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Incidental Recognition Reveals Attentional Tradeoffs Shaped by Categorical Similarity

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Search efficiency suffers when observers look for multiple targets or a single imprecisely defined target. These conditions prevent a narrow target template, resulting in improved delayed distractor recognition. In our first experiment with hybrid visual and memory search, we investigated the interaction of target variety and target number on search efficiency. Results supported the hypothesis that numerous targets impair search efficiency much more when targets are unrelated. These efficiency impairments were linked to distractor processing, indicated by increased delayed recognition. A second experiment manipulated target–distractor similarity to determine whether prioritization of target-defining features is totally eliminated in search for eight unrelated targets. For related and unrelated targets alike, recognition declined for distractors bearing less resemblance to targets and more to each other. This suggests templates for unrelated targets successfully prioritize relevant features at some stage of attention. Avoidance of random distractors was stronger when targets were related, at the price of slower, more error-prone identification of within-category distractors. Within-category processing difficulty for related targets likely stems from categorical interference as previously demonstrated in recognition memory. Thus, target variety versus homogeneity afforded different advantages and limitations depending on target number, target–distractor, and distractor–distractor resemblance.

Public Significance Statement
It is easier to find one object than many simultaneously. The challenge of finding multiple targets mainly occurs when targets are dissimilar. This is true when look-alike distracting objects are absent in the environment. Telling apart targets from look-alike distractors is actually harder when all of our targets resemble each other. We were surprised to discover that search difficulty depends on the unique combination of the number and variety of items you seek, and how similar they are to the distracting items that you encounter in pursuit of your targets.

Keywords: target template, recognition, distractors, visual search, object categories

Who will win the race to the checkout line in an unfamiliar supermarket: Mario looking for Macintosh, Fuji, Granny Smith, and Gala apples, or Luigi looking for a Fuji, romaine lettuce, cantaloupe, and cucumber? Mario should be considerably less distracted, likely able to ignore all nonapples or glance at them only briefly. For Luigi, many other types of products could be distracting; pomegranates and peaches resemble apples, squashes resemble cantaloupe, kale resembles lettuce, and zucchinis resemble cucumbers. The features that define Mario's list are few—small-medium, round, green or red, and shiny. The features that define Luigi's list are many, spanning leafy items with high spatial frequency to large blunt objects (melon), colors including green, beige, and red, and shiny and dull skins. However, many unwanted apple varieties share all Mario's target features (Braeburn, Golden Delicious, Honeycrisp, etc.); discerning the wanted from unwanted varieties will require focused attention. Luigi, on the other hand, has a series of potentially simpler tasks to accomplish—identify a single type of apple, lettuce, melon, and cucumber. The two men are faced with different challenges that highlight the interplay between target variety and number, distractor variety, and target–distractor similarity.

The present study sought to determine the interactive influence of these factors on search efficiency. If search efficiency differs little between varying numbers of related targets, this would attest to observers' capacity to exploit commonalities among targets, or common differences from distractors (see Becker, 2010; Bravo & Farid, 2016), in establishing search templates. For clues into the attentional

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processes mediating these effects, we also measured delayed recognition of distractors that were encountered during the search. In a second experiment, we explored how target variety might interact with target–distractor resemblance to determine search efficiency and recognition probability. Such interactions could speak to the need to characterize all aspects of the search environment in any mechanistic account of attention and oculomotor behavior (e.g., the functional field of view, Hulleman & Olivers, 2017; for an emphasis on search holism, see Wolfe, 2021).

Previous work in visual search has documented the difficulty and slowing incurred by looking for more than one target (for a review, see Ort & Olivers, 2020). These paradigms typically cue observers with new targets on every trial, thus relying on their visual working memory (VWM) to guide attention to candidate objects and decide whether any of the targets are present or indicate the exact location of the target. With the use of eye tracking (Hout & Goldinger, 2012) and surprise assessment of recognition of distractors (Hout & Goldinger, 2010, 2012), studies have implicated distractors in the reduced efficiency of search. Search for more targets leads to recognition of a greater proportion of distractors. Measures of cumulative fixation on distractors throughout the many trials in which they appeared, referred to as "dwell time," have repeatedly shown a correlation between the chance of recognizing a distractor and the time previously spent dwelling on it (Hout & Goldinger, 2012; Lavelle et al., 2021; Thomas & Williams, 2014; Williams, 2010a; Williams et al., 2005). In turn, the distractors that most resemble targets attract the most attention (Alexander & Zelinsky, 2011, 2012; Thomas & Williams, 2014; Williams, 2010a, 2010b; Williams et al., 2005).

The role of target variety has also been demonstrated in VWM-mediated search. Search efficiency suffers as a pair of targets becomes more dissimilar (Hout & Goldinger, 2015). For a single target, the less precise the description of the target (e.g., "vehicle" instead of "ambulance"), the less efficient search is (Castelhano et al., 2008; Malcolm & Henderson, 2009). In rapid serial visual presentation (RSVP), distractor recognition was found to correlate with target specificity (Guevara Pinto & Papesh, 2019) as well as cued target number. In general, it appears that a narrow search template facilitates focused attention to target features, such that distractors devoid of those features will draw little or no attention. Conversely, numerous or ill-defined targets lead to deeper processing of distractors (Guevara Pinto et al., 2020). To date, no study of cued search has independently and simultaneously manipulated the number and variety of targets. Nor has recognition of distractors been assessed during search for more than four targets.

To address these gaps, we adopted the hybrid search paradigm, which requires participants to memorize a set of targets before a block of search trials, in which targets must be identified in arrays containing distractors. One randomly selected target appeared per trial, and on half of the trials there was no target at all. Participants therefore determined whether any of the memorized targets are present (Wolfe, 2012). Though observers can search surprisingly efficiently for up to 100 targets, our first experiment ventured only up to 16 targets in an exploration of the generalizability of previous results based on VWM-mediated targets.

Previous work in hybrid search has explored several similar elements as the present study, but no single study has combined them all. While processing devoted to distractors has been examined in hybrid search (Cunningham & Wolfe, 2014; Drew et al., 2017; Drew & Wolfe, 2014; Nordfang & Wolfe, 2018), subsequent recognition of distractors remains unexamined. One study deliberately manipulated target number and variety independently (Nordfang & Wolfe, 2018), but the composition of distractors and target sets raises questions about generalizability. Within a search block, targets and distractors were only drawn from the same single, two, or four categories. Search arrays were devised such that either all or half (Experiments 1 and 2) or all or none (Experiment 3) of the distracting images would overlap categorically with their target set. In blocks with a singular category target set, they knew further which half would be relevant. This could strongly bias decisions about the need to select areas to examine across the search array without having examined them. Additionally, distractors indicated to participants that some targets would definitely be absent on particular trials. The results, therefore, depended not only on attentional prioritization of target features but also awareness of peculiar environmental contingencies.

Aforementioned studies of VWM-mediated targets have suggested that template effectiveness is dissociable from target number by manipulating target specificity or similarity with a fixed number of targets. We investigated whether this effect would replicate with large numbers of memorized targets. Additionally, we evaluated the complementary dissociation—whether template effectiveness may remain constant for few versus many homogenous targets. If a large number of similar items facilitates efficient search, but dissimilar items reduce search efficiency, this would suggest templates exploit commonalities and individual targets impact attentional prioritization only to the extent that they possess unique visual features compared to the rest of the target set.

Instead of eye tracking, we assessed attention via incidental recognition of distractors based on well-replicated associations of cumulative fixation time and subsequent recognition (Hout & Goldinger, 2012; Lavelle et al., 2021; Thomas & Williams, 2014; Williams, 2010a; Williams et al., 2005). Subsequent recognition of distractors would indicate the relative influence of target number versus variety on distractor processing during search. This helped to rule out the notion that search efficiency is simply determined by the duration of target identification (see Eimer, 2014, for a distinction between *selection* and *identification*) and hinted at the impact of target set characteristics on the effectiveness of the search template(s). For related approaches, see Guevara Pinto et al. (2020), Guevara Pinto and Papesh (2019), Hout and Goldinger (2010, 2012), and Lavelle et al. (2021).

