .02$, $d = 0.82$.

Discussion

Experiment 1 demonstrated that prevalence-based decisions are made in visual search, especially as trials become more difficult and when the

[5] TP button and click RTs were combined into a general target-present RT. Three participants from the 96% condition could not be included due to making no target-absent responses in the hard trials.

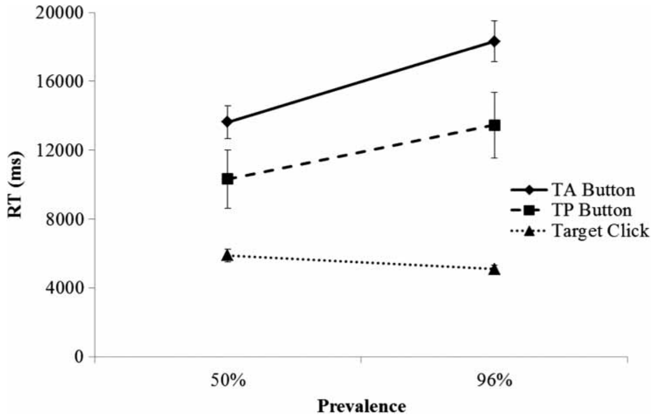

Figure 6. Significant main effect of response type RT found in Experiment 1. The main effect of prevalence and the interaction did not reach significance. Error bars represent standard error of the mean.

probability that a prevalence-based decision will be correct is high (in this case, under high prevalence). In this experiment, TP button responses were used to represent prevalence-based decisions. Although it is possible that participants were seeing the target and then making a TP button response, it is unlikely this occurred for several reasons. First, participants were instructed to click on any perceived target and were rewarded more for identifying targets with clicks than TP button responses. Second, almost no TP button responses were made in easy trials, when the target could be easily perceived. Finally, TP button response RTs were significantly slower than target click RTs. If TP button responses were made immediately after perceiving a target, we would expect those RTs to be similar to target click RTs.

The results of Experiment 1 allow us to draw several other conclusions as well. On average, target-present responses are made faster than target-absent responses in visual search. This is because the search is terminated as soon as the target is located, resulting in only half of the objects being searched on average when a target is present, whereas an exhaustive search of all objects should occur before a target-absent response is made (Wolfe, 1998). However, the TP button response in Experiment 1 represented decisions that were made not as a result of perceiving a target, but from an assumption that a target was present. The results show that these TP button RTs were slower than target click RTs (when the search was terminated due to target detection), but faster than TA button RTs (presumably made after an exhaustive search). Although participants did search longer than the average amount of time needed to identify the target with a click before making a TP button response, the speeding of TP button responses as compared to TA button responses indicates that prevalence-based decisions were likely still made before an exhaustive search occurred, resulting in a different quitting threshold than that used to make target-absent responses.

As expected, TP button responses were much more accurate in the 96% condition than the 50% condition, confirming that prevalence-based decisions are most accurate when the prevalence of the target is extreme. Additionally, prevalence-based decisions are impartial to task difficulty. This was evident by the high hit rate (which target-present decisions would contribute to) sustained throughout difficulties in the 96% condition, whereas correct rejection rates fell. This is an interesting finding in its own respect, considering that one would expect the target to be more difficult to find on hard trials, resulting in the hit rate being diminished. However, participants making prevalence-based decisions were able to counter this effect quite easily.

Prevalence-based decisions were never made exclusively. Even in the hard trials under 96% target prevalence, the majority of target-present responses were target clicks (search-based decisions). The infrequency and rather large variability of prevalence-based decisions in Experiment 1 make it difficult to determine whether these decisions are cognitive 2AFC decisions, which could be modelled with diffusion theory. Overall, the results of Experiment 1 best fit the multiple-decision model. Under higher target prevalence, target-absent responses were slower (predicted by a change in the quitting threshold) and target-present responses were not faster. The only result not predicted by the multiple-decision model is the TP button response behaviour. Our results show that, under certain conditions, a quitting threshold can result in a target-present decision and that this quitting threshold is reached sooner than a traditional target-absent quitting threshold.

EXPERIMENT 2

Prevalence-based decisions were observed in Experiment 1, but search-based decisions were still the primary decision type. Experiment 2 used an extremely difficult visual search task which encouraged frequent prevalence-based decisions and provided a better scenario to investigate how these decisions are made. It was hypothesized that a task which made search-based decisions nearly impossible to use would result in behaviour predicted by the diffusion model, supporting the notion that prevalence-based decisions are 2AFC cognitive decisions, not perceptual ones. Specifically, it was predicted that target-present responses would be faster under high prevalence as compared to moderate prevalence. Accuracy should also be substantially higher in the high prevalence condition due to the accuracy advantage of prevalence-based decisions at extreme prevalence rates, although the

