

UC Davis

UC Davis Previously Published Works

Title

Attentional Guidance and Match Decisions Rely on Different Template Information During Visual Search

Permalink

<https://escholarship.org/uc/item/5dv75726>

Journal

Psychological Science, 33(1)

ISSN

0956-7976

Authors

Yu, Xinger
Hanks, Timothy D
Geng, Joy J

Publication Date

2022

DOI

10.1177/09567976211032225

Peer reviewed

Attentional Guidance and Match Decisions Rely on Different Template Information During Visual Search



Xinger Yu^{1,2} , Timothy D. Hanks^{3,4}, and Joy J. Geng^{1,2}

¹Center for Mind and Brain, University of California, Davis; ²Department of Psychology, University of California, Davis; ³Center for Neuroscience, University of California, Davis; and ⁴Department of Neurology, University of California, Davis

Psychological Science
2022, Vol. 33(1) 105–120
© The Author(s) 2021
Article reuse guidelines:
sagepub.com/journals-permissions
DOI: 10.1177/09567976211032225
www.psychologicalscience.org/PS



Abstract

When searching for a target object, we engage in a continuous “look-identify” cycle in which we use known features of the target to guide attention toward potential targets and then to decide whether the selected object is indeed the target. Target information in memory (the target template or attentional template) is typically characterized as having a single, fixed source. However, debate has recently emerged over whether flexibility in the target template is relational or optimal. On the basis of evidence from two experiments using college students ($N_s = 30$ and 70 , respectively), we propose that initial guidance of attention uses a coarse relational code, but subsequent decisions use an optimal code. Our results offer a novel perspective that the precision of template information differs when guiding sensory selection and when making identity decisions during visual search.

Keywords

visual search, attention, target template, drift-diffusion model, open data

Received 12/28/20; Revision accepted 5/16/21

Imagine that you are doing a field survey in India, and the guide reminds you to be cautious of a tiger hiding in the grasslands. The environment might be filled with different types of animals, but as you look around, there is a limit on how much information can be processed in any given moment. Therefore, you must hold a memory representation of the tiger, known as the *target template* or *attentional template*, in mind while recursively locating and inspecting candidate creatures until the target tiger is found (Malcolm & Henderson, 2010; Wolfe, 2021). Although the concept of a target template has been a staple of attention research for decades (Duncan & Humphreys, 1989; Eriksen, 1953; Green & Anderson, 1956), it has been largely assumed to contain a single, static, and veridical representation of what we are looking for. Recent studies have begun to challenge this notion by showing that template representations are dynamic and shift “off-veridical” when doing so increases the target-to-distractor distinctiveness (Geng & Witkowski, 2019). Our goal in the present study was

to go further and test the hypothesis that two versions of the search template are used at the guidance and decision stages of the “look-identify” cycle (Wolfe, 2021). Although both templates were expected to be off-veridical, we hypothesized that guidance operates on a more relational template, whereas target decisions rely on a more optimal code.

Standard models of feature-based attention posit that the optimal template for a target contains highly specific information about the veridical features of the target (Treue & Trujillo, 1999), but studies in which the search target appears predictably among linearly separable distractors have found that the target representation shifts off-veridical away from distractors (Bauer et al.,

Corresponding Authors:

Xinger Yu, University of California, Davis, Center for Mind and Brain
Email: xeyu@ucdavis.edu

Joy J. Geng, University of California, Davis, Center for Mind and Brain
Email: jgeng@ucdavis.edu

1996; Hodson & Humphreys, 2001; Navalpakkam & Itti, 2007; Scolari et al., 2012). For example, searching for an orange tiger among yellow grasslands results in an attentional bias toward color values that are redder than the actual orange of the tiger. Becker and colleagues (Becker, 2010; Martin & Becker, 2018) proposed that this effect occurs because observers use a relational rule to guide attention and their first saccades toward the reddest object in the visual environment. In contrast, other researchers have argued that the bias is due to an optimal shift in the central tendency of the target tuning curve to more effectively discriminate the target from distractors (Geng et al., 2017; Navalpakkam & Itti, 2007; Scolari et al., 2012; Yu & Geng, 2019).

Even though the two positions may seem similar, they make very different predictions that have implications for understanding how target information is encoded and flexibly used during visual search. In particular, the two theories differ in their predictions about how inclusive the template is of feature values that are opposite from the experienced distractors (i.e., the negative color values in Fig. 1). The relational account predicts very broad inclusion of negative feature values because they all share the relational feature that discriminates the target from expected distractors (e.g., the reddest object; Fig. 1a). There must be a boundary to relational inclusiveness, but this has not been established empirically. The optimal-gain model instead predicts a shift in the central tendency toward a more negative value (e.g., slightly redder than the orange target), but inclusion within the template of both negative and positive color values is scaled by distance from the shifted central value (Fig. 1b). These differences can be visualized as the width of a response filter (Fig. 1, left column) or, more generally, as similarity matrices that capture the second-order pattern of expected responses (Fig. 1, right column).

One possible explanation for why there appears to be evidence for two theories that ostensibly refer to the same target template is that they derive from studies using different methods. Some researchers use response time (RT) or first-saccade destinations as the metric of the template (Martin & Becker, 2018), whereas others use a separate probe task to measure the learned target feature (Navalpakkam & Itti, 2007; Scolari & Serences, 2009; Yu & Geng, 2019). We hypothesize that these differences tap into different stages of the look-identify cycle: The first saccade reflects early guidance of attention to the best match, whereas the probe task requires binary decisions regarding target identity. This leads to an important question of whether attentional guidance and match decisions use the same or different template information during visual search. We hypothesize that guidance relies on a coarser version of the template and

Statement of Relevance

The objects that we look for are often hard to find because they are “hidden” among countless other objects in complex scenes (e.g., keys in a cluttered kitchen). Theories of attention posit that we find what we are looking for by holding a veridical copy of the target, akin to a photograph of the target object, in memory and then guiding our attention (by moving our eyes) to template-matching objects (e.g., shiny metal). However, in two experiments, we found evidence that the target information used to perform visual search is dynamic and may even differ depending on the stage of processing. Our results show that the target representation is shaped by the distractor context and, moreover, that the information used to guide initial attention is coarse and “relational,” but subsequent decisions about the identity of the object (e.g., “those are my keys” or “those are not what I’m looking for”) use a precise and “optimal” code.

match decisions require a more precise representation (Bravo & Farid, 2014; Martin & Becker, 2018; Rajsic & Woodman, 2020; Wolfe, 2021; Wu et al., 2013).

The template has long been hypothesized to guide attention and eye movements to potential targets by modulating sensory gain (Desimone & Duncan, 1995; Reynolds & Heeger, 2009; Treisman & Gelade, 1980), but only more recently has it been explicitly postulated to operate on decision processes about the target match as well (Bravo & Farid, 2014; Geng & Witkowski, 2019; Wolfe, 2012). For example, Hout and Goldinger (2015) hypothesized that the target template serves a dual function: to guide attention to potentially relevant items and to compare visual inputs with the memory template for target verification or rejection (see also Rajsic & Woodman, 2020). Whereas such studies have used eye metrics to measure the effect of the template at two time points within the look-identify cycle, few have considered whether the information used during guidance and decisions is the same or different. One exception to this is a proposal by Wolfe (2021) that posits that the search template can (and should) be divided into two: a guiding template in working memory that is used to direct attention to items that might be the target and a target template in long-term memory that is used to determine whether a candidate object is, in fact, the target. The idea that there may be two active templates, one for guidance and one for target decisions, is consistent with evidence that it is possible to

