Assessing the generality of strategy optimization across distinct attentional tasks

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Abstract

Individuals vary substantially in the degree to which they optimize their performance in attentional tasks. How do such individual markers of attentional strategy relate across different tasks? Previous research has failed to observe significant correlations in strategy optimization between distinct visual search tasks (Clarke et al., 2022), suggesting that strategy optimization is not unitary, or determined by a single trait variable. Here we test whether strategy optimization shows some degree of generality, specifically across tasks with similar attentional components. We employed the Adaptive Choice Visual Search (ACVS; Irons & Leber, 2018a), a visual search paradigm designed to directly measure attentional control strategy. In two studies, we had participants complete the ACVS and a modified, but similar, task with one altered attentional component (specifically, the requirement to use feature-based attention and enumeration, respectively). We found positive correlations in strategy optimization between tasks that do vs. do not involve feature-based attention (r = .38, p = .0068) and across tasks that do vs. do not require enumeration (r = .33, p = .018). These results provide novel evidence for generality of strategy optimization, although the strength of the correlations was weaker than the within-task test-retest reliability of strategy measurements. Thus, while some generality exists, strategy optimization appears to be quite heterogeneous.

Public Significance Statement

People carry out visual search for objects of interest every day, and attentional strategy—how one voluntarily chooses to search—plays a key role in this essential human activity. Researchers have attempted to understand what drives some individuals to use more optimal strategies than others, but this pursuit has been complicated by a recent finding that the degree to

which people chose optimal strategies in one task did not predict how optimal they were at other tasks. The present study investigated whether people's tendencies to optimize performance can be similar across multiple tasks, provided that the tasks themselves are similar to one another. Results showed that people did indeed optimize to similar degrees across tasks that were similar to one another, but only weakly so. These results carry clear implications for research seeking to characterize how individuals use attentional strategy; specifically, strategy is unlikely to be explained by a unitary trait variable but rather a heterogeneous set of multiple variables. These variables remain unknown, and further work to identify and describe them is essential.

Keywords: *Attention*, *Visual search*, *Strategy*, *Individual differences*

Introduction

When navigating an unfamiliar grocery store, how do you quickly find the items you want to buy? Classical research has shown that individuals are able to control attention in a *goal-directed* manner to selectively bias processing to certain features (Folk et al., 1992; Green & Anderson, 1956). The efficiency with which observers find targets is not only dependent on their ability, but also on the *strategy* they choose to control their attention (Irons & Leber, 2020). That is, if the goal is to find apples in a grocery store, two individuals may have equivalent abilities to search for red objects and to search for round objects, but the one who chooses to search for red objects will achieve a faster result than the one who chooses to search for round objects. This is because less fruit is red than is round; also, search tends to be more efficiently guided by color than shape (Wolfe & Horowitz, 2017).

We define attentional strategy as a set of mental plans or rules that guide how an individual selects and prioritizes sensory input in the visual field (Leber & Irons, 2019). How do people choose their attentional strategy? Existing evidence from visual search tasks has shown that strategy tends to be suboptimal overall; that is, when multiple attentional control settings are available, observers might not be sufficiently motivated to choose the strategy that best optimizes performance (Bacon & Egeth, 1994; Egeth et al., 2010; Irons & Leber, 2016). Research using eye-tracking also shows that observers do not always make fixations that maximize information gain (Araujo et al., 2001; Boot et al., 2009; Clarke et al., 2016; Morvan & Maloney, 2012; Nowakowska et al., 2017).

While studies have reported overall suboptimal behavior across aggregate samples of participants, additional work, though somewhat scarce, has also demonstrated a large range of individual differences in tasks such as visual search and foraging (Hogeboom & van Leeuwen, 1997; Kristjánsson et al., 2014; Muhl-Richardson et al., 2018; Nowakowska et al., 2017).

The Adaptive Choice Visual Search (ACVS; Irons & Leber, 2016)

Irons & Leber (2016) set out to systematically investigate individual differences in the optimality of attentional strategy in visual search. They designed the Adaptive Choice Visual Search (ACVS) paradigm, which assesses individuals' strategy through target choices. The ACVS was based on a "subset search" (Egeth et al., 1984; Green & Anderson, 1956; Zohary & Hochstein, 1989), where individuals can use feature-based attention to bias their search to items with a specific feature. In the ACVS, two targets are presented in each display—one red and one blue—and participants are asked to report just one of these. Critically, these targets differ in how efficiently they can be found, which is achieved by manipulating the ratio of the red to blue distractors. For example, when there are more blue distractors than red ones in the display, searching for the red target is considered "optimal." The ratios are changed periodically so that participants seeking to choose the optimal target must monitor the changes and update the visual features they prioritize for search—i.e., their attentional control settings—from trial to trial.