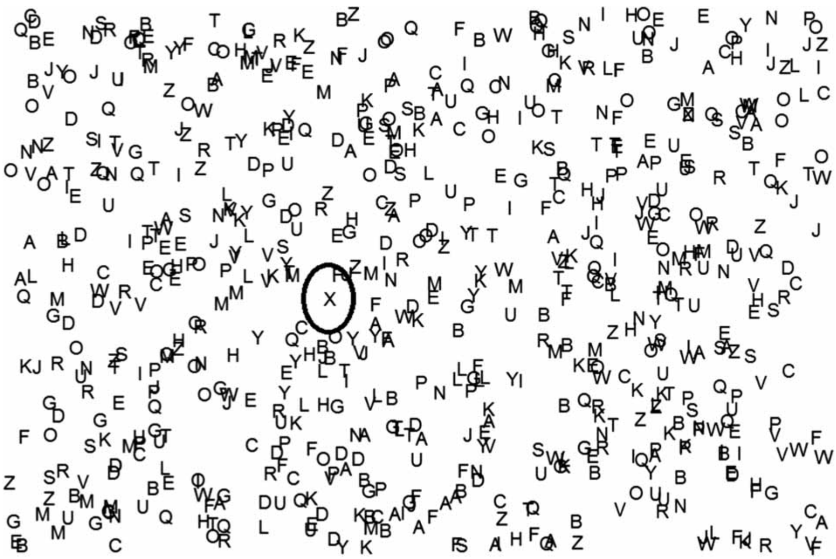

Figure 7. Sample target-present stimulus used in Experiment 2. Target letter X is circled for readers' ease.

frequent target-present responses should also result in an inflated false alarm rate, as seen in Experiment 1. In other words, we predicted a complete reversal of the results typically associated with an LP effect.

Method

Participants. Thirty undergraduate students (11 female, 19 male) from New Mexico State University participated in the experiment for partial course credit. The mean age was 19.1 years ($SD = 2.1$) and all participants reported normal or corrected-to-normal vision.

Materials. The same materials used in Experiment 1 were used in Experiment 2, except each stimulus consisted of 700 randomly placed capital letters set in a 900×600 pixel area (Figure 7). The stimuli were designed to be complex in order to encourage the use of prevalence-based decisions.

Procedure. The same procedure used in Experiment 1 was used in Experiment 2, except target-present and target-absent responses were only made using the "F" and "J" keys. Again, no explicit instructions were given regarding target prevalence. A scoring system similar to the one used in Experiment 1 was used, although no bonus points were used since

TABLE 1
Means and standard deviations (in parentheses) for the variables analysed in Experiment 2

	Condition	
Variables	*96%*	*50%*
Reaction time* (ms)	2774 (2471)	6955 (3778)
Target-present RT*	2421 (2564)	5423 (2961)
Target-absent RT	7163 (3127)	8677 (4660)
Accuracy*	0.88 (0.02)	0.52 (0.06)
Hits*	0.93 (0.02)	0.53 (0.13)
Correct rejections*	0.28 (0.13)	0.52 (0.21)
False alarms*	0.71 (0.13)	0.48 (0.21)
Misses*	0.07 (0.02)	0.47 (0.13)
Criterion (C)*	−1.07 (0.25)	−0.01 (0.46)
Sensitivity (d')*	0.90 (0.34)	0.15 (0.36)
TP response rate*	0.92 (0.03)	0.49 (0.17)

*$p < .01$.

participants could not make target click responses. Participants were also instructed that they had a maximum of 20 s to provide an answer on each trial or the trial would be counted incorrect, which served to further simulate an applied search task, in which some amount of time pressure is always present (Wilson, 2002) and make search-based decisions more difficult.

Participants completed 20 practice trials at 50% target prevalence followed by 200 experimental trials at either 50% prevalence ($n = 15$) or 96% prevalence ($n = 15$), between participants. Optional breaks were provided after 100 experimental trials were completed. The experiment lasted approximately 1 hour and accuracy and RT measures were collected and used as the dependent variables in the following analyses.

Results

Independent-samples t-tests were performed to test for differences between the 50% and 96% prevalence conditions[6] (see Table 1 for means). As predicted, accuracy,[7] $t(28) = 20.42$, $p < .001$, $d = 0.53$, false alarm rates, $t(28) = 3.82$, $p = .001$, $d = 1.43$, and hit rates, $t(28) = 12.03$, $p < .001$, $d = 4.45$, were all higher in the 96% than the 50% prevalence condition (Figure 8). An independent-samples t-test performed on the percentage of target-present responses also revealed that participants made more

[6] Trials which timed out before a response was made (< 1% of trials) were excluded from analyses. The treatment of these trials did not significantly impact the results.

[7] Analyses of total earned points mirrored those of accuracy.