Experiment 1

Target sets contained either two or 16 items which were either all drawn from different categories (*unrelated*) or all from the same category (*related*; Figure 1). Each participant memorized and searched four target sets in separate blocks, wherein each target set appeared alongside a unique set of random distractors. Recognition for every distractor was tested via category-matched two-alternative forced-choice (2AFC) at the end of the experiment.

Predictions

We hypothesized that recognition would be greater for distractors appearing during the search blocks for 16-item target sets than recognition for distractors appearing during search blocks for two-item target sets. We also hypothesized that recognition would be greater

Figure 1
Example Target Set Types and Sizes for Experiment 1

Note. Pairs of 16- or 17-item categories (e.g., dogs and cats) from the Massive Memory database (Konkle et al., 2010) were combined to form 32- or 34-item categories based on semantic and visual similarity. Note, as an illustration, observers were looking for *this* dog and *this* cat, not any dog or cat. See the online article for the color version of this figure.

for distractors appearing during search for unrelated target sets than related target sets. Finally, we hypothesized an interaction between target set size and type such that the effect of target set size would be greater for unrelated target sets than related target sets. For search accuracy and search slopes, we hypothesized the same main effects and the same interaction as that hypothesized for distractor recognition: steeper search slopes and lower accuracy for target set size 16 and unrelated target sets, and a greater search slope increase and accuracy reduction due to target set size for unrelated versus related target sets. Hypotheses, analyses, power, and inclusion criteria were specified in a preregistration before data collection on the Open Science Framework (https://osf.io/y5tgh). Below, we will refer to any analyses not outlined in our preregistration as exploratory.

Method

Participants

We gathered data from 68 participants, with a mean age of 21.5 years ± 6.1 (mean ± *SD*; 19 males and 49 females). Eleven participants enrolled in the study for payment via prolific.com, and the others enrolled for course credit through the psychology participant pool at the University of Utah. Thirteen of these datasets were discarded according to preregistered performance criteria. Eleven failed to exceed chance performance on the distractor recognition task. The remaining two responded incorrectly on greater than 25% of visual search trials in at least one of the four blocks. Therefore, the final sample consisted of 55 participants. Individuals younger than 18 years old or older than 60 years old were not enrolled. All participants reported at least corrected-to-normal vision and no history of concussions.

Design and Procedure

Participants signed up for the study either through the participant pool or through a posting on Prolific.com (https://prolific.co/), between November 19 and December 18, 2020. Paid participants received $7.30. The experiment was hosted online at Pavlovia.org (https://pavlovia.org/) and lasted an average of 27.4 min ± 4.4 (excluding consent and debriefing). Participants were provided a consent form at the beginning of the experiment and a debriefing form at the end. Participants were provided breaks after each of five blocks, which include practice. The procedures were approved by the institutional review board (IRB) at the University of Utah.

Within each block, observers first memorized and passed a recognition test for the target set items. For the "learning" phase, the constituent images appeared in a random order in the center of the screen with a white background for 3 s each, followed by a 300 ms interstimulus interval. The following memory test required observers to indicate whether the image on the screen was part of the target set by pressing the right arrow for "old" and the left arrow for "new." Novel foils were randomly interleaved in an equal proportion with the targets such that there were twice as many test trials as there were items in the target set. Observers completed the learning phase and test until they passed two tests consecutively with 80% or higher accuracy. A practice block preceded the rest of the experiment, consisting of two unrelated targets to memorize. The order of target set sizes and types was counterbalanced across participants.

After passing the memory tests, observers completed 64 trials searching for items of the target set. The practice block consisted of eight trials. Trials were evenly split between visual set size of 8 and 16 and between target-absent and target-present. A single target was randomly selected from the target set on present trials. Twenty-four distractors were used in each search block, sampled randomly without replacement for each trial. Each of the 24 distractors appeared in 30.67 trials during search, on average. Participants were encouraged to respond quickly and accurately using the left arrow key for "absent" responses and the right for "present." Feedback was presented after each response for 500 ms. To initiate each trial, observers pressed the space bar. After completing all four search blocks, participants advanced to the recognition test.

Distractor recognition was tested without prior notice in a 2AFC format. On each trial, two images appeared on the screen, to the left and right of center, with the same scale as visual search items. One image was a distractor previously presented during search. The other was a novel image from the same category as the current distractor. Observers indicated which of two images they recognized with left or right arrow key presses, and accuracy was stressed over speed. Feedback followed each response for 500 ms. The distractor randomly appeared on the left or right side of the screen in equal proportion. Participants had eight practice trials using the distractors from the practice block. Next, recognition was tested for all 96 distractors.

During the preceding search phase, distractors only appeared during search for a particular target set. Therefore, recognition accuracy for each distractor set was associated with a unique target set that appeared alongside said distractors, but across observers target–distractor relationships were random. We calculated the recognition accuracy percentage for each distractor set separately (unrelated memory set size [MSS] 2, related MSS2, unrelated MSS16, and related MSS16) for each observer. To avoid any confusion across different sets of objects, each image category was used in only one search block. Image categories only served one role; for example participant, the dogs supplied a token used as a target, donuts supplied a learning foil, and typewriters supplied a distractor.

Materials

The experiment was developed in the PsychoPy Builder (Version 2020.1.3, Peirce et al., 2019) and with custom code in PsychoJS (https://github.com/psychopy/psychojs). Participants completed the experiment using their own laptops in their own environments. For this reason, absolute stimulus size was not controlled across participants. Using a 13-in. laptop (30 by 16.6 cm) with 1,920 × 1,080 resolution at a viewing distance of 57 cm, we obtained the following measurements. Stimuli were generally square and subtended 1.77° horizontally and vertically. When not square, the larger dimension was 1.77°. Stimuli were randomly placed on a 5 by 4 grid centered left-to-right but closer to the top than bottom of screen. The distance between grid points measured 3.6°. Each stimulus was randomly jittered about the grid positions up to 0.93° in horizontal and vertical directions.

We used the Massive Memory database (Konkle et al., 2010) with minor alterations. This dataset contains 242 categories, each containing 16 or 17 images. Because Experiment 2 needed larger categories, we combined pairs of categories to form categories of 32–34 images. These pairs were formed based on semantic and visual similarity, for example, dogs with cats or boots with shoes (Figure 1). All statistics and graphing were performed in *R* (Version 4.1.0, R Core Team, 2021) using the ez (Version 4.4-0) and ggplot2 (Version 3.3.5, Wickham, 2016) packages.

Analysis

Power. Our target N for usable datasets was 48 (see exclusion criteria in the "Participant" subsection above). We enrolled seven more participants due to administrative error. Our target N would provide over 99% power to detect a main effect of Cohen's $d = 1.03$ of target set size or type on distractor recognition. This effect size was calculated from Hout and Goldinger (2010) Experiment 1, the design of which is overall fairly similar to our own. A sample size of 48 would be 80% powered to detect an effect size down to $d = 0.45$. These calculations were made under the assumption of a repeated-measures correlation for recognition across conditions of $r = .4$ (based on unpublished results from Lavelle et al., 2021).

Data Preparation and Exclusion. Only 0.3% of trials were identified as outliers in visual search reaction time (RT). Visual search trials with a RT less than 200 ms or greater than 3 *SD* above the mean of a condition across observers were removed from RT analyses. For these purposes, trials were combined between participants, then separated into 16 conditions along four binary factors: target set size, target set type, visual set size, and present versus absent. The means and standard deviations on which z-scores were calculated only included correct trials. Observer-specific means were calculated for RT and accuracy after outlier removal. RT was based only on correct trials.

Statistics. Follow-up tests to interactions were not explicitly preregistered. The violin plots contain a large dot marking the mean and error bars depicting ± 1 *SD*. The *SD* was adjusted to reflect correlations among repeated measures, as all tests were within-subject (Cousineau, 2019).

Transparency and Openness

All data, analytic code, and stimulus materials are available for Experiments 1 and 2 at https://osf.io/pj5tb/?view_only=a101750a91ff43718e04e15a5205a0e9. Hypotheses, power, analysis plans, and inclusion criteria were all preregistered.

