Psychonomic Bulletin & Review
https://doi.org/10.3758/s13423-022-02183-0

BRIEF REPORT

The influence of category representativeness on the low prevalence effect in visual search

Ryan E. O'Donnell[1] · Brad Wyble[1]

Accepted: 2 September 2022

Abstract

Visual search is greatly affected by the appearance rate of given target types, such that low-prevalence items are harder to detect, which has consequences for real-world search tasks where target frequency cannot be balanced. However, targets that are highly representative of a categorically defined task set are also easier to find. We hypothesized that targets that are highly representative are less vulnerable to low-prevalence effects because an observer's attentional set prioritizes guidance toward them even when they are rare. We assessed this hypothesis by first determining the categorical structure of "prohibited carry-ons" via an exemplar-naming task, and used this structure to assess how category representativeness interacted with prevalence. Specifically, from the exemplar-naming task we selected a commonly named (knives) and rarely named (gas cans) target for a search task in which one of the targets was shown infrequently. As predicted, highly representative targets were found more easily than their less representative counterparts, but they also were less affected by prevalence manipulations. Experiment 1b replicated the results with targets matched for emotional valence (water bottles and fireworks). These findings demonstrate the powerful explanatory power of theories of attentional guidance that incorporate the dynamic influence of recent experience with the knowledge that comes from life experience to better predict behavioral outcomes associated with high-stakes search environments.

Keywords Visual search · Low prevalence effect · Category membership · Attentional set

Introduction

Task experience is increasingly studied in attention and visual search. For example, in theories of attentional selection, the previous dichotomy of salience-driven versus goal-driven attentional capture has expanded to include a third factor: selection history, which describes behavioral outcomes attributable to recent experience selecting targets and/or inhibiting distractors (Awh et al., 2012; Wolfe, 2021). In visual search, task experience can dramatically impact an observer's ability to find targets at rapid timescales. For example, repetition priming will speed search for repeating targets or target features (Maljkovic & Nakayama, 1994). Additionally, Kramer and colleagues (2022) provided evidence that recent experience with identifying a target strongly predicts future target identification performance, both positively if experience mirrors the current trial, and negatively if the current trial violates experience-defined expectations.

Most notably, the influence of task experience on search is observable through the low-prevalence effect. Specifically, it was demonstrated that a target's appearance rate in a visual search setting dramatically changes search performance, with increased miss errors occurring with decreased prevalence (Horowitz, 2017; Wolfe, 2021; Wolfe et al., 2005, 2007). Thus, in real-world settings where targets are extremely rare, such as radiology screenings or airport baggage checks, the overall rarity of hazardous targets could produce dangerous search omissions. The prevalence effect has been shown to be sensitive to both the overall appearance rate of targets (Fleck & Mitroff, 2007; Godwin et al., 2015; Wolfe et al., 2005, 2007) and relative appearance rate either within a task (i.e., a target becomes rare within a set batch of trials; Mitroff & Biggs, 2014; Wolfe et al., 2007) or compared to the appearance rate of other targets (Wolfe et al., 2007; Biggs et al., 2014; Biggs & Mitroff, 2015). Though some theories have suggested a decrease in selection

✉ Ryan E. O'Donnell
Ryanodonnell7@gmail.com

[1] Department of Psychology, Pennsylvania State University, 142 Moore Building, University Park, PA 16802, USA

or perceptual sensitivity for low-prevalence targets (Horowitz, 2017; Hout et al., 2015; Wolfe & Van Wert, 2010), most theories of the low-prevalence effect have focused on changes in response decisions, where the criterion to select a target becomes more conservative, leading observers to potentially make premature response decisions on a given search trial (Fleck & Mitroff, 2007; Horowitz, 2017; Rich et al., 2008; Schwark et al., 2012; Taylor et al., 2022; Wolfe & Van Wert, 2010).

Though recent experience is a powerful influence on current performance, research suggests that prior knowledge – in particular conceptual knowledge – will also impact attentional guidance. Specifically, Maxfield et al. (2014) showed that a target's representativeness to its target category – a property of conceptual knowledge – influences search, with more representative category members being easier to find.[1] This finding has been replicated even at the superordinate level of categorization (Robbins & Hout, 2015, 2020), and when coupled with the observation that subordinate-level search templates are better guides than less specific basic- or superordinate-level templates (Bravo & Farid, 2009, 2012; Malcolm & Henderson, 2009; Maxfield & Zelinsky, 2012; Schmidt & Zelinsky, 2009; Wolfe & Horowitz, 2017), provides evidence that attentional selection in categorical search is heavily modulated by conceptual organization. This is important to consider because the fact that attentional guidance prioritizes highly representative target types is often overlooked in studies and theories that define target templates by discrete features (Wolfe, 2021; Wolfe et al., 2010).

Because real-world searches like those of baggage screenings often require vigilance for multiple and varied target types (Biggs et al., 2018; Biggs & Mitroff, 2015) that have conceptual overlap through a shared goal rather than shared structure (Barsalou, 1985; Kurtz & Gentner, 2001), accounting for conceptual influences on rare target searches could improve real-world search outcomes. In this article we propose a conceptual model that suggests conceptual knowledge and recent task experience interact with respect to influencing attentional guidance.

Specifically, we propose that visual attention prioritizes highly representative target exemplars, which protects them from the effects of low prevalence, thereby accruing less of a cost to accuracy and response time (RT) when such targets are quite rare within the search environment. To explain this effect, we provide a conceptual model that illustrates the interactive influence of conceptual knowledge and recent search experience (Fig. 1). To elaborate, an observer's attentional set will be initially informed by their conceptual knowledge of the target category, which will prioritize highly representative targets, as demonstrated through increased activation for the blue and green target nodes in Fig. 1. As an individual engages in the search task, however, the experience of finding specific target types biases their attentional set towards recently selected target types, allowing for swifter and easier subsequent selections (Clark et al., 2015). Two additional factors update the observer's attentional set, a small decay in activation for targets not found on each trial, which causes the low prevalence cost, but also a reinforcement for all targets within the categorical search set proportional to its representativeness any time a category member is found (because observers do not forget their initial instructions; Cox et al., 2021). This last input, visualized in Fig. 1 through the variably sized light green arrows, helps to anchor the attentional bias towards highly representative items even if they are contextually rare.