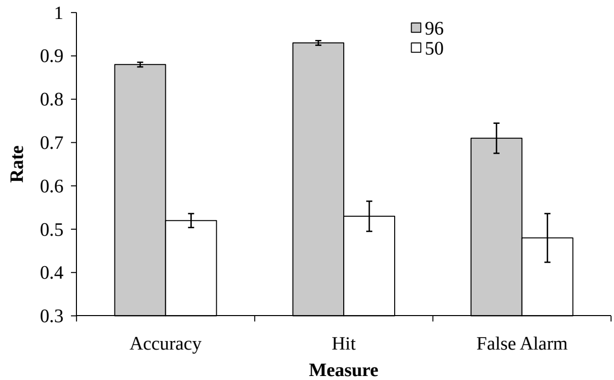

Figure 8. Significant differences found in accuracy, hit rate, and false alarm rate between the 50% and 96% prevalence conditions in Experiment 2. Error bars represent standard error of the mean.

target-present responses in the 96% condition than 50% condition, $t(28) = 9.68$, $p < .001$, $d = 3.66$.

Another independent-samples t-test found that RTs were significantly faster in the 96% condition than the 50% condition, $t(28) = 3.59$, $p = .001$, $d = 1.36$. Further investigation of RT revealed that this was driven by a significant difference in target-present RTs, $t(28) = 2.97$, $p = .006$, $d = 1.12$, rather than target-absent RTs ($p = .31$) (Figure 9).

An SDT analysis was also performed on the data from Experiment 2. Consistent with previous research in target prevalence, a significant difference was found in decision criteria (C), $t(28) = 7.75$, $p < .001$, $d = 2.94$. Interestingly, a significant difference was also found in sensitivity (d'), $t(28) = 5.82$, $p < .001$, $d = 2.22$ (Table 1). Participants were significantly

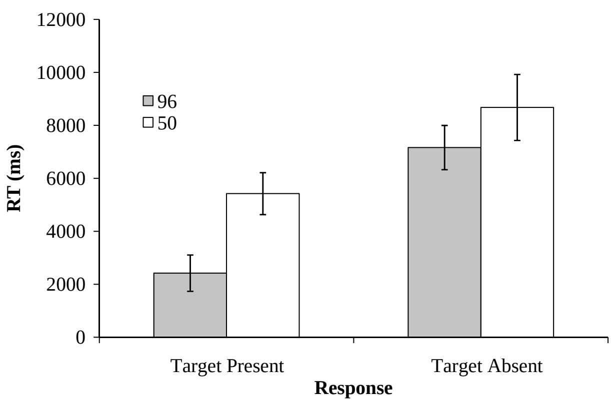

Figure 9. Significant difference found in target-present RTs, but not target-absent RTs, between the 50% and 96% prevalence conditions in Experiment 2. Error bars represent standard error of the mean.

more liberal and apparently more sensitive in their decisions in the 96% prevalence condition.

Discussion

Experiment 2 revealed an increase in hit and false alarm rates and a dramatic speeding of target-present RTs in the 96% as compared to the 50% prevalence condition. The results match the predicted observer behaviour that would result from prevalence-based decisions. Additionally, the SDT analysis showed changes in both criteria and sensitivity, which is inconsistent with prior visual search research that found target prevalence does not result in sensitivity differences (Schwark et al., 2012; Wolfe et al., 2005, 2007; Wolfe & Van Wert, 2010). The implications of this are discussed further in the General Discussion.

The strongest evidence for these prevalence-based decisions being cognitive, rather than perceptual, in nature comes from the target-present RTs, which were more than twice as fast in the 96% condition as in the 50% condition. These findings are contrary to previous research that found no quickening of target-present RT in high prevalence conditions (Wolfe & Van Wert, 2010) and do not fit the predictions of the multiple-decision model. Instead, the results match the prediction made from the diffusion model, which accounts for the speeding of target-present responses under high prevalence. It is unlikely that many decisions were made from actually perceiving targets given the well-established literature on speed–accuracy tradeoffs (Schouten & Bekker, 1967; Wickelgren, 1977) and our finding that decisions made in the 96% condition were more accurate *and* faster. However, it is important to note that prevalence-based decisions were not made exclusively, and that target-absent responses made in the 96% condition could only be explained by search-based decisions since they were contrary to decisions that would be made based on an assumption of target prevalence.

EXPERIMENT 3

Experiment 3 sought to provide stronger evidence that targets were not being identified in Experiment 2, but that decisions were made based primarily on target prevalence. All of the targets in the stimuli were removed, but the task continued to provide feedback *as if the targets were still present*. Previous research has demonstrated the effectiveness of false feedback in shaping search behaviour (Mackworth, 1964; Schwark et al., 2012). Providing feedback as if the target was present 50% or 96% of the time would allow the investigation of whether participants made decisions consistent with the perceived prevalence that was provided through feedback (50% or 96%) or with the *actual* prevalence of the target (0%).