Results

Visual Search Slopes

Search slopes (see Figure 2) were computed for each condition by subtracting observers' average RTs at visual set size 8 from RTs at set size 16, then dividing the difference by 8 to compute the RT cost in milliseconds of each search item. We then submitted slopes from the visual search blocks to a repeated-measures analysis of variance (ANOVA), with the three factors being target set size (2 vs. 16), target set type (related vs. unrelated), and target presence (present vs. absent). All effects were significant, including the three main effects, Fs$(1, 54) > 39.9$, ps $< .001$, η_p^2s $> .43$, three 2-way interactions, Fs$(1, 54) > 29.1$, ps $< .001$, η_p^2s $> .35$, and the three-way interaction, $F(1, 54) = 12.6$, $p < .001$, $\eta_p^2 = .19$. Consistent with much prior visual search work (for a review, Wolfe, 2021), search slope was significantly increased for absent relative to present trials, $F(1, 54) = 408.1$, $p < .001$, $\eta_p^2 = .89$.

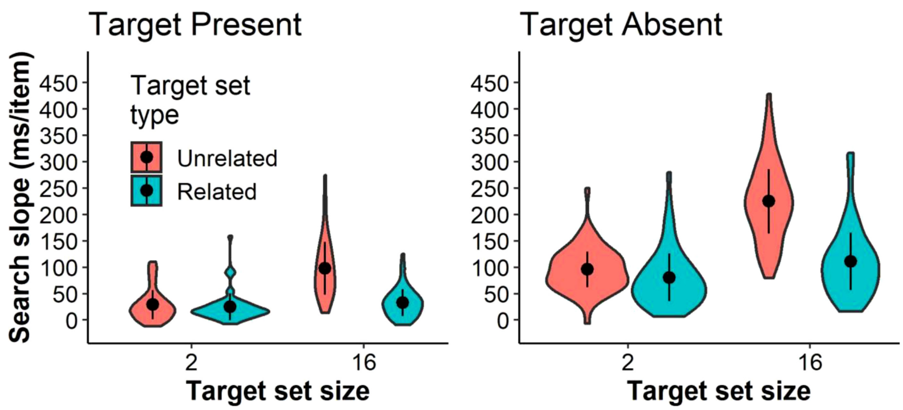
Separate 2-by-2 ANOVAs were run for the target-absent versus present trials to determine whether the interaction between target set type and size depended on target presence. The effect sizes of the interactions were comparable; target-absent: $F(1, 54) = 70.3$, $p < .001$, $\eta_p^2 = .57$, target-present: $F(1, 54) = 63.9$, $p < .001$, $\eta_p^2 = .54$. To understand the nature of these interactions, we decomposed them with paired t tests on the effect of target set size, separated by target type and presence. For target-absent trials, the increase in search slopes due to target set size was larger for unrelated target sets, $t(54) = 12.9$, $p < .001$, $d = 1.73$, compared to related target sets, $t(54) = 3.29$, $p = .002$, $d = 0.44$. That is, the slowing effect of searching for more targets was greatly reduced when all targets came from the same category. The same is true for present trials, except that the slowing effect of larger target sets was not significant for related target search; related: $t(54) = 1.44$, $p = .15$, $d = 0.19$, and unrelated: $t(54) = 8.91$, $p < .001$, $d = 1.20$. Thus, consistent with prior hybrid search work (e.g., Cunningham & Wolfe, 2014; Drew et al., 2017; Wolfe, 2012), we found that search slope increased with MSS for both present and absent trials, though to a greatly diminished degree for same-category targets.

Search Accuracy

The same set of ANOVAs and t tests were conducted for search accuracy as were conducted for search slopes (see Figure 3). We did not anticipate a need to account for target presence in our preregistration. Therefore, the analyses on this factor may be considered

Figure 2

Experiment 1 Visual Search Slopes Separated by Target Presence, Target Set Type, and Target Set Size

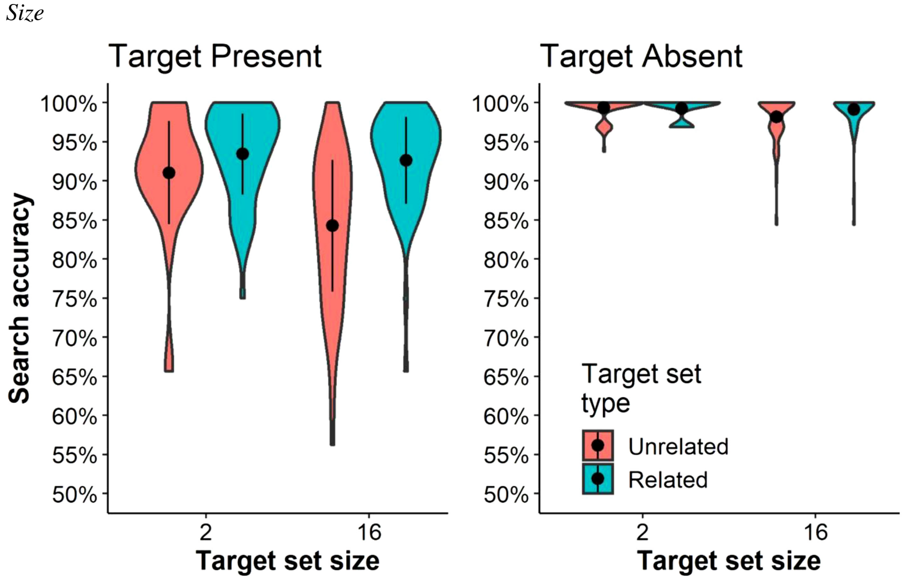


Note. Black dots represent the average search slope for each condition. Error bars depict ± 1 *SD*, scaled in common by the average correlation among repeated measures (see "Statistics" subsection of Experiment 1 Method). Error bars were separately scaled for present and absent trials. See the online article for the color version of this figure.

exploratory. All main effects and interactions were significant in the three-way ANOVA (Target set size × Target set type × Target presence). Only the three-way interaction is reported for brevity, $F(1, 54) = 11.4$, $p = .001$, $\eta_p^2 = .17$. The interaction between target set size and type was examined by follow-up ANOVAs, separated by target presence. For target-absent trials, the interaction was significant, $F(1, 54) = 6.10$, $p = .017$, $\eta_p^2 = .10$, but the main effect of set type was not, $F(1, 54) = 3.29$, $p = .075$, $\eta_p^2 = .06$. This interaction was larger for target-present trials, $F(1, 54) = 17.7$, $p < .001$, $\eta_p^2 = .25$, and the main effects were significant. Overall, given the high accuracy on absent trials, our ability to draw strong conclusions for this aspect of the data may be limited by a ceiling effect. For unrelated targets, target set size reduced accuracy more on present trials, $t(54) = -4.72$, $p < .001$, $d = -0.64$, than absent trials, $t(54) = -2.71$, $p = .009$, $d = -0.37$. For related targets, search accuracy was statistically indistinguishable between two and 16 targets, regardless of target presence; present: $t(54) = -0.78$, $p = .437$, $d = -0.11$, absent: $t(54) = -0.50$, $p = .617$, $d = -0.07$. For both target-present and target-absent trials, the negative impact of the target set size on accuracy was larger for unrelated than related target sets.

Figure 3

Experiment 1 Visual Search Accuracy Separated by Target Presence, and Target Set Type and Size



Note. Error bars around mean depict ± 1 scaled *SD* (see "Statistics" subsection of Experiment 1 Method). See the online article for the color version of this figure.