Thus, in a similar way to how salience was identified as a driver of search behavior (Biggs et al., 2014), the operationalizing of one's attentional set according to both recent experience and longer-term life experience (i.e., conceptual knowledge) informs when and where search misses might likely occur in categorical low-prevalence search environments. Specifically, our key prediction is that prevalence and representativeness will interact, causing both a larger drop in accuracy and elevation in RT for rare poorly representative targets compared to highly representative ones. In other words, even though a gun may be rare, it should still be found more frequently than rare fireworks because the gun's representativeness will preserve its prioritization within the observer's attentional set.

To test our prediction, we used a categorical search set commonly used in low-prevalence effect studies: prohibited carry-on items for air travel. However, research in categorization suggests that categorical structure differs between taxonomic semantic categories like "animals" and what are termed goal-derived categories like "prohibited carry-ons" (Barsalou, 1985; Kurtz & Gentner, 2001). Because of this, traditional goodness-of-fit ratings that characterize the representativeness of taxonomic categorical structures (Rosch, 1975; Rosch & Mervis, 1975) do not serve as good proxies for goal-derived structures. Thus, instead of using goodness-of-fit measurements, we adopted a simplified assessment of the object's within-category representativeness: an exemplar-naming task (Barsalou, 1985; Kurtz & Gentner, 2001). After using the exemplar-naming paradigm to determine representativeness ratings for "prohibited carry-ons," we selected highly representative and poorly representative objects to serve as targets in two visual search tasks where the objects varied in frequency of appearance within the task. To best test our predictions, we elected to sacrifice ecological validity in our search environment by using a tightly controlled classical search task comprised of an array of non-overlapping search items rather than mimicking a baggage-screening environment. This simplified paradigm eliminated factors known to generate search errors

[1] Though Maxfield and colleagues (2014) use the term *typicality* in their study, we choose to use the term *representativeness* because our target category is non-taxonomic and has no clear measure of central tendency through which a prototype might arise.

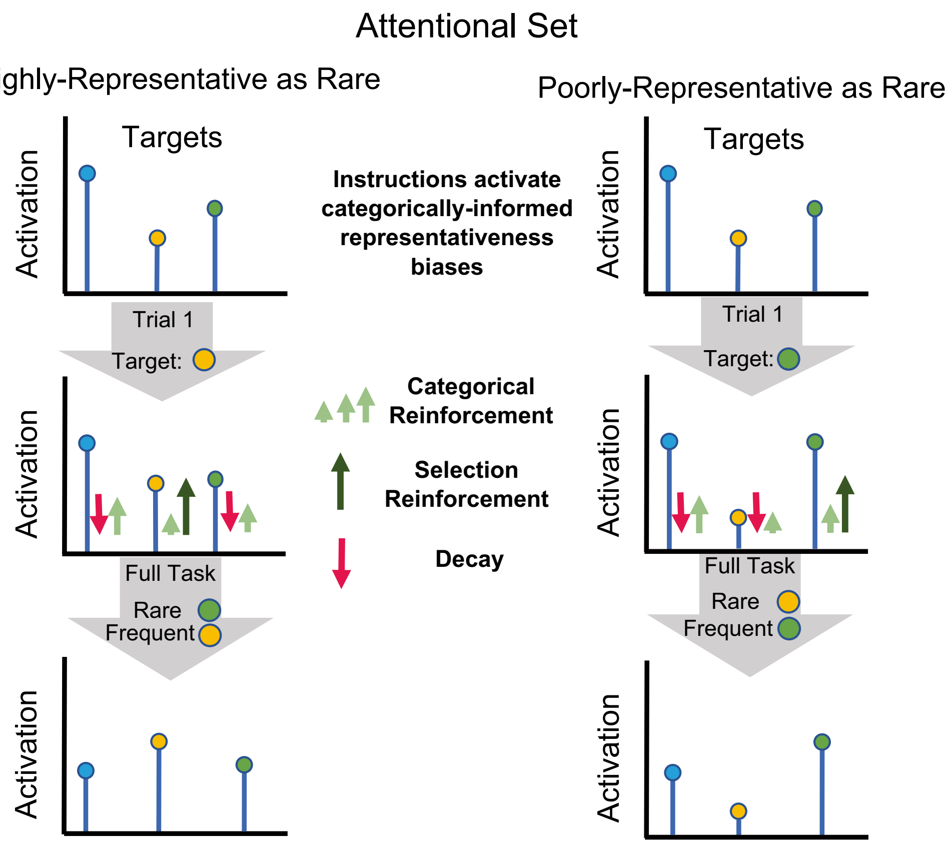

Fig. 1 Conceptual model for an observer's attentional set with interactive influences of recent task experience and categorical knowledge for three different target types, represented by blue, green, and yellow circles (though note the blue target is never selected). Activation represents attentional sensitivity for selecting a target, with higher activation on a given node leading to more frequent and rapid detection. Initially, task instructions activate an attentional set based on categorical biases reflecting representativeness (i.e., greater initial activation to highly representative targets like the green and blue nodes). Then, on each trial, after a target is selected, activation levels update according to three parameters: (1) categorical knowledge reinforcement (boost in activation based on how representative a given target type is, i.e., light green arrows of varying sizes), (2) selection reinforcement (boost in activation for the selected target type, i.e., the dark green arrow), and (3) activation decay (decreasing activation for non-selected targets, i.e., the red arrow). The sum of the influences for each item lead to an overall increase or decrease in activation for each trial. The change in activation accumulates across trials

during baggage-screening environments, such as superposition, baggage complexity, and non-canonical target viewpoints (Bolfing et al., 2008; Schwaninger, 2006) so that we could focus on the factors target prevalence and representativeness.