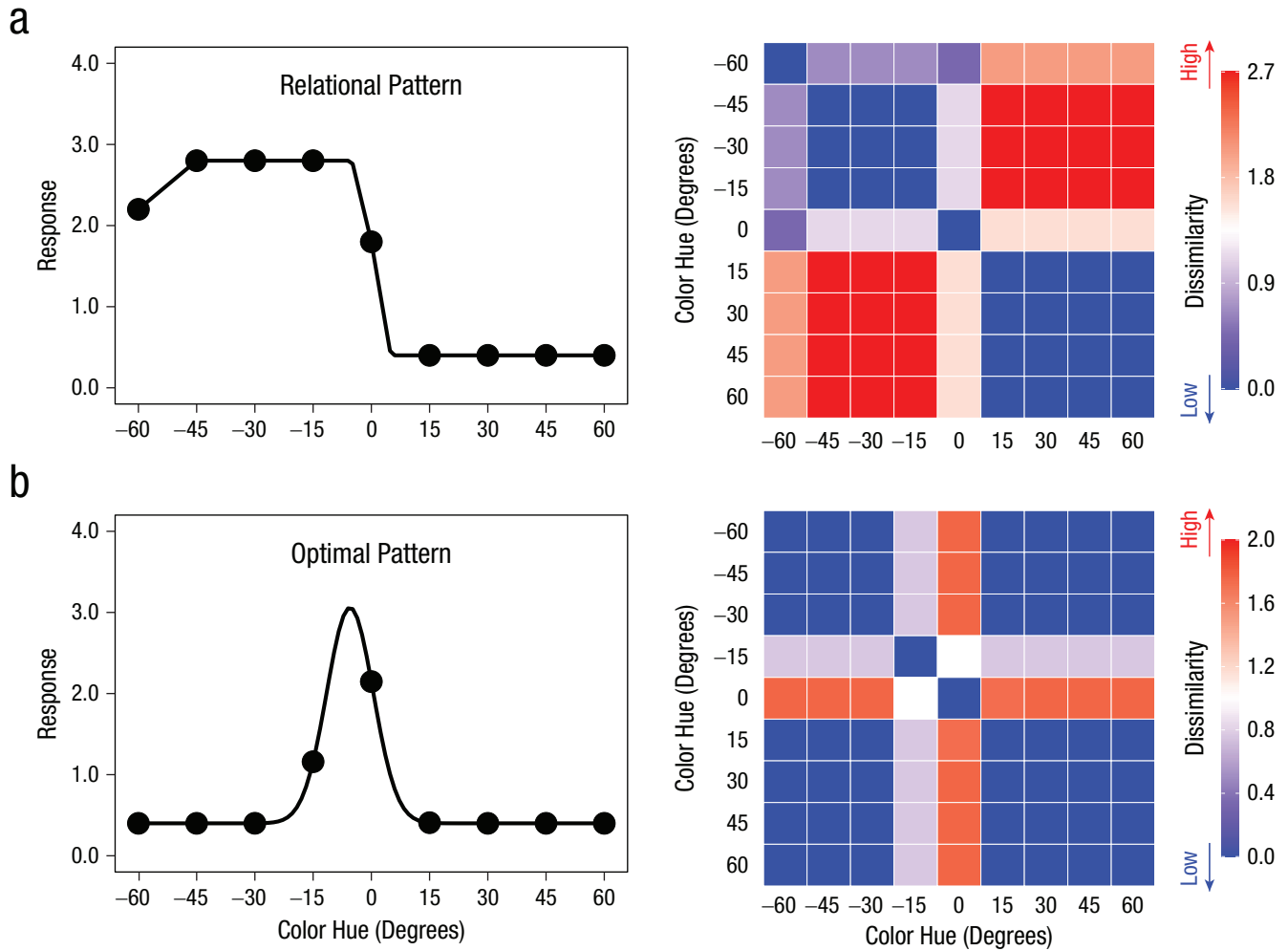


Fig. 1. Simulated responses to colored stimuli (left column) and representational-dissimilarity matrices generated from the same data (RDMs; right column), separately for models in which flexibility in the target template is assumed to be either relational (a) or optimal (b). The graphs on the left show simulated responses in an experimental context in which the target color (e.g., orange) is depicted at 0° and expected distractor colors are positive rotations from the target color (e.g., yellower hues). “Response” refers to any of several possible dependent variables, including the probability of a first saccade to an object or a decision that an object is the target. The RDMs on the right were generated from the same data computed as the absolute difference between responses to each pair of stimuli. The relational account predicts higher attentional priority, and therefore a greater proportion of behavioral responses, to all features that fit the relational rule that distinguishes targets from distractors, such as the target being the reddest object. This results in high similarity in expected responses to all stimuli with negative values, as illustrated by the dissimilarity matrix. The optimal-gain model predicts a shift in the central tendency of the target representation, and all other features are scaled by distance from the center value. This results in scaled similarity for both negative and positive feature values. (For a detailed description of how simulated data points were estimated, see the Statistical Analysis section.)

hold one active template in working memory (to guide search) while holding one or more other target representations in a latent state within working memory or in long-term memory (Olivers et al., 2011; Woodman et al., 2013).

Our aim in the current experiments was to test whether attentional guidance and target-match decisions rely on different information during visual search. Although we framed our hypothesis in terms of a single search template that has two informational formats during guidance versus decisions, the concept is compatible with Wolfe’s (2021) characterization of separate templates for guidance and

the target memory. Using a visual search task for a target among linearly separable distractors, we tested the hypothesis that early attentional guidance will be based on relational information (e.g., prioritizing the reddest object irrespective of its exact hue), whereas subsequent match decisions will be made against an optimal off-target feature (e.g., the slightly redder version of the orange target). If true, this would suggest that attentional guidance operates on a coarser code to weight sensory information and that target-match decisions use a more precise representation to determine identity. Our findings offer a novel perspective on how template information

operates to guide attention and make identity decisions during visual search.

Experiment 1

The purpose of this experiment was to use eye tracking to investigate whether distinct template information is used during the guidance and decision-making stages of the look-identify visual search cycle. We used eye data as our main dependent measure of interest to test the hypothesis that guidance (first saccades) will be driven by the relative target feature (Fig. 1a) but that match decisions (fixation dwell times) will be determined by optimal off-target feature tuning (Fig. 1b).

Method

Participants. To determine the appropriate sample size for Experiment 1, we first conducted a pilot study with seven participants (data were not included in Experiment 1) using similar methods and procedures. The smallest effect size of the two dependent measures of interest (in this case, fixation dwell times; $r = .55$) was entered into G*Power (Version 3.1; Faul et al., 2007), which indicated that a sample size of 30 was necessary to detect significant effects ($p = .05$, two tailed) with a power of .90. Therefore, we recruited 30 participants (20 self-reported as women, 10 self-reported as men; one left-handed; age range = 18–23 years) from the University of California, Davis, who participated in Experiment 1 in partial fulfillment of a course requirement. Each participant provided written informed consent in accordance with the National Institutes of Health's guidelines for ethical research. Each participant's color vision was assessed by self-report and an online color-blindness test (<https://colormax.org/color-blind-test>). All participants had normal or corrected-to-normal vision, and all had typical color vision.

Apparatus. Participants were seated in a sound-attenuated room 60 cm from an ASUS MG279Q monitor with a spatial resolution of $1,920 \times 1,200$ pixels and a refresh rate of 60 Hz. The operating system was Windows 7, and Psychophysics Toolbox (Version 3.0.17; Brainard, 1997; Pelli, 1997) in MATLAB (The MathWorks, Natick, MA) was used to create all stimuli. Eye movements were tracked using a video-based eye-tracking system (Eye-Link 1000; SR Research, Kanata, Ontario, Canada) sampling from the right eye at 500 Hz.

Stimuli. All stimuli were presented against a gray background (luminance = 37.0 cd/m^2). The target (194°) and distractor colors were selected from a color wheel defined in CIELAB color space (coordinates: $a = 0$, $b = 0$;

luminance = 70; from Bae et al., 2015). We used a green-blue hue as the target color to control for the potential color-category effects on responses (Bae et al., 2015). Experiment 1 contained three types of trials: (a) *standard* visual search trials to set up expectations for the distractor colors, (b) *critical* visual search trials to assess how target templates are used during guidance and decision-making stages of visual search, and (c) *template-probe* trials to measure the template contents independently of simultaneous distractor competition.

In standard visual search trials (Fig. 2), a target and five distractor circles ($3^\circ \times 3^\circ$) were located equidistantly along an imaginary circle (diameters: $12^\circ \times 12^\circ$). The locations of all six stimuli were randomly rotated 10° clockwise or counterclockwise along the imaginary circle on every trial to prevent fixed expectations of where each stimulus would be located. The color of the five distractors was either all negatively or all positively rotated 10° from the target color. The rotational direction (positive or negative) was counterbalanced across participants so that each participant saw only one set of distractors (Yu & Geng, 2019). Because the directionality of the distractor colors did not affect performance ($ps > .15$; Bayes factor favoring the null over the alternative hypothesis $[BF_{01}] > 1.30$), this factor was not included in subsequent analyses to maximize power. For simplicity, the distractors from the standard search trials (i.e., "trained" distractor colors) will always be referred to as having positive color rotations from the target. Each object contained either a left- or a right-oriented black line (1° of visual angle). Participants were asked to report the tilt of the line within the target circle.

Critical search displays (Fig. 2) were identical to the standard search displays with one exception: One of the regular circle distractors was replaced with a dodecagon (this was the critical distractor; Martin & Becker, 2018). We used a different shape for the critical distractor because we wished to use the true target color as a critical distractor to test how observers responded to it when the template shifts off-veridical. A different shape was used to avoid the presence of two target objects on a single trial. The critical-distractor color was selected from a range from -60° to 60° from the target color, in steps of 15° . This resulted in a total of nine possible critical-distractor colors. Among the nine colors, the -45° and 45° distractors were focal colors within the green and blue color categories, respectively. Thus, the $\pm 60^\circ$ distractors were beyond the blue-green color category boundary (Bae et al., 2015) and allowed us to interrogate the boundary conditions of the relational and optimal theories.

Probe trials contained a color wheel (12° of visual angle radius; 2.1° of visual angle thickness) defined by the same

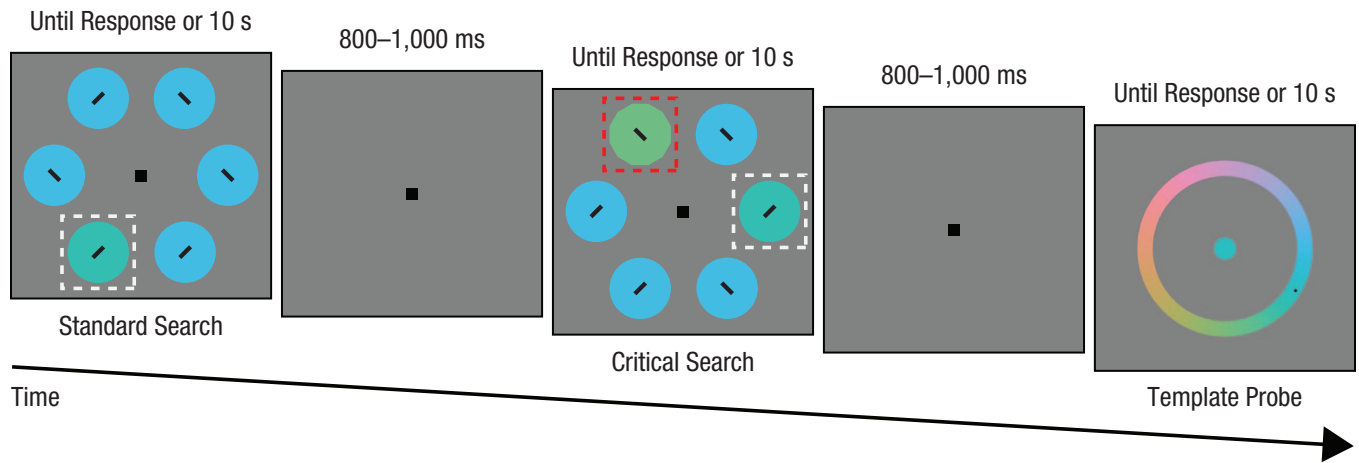


Fig. 2. Example of standard visual search, critical visual search, and template-probe trials in Experiment 1. In standard visual search trials, participants saw a ring of six circles (one target and five distractors); they were instructed to locate the target circle and report the line orientation within it. A high tone (600 Hz) was played for correct responses, and a low tone (200 Hz) was played for incorrect responses. Critical visual search trials were the same as standard visual search trials, except that one of the distractors was a dodecagon. Here, the dashed white squares highlight the target in the standard and critical trials, and the dashed red square highlights the distractor in the critical trial (these squares did not appear in the actual displays). In template-probe trials, participants were instructed to report the target color by clicking the appropriate location on a color wheel using a mouse. The central dot illustrated the color over which the mouse dot hovered. No feedback was provided in the probe task.