Distractor Recognition

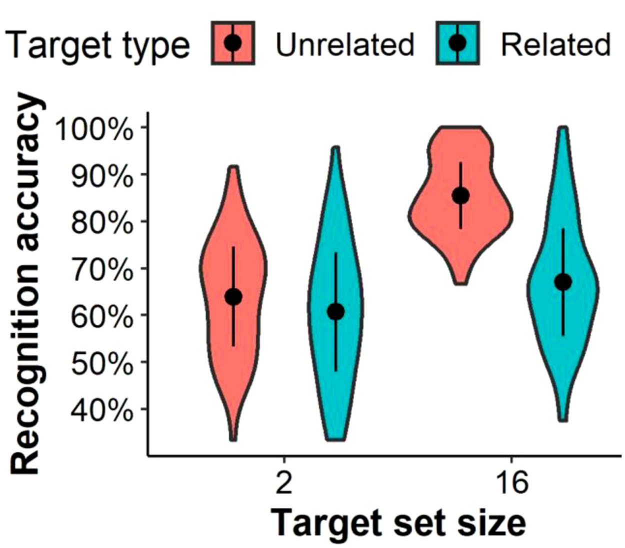
Average distractor recognition accuracy was submitted to a repeated-measures ANOVA with target set size (two or 16) and target set type (related or unrelated) as the factors (see Figure 4). Distractors viewed during search for unrelated-category target sets were recognized significantly better than distractors viewed during search for single category target sets, $F(1, 54) = 57.1$, $p < .001$, $\eta_p^2 = .51$. Likewise, search for a target set size of 16 significantly boosted distractor recognition, $F(1, 54) = 73.9$, $p < .001$, $\eta_p^2 = .58$. These factors also significantly interacted, $F(1, 54) = 33.2$, $p < .001$, $\eta_p^2 = .38$. Paired *t* tests evaluated the effect of target set size separately for distractors viewed during unrelated target set blocks versus related target set blocks. In support of our main hypothesis, the beneficial effect of target set size on distractor recognition was larger for unrelated target sets, $t(54) = 11.4$, $p < .001$, $d = 1.54$, though the effect was also significant for related target sets, $t(54) = 2.80$, $p = .007$, $d = 0.38$.

Discussion

Search speed and accuracy findings were concordant with the distractor recognition results—under conditions of less efficient search (larger target set sizes, heterogenous target categories), subsequent recognition of distractors was improved. This extends and replicates prior work (Guevara Pinto et al., 2020; Guevara Pinto & Papesh, 2019; Hout & Goldinger, 2010, 2012) from the context of VWM-mediated templates to the context of memorized search templates. Distractor recognition confirmed that differences in search performance between blocks were determined by processing of distractors (Cunningham & Wolfe, 2014; Drew et al., 2017; Drew & Wolfe, 2014; Nordfang & Wolfe, 2018) and not solely by target identification. We also extended the findings of Cunningham and Wolfe (2014) by manipulating target similarity while keeping distractor similarity constant (on average), instead of manipulating distractor similarity using only related targets. Our methods converged to show minimal effects of target number on search performance (RT and accuracy) when targets (likely) do not resemble distractors but resemble each other.

Figure 4

Experiment 1 Incidental Recognition Accuracy of Distractors From Different Conditions of Visual Search



Note. Error bars around mean depict ±1 scaled *SD* (see "Statistics" subsection of Experiment 1 Method). See the online article for the color version of this figure.

Our conjecture is the distractors that were subsequently recognized resembled one or more targets such that attentional prioritization of target features caused those distractors to be attended. However, support for this view rests on studies that have only focused on single-target or -category search (Alexander & Zelinsky, 2011, 2012; Thomas & Williams, 2014; Williams, 2010a, 2010b; Williams et al., 2005). Note we did not specifically select distractors to resemble targets. Our only constraint was that they come from a nontarget category. However, in search for keyboards, a laptop might lure your attention, and such coincidental similarities were not deliberately excluded.

Things might be different for unrelated targets. Given the high recognition of distractors (85%) from 16 unrelated target blocks, we wondered whether it might actually be the case that observers were randomly examining the search array because such a variety of targets failed to engender a template (or templates) to attentionally rule out any distractors short of direct examination. Ort and Olivers (2020) seem to advance such a notion, suggesting that hybrid search operates as a "vision guided memory search" (p. 346; we assume they refer to unrelated target sets, which are most common in hybrid search). If the target template(s) for 16 unrelated items fails to limit attention to target features at both the selection and identification phases, then the extent to which distractors impair search efficiency should not depend on their similarity to targets; likewise, distractor recognition should be unrelated to distractor–target similarity. Note that the high search accuracy in all conditions of Experiment 1 does not imply intact attentional identification regardless of target variety. RSVP studies show that imprecise or numerous target templates prolong but do not entirely prevent identification (Drew & Wolfe, 2014; Guevara Pinto & Papesh, 2019; Hout & Goldinger, 2010). In other words, targets can still be recognized despite distractors demanding inordinately long identification and perhaps without a clear internal representation of the targets.

In a second experiment, we sought to test our hypothesis that the probability of recognizing a distractor depends on its similarity to one or more targets. We suspected this might be the case only for related targets, as unrelated targets potentially fail to promote an effective search template to prioritize relevant features and deprioritize irrelevant ones. We deliberately selected different groups of distractors that would be similar or dissimilar to targets. In addition, random distractors were again included. We also wished to determine if the search efficiency advantage of related targets applies to distractor ensembles beyond random distractors. The final goal of Experiment 2 was to link search efficiency more tightly to distractor processing by showing that the probability of delayed distractor recognition depended on the extent to which a distractor incurred a search efficiency cost.

Experiment 2

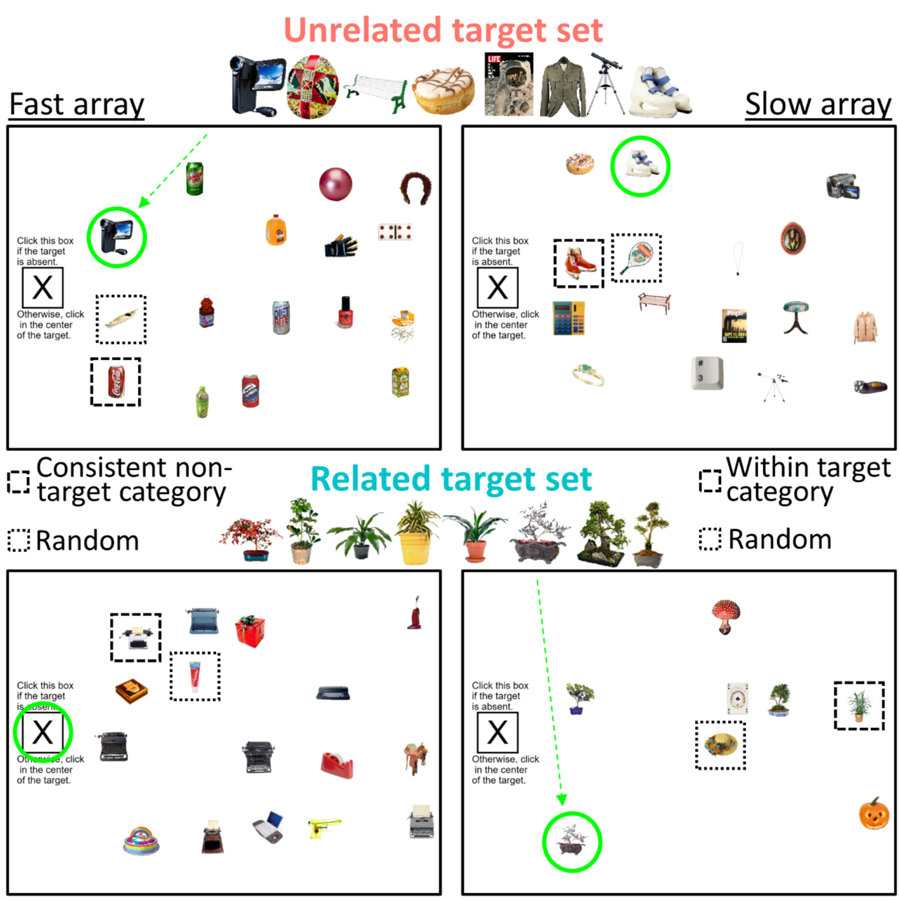
Experiment 2 (Figure 5) was designed to determine the extent to which attention prioritizes distractors varying in similarity to targets, thereby revealing whether the observers were able to establish an effective target template or templates. The design shares the logic of contingent capture paradigms. Template effectiveness would be inferred from enhanced subsequent recognition of distractor groups deliberately selected to resemble targets. An additional indicator of template effectiveness would be the cost imposed on search efficiency of target-similar distractors. We devised search arrays that deliberately elicited unequal RTs, meanwhile showing that the differences in RTs were related to delayed recognition for some distractor groups but not others. Such a dissociation ruled out the possibility that simply responding slowly promotes delayed distractor recognition broadly, and instead affirmed the idea that distractor processing caused both search delays and later recognition.