Individuals performing this task have produced a striking range of different strategies, from near-perfect to below chance *optimality,* which is defined as the proportion of trials in which the optimal target is reported (Irons & Leber, 2016). Further research has shown that the variation in strategy is not explained by cognitive abilities, such as visual search speed, working memory capacity, fluid intelligence, standardized test scores, or grades (for a review, see Irons & Leber, 2020). Indeed, we have found that the vast majority of participants can use the optimal strategy when it is required of them; however, the degree to which individuals choose the optimal strategy when it is not required appears to depend on how subjectively effortful they find the optimal strategy to be (Irons & Leber, 2018a, Experiment 2). Overall, individuals' strategies in the ACVS have appeared to be determined by a trait-like variable, as it has been found to be stable, yielding good test-retest reliability (r = .83) over two sessions spaced an average of 3.1 days apart (Irons & Leber, 2018a).

How General Is the Tendency to Optimize Strategy?

Given the trait-like stability of strategy found by Irons & Leber (2018a), a natural question arises concerning the universality of strategy optimization. Specifically, how does the optimization of strategy in one task relate to that in other tasks? That is, is strategy optimization a trait variable that manifests itself across different tasks? We can consider two possible alternative accounts. By a *unitary strategy* account, strategy optimization is task-general such that individuals who are optimal at one attentional task should be optimal at all other attentional tasks, provided these tasks allow for a strategic component to optimize performance. By a *heterogeneous strategy* account, an individual's strategy optimization at one task will be independent of that in other attentional tasks.

Clarke and colleagues (2022) made an initial attempt to assess the generality of strategy optimization by comparing individuals' strategy in three distinct attentional tasks: the ACVS (Irons & Leber, 2016), the *Split Half Line Segment* task (Nowakowska et al., 2017), and the *Mouse Click Foraging* task (Kristjánsson et al., 2014).

The Split Half Line Segment task assesses saccadic choice strategy, where the target is a specifically tilted line segment on either the left or the right side of the display, among other tilted non-target line segments. Crucially, the two sides of the display contain different kinds of distractors such that if a target appears on the “homogeneous side,” it is conspicuous and pops out among distractors that almost orient at the same direction, while if it appears on the “heterogeneous side,” searching for the target requires a serial search because it is among distractors that are oriented in much more randomized directions. The optimal strategy, then, requires fixations only on the heterogenous side because targets that appear on the homogeneous side can be identified without saccade.

The Mouse Click Foraging Task (conjunction version; Kristjánsson et al., 2014) asks participants to click on every object in the display belonging to two target sets, at which point they can proceed to the next trial. Each set of targets is defined by a distinct conjunction of features (e.g., blue squares and red circles). Exhausting one set of targets before switching to the other typically yields faster performance than alternating more frequently between the sets (likely because alternation incurs task-switching costs). Therefore, a key measure of strategy optimality in this task as used by Clarke et al. was the frequency of switching target sets (or the directly related measure of the mean run length within a set).

While strategy optimality measures from all three tasks showed good test-retest reliability, Clarke et al. (2022) found no significant correlations in strategy optimization across the three tasks. They reasoned that although the three tasks in their study consisted of visual search, each also has unique aspects that could lead to optimality in particular individuals but not others. For example, the optimal strategy in ACVS task requires constantly monitoring the display and updating search goals by finding out the smaller subset of squares. In the Split Half Line Segment task, one needs to fixate the locations that provide more information to achieve optimality. In the Mouse Click Foraging task, minimizing target switching costs is important.

Therefore, it may be that attentional strategy optimization can generalize but not across tasks that tap into markedly different attentional components.

The Clarke et al. (2022) study provides important evidence against the unitary account, in that negligible correlations in optimization were found between the distinct tasks. At the same time, these results raise a new question: is there even a small degree of generality across tasks? By a strong version of the heterogeneity account, every task is distinguished by a unique degree of strategy optimization. It is difficult to conceive of a human information processing system that generates novel approaches to performance for every task. Yet, thus far, no degree of generality between any pairs of attentional tasks has been observed. In the present study, we choose sets of similar tasks to observe whether any evidence of generality can be obtained.

The Present Investigation

The current research attempted to test the hypothesis that attentional strategy optimization spans—at least to some degree—pairs of tasks with similar attentional components or stages of processing. To investigate this, we specifically used visual search as a test bed and conducted studies with modifications of the ACVS paradigm.

To begin we must first consider the different attentional components in the ACVS. To choose the optimal target in the ACVS, participants should first appraise the display and extract relevant statistical summary information. Participants complete this step by discriminating the numerosity difference between red and blue subset. Then, they need to deploy feature-based attention to a subset of squares of a certain color, searching through the subset until finding a target digit. Throughout the task, they also need to proactively monitor the displays and update the attentional sets across trials in order to always choose the optimal target. At least one of these stages of processing has been shown to be crucial in making optimal choices: disrupting the appraisal phase with an irrelevant task reduced optimality (Hansen et al., 2019).