CIELAB color-space coordinates (Fig. 2). The color wheel was randomly rotated on each presentation.

Design. Participants completed 20 practice trials before the experiment started. The main experiment was composed of 324 standard visual search trials, 324 critical visual search trials, and 60 template-probe trials. Trials were presented in six blocks. The three types of trials were randomly interleaved within each block with the constraint that there were no consecutive template-probe trials. The locations of the target and distractors were randomly selected on each visual search trial. The target and critical distractor were equally likely to appear at all six possible locations, but the target and critical distractor were never adjacent to each other within a trial. Each search display contained an equal number of left- or right-oriented lines within the objects. The lines within the target and critical distractor were equally likely to be oriented to the left or right.

Procedure. The target color was presented to the participant before the experiment started. Participants were encouraged to make a fast and precise eye movement to the target but to take their time pressing the response button to ensure high accuracy of the manual response. A 9-point calibration was performed at the beginning of the experiment. To ensure that participants' eyes were fixated on the central square ($0.3^\circ \times 0.3^\circ$; black) at the onset of each search display, we began each trial only after gaze was detected within a $1.5^\circ \times 1.5^\circ$ box around

the fixation square for 200 ms. When the display appeared, participants searched for the predefined target-color circle and reported the line orientation inside by pressing the left or right mouse button with their right hand. The search display was presented until the manual response or up to 10 s. Auditory feedback was provided immediately following the responses (600 Hz tone for correct; 200 Hz tone for incorrect).

In the probe trials, the color wheel remained on screen until the manual response or up to 10 s. Participants were instructed to report the target color on the color wheel by clicking on it with a mouse. No feedback was provided in the probe trials. A central fixation square was presented for 800 to 1,000 ms between trials.

Statistical analysis. The standard visual search trials were mainly used to establish expectations for the distractor colors. Overall search performance was high (proportion of correct responses: $M = .97$, $SD = .02$; RT: $M = 1,158$ ms, $SD = 309$ ms), indicating that participants had a target representation that could be successfully distinguished from distractors. The data of primary interest included only the critical search and probe trials; only data from these trials are described in subsequent analyses.

Trials with errors were excluded from the analyses; these included trials in which participants incorrectly identified the orientation of the line within the target color or the total trial duration exceeded 3 standard

deviations of that participant's mean RT. This resulted in a loss of 4.8% of data (for a full description of error rates and RT data, see the Supplemental Material available online). Furthermore, when the first saccade could not be assigned to a stimulus or when eye movement never left the fixation region, the respective trials were excluded from the analyses, which led to a further loss of 5.2% of data. Trials in which the first saccade started more than 1,000 ms after the trial began were also removed, which accounted for 0.16% of data.

Our goal in Experiment 1 was to use eye data to directly compare the relational and optimal models of template shifting during visual search. Although they share some similarities, the two models make qualitatively different predictions for how critical distractors, particularly those from the negative (i.e., untrained) direction of the target, will be processed. The predictions from the two models, illustrated in Figure 1, were applied to both (a) the proportion of first saccades to the critical distractors and (b) fixation dwell times to decide that the stimulus was not the target. Specifically, if attention was tuned to the relative target feature, first saccades should be captured by all negative critical distractors more than the positive ones (Fig. 1a). In contrast, the optimal-gain theory predicts that first saccades should follow a Gaussian tuning curve with a peak over an optimal off-veridical feature (Fig. 1b). We chose the following values for our simulation parameters on the basis of the findings from our previous study (Yu & Geng, 2019): $\sigma = 6$ (width of the Gaussian tuning curves) and $\mu = -4$ (mean of the Gaussian tuning curves).

To compare our results with the theoretical models, we chose to convert each dependent measure of interest (first saccades and fixation dwell times) into a normalized space on the basis of response similarity. Representational-similarity analysis is commonly used in brain-imaging studies to convert data from very different units including brain, behavior, and computational models into a common space for comparison (Kriegeskorte et al., 2008; Nili et al., 2014). Using representational-similarity analysis in this experiment had several advantages: First, all dependent measures could be compared with both theoretical models without unit conversion or adjustments based on model-specific parameters; second, the overall pattern of the data could be established without the need to directly compare single data points (e.g., using a series of t tests); and third, similarity matrices were "parameter free," and the fit of the data to the theoretical models was determined by a simple correlation between the two patterns.

In the primary analysis, we converted first-saccade and dwell-time data from critical search trials into representational-dissimilarity matrices (RDMs). The value in each cell of the RDM indicates the dissimilarity

(inverse of similarity) of the dependent measures between a pair of stimulus conditions (Figs. 3b and 3d). For example, if the proportion of first saccades to the -15° critical distractor was about the same as to the -30° distractor, similarity would be high irrespective of the actual proportion of first saccades to the -15° and -30° distractors. The diagonal entries in an RDM are values for identical conditions and therefore have zero dissimilarity by definition. After similarity matrices were computed for the first saccades and fixation dwell times, the primary analysis involved correlating each eye-data RDM with each of the two theoretical RDMs to determine which of the two models better described the data. The two theoretical RDMs were not significantly correlated ($r = -.10$, $p = .56$). Thus, any correlation between the eye-data RDMs and each theoretical matrix cannot be explained by partial correlations with the other.

The significance of correlations between the eye-data and theoretical RDMs was evaluated by permutation tests. The null distribution for the correlation was estimated by randomly rearranging the stimulus labels of one of the two RDMs of interest for each participant. Then, we correlated this randomized similarity matrix with another RDM of interest and computed the Spearman correlations between those two RDMs. This step was repeated 10,000 times for each set of data and used to create a null distribution of permuted correlations. The p value of the true correlation was calculated as the rank order of the true correlation in the permuted null distribution. For example, if the real correlation was larger than any of the permuted values within the null distribution, then the p value was estimated as less than .0001. We rejected the null hypothesis if the real correlation was larger than the top 500th permuted correlation ($p < .05$).

Results

Analysis of the first saccades that went to the critical distractors. The proportion of first saccades to each critical distractor (Fig. 3a) was converted to an RDM (Fig. 3b) for comparison with the relational-model (Fig. 1a) and optimal-model (Fig. 1b) matrices using a permutation test in which stimulus labels were randomized (see the Method section). The first-saccade RDM had a significantly positive correlation with the relational RDM ($r = .71$, $p = .0001$) but not the optimal RDM ($r = .003$, $p = .44$). In addition, these correlations were compared with each other using a permutation test and found to be significantly different, $p(r_{\text{relational}} > r_{\text{optimal}}) = .0001$, confirming that the first-saccade RDM was more strongly correlated with the relational RDM than with the optimal RDM. These results strongly support the hypothesis that

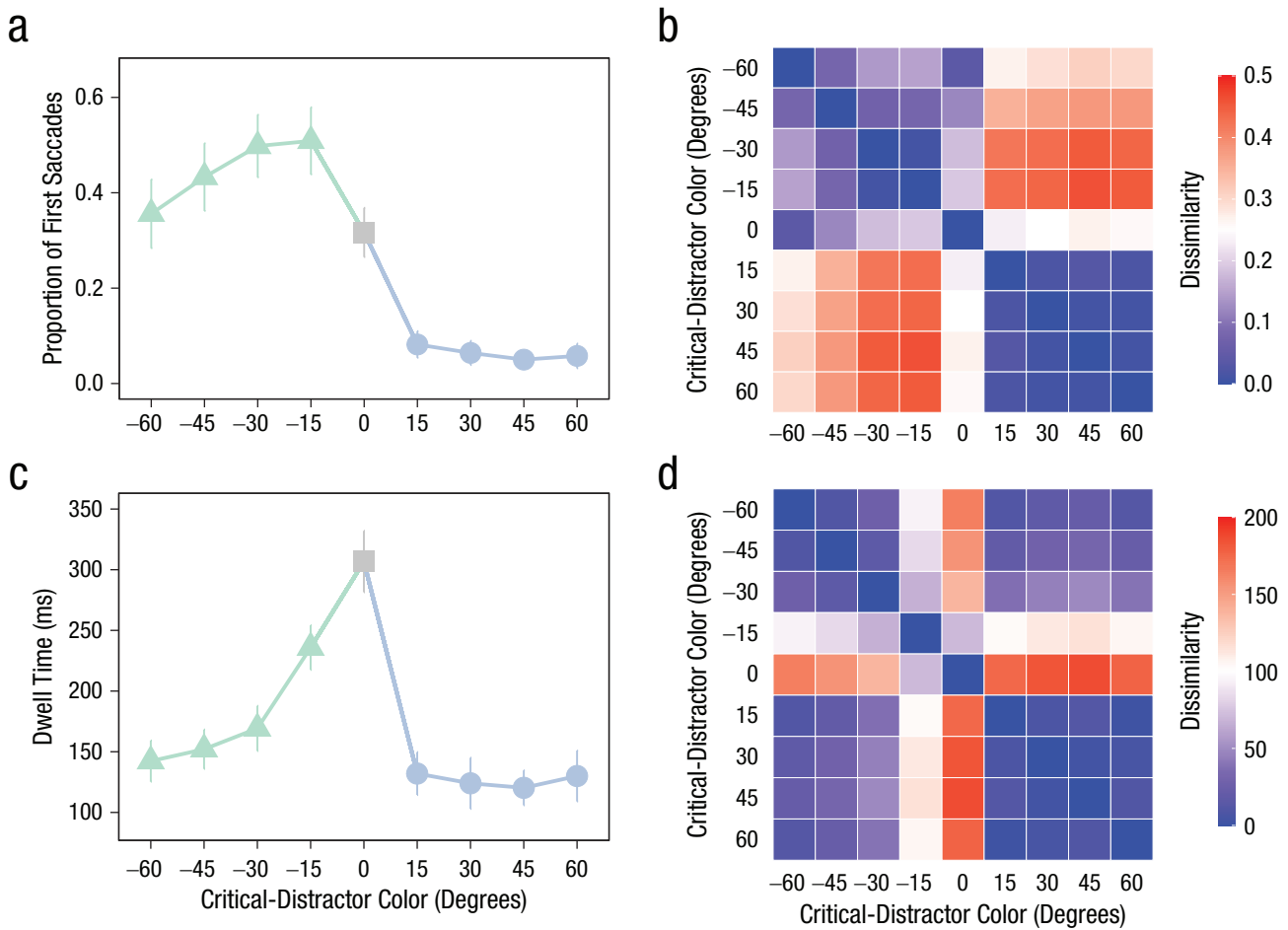


Fig. 3. Results from critical visual search trials in Experiment 1. The mean proportion of first saccades (a) and mean fixation dwell time (c) are shown for each critical-distractor color. Triangles and circles indicate negative and positive values, respectively, on the *x*-axis (squares indicate 0). Error bars represent 95% confidence intervals. The representational-dissimilarity matrices for the proportion of first saccades (b) and fixation dwell times (d) are averaged across participants. Redder colors indicate more dissimilarity between two stimulus conditions (e.g., 0° and 60°); bluer colors indicate more similarity between two stimulus conditions (e.g., -45° and -60°).

