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Selection History and the Strategic Control of Attention

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Attention is biased toward features aligning with task goals and stimuli previously allocated attentional priority (selection history). The relationship between selection history and the strategic control of attention has scarcely been explored. In the present study, we utilized a modified version of the Adaptive Choice Visual Search (ACVS) task to determine whether the choice of visual search strategy varies with the strategies participants have elected to use in the past. Participants were tasked with searching through stimuli presented in two task-relevant colors on each trial to find one of two targets. The distribution of stimuli rendered in these two colors was manipulated between subjects, with one group receiving more imbalanced displays during learning. Participants who experienced the more imbalanced displays quickly learned the optimal visual search strategy of searching through the less abundant color, which maximized performance. Critically, these participants retained their tendency toward this learned strategy in a subsequent test phase in which displays were less imbalanced, in contrast to participants who completed the same test phase but had only experienced the less imbalanced displays. Our results demonstrate that, without explicit instruction, the choice of visual search strategy is to some degree dependent upon selection history.

Keywords: visual search, selection history, strategy

Attentional selection is a cognitive process that determines which among competing stimuli are represented in the brain when representational capacity is limited (Desimone, 1998; Desimone & Duncan, 1995). Although stimuli can be prioritized by the attention system on the basis of their physical salience (Theeuwes, 1991, 1992; Theeuwes et al., 1998, 1999; Yantis, 1993), stimuli that are consistent with an observer's goals are also prioritized (Bacon & Egeth, 1994, 1997; Folk et al., 1992; Wolfe et al., 1989), which is critical for maximizing performance during visual search. In addition, past experience or *selection history* has also been shown to influence how stimuli are prioritized by attention (Anderson et al., 2021). Selection history encompasses a group of experience-driven factors that can implicitly bias attention such as contextual cuing (Chun & Jiang, 2003; Colagiuri & Livesey, 2016), reward learning (Anderson et al., 2013, 2011; Anderson & Yantis, 2013), aversive conditioning (Anderson & Britton, 2020; Schmidt et al., 2015), and statistical learning (Failing et al., 2019; Jiang & Swallow, 2013; Jiang et al., 2013; Wang & Theeuwes, 2018). The influence of physical salience, goals/strategy, and selection history on the control of attention have generally been investigated in isolation (although see Kim & Anderson, 2021), and the study of selection history has been largely constrained to the examination of involuntary influences that run counter to task goals (Anderson et al., 2021). The relationship between selection history and the goal-directed or strategic control of attention remains to be clarified, particularly with respect to how observers choose to prioritize stimuli when conducting goal-directed visual search.

In most studies of goal-directed or strategic attentional control, observers are explicitly instructed in what to search for (Anderson, 2018); such experimental designs result in concrete and straightforwardly defined task goals, but may be limited in the extent to which they capture how goal-directed attentional control unfolds in the real world. Outside of highly constrained situations, people must choose what to prioritize when searching for a target, or even which among multiple possible targets to search for at a given moment. What are the factors that determine how a person chooses to conduct a search? There are at least two possibilities worthy of consideration here. The first is that observers take stock of the stimuli they are presented with and the demands they currently face, and objectively arrive at a visual search strategy that reflects these stimuli and demands. By this account, when different people are faced with a common visual search task, they should tend to arrive at similar visual search strategies. The second possibility is that observers are biased to adopt strategies that they have utilized in similar situations. By this account, the choice of a particular strategy in a particular situation is subject to selection history-dependent influences, analogous to feature-based attentional biases in which observers exhibit a tendency to involuntary orient to stimuli that have previously served as a target (Anderson et al., 2021).