Methods

Before conducting a visual search experiment, we first assessed the categorical structure of the proposed target set. Forty-four Penn State University undergraduates (mean age 18.84 years, range 18–22 years, 93% female, 16% left-handed) who provided informed consent and passed our attention check exclusion criterion (five excluded) completed a Qualtrics survey (version 10/2021; Qualtrics, Provo, UT, USA) that determined the representativeness rating of each item in the target category. Participants were given 45 s to list as many specific items that matched the description:

"Things you are NOT allowed to pack in an airplane carry-on bag"

This category label was further clarified as objects that would be confiscated if found by airport security. Importantly, participants were not instructed to name good examples first; they were simply told to name as many examples as they can. From this data the number of mentions of each item (regardless of whether they are officially prohibited) were counted and ranked according to the number of participants who named it (Table 1).[2] Additionally, in a follow-up question, participants provided emotional valence ratings

[2] Items generated during the exemplar-naming task that were deemed to be non-descript (i.e., "liquids" or "containers") were excluded from the representativeness rankings. The decision to include named exemplars that are not actual members of the "prohibited items" list mirrors the decision to include the mammal "bat" in the typicality measures of the bird category by Rosch (1975).

Table 1 Item rankings for the category "prohibited carry-ons"

Rank	Object	Count	Rank	Object	Count
1	Guns	25	16	Fireworks	2
2	Knives	23	16	Perfume	2
3	Drugs	20	16	Pills	2
4	Bombs	13	21	Swords	1
5	Water Bottles	12	21	Axes	1
6	Alcohol	8	21	Vaseline	1
7	Shampoo	7	21	Hand Soap	1
8	Cigarettes	6	21	Oil	1
9	Lighter	5	21	Marijuana	1
9	Batteries	5	21	Cocaine	1
9	Lotion	5	21	Dayquil	1
12	Humans	4	21	Body Soap	1
12	Conditioner	4	21	Spray Paint	1
14	Razors	3	21	Shaving Cream	1
14	Scissors	3	21	Pepper Spray	1
16	Vapes	2	21	Bananas	1
16	Ammunition	2	NR	Gas Cans	0

Count data represents the total number of participants who named a concept in the survey. Concepts with similar meanings like "Guns" and "Firearms" are grouped together. It should be noted that not all items listed are actually prohibited by aviation security organizations

of items related to airport carry-ons, which would serve as a control in Experiment 1b. The assessed items were predetermined, and not altered according to the participant's naming data. The design of the emotional valence question mirrored the wording used in the self-assessment manikin (SAM) of emotional response to concepts (Bradley & Lang, 1994). The exact wording of the question, as well as the valence scores, can be found in the Online Supplementary Material (OSM) to this article.

Using the representativeness rankings, targets were selected for the visual search tasks in Experiments 1a and 1b. For both experiments, a new sample of Penn State participants – $N = 50$ for Experiment 1a (mean age 19.21 years, range 18–46 years, 72% female, 16% left-handed); $N = 51$ for Experiment 1b (mean age 18.7 years, range 18–21 years, 78.43% female, 11.76% left-handed) –were recruited. All participants provided informed consent to participate in our Penn State Institutional Review Board-approved study and passed exclusion criteria requiring overall search accuracy greater than 50% (two excluded) and passing an attention check (not pressing the spacebar for more than 40 trials in a row; four excluded). Because no a priori estimate for the effect size of the impact of representativeness on prevalence effects was available, we decided on a sample size of 50 per experiment (25 per condition) because it both aligned with the sample sizes used in Wolfe et al. (2007) and allowed us to observe an interaction effect of significant size (medium or greater; Cohen's $d > 0.6$) to be deemed sufficiently relevant as an effect on behavior.

In both experiments, participants were instructed to search for prohibited items that might be present in each search array and identify their location once found or report no target present.[3] In these instructions (Fig. 2a), participants were provided example images to a pseudo-randomly[4] selected set of prohibited target types they could possibly see in the task, which was important for both introducing the target category and ensuring participants knew what targets might look like. Only pre-determined target types were presented during the task, but this was not made known to participants. Participants were explicitly informed that targets may not always appear, and that a rapid judgment would need to be made on each trial.

In Experiment 1a, target types were selected to be "knives" (Rank 2) and "gas cans" (Unranked), a prohibited item that was never mentioned in our exemplar-naming task (i.e., a *very* poorly representative target). Using these types, 180 unique real-world images of knives and gas cans isolated on white backgrounds were obtained through Google Image searches. These targets were presented alongside distractors, which were images of non-prohibited carry-on items (i.e., clothing, portable electronics, non-liquid toiletries, etc.). A complete list of distractor categories can be found in the OSM. Each individual image was presented to the participant only once. Thus, participants saw 1,600 unique images (four per trial) throughout the entire experiment.

Both search experiments were designed in PsychoJS (v2020.2) and run online through Pavlovia (Peirce et al., 2019). Because experiments were conducted online, we cannot provide exact visual sizes for stimuli in these experiments. Instead, stimulus sizes are reported in PsychoJS height units, normalized units designed to fill a certain portion of the screen based on the window size of the participant's personal computer.

For each trial of the search task (Fig. 2b), after an initial waiting interval lasting 200–400 ms, four unique images (0.25 × 0.25 height units) were presented to the participant directly above, below, to the left, and to the right of the fixation cross (0.05 height units). Participants pressed the arrow key that matched the location of the target, or the spacebar if no target was present. Trials timed out 2,000 ms after display onset if no judgement was made before then, and feedback was provided following each trial. The experiment was self-paced, with participants pressing the spacebar following feedback to begin the next trial. Participants completed 400 search trials in

[3] The complete wording of the instructions can be found in the OSM to this article.