"Fast" arrays contained distractors drawn from a single, randomly chosen nontarget category (*consistent distractors*), which was intended to aid search as it is known that self-similar distractors are easier to ignore than heterogenous distractors (Duncan & Humphreys, 1989). "Slow" arrays contained distractors from the same category (in related target blocks) or categories (in unrelated target blocks) as targets (*within-category distractors*). Distractors that resemble targets should draw attention and increase response times (Alexander & Zelinsky, 2011, 2012), at least for related target sets. For unrelated target sets, the potential lack of an effective template would fail to produce selective processing of target–category distractors over any other type of distractor. Both fast and slow arrays contained distractors whose presumed visual similarity to the targets would be random (but on average equal) by selecting images from random, unique, nontarget categories (*random distractors*—equivalent to distractors in Experiment 1). Separate random distractors were assigned to the fast arrays versus the slow arrays.

Predictions

Hypotheses, analyses, and inclusion criteria were specified in a preregistration before data collection on the Open Science Framework (https://osf.io/3svqh). We hypothesized that for related target search, within-category distractors would be recognized better than the

Figure 5
Examples of Fast and Slow Search Arrays for Unrelated and Related Target Sets



Note. Spacing and scale duplicate Experiment 1, which did not have an "absent" box. The target set for both hypothetical search blocks is shown above the respective search arrays. Random distractors from fast arrays versus slow arrays were selected from separate categories. The following illustrative elements were not visible to the participants: dashed and dotted squares indicating distractor types; green circles around the correct click locations; and green arrows relating the target set to the target-present within the trial. Object stimuli from the Massive Memory database (Konkle et al., 2010). See the online article for the color version of this figure.

random and consistent category distractors. Random distractors from either fast or slow arrays should attract little attention. Despite the increased RT for slow arrays, we did not expect the recognition of random distractors to differ between fast and slow arrays.

We evaluated whether the expected within-category distractor recognition benefit could be attributed to the increased prevalence, and hence, salience, of the target category. To do so, we assessed the recognition of consistent distractors. Perhaps the awareness of a particular category frequently appearing facilitates distractor encoding by increasing observers' curiosity for those images or by cueing them to features that differentiate category tokens (a possibility mentioned in Williams, 2010b). Either effect should assist in the subsequent category-matched 2AFC recognition test. If this is the case, then consistent distractors should be recognized better than random distractors, which all represent unique categories.

For distractors appearing during hybrid search for unrelated-category targets, we hypothesized unaltered recognition with respect to distractor–target relationships. That is, consistent, random, and within-category distractors would all be recognized equally well. Further, we hypothesized that distractor recognition would be higher for unrelated than related target sets, except for within-category distractors. This should be the case if unrelated targets fail to promote effective templates that prioritize relevant objects and deprioritize irrelevant ones.

Overall, we expected superior search efficiency for related targets, across fast and slow search arrays.

Method

Besides the noted changes, the methods of Experiment 2 replicate those of Experiment 1.

Participants

We gathered datasets from 58 participants, with a mean age of 26.0 years ± 7.2 (29 males and 29 females). Forty-seven participants enrolled in the study for payment via prolific.com, and the others enrolled for course credit through the psychology participant pool at the University of Utah, between June 10 and August 25, 2021. Four of these datasets were discarded according to preregistered recognition performance criteria. The final sample consisted of 54 participants. Participants completed the experiment (including consent and debriefing) in an average of 53.2 min ± 9.2. The procedures were approved by the IRB at the University of Utah.

Design and Procedure

Seven pilot participants were enrolled to calibrate aspects of the design, difficulty, and power analyses, before finalization of the preregistration. Based on pilot data, stringency for target set memorization was increased. Whereas in Experiment 1 learning foils were from random categories, in Experiment 2 learning foils were drawn from the same category(ies) as the targets and participants had to pass three (rather than two) old–new memorization tests with 90% accuracy or greater (rather than 80%). The search phase of each block consisted of 80 trials, split equally along the following fully crossed factors: search set size (8 vs. 16), target-present versus target-absent, and slow versus fast search arrays. By the end of memory training in each related block, observers had encountered 16 items from the related target category (eight targets and eight learning foils). After memory training in unrelated blocks, observers had only encountered two items (a target and a foil) from each of the eight unrelated categories.

For absent search trials, half the distractors were random and half were either consistent (fast arrays) or within-category (slow arrays). On present trials, one of the distractors was randomly replaced by a target. Within a block, each of these four distractor types (fast-random, slow-random, consistent, and within-category) comprised eight unique images. Thirty-two distractors were used in each search block, appearing in 28 or 29 trials. Unrelated target set blocks were different only because the within-category distractors were unrelated to each other (because the targets were, by definition, unrelated). By the end of each related search block, observers had encountered 24 tokens from the target category (eight targets, eight learning foils, and eight within-category distractors). By the end of each unrelated block, in contrast, observers had encountered only three tokens (target, learning foil, and within-category distractor) from each of the eight target categories. Category exposure appeared to play a role in both search and recognition results (akin to Konkle et al., 2010).

During search, participants were instructed to click on the target if they found it, or to click on a designated box to the left of the search array if they could not find it. A square "absent box" was placed left of the leftmost possible position for search array elements, subtending 1.77° vertically and horizontally. After responses, the correct click location was outlined in green for 500 ms following a correct response or outlined in red for 750 ms following an error. If the target was present, it remained on the screen for this duration, regardless of accuracy; distractors disappeared during feedback.

Two blocks involved memorization and search for unrelated target sets, and the other two involved related target sets. All measures of search behavior and distractor recognition were collapsed between these pairs of blocks. The sequence of blocks (e.g., unrelated, related, related, unrelated) was counterbalanced across participants. Recognition of every distractor was tested at the end of the experiment, totaling 128 2AFC trials (32 distractor objects for each of four blocks).

Analysis

Power. Our target *N* was 54—the closest multiple of six to the *N* from Experiment 1. We conducted simulation power analyses in *R* using the superpower package and the anova_exact function (Caldwell et al., 2020). These simulations suggested we were adequately powered across a range of plausible effect sizes based on seven pilot participants (separate from the main sample included in our results; see "Design and Procedure" section). Our main hypothesis was that recognition for within-category distractors would be higher than for slow-random distractors, only when searching for a related target set. When searching for an unrelated target set, we predicted relations of the distractors to the target categories would not influence distractor recognition. In the pilot data, indeed, within-category distractors were recognized much better than random distractors in the related target block but not the unrelated target block. The observed interaction and covariances among repeated measures were the starting point of the stimulations. Power can be negatively impacted by either reducing the magnitude of the interaction or by decreasing covariances. Fifty-four participants provided 80% power to detect an interaction that was diminished by half compared to the observed pilot effect, or an interaction diminished by one-quarter when covariances were set to zero. Thus, even if the pilot dataset greatly overestimated the true effect, we would have been adequately powered.

Data Preparation and Exclusion. One and a half percent of all RTs were identified as outliers and removed from subsequent analyses. For outlier identification, trials were combined between participants, then separated into 16 conditions along four binary factors: target set type, search array type, visual set size, and target presence.