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There is already some evidence that selection history can influence the strategic control of attention. In a series of related studies, observers are first forced to find a target on the basis of a specific feature (“feature search mode”) or on the basis of its uniqueness in a particular feature dimension (“singleton detection mode”) during a learning phase and are then presented with trials in which the target can be localized on the basis of either a specific feature or its status as a feature singleton (“option trials”). On option trials under these conditions, observers tend to persist in using the strategy they were forced to use during the learning phase (Cosman & Vecera, 2013; Leber & Egeth, 2006a, 2006b; Leber et al., 2009). In these situations, however, participants never actually choose how to search during the initial learning phase and do not learn on the same task, such that selection history-dependent learning may be to some degree linked to how stimulus features are prioritized in much the same way as attention is biased toward prior target-defining features (Anderson et al., 2021), and observers also may not realize the options available to them on option trials. When the target can be one of two colors on a given trial, observers have been shown to more strongly prioritize the color that more frequently served as a target during an initial learning phase (Cosman & Vecera, 2014), although such an effect of statistical learning could be explained by selection history biasing attention to a particular feature independently of current task goals (Anderson et al., 2021). In the present study, we sought to examine a situation in which observers would choose for themselves how to search during an initial learning phase and measure how such choices would subsequently affect how observers continue to conduct search in a task that presents an explicit choice of how to prioritize stimuli.

The Adaptive Choice Visual Search (ACVS) paradigm was developed to examine the control of attention under conditions in which observers can choose how to prioritize color stimuli in the search for one of two targets (Irons & Leber, 2016, 2018). Specifically, there is one red and one blue target among red, blue, and green nontargets on each trial. Participants can search through the red stimuli until a target is found, search through the blue stimuli until a target is found, search through both red and blue stimuli until a target of either color is found, or vacillate between searching through red and searching through blue stimuli (e.g., search through one color cluster at a time). Critically, the distribution of red-to-blue nontargets is imbalanced in this task such that there are sometimes more blue nontargets and sometimes there are more red nontargets, with the optimal visual search strategy being to search through the less abundant color until a target of that color is found. In this respect, searching optimally in this task involves parsing the display into two groups of stimuli based on color (Hansen et al., 2019; Li et al., 2022) and restricting search to one of those groups, which is an attentional strategy that can be used in a variety of contexts involving heterogeneous stimulus displays (Arita et al., 2012; Beck & Hollingworth, 2015; Becker et al., 2015). Observers tend to reliably favor the optimal search strategy in the ACVS task, albeit quite modestly (Irons & Leber, 2016, 2018), although optimality may be higher under conditions of high arousal (Kim et al., 2021).

In the present study, using the ACVS task, we sought to introduce a manipulation that would lead some participants to more strongly favor the optimal search strategy in order to examine whether such selection history would translate to continued favoritism of the optimal strategy above-and-beyond participants performing the same visual search task without such selection history. Specifically, we had two groups of participants each complete an initial learning phase in which they performed an equal number of ACVS trials. The Control group experienced the standard ACVS task in which each trial had 13 boxes rendered in one task-relevant color and 27 rendered in the other. The Biased-Learning group, however, experienced these same trials in addition to more imbalanced displays consisting of an 8/32 and 3/37 distribution. We hypothesized that these more imbalanced displays would provide a strong incentive to first identify which task-relevant color had fewer boxes and then search selectively through stimuli of this less abundant color, which would result in more frequent adopting of the optimal visual search strategy. All participants then completed a common test phase consisting of only trials with a 13/27 color distribution (which had been previously experienced by all participants on at least some trials during the learning phase). Of interest was whether participants in the Biased-Learning group would come to more strongly prefer the optimal strategy during the learning phase, and whether this preference would translate into a stronger preference for the optimal strategy in the test phase compared to the Control group.

Method

Participants

For the Biased-Learning group, 37 participants (25 female), between the ages of 18 and 35 inclusive (M = 18.9, SD = 1.0), were recruited from the Texas A&M University community. For the Control group, 40 participants (21 female), between the ages of 18 and 35 inclusive (M = 18.9, SD = .7) were recruited from the Texas A&M University community. All participants were English-speaking and reported normal or corrected-to-normal visual acuity and normal color vision. All procedures were approved by the Texas A&M Institutional Review Board. Participants were compensated with course credit. Based on pilot data, we estimated the effect size for the critical between-groups comparison in the test phase to be d = .819, which indicated that a sample size of n = 25 per group would be needed to achieve power $(1 - \beta) > .8$ with $\alpha = .05$ (computed using G*Power 3.1). The final sample size for each group (see Data Analysis) was at least this large.