[4] The four items in the instruction list never shown to participants were randomly chosen.

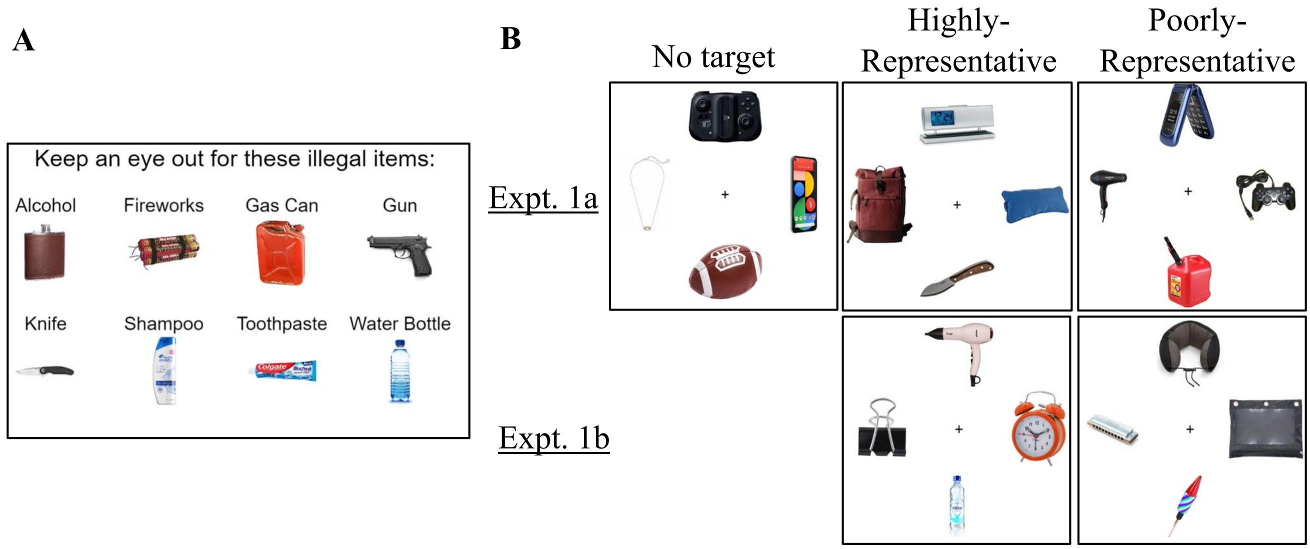

Fig. 2 Layout of Experiment. **A** Participants were provided a list of possible prohibited item types to search for during the task. Unbeknownst to searchers, only two of the eight options were used as targets during the experiment. **B** Example trial displays for Experiments 1a and 1b. Participants were to locate the target using the arrow key that matched the target's location or press the spacebar when no target was present. One selected target was highly representative of the target category ("knife," "water bottle") while the other was not ("gas can," "firework"). Which target was rare was counterbalanced across participants

total, with targets appearing half the time. On these 200 target-present trials, one target option appeared 90% of the time (180 trials) while the other target appeared 10% of the time (20 trials). Whether the knife or the gas can was the frequent target was counterbalanced across participants.

Experiment 1b was identical to Experiment 1a, except that target types were changed to water bottles (rank 5; valence = 6.77) and fireworks (rank 16; valence = 6.16). These two target types were selected because they were both listed in the categorization task and were found to not significantly differ in emotional valence, $t(43) = -1.73$, $p = .17$. In other words, Experiment 1b controlled for the influence of emotion on attentional guidance (Flykt et al., 2012; Lamy et al., 2008) and a presumed lack of knowledge of gas cans among the participant pool (Qin et al., 2014). In both experiments, target search accuracy (i.e., hit rate) and the median correct search RT of individual participants assessed the interaction of prevalence and representativeness on attentional guidance.[5] Because trials timed out, there are no individual trial exclusions applied to RT data.

Results

Experiment 1a, knife versus gas can Overall participants were ~92% accurate (combined hits and correct rejections) in the task ($SD = 3.67\%$), with an average false alarm rate of 4.7%.[6] A 2 × 2 mixed-effects ANOVA with the within-subject factor Prevalence (Frequent vs. Rare) and between-subject factor "Which Is Rare" (Knife vs. Gas Can) was used to assess significance of the interaction (Fig. 3).[7] A significant main effect of Prevalence was observed, $F(1,49) = 151.84$, $p < .001$, $\eta_p^2 = .76$, with search for the prevalent target being more successful than the rare target. Additionally, a main effect of "Which Is Rare" was observed, $F(1,49) = 37.71$, $p < .001$, $\eta_p^2 = .44$, such that accuracy was overall higher in the condition where knives were rare compared to when gas cans were rare. Importantly, there was a significant interaction between factors, $F(1,49) = 109.72$, $p < .001$, $\eta_p^2 = .70$, *Cohen's d* = 2.94. Post hoc analyses revealed that frequent knives ($M = 94.7\%$, $SD = 3.4\%$) were more accurately found than frequent gas cans ($M = 87.8\%$, $SD = 6\%$), $t(49) = 5.01$, $p < .001$, with the same pattern observed for rare knives ($M = 83.8\%$, $SD = 7.7\%$) and rare gas cans ($M = 44.8\%$, $SD = 21.8\%$), $t(49) = 8.43$, $p < .001$. Additionally, frequent gas cans were more accurately found than rare knives, $t(24) = -2.82$, $p = .009$.

RTs mirrored the pattern of significance observed in accuracy. Main effects of prevalence, $F(1,48) = 146.48$, p

[5] For RT, reported group averages are the mean of individual participant medians.

[6] There was no difference in false alarm rate between conditions: $t(49) = .68$, $p = .499$.