early attentional guidance, indexed by the first saccade, was tuned to the relative feature of the target, replicating the work by Becker and colleagues (Becker, 2010; Martin & Becker, 2018). However, although all negative critical distractors had a high likelihood of capturing attention, the proportion of first saccades to negative distractors did gradually decrease as color similarity decreased, suggesting that the strength of capture was weakly modified by color similarity (Fig. 3a).

Analysis of the fixation dwell times on the critical distractors. We next compared the RDM (Fig. 3d) converted from the mean fixation dwell times (Fig. 3c) with each of the two theoretical-model RDMs. The dwell-time RDM was significantly correlated with the optimal RDM ($r = .67, p = .004$) but not with the relational RDM ($r = .04, p = .28$). Additionally, the correlation between the dwell-time

RDM and the optimal RDM was stronger than between the dwell-time RDM and the relational RDM, $p(r_{\text{optimal}} > r_{\text{relational}}) = .0001$. These results demonstrate that the target-match decisions, occurring after an object was fixated, followed the optimal tuning mode (Navalpakkam & Itti, 2007; Yu & Geng, 2019). These results were replicated in a supplemental experiment that used a finer grained measurement for near-target ($\pm 5^\circ$) critical distractors (see Experiment 1b in the Supplemental Material). It should be noted that the modulation of color similarity on the fixation dwell times, as seen in Figure 3c, was asymmetrical between the positive and negative directions. The negative distractors appeared to be more difficult to reject as nontargets than the corresponding positive ones, suggesting that the match decisions were more difficult overall in the negative direction, hinting at a contribution from the relational model.

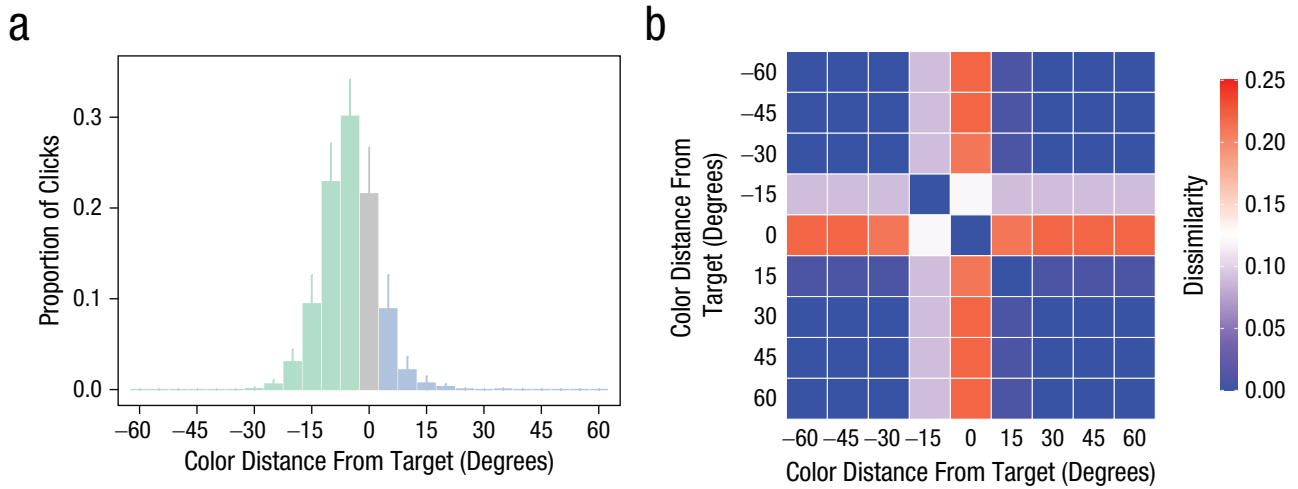


Fig. 4. Results from template-probe trials in Experiment 1. The group-averaged proportion of clicks (a) is shown for each relative click distance from the veridical target color (raw data were divided into 5° bins). Green and blue hues indicate negative and positive values, respectively, on the x -axis (gray indicates 0). Error bars represent upper bounds of 95% confidence intervals. For the probe representational-dissimilarity matrix (b), values were averaged across participants. Redder colors indicate more dissimilarity between two stimulus conditions (e.g., 0° and 60°); bluer colors indicate more similarity between two stimulus conditions (e.g., -45° and -60°).

Analysis of the probe task. The probe task measured the contents of the target template, which are presumed to be held in memory (Giesbrecht et al., 2013; Woodman et al., 2013) uncontaminated by many processes involved in concurrent visual search, such as those necessary for resolving target selection and distractor suppression. The relative click distance from the true target color was divided into 5° bins (Fig. 4a) and then converted to an RDM (Fig. 4b). As expected, there was a significantly positive correlation between the probe RDM and the optimal RDM ($r = .80$, $p = .004$) but a nonsignificant correlation between the probe RDM and the relational RDM ($r = -.05$, $p = .48$). A comparison confirmed that the probe RDM was more strongly correlated with the optimal RDM than with the relational RDM, $p(r_{\text{optimal}} > r_{\text{relational}}) = .0001$. This replicated previous findings (Geng et al., 2017; Navalpakkam & Itti, 2007; Scolari & Serences, 2009; Yu & Geng, 2019) that the target representation was shifted away from distractors to enhance optimal off-target features to increase the template-to-distractors distinctiveness (Geng & Witkowski, 2019).

Experiment 2

We concluded from Experiment 1 that attentional guidance and target-match decisions rely on a relational and an optimal code, respectively. However, dwell times, which were used to infer decision processes, may not have been a pure measurement of target decisions because they were terminated on the basis of a final nontarget decision that could also rely on shape information. Furthermore, whereas first saccades are routinely considered a reflection of guiding templates, fixation

dwell times are a less standard measurement of decision processes. To address this in Experiment 2, we applied the drift-diffusion model (DDM) to visual search performance to characterize how accurately and quickly the target was discriminated from distractors. To do this, we modified the search paradigm to consist of only one target and one distractor, which were always the same shape. Additionally, to test the relationship between long-term memory representations of the target and the drift rates, we again included the independent continuous memory-probe task. Finding a correlation between the long-term memory of the target color and the target-match decision (drift rates) would suggest that the target template held in long-term memory is used to generate target-match decisions (Wolfe, 2021).

Method

Participants. To determine the sample size for Experiment 2, we first conducted a pilot study with 25 participants (data were not included in Experiment 2) using similar methods and procedures. The effect size for the correlation between drift rates and probe responses ($r = .377$) was entered into G*Power (Version 3.1), which estimated that a sample size of 69 was necessary to detect significant effects ($p = .05$, two tailed) with a power of .90. We opted for a sample size of 70 to allow counterbalancing of the distractor colors in the standard visual search trials. Data were collected online until we obtained a sample of 70 participants after exclusion criteria (accuracy in the standard search was below 75%) were applied. Forty participants were excluded from data analysis. A large number of outliers was expected because the experiment