Apparatus

A Dell OptiPlex 7040 desktop computer equipped with the JATOS framework (Lange et al., 2015) managed participants with experiments written using jsPsych (De Leeuw, 2015), as previously utilized (Liao et al., 2021). This was an online study and each participant used their own device to complete the experiment in a web browser.

Stimuli

Each visual search array was composed of 54 colored squares arranged in three concentric rings around the center of the screen. The inner ring consisted of 12 boxes, the middle ring consisted of 18 boxes, and the outer ring consisted of 24 boxes. Each square in each ring was positioned equidistant from each other and contained a digit between 2 and 9. The size of the stimuli were scaled for display size to approximate the stimulus proportions used in Kim et al. (2021), regardless of monitor resolution (each square approximately 1.1° × 1.1° containing a .4° × .4° digit, with the radius of the inner, middle, and outer ring being approximately 7.3°, 10.1°, and 13°, respectively), although viewing distance could not be controlled and so the actual size of the stimuli with respect to degrees visual angle was likely somewhat variable. The size of the boxes was uniform throughout the display and not scaled by eccentricity (as in prior studies using the ACVS task).

Task Procedure

Following consent, participants completed a practice session to learn the ACVS task. The practice session consisted of 16 trials, with eight trials having no time limit and eight trials requiring a response within 5,500 ms. Participants were instructed to search for one of two targets: a red or blue color square containing a digit between 2 and 5, inclusive. While one red and one blue target appeared in each trial, participants were required to report only one of them. The location of each of the two targets was randomly determined on each trial. All red and blue squares besides the two targets contained a digit from 6 to 9. The two target squares never contained the same digit (which were otherwise randomly determined on each trial), such that which digit participants reported on a given trial was diagnostic of which color target they had found. Green color boxes were irrelevant to the task and contained digits between 2 to 9 to prevent participants from searching for numerical digits without respect to their color. Each trial consisted of the standard ACVS search array that consisted of either 13 red and 27 blue squares or 27 red and 13 blue squares; all trials contained 14 green squares (Irons & Leber, 2018). Searching through the squares rendered in the less abundant task-relevant color on each trial would be optimal for finding one of the two potential targets faster and thereby maximizing performance. After the practice session, participants completed the learning phase and the subsequent test phase.

Learning Phase

The learning phase consisted of a fixation display (1,000 ms), search array (5,500 ms or until response), and an intertrial interval (1,000 ms; see Figure 1A). The fixation display consisted of a white plus sign at the center of the screen. Participants in the Biased-Learning group were shown three different trial types in which the ratio of the less abundant to more abundant target color varied: 3/37, 8/32, and 13/27 (see Figure 1B). Each trial type was presented equally often, and within each trial type, each target color (red [black] and blue [light gray]) served as the less abundant color equally often. Participants in the Control group were only shown 13/27 trials (with the less abundant color again red [black] or blue [light gray] equally often). For both groups, the learning phase consisted of 240 trials, which were presented in a random order. Participants were instructed to report the target digit 2–5 by pressing the *z*, *x*, *n*, and *m* keys on their keyboard, respectively. If participants responded with a digit other than the digits in the red [black] or blue [light gray] target box, they were presented with the word *Miss* for 1,200 ms. If participants did not respond within 5,500 ms, they were presented with the words *Too Slow* for 1,200 ms. A 30-second break was provided every 60 trials.