Notably, feedback is not always available after each trial in applied visual search tasks. For example, airport luggage screeners may receive feedback after they report the presence of a dangerous object because the bag is immediately searched. However, they would not receive immediate feedback if they missed a target, because it would pass through the screening process undetected. Therefore, Experiment 3 also investigated whether prevalence-based decisions would still be shaped by prevalence if no feedback was provided, but the prevalence of the target was known. The prevalence of a target is often known in applied search tasks, such as medical screening, where the prevalence of a tumour is often less than 1% (Fenton et al., 2007; Gur et al., 2004).

It is unlikely that many of the fast target-present responses found in Experiment 2 were a result of identifying a target, so it was hypothesized that participants would continue to make faster target-present decisions under high prevalence in Experiment 3 even though the targets were removed. We also predicted that feedback was not necessary to make prevalence-based decisions and that the same results could be obtained from simply providing target prevalence information to the observers.

Method

Participants. Twenty-eight undergraduate students (18 female, 10 male) from New Mexico State University participated in the experiment for partial course credit. The mean age was 21.3 years ($SD = 6.0$) and all participants had self-reported normal or corrected-to-normal vision.

Materials. The same materials used in Experiment 2 were used in Experiment 3, except X was removed from every target-present stimulus and replaced with a non-X letter.

Procedure. The only difference in the procedure from Experiment 2 was the introduction of feedback availability. Participants were assigned to either the 50% ($n = 14$) or 96% ($n = 14$) perceived prevalence condition. In one block of 100 experimental trials, feedback was given in an identical manner as Experiment 1 at the participant's perceived target prevalence. In the other block of 100 experimental trials, participants were told at the beginning of the block what the prevalence of the target was (50% or 96%, between participants) instead of receiving feedback. They also had to answer questions pertaining to the target prevalence before they began, in order to demonstrate a sufficient understanding of the concept. Target prevalence was displayed in place of the feedback screen after each trial during this block as a reminder. Points were not shown on this screen, but participants were instructed that the points were being tallied even though they would not see the total until the end of the block. These two blocks of trials were counterbalanced in each prevalence condition, thus feedback availability was manipulated within subjects.

Participants were told that the second block of trials was drawn from a new set of stimuli and that they should forget what they may have been told for the first block of trials. However, the apparent target prevalence always remained the same across blocks for all participants. Practice trials were always presented with feedback screens and did contain targets at 50% prevalence. The study took approximately 1 hour and RTs and the number of target-absent or target-present responses were collected.

Results

A 2×2 (Feedback availability $\times$ Prevalence) mixed ANOVA[8] performed on target-present RTs revealed a significant main effect of feedback availability, $F(1, 25) = 12.11$, $p = .002$, $\eta_p^2 = .33$, a significant main effect of prevalence, $F(1, 25) = 7.25$, $p = .01$, $\eta_p^2 = .23$, and no interaction, $p = .96$ (Figure 10). Target-present RTs were faster in the 96% condition ($M = 5408$ ms, $SD = 3796$ ms) than the 50% condition ($M = 9154$ ms, $SD = 2821$ ms), and faster when feedback was given after each trial ($M = 5685$ ms, $SD = 725$ ms) than

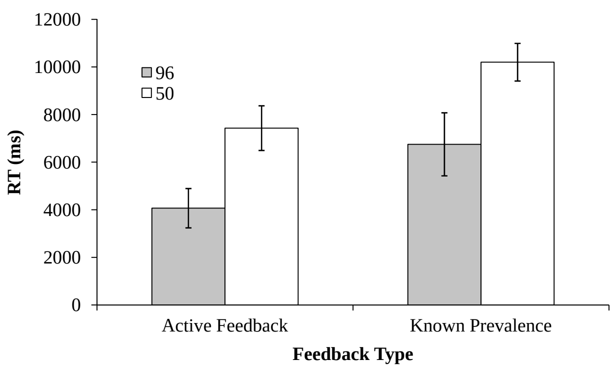

Figure 10. Significant main effect of feedback type and perceived prevalence in target-present RTs found in Experiment 3. Error bars represent standard error of the mean.

[8] One participant was removed from RT analysis due to never making a target-present response during the known prevalence block of trials, making it impossible to include them in any analysis of target-present RT. This is the only participant that did not make any prevalence-based decisions during this block, and in a sense their behaviour is contrary to our hypotheses. They did make target-present responses in the second block of trials (active feedback).

when only the prevalence was known ($M = 8412$ ms, $SD = 873$ ms). The same analysis performed on target-absent RTs found no significant main effects or interaction (all $ps > .10$). Participants reached the 20 s time limit on less than 1% of trials.

The same 2 × 2 mixed ANOVA performed on the percentage of target-present responses revealed solely a significant main effect of prevalence, $F(1, 26) = 72.72$, $p < .001$, $\eta_p^2 = .95$, whereby participants in the 96% prevalence condition made more target-present responses ($M = 0.83$, $SD = 0.13$) than participants in the 50% prevalence condition ($M = 0.37$, $SD = 0.16$), despite no target appearing in either condition. Analyses using accuracy and SDT could not be performed due to the lack of real target-present trials in the design.