Statistics. Preregistered search slopes analyses revealed a surprising null effect of target type for slow arrays, which invited direct examination of RT. While search slopes help reduce dimensions of analysis for RT data and help standardize analyses across experiments, we wanted to rule out a main effect of set size for slow array RTs. Analyses of error click data were exploratory, based upon surprising accuracy results. For null effects of theoretical import, 95% confidence intervals on Cohen's d are reported

Results

Search Slopes

Search slopes were calculated as in Experiment 1 and submitted to a repeated-measures ANOVA with three binary factors of target type (unrelated or related), array type (fast or slow), and target presence (present or absent; Figure 6). All main effects and interactions were significant. The main effect of array type, $F(1, 53) = 406.1$, $p < .001$, $\eta_p^2 = .88$, indicates search through fast arrays was more efficient and it took less time. The RT benefit of fast arrays was confirmed by via direct analysis of RTs. An exploratory four-way ANOVA on RTs (the additional factor being visual set size 8 or 16) revealed all effects and interactions involving array type were significant, $F\text{s}(1, 53) \geq 22.7$, $p\text{s} < .001$, $\eta_p^2\text{s} \geq .30$. The fast versus slow manipulation worked as intended.

Separate two-way ANOVAs on search slopes for slow versus fast arrays yielded a surprising result, though. The effect of target type and its interaction with target presence were nonsignificant for slow arrays, $F\text{s}(1, 53) \leq 0.3$, $p\text{s} \geq .59$, $\eta_p^2\text{s} \leq .02$. This suggests that unrelated and related targets afforded equivalent search speed as confirmed by nonsignificant effects of target type on RT, across the levels of target presence crossed with visual set size ($|t\text{s}[53]| \leq 0.4$ [absolute value], $p\text{s} > .67$, $|d\text{s}| \leq 0.06$, all 95% CIs on d bounded by $[-0.33, 0.33]$). On the contrary, we hypothesized that unrelated targets would reduce search speed because both distractor groups (random and within-category) would lure attention but for related targets only within-category distractors would lure attention. Distractor recognition and search error types (below) clarified this result. Search slope was significantly higher on absent trials compared to present trials for slow arrays, $F(1, 53) = 276.3$, $p < .001$, $\eta_p^2 = .84$.

For fast arrays, the main effects were significant for target presence, $F(1, 53) = 395.7$, $p < .001$, $\eta_p^2 = .88$, and target type, $F(1, 53) = 138.3$, $p < .001$, $\eta_p^2 = .72$, as was as their interaction, $F(1, 53) = 75.9$, $p < .001$, $\eta_p^2 = .59$. Follow-up t tests revealed unrelated target search slope was even higher than related search slope on absent trials, $t(53) = 12.3$, $p < .001$, $d = 1.68$, compared to present trials, $t(53) = 6.1$, $p < .001$, $d = 0.83$.

As in Experiment 1, search was slower for unrelated than related targets, but contrary to our hypothesis, not on slow arrays (Figure 6).

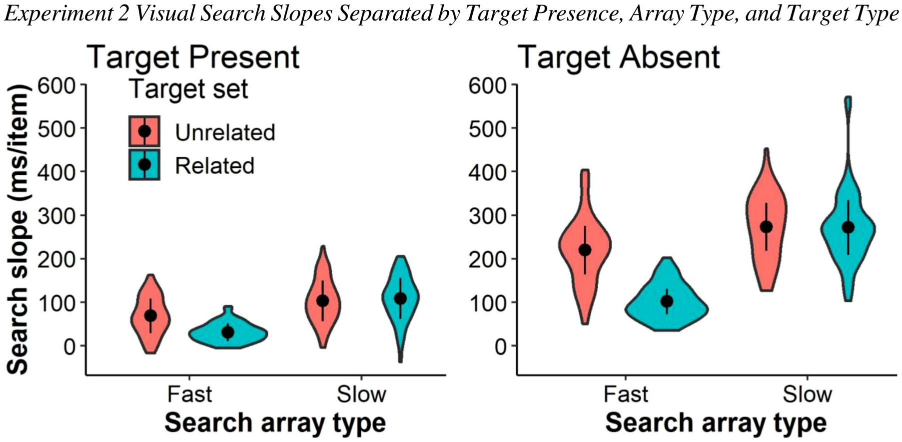
Search Accuracy

Search accuracy was examined with a three-way repeated-measures ANOVA, collapsed across visual set sizes (Figure 7). The main effects of search array type and target presence were significant, respectively, $F(1, 53) = 32.9$, $p < .001$, $\eta_p^2 = .38$, and $F(1, 53) = 60.3$, $p < .001$, $\eta_p^2 = .53$, as was the interaction between target set type and target presence, $F(1, 53) = 16.1$, $p < .001$, $\eta_p^2 = .23$. On target-present trials, unrelated target set accuracy was lower than related, $t(53) = -2.8$, $p = .008$, $d = -0.38$, but on absent trials, accuracy was marginally higher for unrelated target sets, $t(53) = 1.8$, $p = .076$, $d = 0.25$. This unanticipated interaction between target set type and target presence was small but suggested a differential susceptibility to miss versus false-alarm error types depending on the target set type. The main effect of target set type and other interactions were not significant ($p\text{s} > .157$, $\eta_p^2\text{s} \leq .04$).

Error Types. We examined click locations on error trials for greater insight into this interaction. Counts of clicks on different

Figure 6

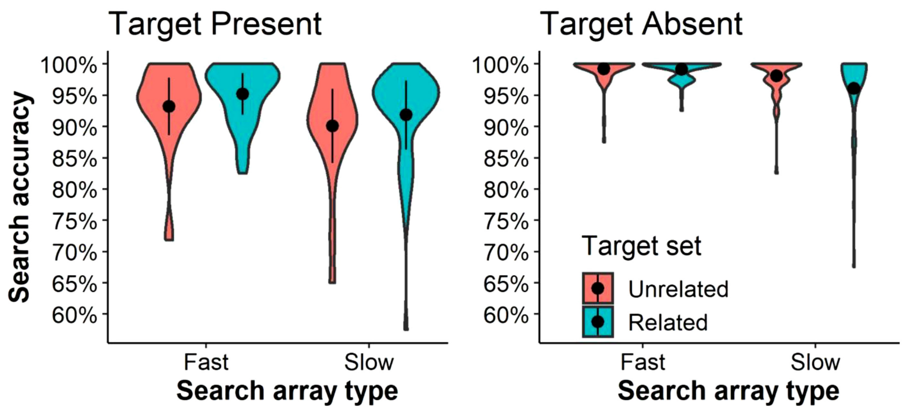
Experiment 2 Visual Search Slopes Separated by Target Presence, Array Type, and Target Type



Note. Error bars around mean depict ±1 scaled *SD* (see "Statistics" subsection of Experiment 1 Method). See the online article for the color version of this figure.

Figure 7

Experiment 2 Visual Search Accuracy Separated by Target Presence, Array Type, and Target Type



Note. Error bars around mean depict ±1 scaled *SD* (see "Statistics" subsection of Experiment 1 Method). See the online article for the color version of this figure.

distractor types (false alarms), as well as misses and errant clicks on blank space, are presented in Table 1. The error click data were highly positively skewed, with a mode of zero errors per observer per condition, prompting the use of the Wilcoxon signed rank sums test. Within-category distractors were confused for targets significantly more often during search for related than unrelated target sets ($z = 2.78$, $p = .005$). In conjunction with search slope and distractor recognition data (below), this suggests within-category distractors disproportionately drew attention in related compared to unrelated blocks (see "Discussion" section). Misses were the most common type of search error, significantly more likely with unrelated target sets ($z = -3.51$, $p < .001$) and when the target appeared among within-category distractors (i.e., slow arrays; $z = 3.58$, $p < .001$). Errant clicks were equally likely for slow and fast arrays ($z = -0.35$, $p = .73$), as well as related and unrelated blocks ($z = -0.51$, $p = .61$), suggesting the above results were not driven by haste or carelessness. Random category distractors in either fast or slow search arrays were almost never confused with the target set; neither were consistent distractors. In summary, among the small number of errors overall, unrelated targets yielded more misses and related targets more false alarms on within-target distractors.