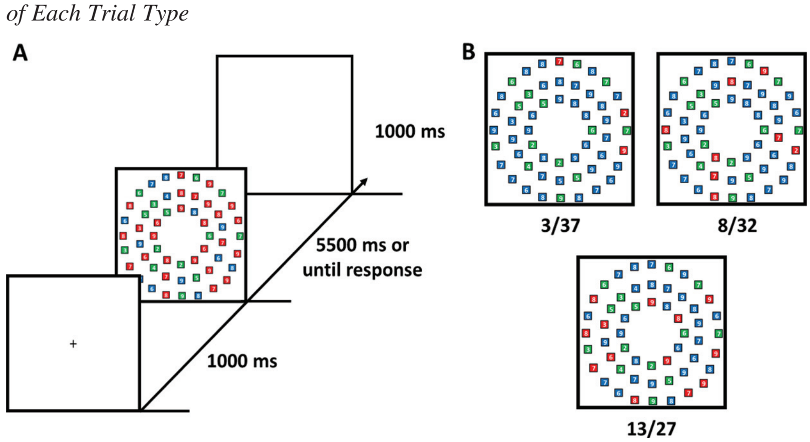
Test Phase

The sequence and timing of trial events in the test phase was identical to the learning phase. Participants in both groups completed 120 trials with the 13/27 color distribution. The same feedback was used for responses that did not correspond to a target digit or were too slow, and a 30 second break was again provided every 60 trials.

Data Analysis

We excluded data from nine participants due to low accuracy in the task from the Biased-Learning group and twelve participants from the Control group (<75% accuracy over all

Figure 1
Experiment Task (A) Sequence of Trial Events; (B) Example Visual Search Array of Each Trial Type



Note. The numbers below each box indicate the ratio of the less abundant to more abundant target color (in the example displays, red-to-blue [black-to-light gray]). See the online article for the color version of this figure.

trials). Thus, 28 data sets were fully analyzed for the Biased-Learning group and 29 data sets for the Control group. The rate of data exclusion due to poor performance was higher than in most in-person studies using the ACVS paradigm (e.g., Irons & Leber, 2016, 2018; Kim et al., 2021), likely due to the online delivery of the study and a subset of participants exhibiting low engagement. For both groups, we evaluated the response time (RT; time to manually report a target digit from the onset of the search array), miss rate (percentage of trials in which no response was made and the participant timed out), and optimality (percentage of trials in which the target in the less abundant color was reported). Bonferroni correction was applied to posthoc pairwise comparisons following a significant main effect, which are assessed for significance using $\alpha = .05/3 = .0167$.