A 2 × 2 (Prevalence × Experiment) ANOVA was performed across Experiments 2 and 3 on target-present response rate to see whether the removal of the target impacted the rate of target-present responses. Significant main effects were found for both prevalence, $F(1, 54) = 128.24$, $p < .001$, $\eta_p^2 = .70$, and experiment, $F(1, 54) = 6.59$, $p = .005$, $\eta_p^2 = .11$. Overall, significantly more target-present responses were made in Experiment 2, providing evidence that the presence of targets and thus, search-based decisions, did contribute to the results of Experiment 2.

Discussion

The results from Experiment 3 are consistent with the hypothesis that participants would continue making prevalence-based decisions even when targets were absent. These results replicate the findings of Experiment 2, providing additional support for the assertion that decisions are prevalence based. Removing the targets while providing false feedback ensured that a target-present response could not be based on successful target identification, yet target-present responses occurred on approximately 83% of the trials (for 96% target prevalence) and 37% of the trials (for 50% target prevalence). Experiment 3 also helps demonstrate that search-based decisions still occurred in Experiment 2, even though the task was much more difficult, because target-present response rates were higher in Experiment 2 than in Experiment 3.

GENERAL DISCUSSION

The current results identify the presence of prevalence-based decisions and demonstrate their importance in visual search tasks. The influence of prevalence was demonstrated in Experiment 1 by participants who terminated searches with target-present responses before finding the target, especially in difficult trials and when target prevalence was high. These prevalence-based decisions were quite accurate at extreme prevalence rates and contributed to overall high hit rates (and subsequent false alarm rates). In Experiment 2, prevalence-based decisions were frequently made at RTs that were likely too fast to be a result of target detection, and target-present responses were faster under high prevalence. Experiment 3 confirmed that these responses were not primarily a result of actual target perception.

Prevalence-based decision behaviour

This study is the first identification of prevalence-based decisions, which we define as decisions based predominantly on target likelihood, whereas search-based decisions are decisions based on target perception. It may seem obvious that decisions are based primarily on target prevalence rather than perception when perceiving a target is extremely difficult, as was the case in Experiments 2 and 3. However, prevalence-based decisions were still observed in Experiment 1 when the target was easily perceptible. Before discussing the impact of these results on our current understanding of visual search behaviour, it is necessary to assess the behaviour itself.

The presence of prevalence-based decisions does not imply that other decision behaviours are not used. Even when the task was so difficult that targets were rarely perceived, search-based decisions still occurred. Experiment 3 reveals evidence of this, as the percentage of target-present responses was significantly less than the perceived target prevalence rates of 96%, $t(13) = 3.79$, $p = .002$, and 50%, $t(13) = 3.12$, $p = .008$. These data indicate that some decisions were not based on prevalence, but were the result of unsuccessful target searches. The low rate of prevalence-based as compared to search-based decisions in Experiment 1, even for difficult trials, demonstrate that prevalence-based decisions serve as a shortcut for decision making rather than a total replacement for perceptual search.

A possible explanation is that prevalence-based decisions are the result of adopting a liberal decision criterion, which is typically observed under high prevalence (Wolfe & Van Wert, 2010). Perhaps participants in the high prevalence condition were more likely to classify an ambiguous object as the target letter X due to liberal criteria, resulting in what appeared to be prevalence-based decisions. However, if this were the case, accuracy of target clicks would decrease under high target prevalence as trials became more difficult, because there would be more ambiguous objects that could be falsely identified as targets. This did not occur; target click accuracy only dropped to approximately 93% accuracy in hard trials and this drop was almost identical between high and moderate prevalence conditions. This suggests that prevalence-based decisions were not the result of increased readiness to classify ambiguous objects as targets, but target-present biases made prior to the identification of a target.

The same logic argues against the possibility that the frequent overlap of distractor letters in hard trials caused participants to falsely perceive Xs in these trials. If participants perceived these overlapping letters as targets, then they should have been more biased to click on and identify these occurrences as targets in the high prevalence condition, and target–click accuracy would have decreased more in the high prevalence condition than in the moderate prevalence condition. Additionally, if this were purely a perceptual phenomenon, the number of times this occurred should be similar across both prevalence conditions, since the stimuli were identical. Instead, the TP button response rate varied significantly with prevalence condition.

Another possibility is that target prevalence reduces the threshold need to elicit a response, resulting in faster target-present responses in high prevalence. The 20-s time limit used in Experiments 2 and 3 was intended to prevent an exhaustive search and this may have encouraged snap decisions to be made upon perceiving a potential target. Prevalence may have lowered the threshold for these decisions to be made, allowing responses before full recognition of a target. If that is the case, overlapping letters would be judged to be targets sooner. This explanation may have contributed somewhat to the results of Experiments 2 and 3, but would not be sufficient to explain prevalence-based decisions in Experiment 1. In Experiment 1, there was no time limit and the task was much easier, eliminating the need for snap judgements and reducing the likelihood of overlapping targets being misinterpreted as targets.