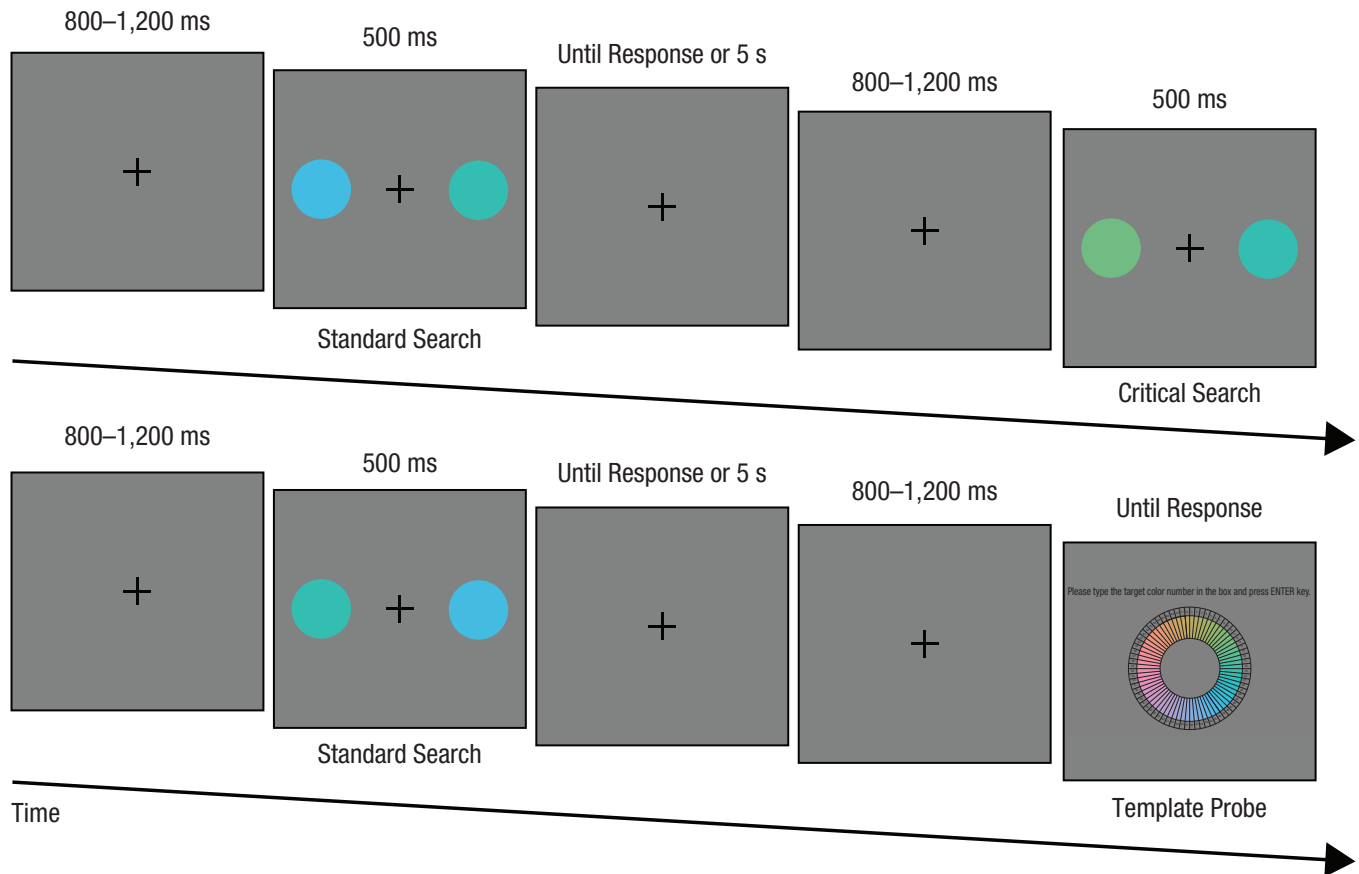


Fig. 5. Example of standard visual search trials, critical visual search trials, and template-probe trials in Experiment 2. In search trials, participants saw two circles (one target and one distractor), and they indicated whether the target color appeared at the left or right by left- or right-clicking on the mouse. The color of the distractor in standard search trials was always positively rotated 10° from the target color. The selected color of the distractor in critical search trials ranged between -60° and 60° in steps of 5° from the target color. On probe trials, participants saw a color wheel divided into 72 bins, each of which was numbered; their task was to type the number corresponding to the estimated target color. There was no feedback given on any of the trials.

was conducted online and we did not provide any feedback (for detailed information, see the Procedure section). Seventy participants (54 self-reported as women, 16 self-reported as men; six left-handed; age range = 18–31 years) from the University of California, Davis, participated in partial fulfillment of a course requirement. Each participant provided written informed consent in accordance with the National Institutes of Health’s guidelines for ethical research. Each participant’s color vision was assessed by self-report. All participants had normal or corrected-to-normal vision, and all had normal color vision.

Stimuli. The experiment was conducted entirely online through the Testable platform (<https://www.testable.org/>). All stimuli were created in Adobe Illustrator, saved as PNG files, and uploaded to Testable. Although we expected colors to vary when viewed on different monitors, the relationship between the target and distractors was expected to remain apparent to all participants. Variability

was expected to disadvantage our ability to detect the hypothesized optimal pattern in the data because the optimal pattern requires greater precision in distinguishing colors. All stimuli were presented against a gray background (color hue = 808080). The target and distractor colors (10°) in the standard visual search trials were identical to those in Experiment 1. Each search trial (Fig. 5) consisted of one target and distractor circle (radius: 135 pixels) presented bilaterally at the center of the screen (distance between the centers of the two circles: 400 pixels). The two directions of distractor colors were again counterbalanced between participants, and because there were no spurious differences ($p_s > .45$, $BF_{01} > 3.2$), the data were collapsed in all subsequent analyses. The selected colors of the distractor set in critical search trials ranged between -60° and 60° in steps of 5° from the target color, resulting in a total of 24 distractor colors.

The color wheel in the probe trials (Fig. 5) was divided into 72 bins (5° per bin), and each bin had a number attached. Participants reported the number of

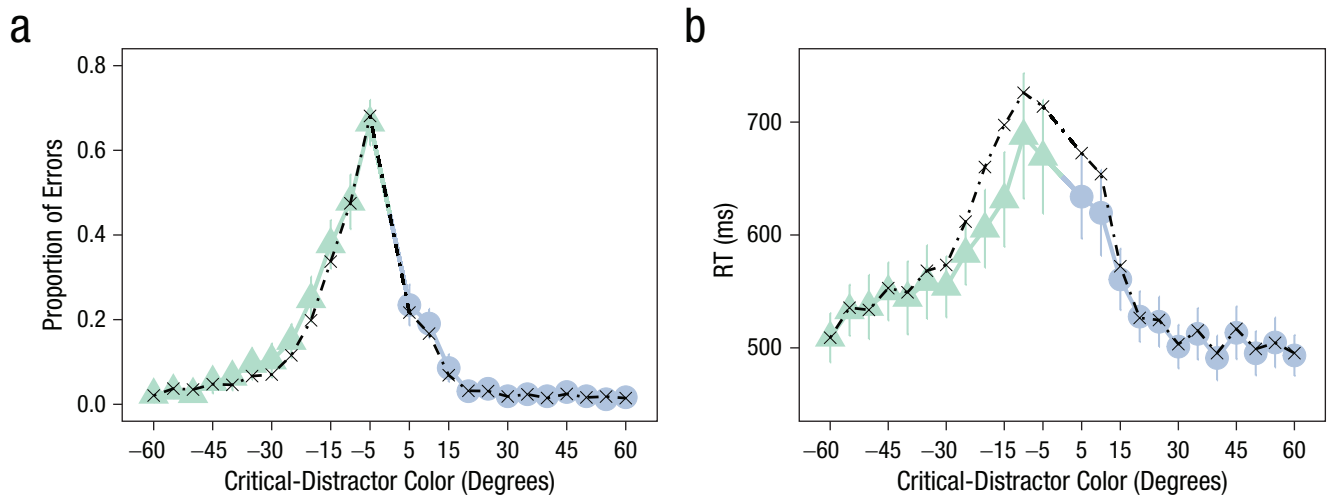


Fig. 6. Observed data and model fits for critical visual search trials in Experiment 2. The mean proportion of errors (a) and mean response time (RT; b) is shown for each critical-distractor color. The black dashed lines represent the fitted curves from the drift-diffusion model (DDM) for the best-fitting DDM parameters. Observed data are indicated by triangles (for negative color values) and circles (for positive color values). Error bars represent 95% confidence intervals.

the color wedge that best matched the target color in memory. There were six possible rotations of the color wheel.

Design. Participants completed 20 practice standard visual search trials with feedback before the main experiment started. The main experiment was composed of 144 standard visual search trials, 144 critical visual search trials, and 12 template-probe trials. The three types of trials were presented in 12 blocks and randomly interleaved within each block, with the limitations that the probe trials appeared only after the standard search trials and that there were no consecutive probe trials.

Procedure. An example of the target color was presented prior to the beginning of the experiment. On search trials, participants were instructed to indicate whether the target color appeared at the left or right by left- or right-clicking on the mouse. The stimuli appeared on the screen for 500 ms, and participants had up to 5 s to make their responses. On probe trials, participants were required to type the number of the color wedge that best matched the target color in memory in a response box at the bottom of the screen. The color wheel would remain on the screen until response. Because Experiment 2 used a two-alternative forced-choice design to measure the decision process through the pattern of choices and RTs, we did not provide any feedback in the critical search trials to keep the responses unbiased from feedback. To equate the absence of feedback, we gave no feedback in the other two types of trials as well. After responses, a central fixation cross was presented for 800 to 1,200 ms before the next trial started. Participants were instructed

to fixate on the center cross when no stimuli were presented on the screen.

Statistical analysis. Our goal in the standard search trials was consistent with our goal in Experiment 1: to set up expectations for the distractor colors. Overall performance was significantly higher than chance (proportion of correct responses: $M = .89$, $SD = .07$; RT: $M = 583$ ms, $SD = 106$ ms), suggesting that these participants held an effective target representation. Trials were excluded when search RTs were below 200 ms or above 2,500 ms or when the responses in the probe task were outside of the blue-green color range, which accounted for a total of 2% of the data.

The main analysis consisted of modeling visual search performance (error rate and RT; Fig. 6) from the critical trials using a DDM. The separation between the two decision boundaries (a) and the nondecision time (t) was estimated as a fitted free parameter, both of which were the same across color distractor values for each participant, whereas the drift rate (v) was estimated as a free parameter in each distractor condition. There was no theoretical reason to believe that the decision boundary and nondecision time should vary between critical distractors (see the Supplemental Material). Instead, we were interested in how the drift rate, which characterizes the accumulation of noisy evidence over time until one of two decision boundaries is reached, differed across conditions (Ratcliff & McKoon, 2008). Drift rates in this experiment represent how easily the target could be distinguished from the distractor: Higher drift rates indicate stronger evidence, whereas lower drift rates suggest weaker evidence.