[7] Representativeness and prevalence are both within-subject factors, because participants see both target types and both prevalence rates. However, because each target is presented at different frequencies for two participant groups, a between-subject factor is required for the ANOVA, or the "Which Is Rare" factor we present here.

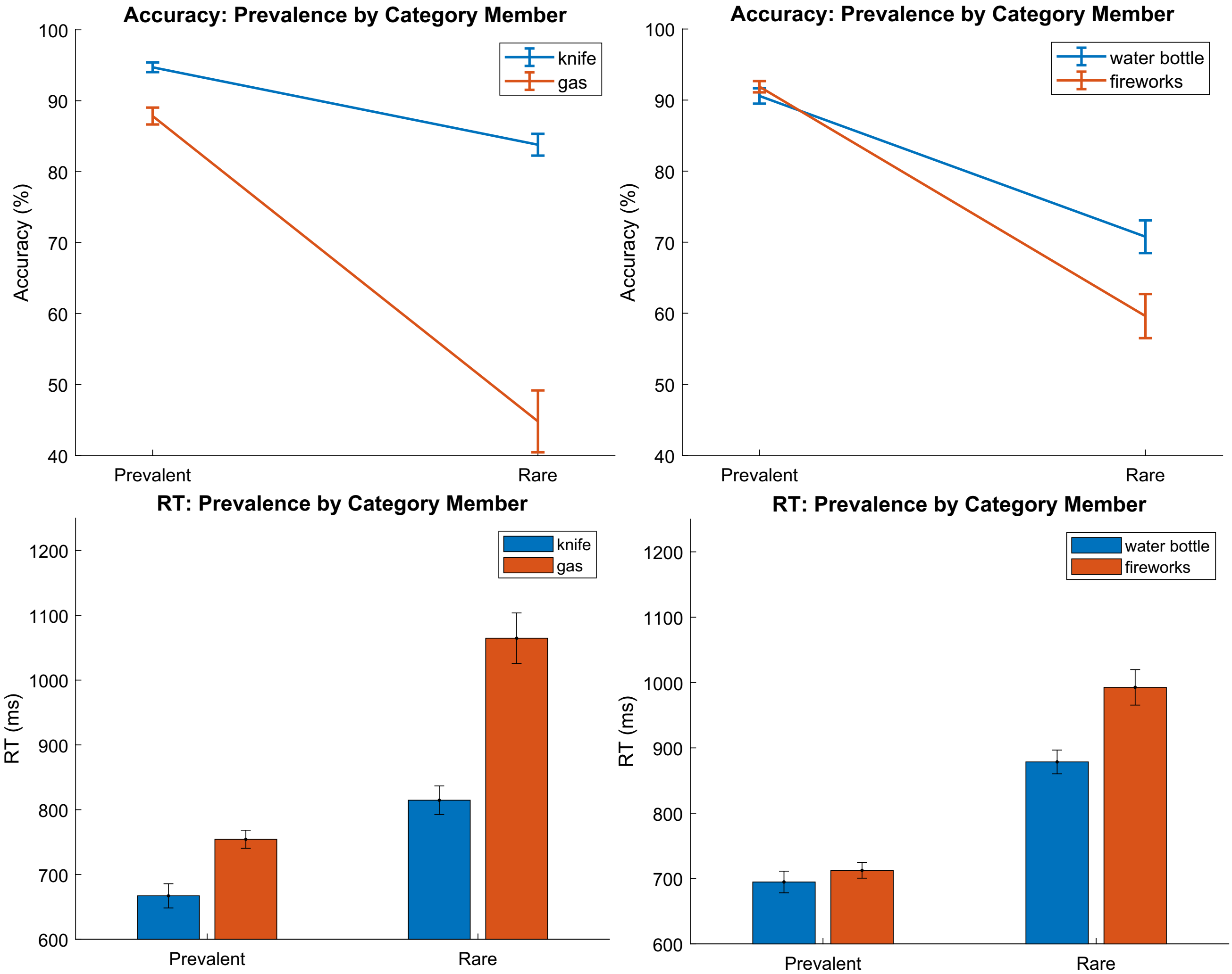

Fig. 3 Search accuracy and response time (RT) for Experiments 1a and 1b. As items become rare, search accuracy decreases and the search RT slows. However, this low-prevalence effect is moderated by the target item's representativeness within the category "prohibited carry-ons." Search accuracy is presented in top graphs while RT is presented in bottom graphs. Highly representative items are shown in blue while poorly representative are in orange. Error bars represent ±1 SEM

$< .001$, $\eta_p^2 = .76$, and "Which Is Rare," $F(1,48) = 7.40$, $p = .009$, $\eta_p^2 = .14$, as well as a significant interaction were observed, $F(1,48) = 79.54$, $p < .001$, $\eta_p^2 = .63$. Post hoc analyses revealed that frequent knives ($M = 667.09$ ms, $SD = 91.64$ ms) were found faster than frequent gas cans ($M = 754.39$ ms, $SD = 70.06$ ms), $t(48) = -3.76$, $p < .001$, with the same pattern observed for rare knives ($M = 814.62$ ms, $SD = 110.24$ ms) and rare gas cans ($M = 1064.64$ ms, $SD = 191.04$ ms), $t(48) = -5.64$, $p < .001$. Additionally, frequent gas cans were found faster than rare knives, $t(24) = -3.75$, $p < .001$.