Transparency and Openness

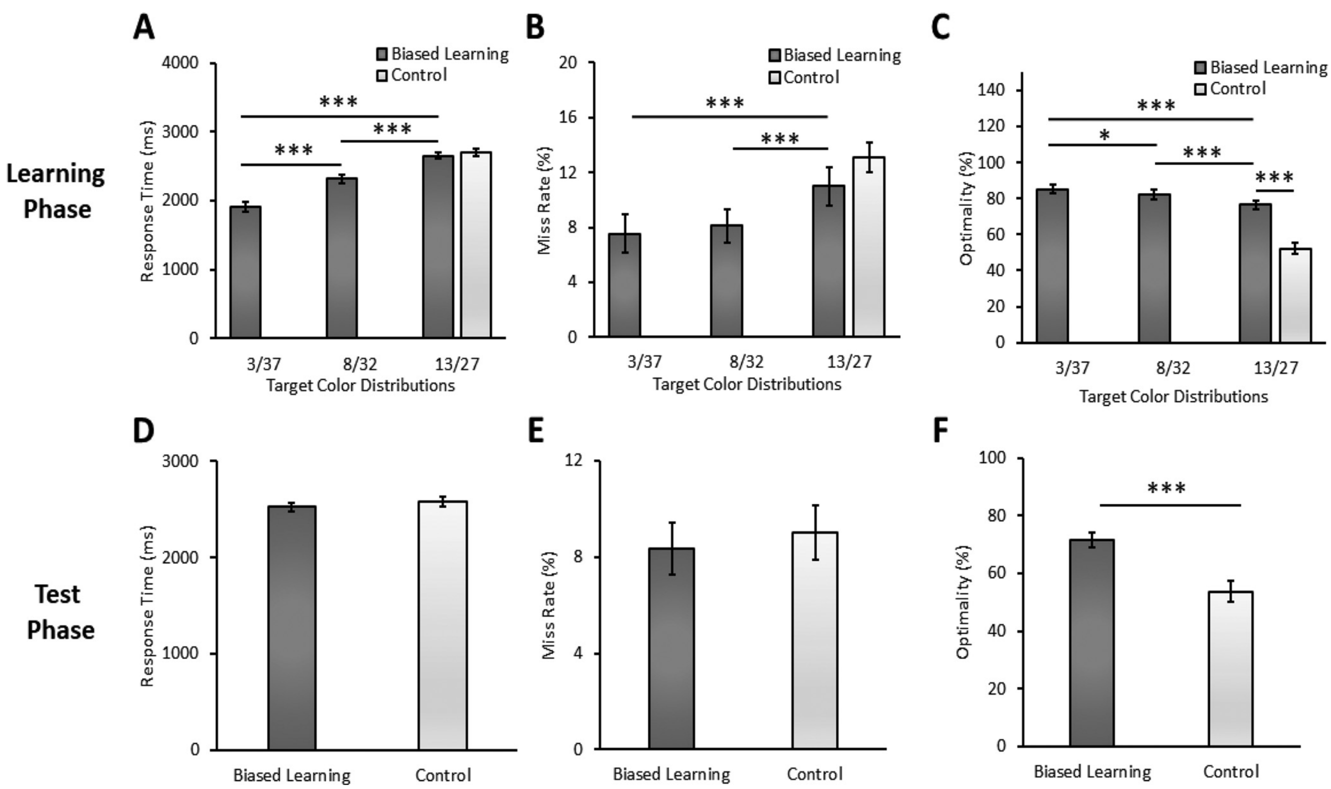
We report how we determined our sample size, all data exclusions, and all measures in the study. All data, analysis code, and research materials are available with reasonable request by email to the corresponding author. Data were analyzed with SPSS (IBM, New York, NY). This study's design and its analysis were not preregistered.

Results

For participants in the Biased-Learning group, we conducted a one-way repeated-measures analysis of variance (ANOVA) with trial type as a factor (3/37, 8/32, 13/27 color distributions) and found a significant main effect in response time, $F(2, 54) = 112.70$, $p < .001$, $\eta_p^2 = .807$ (see Figure 2A), miss rate, $F(2, 54) = 13.18$, $p < .001$, $\eta_p^2 = .328$ (see Figure 2B), and optimality, $F(2, 54) = 19.27$, $p < .001$, $\eta_p^2 = .416$ (see Figure 2C). We then completed posthoc pairwise comparisons over each measure. Participants were faster on 3/37 trials compared to 8/32, $t(27) = 10.04$, $p < .001$, $d = 1.032$, and 13/27 trials, $t(27) = 11.74$, $p < .001$, $d = 2.050$, and also faster on 8/32 compared to 13/27 trials, $t(27) = 8.12$, $p < .001$, $d = 1.098$. Miss rate was lower on 3/37 trials compared to 13/27 trials, $t(27) = 4.53$, $p < .001$, $d = .468$, but not compared to 8/32 trials, $t(27) = .97$, $p = .343$, and also lower on 8/32 trials compared to 13/27 trials, $t(27) = 3.68$, $p < .001$, $d = .401$. Lastly, participants were more optimal on 3/37 trials compared to 8/32, $t(27) = 2.59$, $p = .015$, $d = .206$, and 13/27 trials, $t(27) = 5.05$, $p < .001$, $d = .656$, and also were more optimal on 8/32 trials compared to 13/27 trials, $t(27) = 4.28$, $p < .001$, $d = .396$.

To determine the influence of the learning phases in both groups, we first compared the optimality over chance (50%) in both the learning and test phases. Participants in the Biased-

Figure 2
Behavioral Results



Note. Learning phase performance in the Biased-Learning and Control groups with respect to (A) Response Time, (B) Miss Rate, and (C) Optimality. Test phase performance comparing the Biased-Learning and Control groups with respect to (D) Response Time, (E) Miss Rate, and (F) Optimality. Error bars reflect the SEM.
* $p < .05$. *** $p < .001$.