Perhaps the best explanation for prevalence-based decisions comes from research in selective and nonselective pathways in visual search (Wolfe, Vo, Evans, & Greene, 2011). The nonselective pathway uses a Gestalt impression that extracts global or statistical information from the entire visual field, whereas the selective pathway is used for selecting and identifying individual objects, which is necessary for target localization. Evidence for a nonselective pathway comes from the demonstration that radiologists have greater than chance accuracy when determining whether a tumour is present in an image displayed for only 250 ms, which is too brief for target identification (Drew, Evans, Vo, Jacobson, & Wolfe, 2013; Kundel & Nodine, 1975). Prevalence-based decisions may involve prevalence information from the nonselective pathway. The probability of successful target identification using the selective pathway would decrease as trials become more difficult, increasing the appeal of making a decision based on prevalence rather than target perception.

Prevalence in visual search models

The identification of prevalence-based decisions has several implications for models of visual search (Wolfe, 2007; Wolfe & Van Wert, 2010). First, the finding that target-present responses can be made without target perception presents a challenge to current models, which assume that target-present decisions are dependent on perception (even if this perception is incorrect). Second, visual search models assume that terminating a search before a target is perceived will always result in a target-absent response. Prevalence-based decisions also demonstrate that this assumption is not always correct. These findings suggest that current models need to be adapted to account for prevalence-based decisions in visual search. This could mean introducing a quitting threshold that elicits target-present responses or adjusting the current quitting threshold to differentially yield target-absent or target-present responses. Further research is needed to determine how current models can be adjusted to best account for the full range of visual search decisions.

Current perceptual and visual search models adequately model search-based decisions. Even in Experiment 1, in which prevalence-based decisions were rare, but still occurred, the multiple-decision model accurately accounts for RTs. Target-absent RTs became slower, but target-present RTs were not faster in high prevalence. However, when search-based decisions were discouraged through the use of the difficult tasks in Experiments 2 and 3, the results were not consistent with visual search models. Instead, results fit the diffusion model, which accurately predicts faster target-present responses in high prevalence (Wolfe & Van Wert, 2010). A parsimonious model of visual search should aim to predict not only perceptual, search-based decisions but also cognitive, prevalence-based decisions.

Experiment 2 also demonstrates that SDT struggles to account for prevalence-based decisions. Analyses based on SDT revealed a large difference in sensitivity due to prevalence, which is an unusual finding in visual search (Schwark et al., 2012; Wolfe et al., 2007). Sensitivity was near 0 in the 50% prevalence condition, as expected given the difficulty of the task. The inflation of sensitivity in high prevalence may be the result of SDT classifying all correct target-present decisions as hits, even if they were prevalence based (the same can be said of incorrect decisions and false alarms). It seems likely that hits resulting from prevalence-based decisions may not have the same impact on operator behaviour as hits resulting from search-based decisions. To be fair, SDT was designed as a perceptual theory, not a cognitive one, so its struggle to measure all decision types in visual search is a problem in its application rather than its validity as a theory. Still, this inability of SDT to distinguish between a hit resulting from the identification of a target and a hit resulting from a prevalence-based decision may result in misleading analyses, which likely explains the sensitivity difference found in Experiment 2. The presence of prevalence-based decisions in Experiment 1 suggests that these decisions may well be occurring in visual search studies that are being inappropriately analysed with SDT.

Finally, the current study suggests that it may be inaccurate to assume that target-present RTs represent the speed of target perception. Many visual search studies, perhaps the majority, use 2AFC methodologies in which participants do not need to locate a target, only report whether it is present or absent. Correct target-present RTs are used to assess the speed of target perception, but Experiment 1 clearly demonstrates that not all accurate target-present responses are solely the result of target perception. Studies investigating task difficulty are at the highest risk of faulty inferences because prevalence-based decisions increase with task difficulty, but any study drawing inferences about perception from target-present RTs should take into account the possibility of prevalence-based decisions.

Implications for low prevalence search

The current study investigated the impact of extreme prevalence on search behaviour in high prevalence only, but the findings may be extended to the current understanding of low prevalence search behaviour as well. In low prevalence, searches are terminated with target-absent responses before sufficient evidence that a target is actually absent is gathered, resembling a type of prevalence-based decision. Up to this point, a dichotomous distinction has been made between prevalence-based and search-based decisions. This distinction is useful to describe target-present responses (the target is perceived or it is not), but target-absent decisions are more complex. These decisions likely exist along a continuum ranging from target-absent decisions based on little to no perceptual evidence to those based on a large accumulation of perceptual evidence.