Experiment 1b, water bottle versus fireworks Like Experiment 1a, participants were ~92% accurate in completing the search task ($SD = 3.43\%$), with an average false alarm rate of 4.6%.[8] Using the same mixed-factors ANOVA design from Experiment 1a (Fig. 3), significant main effects of Prevalence, $F(1,50) = 218.29$, $p < .001$, $\eta_p^2 = .82$, with increased accuracy observed for frequent targets, and "Which Is Rare", $F(1,50) = 7.52$, $p = .009$, $\eta_p^2 = .13$, with increased accuracy among participants who saw water bottles as rare, were observed. There was a significant interaction between factors, $F(1,50) = 7.83$, $p = .007$, $\eta_p^2 = .14$, *Cohen's d* = 0.72. Post hoc analyses revealed that frequent water bottles ($M = 90.6\%$, $SD = 5.4\%$) were no better found than frequent fireworks ($M = 91.9\%$, $SD = 4.1\%$), $t(50) = -0.98$, $p = .33$, but *crucially* rare water bottles ($M = 70.8\%$, $SD = 11.7\%$)

[8] There was no difference in false alarm rate between conditions: $t(50) = 1.10$, $p = .278$.

were more accurately found than rare fireworks ($M = 59.6\%$, $SD = 15.5\%$), $t(50) = 2.91$, $p = .005$. Additionally, frequent fireworks were more accurately found than rare water bottles, $t(25) = 9.07$, $p < .001$.

RTs mirrored the pattern of significance observed in accuracy. Significant main effects of Prevalence, $F(1,50) = 277.39$, $p < .001$, $\eta_p^2 = .85$, and "Which Is Rare," $F(1,50) = 4.31$, $p = .043$, $\eta_p^2 = .08$, as a well as a significant interaction, $F(1,50) = 22.43$, $p < .001$, $\eta_p^2 = .31$, were observed. Post hoc analyses revealed that frequent water bottles ($M = 712.57$ ms, SD = 61.13 ms) were found no faster than frequent fireworks ($M = 694.82$ ms, $SD = 82.71$ ms), $t(50) = 0.87$, $p = .39$, but *crucially* rare water bottles ($M = 878.52$ ms, $SD = 92.61$ ms) were found faster than rare fireworks ($M = 992.65$ ms, $SD = 135.99$ ms), $t(50) = -3.52$, $p < .001$. Additionally, frequent fireworks were found faster than rare water bottles, $t(25) = -8.66$, $p < .001$.

Discussion

In this study, we confirmed our prediction that task experience (i.e., prevalence) and prior conceptual knowledge (i.e., representativeness) interact in guiding attentional selection during visual search. As predicted by previous findings, it was clear that rare items were more likely to be missed by observers, and highly representative items were detected more readily. But crucially, poorly representative targets were more vulnerable to low-prevalence effects than highly representative targets.

Our results support a model of visual search in which attention to targets is guided by the combination of categorical knowledge and a dynamic updating of one's attentional set through recent experience. Specifically, as an observer searches for multiple possible targets, attention will prioritize selection of objects with the highest level of activation within one's attentional set, leading to more hits and faster search times for said targets. With respect to categorically defined search, the highest activation will initially belong to representative category members at the onset of a search task, but this can change over the course of the task based on recent experience. Our proposed activation account updates throughout a task according to three factors: a selection-based reinforcement that boosts activation for recently found targets, a reinforcement of the categorical structure through a relative activation boost to all category members in proportion to their representativeness (which serves to reinforce the instructionally defined search template that remains active throughout the task; Cox et al., 2021), and a small decay in activation for non-selected targets. Crucially, the decay for non-selected targets becomes mitigated by the categorical reinforcement, such that the activation nodes of highly representative targets decay slower than poorly representative ones. That said, it should be noted that highly representative targets still incurred a low prevalence cost that would presumably amplify as rarity increased (Mitroff & Biggs, 2014);[9] however, the observations presented here suggest that even ultra-rare, highly representative targets should be better detected than their rare poorly representative counterparts. Additionally, we suggest that the selection-based reinforcement for recently found targets is strong but transient, accounting for greater hits for frequent poorly representative targets compared to rare highly representative targets. This transiency can also explain established search effects like repetition priming (Maljkovic & Nakayama, 1994; Talcott et al., 2022) and the impact of relative rarity on attentional guidance (Cosman & Vecera, 2014; Mitroff & Biggs, 2014; Wolfe et al., 2007).

Though our observations, and those of previous research, suggest that recent task experience will transiently affect attentional selection, the long-term impact of search experience on categorical knowledge is an unresolved question. That said, observers have developed expectations as to categorical structure according to real-life experience; thus, it seems likely that task experience (a microcosmic form of real-life experience) should eventually update categorical knowledge. Therefore, understanding the categorical target structure of trained searchers (and its subsequent impact on search behavior) could inform how task experience eventually updates knowledge (Schwaninger et al., 2005). Research by Schwaninger and colleagues has shown that training time correlates with the ability to detect improvised explosive devices (IED), providing initial support that substantial task experience could serve to permanently increase target representativeness within an attentional set and improve search outcomes (Bolfing et al., 2008; Koller et al., 2008). However, it should be noted that baggage-screening training does not necessarily transfer to novel testing environments, especially when the training target set is small (Schwaninger, 2006). Thus, implementing a larger training set (as suggested by Schwaninger, 2006) comprised of a comprehensive list of prohibited items could both better determine the impact of expertise on the conceptual layout of search sets and potentially improve the odds of transfer learning, bettering search performance overall.

Regardless of the impact of expertise on conceptual knowledge, our results provide initial support for our proposed conceptual model. However, there are still many unanswered questions regarding the scope and generalizability of our claims that category representativeness interacts with

[9] That representative targets suffer from prevalence effects demonstrates that our results do not refute previous observations. An ultra-rare gun would still be susceptible to miss errors because it is rare!

prevalence to guide search. For example, our model makes no claims about the influence of distractors on search performance, yet it is clear from previous findings that distractor heterogeneity can heavily influence search (Duncan & Humphreys, 1989; Rosenholtz, 2001; Wang et al., 2017; Xu et al., 2021). Thus, future development of the model should incorporate the influence of target-distractor interactions – in particular distractor salience and conceptual overlap with targets (Yeh & Peelen, 2022) – to provide further explanatory power. Despite these limitations, our conceptual model does generate predictions for future study that could further our understanding of search behaviors. For example, our model suggests that when novel targets without an a priori link to the categorical search set appear, search performance should only be impacted by repetition, and would not benefit from representativeness effects.