Table 1

Frequency of Click Categories for Incorrect Visual Search Trials

	Mean clicks per observer (*SD*)	
Click category	Unrelated[a]	Related[a]
Fast search arrays		
Errant[b]	0.50 (1.06)	0.44 (0.69)
Miss[c]	2.48 (2.31)	1.72 (1.74)
Fast-random[d]	0.02 (0.14)	0.02 (0.14)
Consistent[d]	0.00 (0.00)	0.04 (0.19)
Slow search arrays		
Errant[b]	0.57 (1.41)	0.31 (0.72)
Miss[c]	3.57 (2.98)	2.65 (2.37)
Slow-random[d]	0.02 (0.14)	0.02 (0.14)
Within-category[d]	0.52 (0.86)	1.80 (3.05)

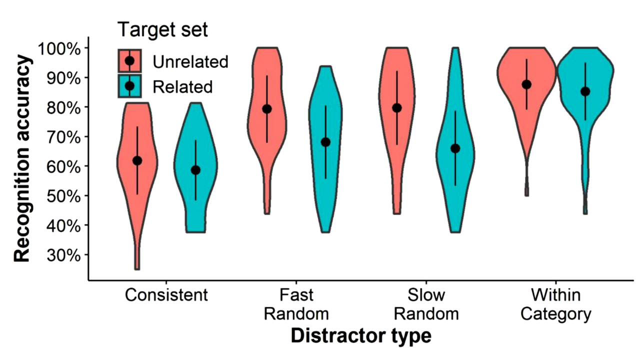
[a] Target set type. [b] Clicks on blank space. [c] Clicks on the absent box for target-present trials. [d] Clicks on distractors of the specified type.

Distractor Recognition

A 2-by-2 repeated-measures ANOVA focused on distractors from slow search arrays, that is, within-category distractors and slow-random distractors (Figure 8). The factors were distractor type and target set type (unrelated or related). Distractor recognition was significantly higher for unrelated target sets, $F(1, 53) = 32.7$, $p < .001$, $\eta_p^2 = .38$, and for within-category distractors, $F(1, 53) = 88.8$, $p < .001$, $\eta_p^2 = .63$. These main effects were qualified by a significant interaction, $F(1, 53) = 13.5$, $p < .001$, $\eta_p^2 = .20$, which was examined with paired *t* tests. The interaction was driven by the fact that the enhancement of recognition for within-category distractors over slow-random distractors was larger for related target sets,

Figure 8

Experiment 2 Incidental Recognition Accuracy of Separate Distractor Groups, Split by Target Type Alongside Which Distractors Were Encountered



Note. Error bars around mean depict ±1 scaled *SD* (see "Statistics" subsection of Experiment 1 Method). See the online article for the color version of this figure.

$t(53) = 9.6$, $p < .001$, $d = 1.31$, than for unrelated target sets, $t(53) = 3.6$, $p = .001$, $d = 0.5$. This confirmed our hypothesis that target–distractor similarity would influence distractor recognition more for related than unrelated target sets but contradicted our hypothesis that target–distractor similarity would not impact recognition for unrelated target sets.

A tight inferential link between search delays incurred by distractors and their likelihood of delayed recognition is demonstrated by comparing recognition (a) between unrelated and related blocks on slow arrays or (b) between fast and slow arrays while holding target type constant. First, the already-mentioned superiority of within-category distractor recognition cannot be explained by a benefit to encoding merely by spending more time on the search array. If this were the case, slow-random distractor recognition should not have differed between unrelated and related blocks (but we demonstrated this difference in the previous paragraph), because slow array RT was equivalent between unrelated and related targets. Second, slow-random distractors should have been recognized better than fast-random distractors, mirroring slow versus fast array RT differences. Paired t tests failed to reveal a difference in recognition of slow- versus fast-random distractors for either unrelated, $t(53) = 0.2$, $p = .874$, $d = 0.02$, 95% CI on $d = [-0.25, 0.29]$, or related target sets, $t(53) = -0.8$, $p = .405$, $d = -0.11$, $[-0.38, 0.16]$. For a third dissociation of recognition and RT, despite slower RT on fast arrays compared to related targets, unrelated targets did not improve recognition of consistent distractors; exploratory: $t(53) = 1.3$, $p = .20$, $d = 0.18$, $[-0.09\ 0.45]$. This links the enhanced recognition of random distractors in unrelated compared to related blocks specifically to the RT cost they incurred, evident on fast arrays. Slow array RT appears to be influenced by additional, competing factors (see "Discussion" section).

For the second alternative explanation, if the within-category distractors were recognized better due to prevalence of the category(ies), then consistent distractors should have been recognized better than fast-random distractors. However, the opposite is true for both unrelated, $t(53) = -8.2$, $p < .001$, $d = -1.11$, and related targets sets, $t(53) = -3.9$, $p < .001$, $d = -0.53$. As mentioned, we furthermore observed that within-category distractors were recognized equally well in unrelated blocks versus related, despite the reduced categorical prevalence of these distractors in unrelated compared to related blocks.

A likely explanation for the diminishing return on subsequent recognition for extra time during search spent attending related within-category distractors (see "Discussion" section) is categorical interference (Konkle et al., 2010). The following exploratory analyses were conducted to investigate whether greater confusion among exemplars from consistent distractor categories, as well, contributed to their lower recognition compared to fast-random distractors. If consistent categories were attended in unrelated and related blocks, consistent distractor recognition should be higher in unrelated than related, mirroring fast-random distractor recognition, $t(53) = 5.5$, $p < .001$, $d = 0.75$. But, as already noted, we did not detect a difference in consistent distractor recognition between unrelated and related. Thus, the explanation as presented cannot account for the results without postulating a greater categorical interference effect in unrelated than related blocks. Furthermore, the inferred reduction of attention to consistent category distractors aligns with prior work showing distractor–distractor similarity improves deprioritization of distractors (Duncan & Humphreys, 1989).

Discussion

Fast and slow search arrays successfully elicited unequal RTs while yielding equivalent recognition of their respective random distractors. From this, we confidently infer within-category distractors attracted attention, which slowed search and led to their superior delayed recognition. On the other hand, consistent category distractors minimally attracted attention, thereby facilitating search speed and leading to their poor delayed recognition. This confirmed our hypothesis in the case of related targets that distractors resembling targets would be preferentially processed during search and subsequently remembered. We were wrong, however, in hypothesizing that unrelated targets would fail to promote attention to relevant distractors and away from irrelevant ones. This suggests that observers were indeed capable of establishing templates for at least some of the eight unrelated targets. Additionally, the ability to ignore irrelevant distractors appeared to be fully intact regardless of target variety. This is consistent with the perspective that target enhancement and distractor suppression rely on dissociable mechanisms (van Moorselaar & Slagter, 2020).

Thanks to the visual similarities of same-category targets, observers appeared to establish narrow templates in related target blocks. This is apparent from the low recognition of random distractors, and the search efficiency advantage over unrelated targets for fast arrays. Additionally, within-category distractors attained a greater relative attentional priority relative to random distractors, in comparison with unrelated target blocks where the within-category recognition advantage over random distractors was substantially smaller.

The most surprising result was that despite lower recognition of random distractors and equivalent recognition of within-category distractors, slow array search efficiency was indistinguishable in related target versus unrelated blocks. This indicates a trade-off in search efficiency when faced with multiple related targets, shaped by the presence of different types of distractors. As in Experiment 1, similarity among these targets promoted a narrow search template such that random distractors were mostly ignored (save for the ones that by coincidence resemble that target category). But the task of distinguishing distractors from targets within the same category was more error-prone (based on error click data) and time-consuming. We suggest that slow arrays imposed search efficiency costs for different reasons in the unrelated versus related blocks. In the unrelated blocks, a greater proportion of objects (within-category and, to a smaller extent, random distractors) attracted attention, but each for a relatively brief duration. In related blocks, most random distractors were ignored or considered only momentarily, whereas within-category distractors required detailed scrutiny to be identified as nontargets. Despite this extra scrutiny, within-category distractors were more likely to be confused as targets in related target blocks. These arguments on the proportion of items selected versus duration of identification await explicit testing with eye tracking.