Learning group exhibited significantly above-chance levels of optimality in all trial types in the learning phase, ts(27) > 10.89, ps < .001, ds > 2.058, and also in the test phase, $t(27) = 8.12$, $p < .001$, $d = 1.535$. In contrast, participants in the Control group were neither above-chance with respect to optimality in the learning phase, $t(28) = .76$, $p = .457$, nor the test phase, $t(28) = 1.03$, $p = .310$. Next, we conducted independent-samples t-tests comparing test phase performance between groups. Participants in the Biased-Learning group were significantly more optimal compared to participants in the Control group, $t(55) = 3.97$, $p < .001$, $d = 1.052$ (see Figure 2F), but no significant differences were found over response time, $t(55) = .86$, $p = .396$ (see Figure 2D), or miss rate, $t(55) = .42$, $p = .677$ (see Figure 2E).

Although differences between groups in the test phase with respect to RT and miss rate were not significant, on a more continuous level, more frequent adoption of the optimal search strategy might still be associated with improved task performance. For participants in the Biased-Learning group who experienced the 3/37 and 8/32 displays during the learning phase, a higher frequency of reporting the more optimal target was associated with faster RT and a lower miss rate on these trials, rs < −.57, ps < .001. For the 13/27 displays, across all participants, the frequency of reporting the more optimal target was significantly correlated with miss rate in both the learning phase, $r = -.42$, $p < .001$, and test phase, $r = -.43$, $p < .001$ (see Figure 3), while the correlations with RT were not significant, $r = -.21$, $p = .110$, and $r = -.10$, $p = .461$, across the learning and test phase, respectively.

To examine use of the optimal strategy over time, we calculated the frequency of reporting the optimal target after dividing each phase into 40-trial blocks. For the Biased-Learning group, there was a significant main effect of block for each display type, Fs > 6.08, ps < .001, $\eta_p^2 > .183$, that was captured by a linear trend over block, Fs > 17.11, ps < .001, $\eta_p^2 > .387$ (see Figure 4). The Control group, in contrast, did not exhibit a significant main effect of block, $F(5, 140)$, = 1.54, $p = .183$. Neither was the effect of block significant in the test phase for either group of participants, Fs < 1.39, ps > .259, suggesting fairly stable search tendencies at that point in the task.

Finally, we examined the frequency of reporting a target of the optimal color in the test phase as a function of participant group and whether the optimal color switched or repeated from the prior trial via a 2 × 2 ANOVA. The percentage of targets reported in the optimal color was 74.3% (SD = 15.6%) on repeat trials and 68.5% (SD = 13.3%) on switch trials for the Biased-Learning group, and 52.8% (SD = 20.8%) on repeat trials and 54% (SD = 19.2%) on switch trials for the Control group. There was a main effect of participant group that recapitulates the effect of learning described above, $F(1, 55) = 15.79$, $p < .001$, $\eta_p^2 = .223$. There was also a main effect of switch vs. repeat in which participants were less optimal on switch trials, $F(1, 55) = 5.02$, $p = .029$, $\eta_p^2 = .084$, potentially reflecting a priming effect in which participants were biased to report a target of the color they had reported on the prior trial. The interaction between the two factors was also significant, $F(1, 55) = 11.59$, $p = .001$, $\eta_p^2 = .174$, with the difference between switch and repeat trials being greater in the Biased-Learning group, which is unsurprising given that only participants in this group searched optimally in general. Importantly, participants in the Biased-Learning group were significantly more optimal than chance on both switch and repeat trials, ts > 7.38, ps < .001, ds > 1.396.