One final caveat to our results is the use of a controlled setting. Though the controlled nature of this experiment was invaluable in isolating the impact of category representativeness of low-prevalence search settings, it limits the generalizability of our effects to uncontrolled search environments like baggage screening. Thus, understanding how conceptual knowledge impacts real-world search environments when targets are occluded by non-targets, appear in non-canonical frames of reference (Bolfing et al., 2008), or when the actualized search set is not limited to two particular exemplars within the category (Biggs et al., 2018) will both further validate our model and potentially better explain search behaviors in high stakes settings. Despite these limitations, the cognitive implications behind these results suggest that attentional sets initially informed by instruction are dynamically molded by both recent task experience and prior conceptual knowledge. Not only will current experience inform behavior on the current search trial, but pre-existing notions of likely targets also enable persistent attentional prioritization of representative targets even if they are rarely encountered. These considerations will paint a fuller picture in understanding search behavior in complex search environments, lending crucial insight for both theoretical and practical advances in attentional guidance.

Supplementary Information The online version contains supplementary material available at https://doi.org/10.3758/s13423-022-02183-0.

Acknowledgements The experiments reported in this article were conducted as part of Ryan E. O'Donnell's dissertation. The authors would like to thank the members of Ryan E. O'Donnell's dissertation committee, Nancy A. Dennis, Richard A. Carlson, and John Collins, for helpful comments and insight during this project's development, John D. Patterson for his insight into the concepts and categories literature, and as well as lab members for their helpful comments and suggestions on the manuscript. Finally, the first author would like to dedicate this paper to Brook Ginsburgh, a beloved family member who was always supportive and incredibly proud of his academic accomplishments. This research was supported by NSF Grant 1734220.

Data availability Experimental stimuli, scripts, data, and analysis files can be found on our Open Science Framework repository: https://osf.io/576kj/. No experiments were pre-registered, but the experimental design, sample size, sample population, and statistical tests were proposed and approved as part of the Penn State dissertation process.

Declaration

Competing interest The authors declare no potential competing interest with respect to this article's findings.

References

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

Barsalou, L. W. (1985). Ideals, central tendency, and frequency of instantiation as determinants of graded structure in categories. *Journal of Experimental Psychology: Learning, Memory, and Cognition, 11*(4), 629–654.

Biggs, A. T., & Mitroff, S. R. (2015). Improving the efficacy of security screening tasks: A review of visual search challenges and ways to mitigate their adverse effects. *Applied Cognitive Psychology, 29*(1), 142–148.

Biggs, A. T., Adamo, S. H., & Mitroff, S. R. (2014). Rare, but obviously there: Effects of target frequency and salience on visual search accuracy. *Acta Psychologica, 152*, 158–165.

Biggs, A. T., Kramer, M. R., & Mitroff, S. R. (2018). Using cognitive psychology research to inform professional visual search operations. *Journal of Applied Research in Memory and Cognition, 7*(2), 189–198.

Bolfing, A., Halbherr, T., & Schwaninger, A. (2008, November). How image based factors and human factors contribute to threat detection performance in X-ray aviation security screening. In: *Symposium of the Austrian HCI and Usability Engineering Group* (pp. 419-438). Springer, Berlin, Heidelberg.

Bradley, M. M., & Lang, P. J. (1994). Measuring emotion: the self-assessment manikin and the semantic differential. *Journal of Behavior Therapy and Experimental Psychiatry, 25*(1), 49–59.

Bravo, M. J., & Farid, H. (2009). The specificity of the search template. *Journal of Vision, 9*(1), 1–9.

Bravo, M. J., & Farid, H. (2012). Task demands determine the specificity of the search template. *Attention, Perception, & Psychophysics, 74*(1), 124–131.

Clark, K., Appelbaum, L. G., van den Berg, B., Mitroff, S. R., & Woldorff, M. G. (2015). Improvement in visual search with practice: Mapping learning-related changes in neurocognitive stages of processing. *Journal of Neuroscience, 35*(13), 5351–5359. https://doi.org/10.1523/JNEUROSCI.1152-14.2015

Cosman, J. D., & Vecera, S. P. (2014). Establishment of an attentional set via statistical learning. *Journal of Experimental Psychology: Human Perception and Performance, 40*(1), 1–6.

Cox, P. H., Kravitz, D. J., & Mitroff, S. R. (2021). Great expectations: minor differences in initial instructions have a major impact on visual search in the absence of feedback. *Cognitive Research: Principles and Implications, 6*(1), 1–14.

Duncan, J., & Humphreys, G. W. (1989). Visual search and stimulus similarity. *Psychological Review, 96*(3), 433–458.

Fleck, M. S., & Mitroff, S. R. (2007). Rare targets are rarely missed in correctable search. *Psychological Science, 18*(11), 943–947.

Flykt, A., Lindeberg, S., & Derakshan, N. (2012). Fear makes you stronger: Responding to feared animal targets in visual search. *Attention, Perception, & Psychophysics, 74*(7), 1437–1445.

Godwin, H. J., Menneer, T., Cave, K. R., Thaibsyah, M., & Donnelly, N. (2015). The effects of increasing target prevalence on information processing during visual search. *Psychonomic Bulletin & Review, 22*(2), 469–475.

Horowitz, T. S. (2017). Prevalence in visual search: From the clinic to the lab and back again. *Japanese Psychological Research, 59*(2), 65–108.

Hout, M. C., Walenchok, S. C., Goldinger, S. D., & Wolfe, J. M. (2015). Failures of perception in the low-prevalence effect: Evidence from active and passive visual search. *Journal of Experimental Psychology: Human Perception and Performance, 41*(4), 977–994.