If target-absent decisions in low prevalence are a type of prevalence-based decision, this could explain why successful methods for minimizing miss rates in low prevalence situations involve changing the perception of target prevalence, whereas remedies that aim to improve the perception of targets (such as extending search times) have relatively little impact. It also explains why plots of RT as a function of set size have shallower slopes in lower prevalence (Rich et al., 2008). If less evidence is needed for target-absent responses in low prevalence, this benefit should grow with each additional object that needs to be searched. This prediction is supported by the larger differences in RTs at higher set sizes (Rich et al., 2008). Overall, it seems that extremes in target prevalence reduce an observer's reliance on perception, moving visual search decisions from perceptual to a more cognitive decision type, influenced by the observer's belief that a target is probably present or absent.

One question that remains unanswered is, if the fast target-absent decisions routinely observed in low prevalence search are primarily prevalence based, why are these decision types so frequent? In Experiment 1, the highest frequency of prevalence-based decisions occurred in difficult search trials, but their rate of occurrence was still less than 50% of these difficult target-present trials. The answer may reside in how observers perceive the difficulty of a search task. Assuming the goal of a search is to identify a target that is present, the best measure of task difficulty might be the observer's ability to detect the target when it is present (hit rate). A radiologist's overall accuracy in medical imaging would matter very little if they were constantly missing malignancies. Similarly, a single bomb passing through security undetected would have serious consequences, regardless of how many bags had previously been correctly classified as target absent. High hit rates would indicate a task is less difficult due to the ease of finding a target that is present. Interestingly, this would imply that low prevalence searches are generally difficult due to the low hit rates.

Finally, one may note that prevalence-based decisions occurred in Experiment 1 because the design allowed for it: If the TP button was removed and participants had to identify the target, target-present prevalence-based decisions would be excluded. However, target identification is not always required in applied settings, especially under low prevalence. For example, a radiologist might make a "call back" decision without actually identifying a tumour (Drew et al., 2013). Target identification is also not necessary to make prevalence-based decisions under low prevalence, where target-absent decisions can be used to quickly terminate the search. Therefore, requiring the identification of targets would not eliminate the impact of prevalence-based decisions from all scenarios and would do little to remedy the problem in low prevalence. Perhaps the best way to improve the performance of radiologists or security personnel in low prevalence searches will focus on changing the way that decisions are made rather than attempting to increase the odds of perceiving a target. There are clear theoretical and practical needs for future research to investigate the decision behaviour of low prevalence searches using the framework of prevalence-based decisions outlined in the current study.

CONCLUSION

In summary, Experiment 1 revealed that prevalence-based decisions were used to make judgements about target presence or absence, especially in more difficult trials. Experiment 2 confirmed this finding and demonstrated that prevalence-based decisions function similarly to cognitive choices, not perceptual ones. Experiment 3 revealed that prevalence-based decisions could be elicited by simply deceiving participants about a target's likelihood of occurrence and that target-present responses were made in the absence of actual targets. These prevalence-based decisions are problematic for attempts to improve perception in visual search, as decisions made before perceptual evidence has accumulated may undermine improvements made to the perceptibility of a target. The results also illustrate a need for a visual search model that can successfully account for an observer's use of both perceptual and cognitive strategies in executing visual search decisions.

REFERENCES

Chun, M. M., & Wolfe, J. M. (1996). Just say no: How are visual searches terminated when there is no target present? *Cognitive Psychology*, *30*, 39–78. doi:10.1006/cogp.1996.0002

Drew, T., Evans, K., Vo, M., Jacobson, F. L., & Wolfe, J. M. (2013). Informatics in radiology: What can you see in a single glance and how might this guide visual search in medical images? *Radiographics*, *33*, 263–274. doi:10.1148/rg.331125023

Fenton, J. J., Taplin, S. H., Carney, P. A., Abraham, L., Sickles, E. A., D'Orsi, C., . . . Elmore, J. G. (2007). Influence of computer-aided detection on performance of screening mammography. *New England Journal of Medicine*, *356*, 1399–1409. doi:10.1056/NEJMoa066099

Fleck, M. S., & Mitroff, S. R. (2007). Rare targets are rarely missed in correctable search. *Psychological Science*, *18*, 943–947. doi:10.1111/j.1467-9280.2007.02006.x

Gomez, P., Ratcliff, R., & Perea, M. (2007). A model of the go/no-go task. *Journal of Experimental Psychology: General*, *136*, 389–413. doi:10.1037/0096-3445.136.3.389

Green, D. M., & Swets, J. A. (1966). *Signal detection theory and psychophysics.* New York, NY: Wiley.

Gur, D., Sumkin, J. H., Rockette, H. E., Ganott, M., Hakim, C., Hardesty, L., . . . Wallace, L. (2004). Changes in breast cancer detection and mammography recall rates after the introduction of a computer-aided detection system. *Journal of the National Cancer Institute*, *96*, 185–190. doi:10.1093/jnci/djh067

Johnson, J. G., & Busemeyer, J. R. (2005). A dynamic, stochastic, computational model of preference reversal phenomena. *Psychological Review*, *112*, 841–861. doi:10.1037/0033-295X.112.4.841

Kunar, M. A., Rich, A. N., & Wolfe, J. M. (2010). Spatial and temporal separation fails to counteract the effects of low prevalence in visual search. *Visual Cognition*, *18*, 881–897. doi:10.1080/13506280903361988

Kundel, H. L., & Nodine, C. F. (1975). Interpreting chest radiographs without visual search. *Radiology*, *116*, 526–532.