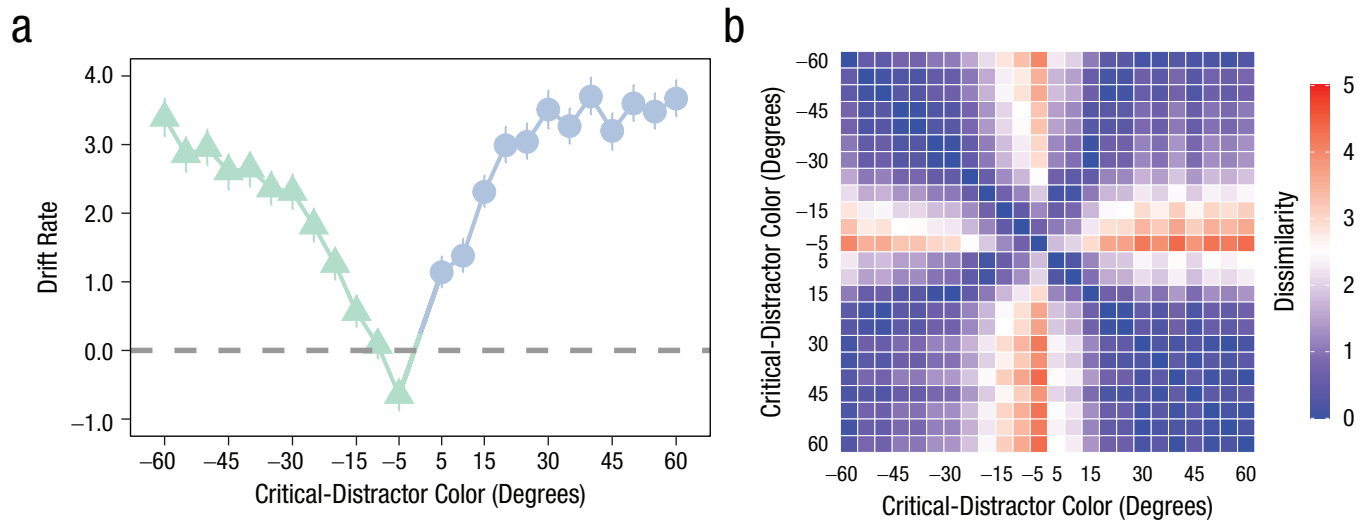


Fig. 7. Results from critical visual search trials in Experiment 2. The mean posterior drift-rate estimate (a) is shown for each critical-distractor color. Triangles and circles indicate negative and positive values, respectively, on the x -axis. Error bars represent 95% confidence intervals. For the drift-rate representational-dissimilarity matrix (b), values were averaged across participants. Redder colors indicate that drift rates were more dissimilar between two stimulus conditions (e.g., -5° and 60°); bluer colors indicate that drift rates were more similar between two stimulus conditions (e.g., -45° and -60°).

All parameters were estimated using hierarchical Bayesian parameter estimation. The hierarchical approach is particularly useful for this experiment given the small number of choices and RT values measured per participant. This method captures commonalities across individuals and also estimates each individual's parameter values (Ratcliff & Childers, 2015). To conduct hierarchical drift-diffusion modeling, we used the Python-based toolbox *HDDM* (Wiecki et al., 2013). The hierarchical drift-diffusion model was fitted to accuracy-coded data (i.e., the upper and lower boundaries corresponded to correct and incorrect responses, and the starting point was fixed at 0.5).

For each participant's data, we used Markov chain Monte Carlo sampling to estimate the posterior distribution of each parameter. Each chain was run with 10,000 samples, and the first 5,000 warm-up samples were discarded as burn-in. Five chains were run. Convergence was assessed by computing the Gelman-Rubin \hat{R} statistic for each parameter. If the samples of the different chains converged, the \hat{R} statistic should be close to 1. The range of \hat{R} values across all group parameter estimates was 0.99 to 1.10, suggesting satisfactory convergence. Goodness of fit was visually inspected with a posterior predictive check (Fig. 6).

Results

Analysis of the drift rates. Figure 7a shows the group-mean posterior estimates of the drift rates for each search condition. Following the analysis strategy from Experiment 1, we converted each participant's drift rates to a

dissimilarity matrix (Fig. 7b) for comparison with the relational- and optimal-model matrices (Fig. 1) using a permutation test in which stimulus labels were randomized. The theoretical RDMs were up-sampled to match the number of conditions in the drift-rate RDM. The two theoretical RDMs were only weakly correlated ($r = .12$, $p = .05$). The drift-rate RDM was significantly correlated with both theoretical RDMs ($r_{\text{optimal}} = .77$, $p = .0001$; $r_{\text{relational}} = .22$, $p = .005$), but the correlation with the optimal RDM was significantly greater than the correlation with the relational RDM, $p(r_{\text{optimal}} > r_{\text{relational}}) = .0001$. As shown in Figure 7a, the drift rates for positive critical distractors were larger overall than those for negative distractors, but there was a monotonic increase in drift rates for both negative and positive distractors as they became more dissimilar from the target. Interestingly, the nadir was at the -5° distractor, and the drift rate was negative. This indicates that the accumulation of evidence was slow and that the "wrong" decision was made more often than not. These results support the conclusion that the target-match decisions were strongly modulated by the similarity to the optimal off-target feature centered over -5° , but there was also an overall directional bias. The blend of both models in these data was not unexpected given that the dependent variable here involved accuracy and RT data, which would include combined effects of covert attentional guidance and decision processes, but it is noteworthy that the optimal model explained significantly more variance in the results.

Analysis of the probe task. The color wheel was composed of 72 color wedges sampling color hues in steps

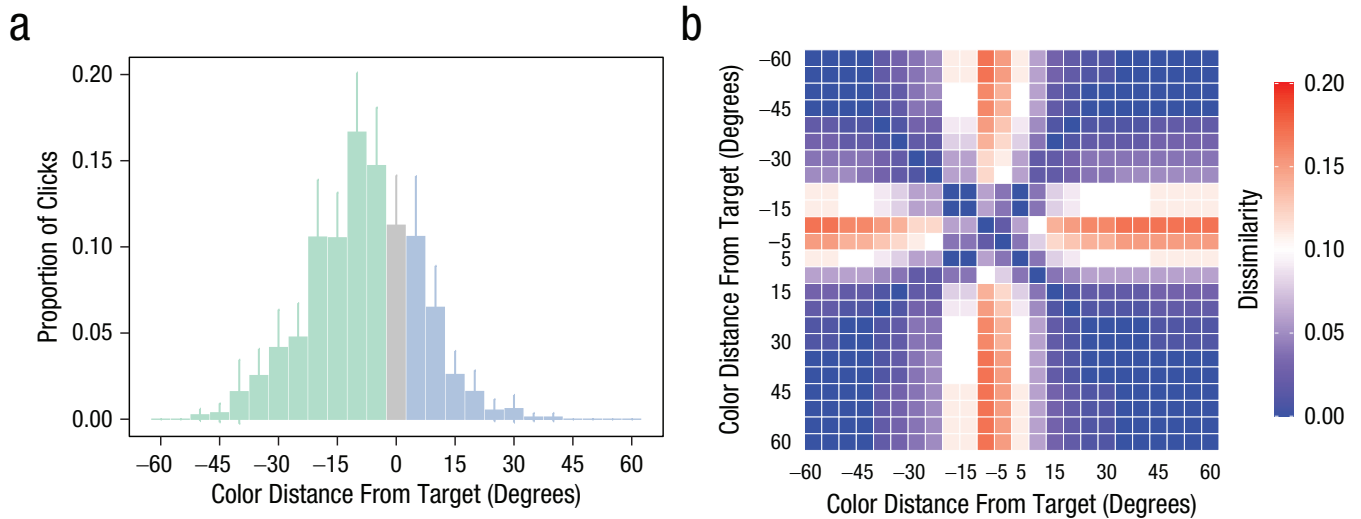


Fig. 8. Results from the color-wheel probe trials in Experiment 2. The group averaged proportion of clicks (a) is shown for each relative click distance from the veridical target color (raw data are divided into 5° bins). Green and blue hues indicate negative and positive values, respectively, on the x -axis (gray indicates 0). Error bars represent upper bounds of 95% confidence intervals. For the probe representational-dissimilarity matrix (b), values were averaged across participants. Redder colors indicate more dissimilarity between two stimulus conditions (e.g., -5° and 60°); bluer colors indicate more similarity between two stimulus conditions (e.g., -45° and -60°).

of 5° . Therefore, the relative click distance from the veridical target color was divided into 5° bins (Fig. 8a) and then converted to an RDM (Fig. 8b). The probe RDM was significantly correlated with both theoretical-model matrices, $r_{\text{optimal}} = .56$, $p = .0001$, $r_{\text{relational}} = .11$, $p = .001$. Comparisons confirmed that the probe RDM was more strongly correlated with the optimal RDM than with the relational RDM, $p(r_{\text{optimal}} > r_{\text{relational}}) = .0001$. These results converged with those of Experiment 1, suggesting that the target representation was shifted away from distractors to enhance optimal off-target features.

Correlation between performance on the memory-probe and search tasks. Next, we conducted a correlation analysis on individual differences between how well the probe data matched the optimal RDM and drift rates. A positive correlation between these two metrics would suggest that individuals whose responses on the probe task were closer to the optimal model also made faster and more accurate decisions about which of the two objects was the target during visual search. First, the correlation between each participant's probe matrix and the optimal RDM from above was used as a measurement of how well their target templates fitted the optimally tuned template. Second, new drift-rate parameters were estimated for each participant with data collapsed across color directions (negative, positive) to reduce the feature space (cf. a drift-rate parameter per distractor color). The resulting values were then correlated with their drift-rate parameter from visual search. We found that participants who had more optimally tuned templates showed faster drift rates, reflecting an easier discrimination of target

from both negative and positive distractors (negative: $r = .28$, $p = .02$, $\text{BF}_{10} = 3.50$, $R^2 = .06$; positive: $r = .35$, $p = .003$, $\text{BF}_{10} = 14.70$, $R^2 = .11$; Fig. 9). These results highlight the underlying relationship between the target-decision processes and the target color held in long-term memory over time.

General Discussion

The purpose of these experiments was to test hypotheses of how template information is used during the guidance and decision stages of visual search. Using a visual search task for a target among linearly separable distractors, we demonstrated that early attentional guidance was a coarse process mainly based on relational sensory information, whereas subsequent match decisions were compared with a more precisely tuned template centered on an optimal off-target feature. Although previous studies have found evidence for coarse guidance (Kerzel, 2019; Martin & Becker, 2018) and precise decisions (Rajsic & Woodman, 2020) separately, our experiments provide direct evidence that the informational content of a single target object is used differently on these two subprocesses of visual search.