Discussion

In the present study, we investigated the influence of selection history on the strategic control of attention, specifically with respect to visual search strategy. The presence of more imbalanced visual search arrays in the learning phase promoted selection of the optimal strategy of searching through the less abundant task-relevant color, which resulted in significantly faster times to find and report a target as the display became more imbalanced. Adoption of this strategy became more frequent as the task progressed, consistent with the idea that it developed as a consequence of experience with the displays that participants encountered. Importantly, this tendency to search through the less abundant color persisted into the test phase, resulting in a significantly stronger preference for this strategy than exhibited by participants who had a comparable amount of prior experience with the ACVS task but had not previously experienced the more imbalanced displays. That is, the search strategy that participants chose to use during the learning phase influenced their choice of strategy in the test phase, with prior experience exerting a strong influence on how participants approached the task of finding a target.

Prior investigations of the role of selection history in the control of attention predominantly focus on learned attentional biases

Figure 3

Relationship Between Optimality and Miss Rate in the Learning Phase and Test Phase Over All Participants on 13/27 Trials

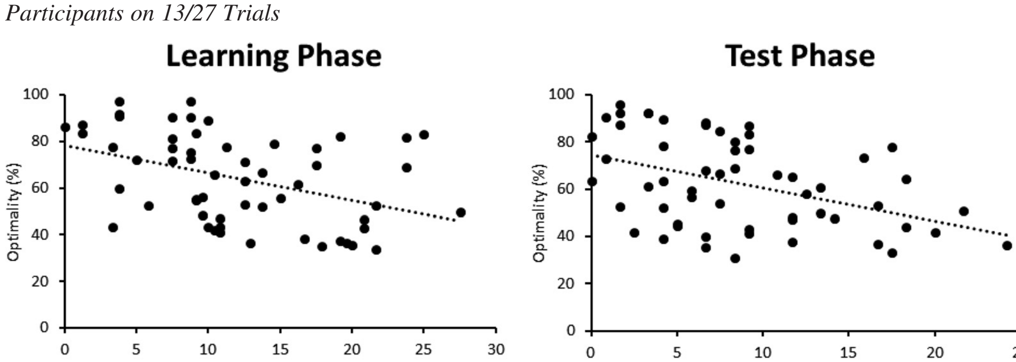
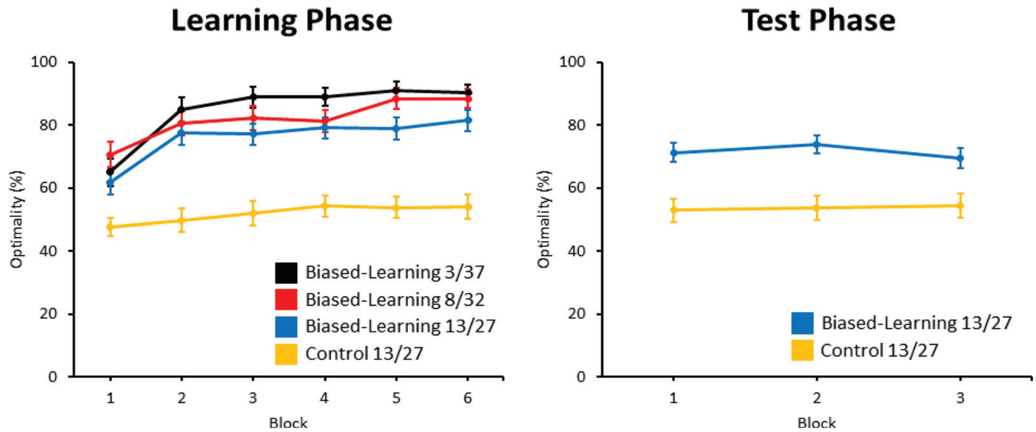


Figure 4

Change in Optimality Over Blocks of the Learning Phase and Test Phase



Note. Each block consisted of 40 trials. Error bars reflect the standard error of the mean. See the online article for the color version of this figure.