Leite, F. P., & Ratcliff, R. (2011). What cognitive processes drive response biases? A diffusion model analysis. *Judgment and Decision Making*, *6*, 651–687.

Mackworth, J. F. (1964). The effect of true and false knowledge of results on detectability of signals in a vigilance task. *Canadian Journal of Psychology*, *18*, 106–117. doi:10.1037/h0083493

Nothdurft, H.-C. (2006). Salience and target selection in visual search. *Visual Cognition*, *14*, 514–542. doi:10.1080/13506280500194162

Ratcliff, R. (1978). A theory of memory retrieval. *Psychological Review*, *85*, 59–108. doi:10.1037/0033-295X.85.2.59

Ratcliff, R. (2001). Diffusion and random walk processes. In *International encyclopedia of the social and behavioral sciences* (pp. 3668–3673). Oxford: Elsevier Science.

Ratcliff, R., & Rouder, J. N. (1998). Modeling response times for two-choice decisions. *Psychological Science*, *9*, 347–356. doi:10.1111/1467-9280.00067

Rich, A. N., Kunar, M. A., Van Wert, M. J., Hidalgo-Sotelo, B., Horowitz, T. S., & Wolfe, J. M. (2008). Why do we miss rare targets? Exploring the boundaries of the low prevalence effect. *Journal of Vision*, *8*, 1–17. doi:10.1167/8.15.15

Russell, N. C., & Kunar, M. A. (2012). Colour and spatial cueing in low-prevalence visual search. *Quarterly Journal of Experimental Psychology*, *65*, 1327–1344. doi:10.1080/17470218.2012.656662

Schouten, J. F., & Bekker, J. A. M. (1967). Reaction time and accuracy. *Acta Psychologica*, *27*, 143–153. doi:10.1016/0001-6918(67)90054-6

Schwark, J., Sandry, J., & Dolgov, I. (2013). Evidence for a positive relationship between working-memory capacity and detection of low-prevalence targets in visual search. *Perception*, *42*, 112–114. doi:10.1068/p7386

Schwark, J., Sandry, J., MacDonald, J., & Dolgov, I. (2012). False feedback increases detection of low-prevalence targets in visual search. *Attention, Perception, and Psychophysics*, *74*, 1583–1589. doi:10.3758/s13414-012-0354-4

Smith, P. L. (1995). Psychophysically principled models of visual simple reaction time. *Psychological Review*, *102*, 567–593. doi:10.1037/0033-295X.102.3.567

Van Wert, M. J., Horowitz, T. S., & Wolfe, J. M. (2009). Even in correctable search, some types of rare targets are frequently missed. *Attention, Perception, and Psychophysics*, *71*, 541–553. doi:10.3758/APP.71.3.541

Wickelgren, W. A. (1977). Speed-accuracy tradeoff and information processing dynamics. *Acta Psychologica*, *41*, 67–85. doi:10.1016/0001-6918(77)90012-9

Wilson, M. (2002). Six view of embodied cognition. *Psychonomic Bulletin and Review*, *9*, 625–636. doi:10.3758/BF03196322

Wolfe, J. M. (1998). What can 1 million trials tell us about visual search? *Psychological Science*, *9*, 33–39. doi:10.1111/1467-9280.00006

Wolfe, J. M. (2007). Guided Search 4.0: Current progress with a model of visual search. In W. Gray (Ed.), *Integrated models of cognitive systems* (pp. 99–119). New York, NY: Oxford University Press.

Wolfe, J. M., Horowitz, T. S., & Kenner, N. M. (2005). Rare items often missed in visual searches. *Nature*, *435*, 439–440. doi:10.1038/435439a

Wolfe, J. M., Horowitz, T. S., Van Wert, M. J., Kenner, N. M., Place, S. S., & Kibbi, N. (2007). Low target prevalence is a stubborn source of errors in visual search tasks. *Journal of Experimental Psychology: General*, *136*, 623–638. doi:10.1037/0096-3445.136.4.623

Wolfe, J. M., & Van Wert, M. J. (2010). Varying target prevalence reveals two dissociable decision criteria in visual search. *Current Biology*, *20*, 121–124. doi:10.1016/j.cub.2009.11.066

Wolfe, J. M., Vo, M., Evans, K. K., & Greene, M. R. (2011). Visual search in scenes involves selective and non-selective pathways. *Trends in Cognitive Sciences*, *15*, 77–84. doi:10.1016/j.tics.2010.12.001

Manuscript received November 2012
Revised manuscript received May 2013
First published online July 2013