There is a long history of work showing that the contents of the template can bias the deployment of attention and saccades toward potential targets (Chelazzi et al., 1998; Olivers et al., 2011; Soto et al., 2008). Recent research has shown that the template may not be precisely centered over the specific target feature, as previously assumed, but instead may be shifted to

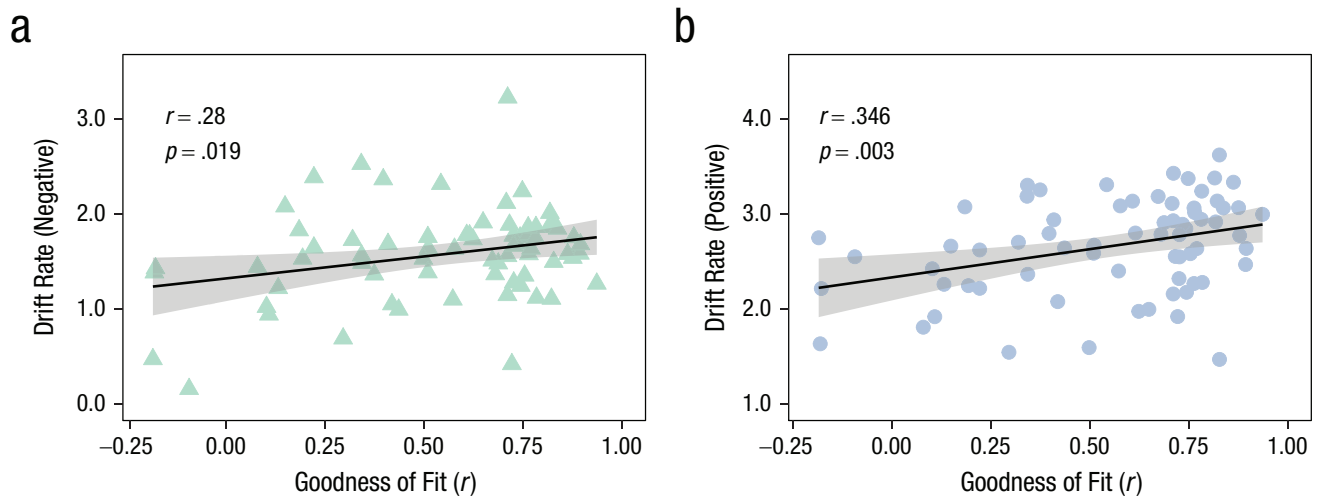


Fig. 9. Scatterplots (with best-fitting regression lines) showing the relationship between drift rate during visual search and goodness of fit of each participant's template to the optimally tuned template in Experiment 2. Results are shown separately for negative (a) and positive (b) drift rates. Error bands represent 95% confidence intervals.

increase the distinctiveness of the target from distractors (Hodsoll & Humphreys, 2001; Navalpakkam & Itti, 2007; Scolari & Serences, 2009). In line with Becker and colleagues' relational account (Becker, 2010; Martin & Becker, 2018), the eye data in Experiment 1 showed that all negative critical distractors that were relational matches captured attention and first saccades more strongly than positive distractors. Thus, attention appears to be initially guided by the relative feature of the target, not specific feature values. This coarse representation of the target might be well suited for rapid stimulus prioritization under noisy sensory conditions, for example, when many stimuli are in peripheral vision where color and spatial acuity are poor (Hulleman, 2010; Hulleman & Olivers, 2017; Rosenholtz, 2017).

After one item is selected, however, a decision must be made regarding the exact identity of the stimulus as a match or nonmatch to the target. Unlike in attentional guidance, the importance of this decision process on visual search has been explored only more recently (Hout & Goldinger, 2015; Malcolm & Henderson, 2010; Rajsic & Woodman, 2020). In the current study, we used fixation dwell times (Experiment 1) and DDM drift rates (Experiment 2) as measurements of target-match decisions. The optimal model fitted both dwell times and drift rates, indicating that the decision process operates on an optimally shifted and precisely tuned template. The precision appears necessary for accurate decisions to be made, and the shift increases the target-to-distractor discriminability to speed decisions.

It should be pointed out that although the first saccades were better described by the relational model, and the dwell times and drift rates were better described

by the optimal model, both sets of data showed hints of the other pattern. Therefore, it is possible that guidance and decision are influenced by both relational and optimal tuning, but the relative bias toward one or the other is weighted by the pressure to perform fast guidance or precise decisions. These results raise an open question about whether guidance and decisions during the visual search cycle operate using two discrete representations or a single, flexible template that is weighted by the exact computation required at each stage of visual search.

Both ideas, that of separate templates and that of flexible weighting of a single template source, are present in the literature. For example, Wolfe and colleagues suggest that there is a guiding template in working memory and a separate target template in long-term memory to guide search when there is a large number (> 100) of potential targets (Cunningham & Wolfe, 2014; Wolfe, 2021). Our results are compatible with this framework and further suggest that the target template in long-term memory serves as the template on which match decisions are made. Participants who established more optimally tuned target templates in long-term memory had higher drift rates, suggesting that decisions during visual search are directly related to the off-veridical target representation in memory (Geng & Witkowski, 2019; Lleras et al., 2020). This finding is consistent with the characterization of target templates held in long-term memory in Guided Search 6.0 (Wolfe, 2021), in which a potential target in working memory selected by the guiding template is compared with a target template held in long-term memory through a drift-diffusion process.

Our findings also recall the literature surrounding questions about how active representations are used in working and long-term memory to guide attention during visual search. Our results are also consistent with the finding that stable search targets are stored in long-term memory and that this information can be used for target-match decisions (Carlisle et al., 2011; Woodman et al., 2013). We do not have a position at this time on whether relational guidance is based on an active working memory template that is separate from the optimal memory representation of the target or whether relational guidance reflects a coarser manifestation of the same target template in memory. The former is a possibility given that one target representation can be held in active working memory, whereas the other is held as an accessory or latent item in working or long-term memory (Olivers et al., 2011; Woodman et al., 2013). The latter is also a possibility given findings that there are versions of a single target representation in multiple brain regions and that the exact computation being done on the target information is dependent on the stage of processing (Lee et al., 2013; Long & Kuhl, 2018). Another possibility is that participants simply set different criteria on a single template for each stage of processing: a liberal criterion to broadly capture all potential targets in the visual field (possibly also accounting for acuity degradations in peripheral vision) and then a more conservative criterion for more precise decisions. Future work is necessary to determine the exact mechanisms by which guidance and decisions operate on different information patterns. Finally, the current findings were based on the special case of search for a target among linearly separable distractors. Real-world search targets, however, are infrequently linearly separable from distractors. The generalizability of our findings should be further investigated under more typical conditions to determine whether the differences in the precision of guidance and decision are a general property of visual search.

Taken together, our findings suggest that the target template operates distinctively during guidance and decision stages of visual search. Early attentional guidance is a coarse process to weight sensory information, but later match decisions depend on a more precise representation of the target to efficiently determine identity. To return to our example of searching for a tiger in the grasslands, our results suggest that out in the field, guidance is coarse and will select anything that might be a tiger. In contrast, after attention has selected an object, an optimal target template is more useful for deciding whether the object is indeed a tiger. Although the current behavioral data do not allow us to fully address whether the information source for the two stages of processing is identical or separate, the

results offer a resolution to the debate in the literature over how template information is shifted in response to expected distractor features.

Transparency

Action Editor: M. Natasha Rajah

Editor: Patricia J. Bauer

Author Contributions

X. Yu and J. J. Geng developed the study concept. All the authors contributed to the study design. X. Yu conducted testing and data collection. X. Yu analyzed and interpreted the data under the supervision of J. J. Geng and T. D. Hanks. X. Yu drafted the manuscript, and J. J. Geng and T. D. Hanks provided critical revisions. All the authors approved the final manuscript for submission.

Declaration of Conflicting Interests

The author(s) declared that there were no conflicts of interest with respect to the authorship or the publication of this article.

Funding

This work was supported by National Institutes of Health Grant R01MH113855-01 (to J. J. Geng).

Open Practices

All data have been made publicly available via OSF and can be accessed at <https://osf.io/d7ght/>. The design and analysis plans for the experiments were not preregistered. This article has received the badge for Open Data. More information about the Open Practices badges can be found at <http://www.psychologicalscience.org/publications/badges>.



ORCID iDs

Xinger Yu  <https://orcid.org/0000-0002-9424-6348>

Joy J. Geng  <https://orcid.org/0000-0001-5663-9637>

Acknowledgments

We thank Dijia Liu and Zhuojun Zhang for eye-data collection and Sarah Shomstein for helpful comments.