Thus, related target search had its advantages but also unique disadvantages, likely related to category interference effects, which have already been established in recognition memory (Konkle et al., 2010). While the inordinate search cost of within-category distractors for related targets might have been anticipated from Konkle et al. (2010), our findings extend their results from the context of fixed-duration viewing of single items to free viewing visual search. Furthermore, our results raise the intriguing possibility that observers spontaneously spend more time examining these related within-category distractors without a benefit to subsequent recognition compared to unrelated within-category distractors.

Distractor encoding in Experiments 1 and 2 cannot be explained away as byproducts of responding slowly nor of categorical prevalence as we experimentally manipulated both variables and found that these factors did not drive distractor recognition rates. Rather, it is clear that target–distractor resemblance determines whether distractors attract attention, incur search efficiency costs, and are encoded into visual long-term memory.

General Discussion

Experiments 1 and 2 bridged prior work that manipulated target precision (Castelhano et al., 2008; Guevara Pinto & Papesh, 2019; Malcolm & Henderson, 2009), number (Guevara Pinto et al., 2020; Hout & Goldinger, 2010, 2012), and variety (Hout & Goldinger, 2015), exploring the interaction of these factors and replicating their impact in the context of long term memory-mediated targets. Target number had a greatly reduced effect on search efficiency when all targets were visually and semantically related, among a group of random distractors. In line with prior work, reduced search efficiency for large numbers of unrelated targets was mediated, in part, by enhanced processing of distractors as revealed by delayed recognition.

By manipulating target–distractor similarity, Experiment 2 revealed that for even eight unrelated targets, observers can establish a target template that spares attention from irrelevant distractors at either the selection or identification phase (see Eimer, 2014). Regardless of target relatedness, consistent distractors imposed little search cost and were recognized the worst. This is in line with much prior work (see van Moorselaar & Slagter, 2020 for a review) that suggests distractor inhibition is independent from target facilitation and likely relies on myriad distinct processes, such as grouping by similarity (Duncan & Humphreys, 1989). Furthermore, within-category distractors were always recognized better than random ones and prolonged search. The enhanced efficiency of related target search was replicated in Experiment 2, but, to our surprise, only on fast search arrays. This suggests that the use of random distractors in prior VWM-mediated visual search work is a crucial element for revealing differences in search efficiency between different types and numbers of targets.

Multiple related targets begin to pose a unique search challenge when distractors from the target category appear. These likely take longer to identify as nontargets and have a greater risk of ultimately being mistaken for targets indicated by error click types. This replicates and extends findings from a continuous recognition task, showing that as the number of encountered items from a single category increases, recognition performance in that category declines (Konkle et al., 2010). Thus, despite the posited extra time devoted to within-category distractors in related blocks, they showed no advantage in delayed recognition compared to within-category distractors in unrelated blocks.

Computational modeling of cognitive processes in expert versus nonexpert category recognition (Annis & Palmeri, 2019) provides some clue as to the source of these within-category ceiling effects. Recognition performance improves for experts via increased representational distinctiveness of tokens and a higher asymptote of delay-induced forgetting within the expert domain category. Observers in our study likely did not develop expertise, nor were they experts to begin with for the target categories in related blocks. Thus, their memory likely suffered from blurring between and more complete forgetting of memory tokens—the deficits observed by Annis and Palmeri (2019) in novice-domain recognition.

Prior work that assumed a fixed-radius functional visual field regardless of target–distractor (or distractor–distractor) similarity (Drew et al., 2017; Young & Hulleman, 2013) has likely underestimated the proportion of search items that are processed before observers correctly respond on target-absent trials. The natural assumption that not all distractors are equally distracting lends itself to the idea that while you can safely ignore some distractors at high eccentricity from fixation, others will require greater processing with the macula or fovea. That is, we should consider visual fields *for* various functions (Wolfe, 2021). It would be interesting to know whether the peripheral probe performance in Guevara Pinto and Papesh (2019) varied according to target–distractor similarity of distractors concurrent with and temporally adjacent to the probe. The present research suggests there may be a benefit in calculating separate visual field diameters for distractors that differ in resemblance to targets and to other distractors.

Limitations and Future Directions

Further addressing the role of memorized target sets in attentional prioritization requires finer-grained measures of attention than distractor recognition. Specifically, eye tracking or electroencephalography may permit the delineation of attentional selection, identification, and inhibition (e.g., N2pc, contralateral delay activity, and Pd event-related potentials (ERPs), Eimer, 2014; Hickey et al., 2009). Prior work found that both selection and identification phases are initiated (or prolonged) by a greater proportion of distractors as target heterogeneity increased (Hout & Goldinger, 2015). Target–distractor resemblance likely has a similar effect spanning both attentional phases (Alexander & Zelinsky, 2011, 2012; Thomas & Williams, 2014; Williams, 2010a; Williams et al., 2005). Experiment 2 suggests these phases of attention can be differentially impacted, specifically with related targets improving selection (by ignoring random distractors) but hindering identification (of within-category distractors). Prior hybrid search work that manipulated target–distractor similarity with related targets makes the case even more strongly (Cunningham & Wolfe, 2014; Drew & Wolfe, 2014; Nordfang & Wolfe, 2018). Our results cannot adjudicate whether one stage or another has a bigger influence on distractor recognition.

Prior work suggests that identification may not always be synonymous with "memory search" or long-term memory retrieval. For related category targets, rapid categorization of distractors may preclude memory search (Cunningham & Wolfe, 2014; Drew & Wolfe, 2014). The operation of this categorization phase and its influence on distractor recognition are also undetermined in the present results. It is possible that mere selection may not contribute to subsequent recognition, especially if items can be quickly categorized as irrelevant. By forcing all distractors to be selected with the use of RSVP, recognition has been found to increase with greater numbers of VWM-mediated targets (Guevara Pinto & Papesh, 2019; Hout & Goldinger, 2010), imprecise target descriptions (Guevara Pinto & Papesh, 2019), and increasing target–distractor similarity (Williams, 2010b). A narrowing of the functional visual field to afford more detailed distractor processing likely mediated the effects of target specificity and number (Guevara Pinto & Papesh, 2019).

As previously demonstrated (Konkle et al., 2010), recognition memory is influenced by factors beyond attentional history. The most obvious moderating factor in the current work was categorical interference. Future research dedicated to factors moderating the relationship of dwell time (or time within the functional visual field) and subsequent recognition could examine conditions that improve encoding efficiency or retrieval. Candidates include encountering an image as a target rather than a distractor (Thomas & Williams, 2014), reinforcement prediction error concurrent with image presentation (Jang et al., 2019), image memorability (Khosla et al., 2015), image category expertise (Annis & Palmeri, 2019), and avoiding mind wandering (Blondé et al., 2022).

Visual resemblance based on category membership is a rough approximation. Stronger conclusions regarding the relationships of resemblance to attention prioritization and recognition memory interference await a more precise manipulation. Extant metrics of resemblance in terms of multidimensional scaling (Hout et al., 2013) are limited to within-category comparisons. Resemblance metrics between categories, or perhaps between prototypical category members, would facilitate future studies. Computer vision methods (e.g., Alexander & Zelinsky, 2011) could be of great benefit for this line of inquiry. Nevertheless, investigators should be encouraged to investigate similarity by the success of our current techniques based on relatively coarse, category-level manipulations of similarity.

Conclusion

Attention provides a way to prioritize the objects and features likely to satisfy our goals. As the number of sought-after memorized targets increases, speed and accuracy in locating and identifying them decreased, in part because attention was drawn to distractors. When all targets were similar, the negative effects of the target number were dramatically reduced. Thus, search templates mediated by long-term memory functioned similarly to those held in working memory. Distractors that resembled targets drew the most attention, suggested by their impact on search speed and high probability of later recognition. This occurred regardless of target variety. Low target variety reduced attentional luring by random distractors, but multiple related targets became hard to distinguish from distractors in the same category. In short, the interference of distractors depended on their similarity to targets and to each other, as well as similarity among targets. Assuming differential degrees of interference from distractors could improve estimates of the functional visual field. Future use of eye tracking and ERP studies informed by the present research could better parse attentional stages underlying distractor encoding and search performance.

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