toward or away from a specific feature or location (Anderson & Kim, 2018a, 2018b; Anderson et al., 2011; Chun & Jiang, 1998; Della Libera & Chelazzi, 2009; Geng & Behrmann, 2002, 2005; Jiang, 2018; Jiang & Wagner, 2004). The findings of the present study demonstrate that selection history is not limited to learning tied to specific stimuli or locations, but also applies to "top-down" attentional control settings. Given that the optimal color to search through varies unpredictably across trials in the present study, participants were unable to create an attentional control setting toward a specific color or otherwise learn to prioritize a particular feature, but rather had to establish a strategy of evaluating the presented search array and determining what the optimal color to search through would be (Arita et al., 2012; Beck & Hollingworth, 2015; Becker et al., 2015; Hansen et al., 2019). In this respect, our findings go beyond demonstrations of history-dependent influences on whether a specific stimulus feature (feature-search mode) or a feature singleton (singleton-detection mode) is prioritized (Leber & Egeth, 2006a, 2006b; Leber et al., 2009), which could be explained, at least in part, as reflecting learning that is tied to the prioritization of specific stimuli.

Likewise, studies of goal-directed attentional control tend to explain attentional strategy or control settings as the joint product of task instruction and the demands of the currently experienced search displays (Bacon & Egeth, 1994, 1997; Folk et al., 1992; Wolfe et al., 1989). For instance, observers have been shown to utilize feature cues indicating the nontarget color on a trial to establish a "template for rejection" that facilitates visual search (Arita et al., 2012; Beck & Hollingworth, 2015; Becker et al., 2015). In the present study, participants who experienced the same task instruction and were exposed to the same visual search displays during the test phase searched differently as a product of their prior experience in the learning phase. By evaluating how participants chose to search when given the considerable flexibility afforded by the ACVS task, our findings can only be explained by selection history operating over a visual search strategy per se, with the choice of attentional strategy significantly impacted by prior experience. Our results provide evidence that beyond the interplay between the specific features of a search display and task instruction, learning history can also modulate attentional strategies.

A natural question that arises from the present study is why search strategies would tend to persist at all. One potential answer to this question involves appealing to the principle of effort minimization in the domain of cognition. When given the choice, participants tend to favor tasks that minimize cognitive demand (Dunn et al., 2016; Irons & Leber, 2016; Kool & Botvinick, 2014; Kool et al., 2010). One potential adaptive function of attentional control is to minimize effort in the accomplishment of a task goal (Anderson, 2021). Participants who had experienced more imbalanced displays during the learning phase continued to experience displays for which they previously favored the strategy of identifying and searching through the less abundant color in the test phase (albeit only the least imbalanced displays), and these participants may have simply engaged in the same search strategy that they had been using in like displays without evaluating whether this strategy was still worth the effort. Just how inefficient a continued strategy would need to be before participants would consider abandoning this strategy is an empirical question.

Although engagement of the more optimal search strategy was associated with a benefit in the speed of localizing and reporting a target for the more imbalanced visual search displays during the learning phase, we did not observe an overall speeding of responses associated with the use of this strategy in the test phase when comparing across participant groups. On a more continuous level, however, more frequent use of the optimal strategy was associated with superior task performance in the test phase with respect to fewer failures to find a target before the trial timed out. A more robust difference in response time between participant groups may have been suppressed by the fact that participants in the Control group had more practice navigating the more difficult 13/27 displays. The use of the optimal strategy also comes at some cost to time on task that is balanced with its benefits, as the process of evaluating the displays to determine which color is the less abundant one is itself attentionally demanding (Hansen et al., 2019; see also Li et al., 2022), along with the corresponding need to then update attentional priorities before search commences. On the whole, we see robust evidence that prior experience had a powerful influence on how participants chose to approach the visual search task, and more limited evidence that this choice had consequences for the efficiency of task performance.

The present study extends the concept of selection history to the strategic control of attention. Not only does prior experience influence how features and locations are prioritized by the attention system, but it also influences how participants engage goal-directed attentional processes. In this way, attentional control settings should be conceptualized as the joint product of the current environment, current task demand, and how the individual has chosen to configure their attentional control settings in the past.

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