Supplemental Material

Additional supporting information can be found at <http://journals.sagepub.com/doi/suppl/10.1177/09567976211032225>

References

- Bae, G.-Y., Olkkonen, M., Allred, S. R., & Flombaum, J. I. (2015). Why some colors appear more memorable than others: A model combining categories and particulars in color working memory. *Journal of Experimental Psychology: General*, *144*(4), 744–763. <https://doi.org/10.1037/xge0000076>
- Bauer, B., Jolicoeur, P., & Cowan, W. B. (1996). Visual search for colour targets that are or are not linearly separable from distractors. *Vision Research*, *36*(10), 1439–1466. [https://doi.org/10.1016/0042-6989\(95\)00207-3](https://doi.org/10.1016/0042-6989(95)00207-3)

- Becker, S. I. (2010). The role of target–distractor relationships in guiding attention and the eyes in visual search. *Journal of Experimental Psychology: General*, *139*(2), 247–265. <https://doi.org/10.1037/a0018808>
- Brainard, D. H. (1997). The psychophysics toolbox. *Spatial Vision*, *10*(4), 433–436. <https://doi.org/10.1163/156856897x00357>
- Bravo, M. J., & Farid, H. (2014). Informative cues can slow search: The cost of matching a specific template. *Attention, Perception, & Psychophysics*, *76*(1), 32–39. <https://doi.org/10.3758/s13414-013-0532-z>
- Carlisle, N. B., Arita, J. T., Pardo, D., & Woodman, G. F. (2011). Attentional templates in visual working memory. *The Journal of Neuroscience*, *31*(25), 9315–9322. <https://doi.org/10.1523/JNEUROSCI.1097-11.2011>
- Chelazzi, L., Duncan, J., Miller, E. K., & Desimone, R. (1998). Responses of neurons in inferior temporal cortex during memory-guided visual search. *Journal of Neurophysiology*, *80*(6), 2918–2940. <https://doi.org/10.1152/jn.1998.80.6.2918>
- Cunningham, C. A., & Wolfe, J. M. (2014). The role of object categories in hybrid visual and memory search. *Journal of Experimental Psychology: General*, *143*(4), 1585–1599. <https://doi.org/10.1037/a0036313>
- Desimone, R., & Duncan, J. (1995). Neural mechanisms of selective visual attention. *Annual Review of Neuroscience*, *18*(1), 193–222. <https://doi.org/10.1146/annurev.ne.18.030195.001205>
- Duncan, J., & Humphreys, G. W. (1989). Visual search and stimulus similarity. *Psychological Review*, *96*(3), 433–458. <https://doi.org/10.1037/0033-295x.96.3.433>
- Eriksen, C. W. (1953). Object location in a complex perceptual field. *Journal of Experimental Psychology*, *45*(2), 126–132. <https://doi.org/10.1037/h0058018>
- Faul, F., Erdfelder, E., Lang, A.-G., & Buchner, A. (2007). G*Power 3: A flexible statistical power analysis program for the social, behavioral, and biomedical sciences. *Behavior Research Methods*, *39*, 175–191.
- Geng, J. J., DiQuattro, N. E., & Helm, J. (2017). Distractor probability changes the shape of the attentional template. *Journal of Experimental Psychology: Human Perception and Performance*, *43*(12), 1993–2007. <https://doi.org/10.1037/xhp0000430>
- Geng, J. J., & Witkowski, P. (2019). Template-to-distractor distinctiveness regulates visual search efficiency. *Current Opinion in Psychology*, *29*, 119–125. <https://doi.org/10.1016/j.copsyc.2019.01.003>
- Giesbrecht, B., Sy, J. L., & Guerin, S. A. (2013). Both memory and attention systems contribute to visual search for targets cued by implicitly learned context. *Vision Research*, *85*, 80–89. <https://doi.org/10.1016/j.visres.2012.10.006>
- Green, B. F., & Anderson, L. K. (1956). Color coding in a visual search task. *Journal of Experimental Psychology*, *51*(1), 19–24. <https://doi.org/10.1037/h0047484>
- Hodsoll, J., & Humphreys, G. W. (2001). Driving attention with the top down: The relative contribution of target templates to the linear separability effect in the size dimension. *Perception & Psychophysics*, *63*(5), 918–926. <https://doi.org/10.3758/bf03194447>
- Hout, M. C., & Goldinger, S. D. (2015). Target templates: The precision of mental representations affects attentional guidance and decision-making in visual search. *Attention, Perception, & Psychophysics*, *77*(1), 128–149. <https://doi.org/10.3758/s13414-014-0764-6>
- Hulleman, J. (2010). Inhibitory tagging in visual search: Only in difficult search are items tagged individually. *Vision Research*, *50*(20), 2069–2079. <https://doi.org/10.1016/j.visres.2010.07.017>
- Hulleman, J., & Olivers, C. N. L. (2017). The impending demise of the item in visual search. *Behavioral and Brain Sciences*, *40*, Article e132. <https://doi.org/10.1017/S0140525X15002794>
- Kerzel, D. (2019). The precision of attentional selection is far worse than the precision of the underlying memory representation. *Cognition*, *186*, 20–31. <https://doi.org/10.1016/j.cognition.2019.02.001>
- Kriegeskorte, N., Mur, M., & Bandettini, P. (2008). Representational similarity analysis—connecting the branches of systems neuroscience. *Frontiers in Systems Neuroscience*, *2*, Article 4. <https://doi.org/10.3389/neuro.06.004.2008>
- Lee, S.-H., Kravitz, D. J., & Baker, C. I. (2013). Goal-dependent dissociation of visual and prefrontal cortices during working memory. *Nature Neuroscience*, *16*(8), 997–999. <https://doi.org/10.1038/nn.3452>
- Lleras, A., Wang, Z., Ng, G. J. P., Ballew, K., Xu, J., & Buetti, S. (2020). A target contrast signal theory of parallel processing in goal-directed search. *Attention, Perception, & Psychophysics*, *82*(2), 394–425. <https://doi.org/10.3758/s13414-019-01928-9>
- Long, N. M., & Kuhl, B. A. (2018). Bottom-up and top-down factors differentially influence stimulus representations across large-scale attentional networks. *The Journal of Neuroscience*, *38*(10), 2495–2504. <https://doi.org/10.1523/jneurosci.2724-17.2018>
- Malcolm, G. L., & Henderson, J. M. (2010). Combining top-down processes to guide eye movements during real-world scene search. *Journal of Vision*, *10*(2), Article 4. <https://doi.org/10.1167/10.2.4>
- Martin, A., & Becker, S. I. (2018). How feature relationships influence attention and awareness: Evidence from eye movements and EEG. *Journal of Experimental Psychology: Human Perception and Performance*, *44*(12), 1865–1883. <https://doi.org/10.1037/xhp0000574>
- Navalpakkam, V., & Itti, L. (2007). Search goal tunes visual features optimally. *Neuron*, *53*(4), 605–617. <https://doi.org/10.1016/j.neuron.2007.01.018>
- Nili, H., Wingfield, C., Walther, A., Su, L., Marslen-Wilson, W., & Kriegeskorte, N. (2014). A toolbox for representational similarity analysis. *PLOS Computational Biology*, *10*(4), Article 1003553. <https://doi.org/10.1371/journal.pcbi.1003553>
- Olivers, C. N. L., Peters, J., Houtkamp, R., & Roelfsema, P. R. (2011). Different states in visual working memory: When it guides attention and when it does not. *Trends in Cognitive Sciences*, *15*(7), 327–334. <https://doi.org/10.1016/j.tics.2011.05.004>

- Pelli, D. G. (1997). The VideoToolbox software for visual psychophysics: Transforming numbers into movies. *Spatial Vision, 10*(4), 437–442. <https://doi.org/10.1163/156856897x00366>
- Rajsic, J., & Woodman, G. F. (2020). Do we remember templates better so that we can reject distractors better? *Attention, Perception, & Psychophysics, 82*(1), 269–279. <https://doi.org/10.3758/s13414-019-01721-8>
- Ratcliff, R., & Childers, R. (2015). Individual differences and fitting methods for the two-choice diffusion model of decision making. *Decision, 2*(4), 237–279. <https://doi.org/10.1037/dec0000030>
- Ratcliff, R., & McKoon, G. (2008). The diffusion decision model: Theory and data for two-choice decision tasks. *Neural Computation, 20*(4), 873–922. <https://doi.org/10.1162/neco.2008.12-06-420>
- Reynolds, J. H., & Heeger, D. J. (2009). The normalization model of attention. *Neuron, 61*(2), 168–185. <https://doi.org/10.1016/j.neuron.2009.01.002>
- Rosenholtz, R. (2017). Those pernicious items. *Behavioral and Brain Sciences, 40*, Article e154. <https://doi.org/10.1017/S0140525X16000248>
- Scolari, M., Byers, A., & Serences, J. T. (2012). Optimal deployment of attentional gain during fine discriminations. *The Journal of Neuroscience, 32*(22), 7723–7733. <https://doi.org/10.1523/jneurosci.5558-11.2012>
- Scolari, M., & Serences, J. T. (2009). Adaptive allocation of attentional gain. *The Journal of Neuroscience, 29*(38), 11933–11942. <https://doi.org/10.1523/jneurosci.5642-08.2009>
- Soto, D., Hodsoll, J., Rotshtein, P., & Humphreys, G. W. (2008). Automatic guidance of attention from working memory. *Trends in Cognitive Sciences, 12*(9), 342–348. <https://doi.org/10.1016/j.tics.2008.05.007>
- Treisman, A. M., & Gelade, G. (1980). A feature-integration theory of attention. *Cognitive Psychology, 12*(1), 97–136. [https://doi.org/10.1016/0010-0285\(80\)90005-5](https://doi.org/10.1016/0010-0285(80)90005-5)
- Treue, S., & Trujillo, J. C. M. (1999). Feature-based attention influences motion processing gain in macaque visual cortex. *Nature, 399*(6736), 575–579. <https://doi.org/10.1038/21176>
- Wiecki, T. V., Sofer, I., & Frank, M. J. (2013). HDDM: Hierarchical Bayesian estimation of the drift-diffusion model in Python. *Frontiers in Neuroinformatics, 7*, Article 14. <https://doi.org/10.3389/fninf.2013.00014>
- Wolfe, J. M. (2012). Saved by a log: How do humans perform hybrid visual and memory search? *Psychological Science, 23*(7), 698–703. <https://doi.org/10.1177/0956797612443968>
- Wolfe, J. M. (2021). Guided Search 6.0: An updated model of visual search. *Psychonomic Bulletin & Review, 28*, 1060–1092. <https://doi.org/10.3758/s13423-020-01859-9>
- Woodman, G. F., Carlisle, N. B., & Reinhart, R. M. G. (2013). Where do we store the memory representations that guide attention? *Journal of Vision, 13*(3), Article 1. <https://doi.org/10.1167/13.3.1>
- Wu, R., Scerif, G., Aslin, R. N., Smith, T. J., Nako, R., & Eimer, M. (2013). Searching for something familiar or novel: ERP correlates of top-down attentional selection for specific items or categories. *Journal of Cognitive Neuroscience, 25*(5), 719–729. https://doi.org/10.1162/jocn_a_00352
- Yu, X., & Geng, J. J. (2019). The attentional template is shifted and asymmetrically sharpened by distractor context. *Journal of Experimental Psychology: Human Perception and Performance, 45*(3), 336–353. <https://doi.org/10.1037/xhp0000609>