Koller, S. M., Hardmeier, D., Michel, S., & Schwaninger, A. (2008). Investigating training, transfer and viewpoint effects resulting from recurrent CBT of X-Ray image interpretation. *Journal of Transportation Security, 1*(2), 81–106.

Kramer, M. R., Cox, P. H., Mitroff, S. R., & Kravitz, D. J. (2022). A precise quantification of how prior experience informs current behavior. *Journal of Experimental Psychology: General, 151*(8), 1854–1865.

Kurtz, K. J., & Gentner, D. (2001). Kinds of kinds: Sources of category coherence. In: *Proceedings of the Annual Meeting of the Cognitive Science Society* (Vol. 23, No. 23).

Lamy, D., Amunts, L., & Bar-Haim, Y. (2008). Emotional priming of pop-out in visual search. *Emotion, 8*(2), 151.

Malcolm, G. L., & Henderson, J. M. (2009). The effects of target template specificity on visual search in real-world scenes: Evidence from eye movements. *Journal of Vision, 9*(11), 8.

Maljkovic, V., & Nakayama, K. (1994). Priming of pop-out: I. Role of features. *Memory & Cognition, 22*(6), 657–672.

Maxfield, J. T., & Zelinsky, G. J. (2012). Searching through the hierarchy: How level of target categorization affects visual search. *Visual Cognition, 20*(10), 1153–1163.

Maxfield, J. T., Stalder, W. D., & Zelinsky, G. J. (2014). Effects of target typicality on categorical search. *Journal of Vision, 14*(12), 1.

Mitroff, S. R., & Biggs, A. T. (2014). The ultra-rare-item effect: Visual search for exceedingly rare items is highly susceptible to error. *Psychological Science, 25*(1), 284–289.

Peirce, J. W., Gray, J. R., Simpson, S., MacAskill, M. R., Höchenberger, R., Sogo, H., Kastman, E., & Lindeløv, J. (2019). PsychoPy2: experiments in behavior made easy. *Behavior Research Methods, 51*, 195–203.

Qin, X. A., Koutstaal, W., & Engel, S. A. (2014). The hard-won benefits of familiarity in visual search: Naturally familiar brand logos are found faster. *Attention, Perception, & Psychophysics, 76*(4), 914–930.

Rich, A. N., Kunar, M. A., Van Wert, M. J., HidalgoSotelo, 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*(15), 15.

Robbins, A., & Hout, M. C. (2015). Categorical target templates: Typical category members are found and identified quickly during word-cued search. *Visual Cognition, 23*(7), 817–821.

Robbins, A., & Hout, M. C. (2020). Typicality guides attention during categorical search, but not universally so. *Quarterly Journal of Experimental Psychology, 73*(11), 1977–1999.

Rosch, E. (1975). Cognitive representations of semantic categories. *Journal of Experimental Psychology: General, 104*(3), 192–233.

Rosch, E., & Mervis, C. B. (1975). Family resemblances: Studies in the internal structure of categories. *Cognitive Psychology, 7*(4), 573–605.

Rosenholtz, R. (2001). Visual search for orientation among heterogeneous distractors: experimental results and implications for signal-detection theory models of search. *Journal of Experimental Psychology: Human Perception and Performance, 27*(4), 985–999.

Schmidt, J., & Zelinsky, G. J. (2009). Search guidance is proportional to the categorical specificity of a target cue. *The Quarterly Journal of Experimental Psychology, 62*(10), 1904–1914.

Schwaninger, A. (2006). Threat image projection: enhancing performance?. *Aviation Security International,* 36–41.

Schwaninger, A., Hardmeler, D., & Hofer, F. (2005). Aviation security screeners visual abilities & visual knowledge measurement. *IEEE Aerospace and Electronic Systems Magazine, 20*(6), 29–35.

Schwark, J. D., Sandry, J., Macdonald, J., & Dolgov, I. (2012). False feedback increases detection of low-prevalence targets in visual search. *Attention, Perception, & Psychophysics, 74*, 1583–1589.

Talcott, T. N., Levy, A. P., & Gaspelin, N. (2022). Covert attention is attracted to prior target locations: Evidence from the probe paradigm. *Attention, Perception, & Psychophysics, 84*(4), 1098–1113.

Taylor, J. E. T., Hilchey, M. D., Weidler, B. J., & Pratt, J. (2022). Eliminating the Low Prevalence Effect in Visual Search with a Remarkably Simple Strategy. *Psychological Science, 33*(5), 716–724.

Wang, Z., Buetti, S., & Lleras, A. (2017). Predicting search performance in heterogeneous visual search scenes with real-world objects. *Collabra: Psychology, 3*(1), 6.

Wolfe, J. M. (2021). Guided Search 6.0: An updated model of visual search. *Psychonomic Bulletin & Review, 28*(4), 1060–1092.

Wolfe, J. M., & Horowitz, T. S. (2017). Five factors that guide attention in visual search. *Nature Human Behaviour, 1*(3), 1–8.

Wolfe, J. M., & Van Wert, M. J. (2010). Varying target prevalence reveals two dissociable decision criteria in visual search. *Current Biology, 20*(2), 121–124.

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

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*(4), 623–638.

Wolfe, J. M., Palmer, E. M., & Horowitz, T. S. (2010). Reaction time distributions constrain models of visual search. *Vision Research, 50*(14), 1304–1311.

Xu, Z. J., Lleras, A., Shao, Y., & Buetti, S. (2021). Distractor–distractor interactions in visual search for oriented targets explain the increased difficulty observed in nonlinearly separable conditions. *Journal of Experimental Psychology: Human Perception and Performance, 47*(9), 1274–1297.

Yeh, L.-C., & Peelen, M. V. (2022). The time course of categorical and perceptual similarity effects in visual search. *Journal of Experimental Psychology: Human Perception and Performance*. https://doi.org/10.1037/xhp0001034

Publisher's note Springer Nature remains neutral with regard to jurisdictional claims in published maps and institutional affiliations.