Here, we devised pairs of tasks that differ in just one of these components, reasoning that the tasks would be distinct but still share a good measure of similarity. We focused on two strategy components: feature-based attention (Study 1) and enumeration (Study 2). Specifically, in Study 1, we compared the original ACVS (henceforth, Standard ACVS) to a modified task that does not require feature-based attention for optimal performance. In Study 2, we compared the Standard ACVS to a modified task that does not require enumeration for optimal performance. Will-we observe some degree of task-general strategy optimization—or will optimization be independent—across the pairs of tasks?

Study 1: Feature-based vs. Space-based Attention

In this study, we compare the Standard ACVS with a new paradigm, the Spatial ACVS. In the Spatial ACVS, all target and distractor squares are grey, but the optimal target in each trial can be found within the less numerous subset of squares on the left or right of the display. The optimal strategy in the Standard ACVS requires feature-based attention to enumerate among multiple color-based subsets, followed by a search within the specific optimal color subset on each trial, while the Spatial ACVS places no such demands on feature-based attention. Instead, participants can use spatial attention to enumerate among two spatially grouped subsets and then search within the less numerous subset in the display to find the optimal target.

We had participants complete both Standard ACVS and Spatial ACVS in one session and assessed strategy generality by calculating the correlation between the key strategy metric—

proportion of optimal choices—as well as other performance metrics of the ACVS, including accuracy, response time, and frequency of target switching.

Method

Transparency and Openness. We describe our efforts to conform to the Center for Open Science's Transparency and Openness Promotion Guidelines (Nosek et al., 2015) below:

Citation: While we do not use previously collected data by others, all code (e.g., libraries) and methods developed by others are cited in this article.

Data, Analysis Methods (Code), and Research Materials: All data collected, the code used to analyze the data, and the code used to generate stimuli and record responses are publicly available, at https://osf.io/rx2c5.

Design and Analysis (Reporting Standards): We made our best effort to comply with the American Psychological Association's (APA) Journal Article Reporting Standards for Quantitative Research in Psychology (JARS-Quant; see Appelbaum et al., 2018).

Study and Analysis Plan Preregistration: The study was preregistered (https://osf.io/57yhc) with all details of the sample size, design, and analyses. The preregistration was posted after the data collection of 24 participants but before any data were opened or analyzed. Any analyses not included in the preregistration are declared as such. All methods were approved by The Ohio State University Institutional Review Board.

Participants. Fifty-seven individuals (29 female and 28 male) aged 18 to 32 (M = 19.23) from The Ohio State University community participated in this study for course credit. All participants had self-reported normal or corrected-to-normal visual acuity and normal color vision. Data from one participant who completed the two tasks with a different order than was predetermined, due to experimenter error, was excluded. Additionally, six participants whose overall accuracy was three standard deviations lower than the group mean were excluded from analyses. The final sample included 50 participants, as specified in the preregistration, which would give us a power of .98 of finding a medium effect size for the critical Pearson correlation (r = .50).

Stimuli, Apparatus, and Design

Participants sat in a dimly lit, sound-attenuated room approximately 60 cm from the display (all stimulus sizes reported assume this viewing distance, although head position was not fixed). The stimuli were presented using Psychophysics Toolbox (Brainard, 1997; Kleiner et al., 2007; Pelli, 1997) implemented in MATLAB (Mathworks, Natick, MA, USA) and were displayed on a 24-inch LCD monitor (resolution: 1920 × 1080; refresh rate: 60 Hz).

Standard ACVS The Standard ACVS used displays that were based on that of Irons and Leber (2018a, Experiment 2). Each search display contained 54 squares (sized 1° x 1°) with 13 red (RGB: 255, 0, 0), 13 blue (RGB: 0, 0, 255), 14 green (RGB: 0, 150, 0), and 14 variable-colored (red or blue) items. The squares were arranged in three concentric rings (eccentricities: 6.3°, 9.4°, and 12.4°) centering around a fixation cross. The inner ring, the middle ring, and the outer ring contained 12, 18, and 24 evenly spaced squares, respectively. There were two targets on every trial, one red and one blue square, each containing a digit (height: 0.48°) between 2 and 5 (all other red, blue, and variable-colored squares contain digits between 6 and 9). Green squares had an equal probability of containing any digit between 2 and 9, and only served as distractors (see Figure 1).

The variable color was red on half of the trials and blue on the remaining trials. The effect of the variable color was essentially to add 14 more nontargets to one of the target color subsets, thus rending it the nonoptimal color. That is, when the variable color was red, the optimal target was blue, and vice-versa. The variable color value was presented in runs, ranging from 1 to 6 trials, with each run length appearing equally often for each variable color. The optimal target digit was selected equally often for each target color, from the set of 2, 3, 4, and 5. The non-optimal target digit was similarly selected from the same set of 2, 3, 4, and 5, with the constraint that it was never the same as the optimal target digit. Each block of Standard ACVS contained 84 trials, and the presentation order of the runs of trials was randomized.

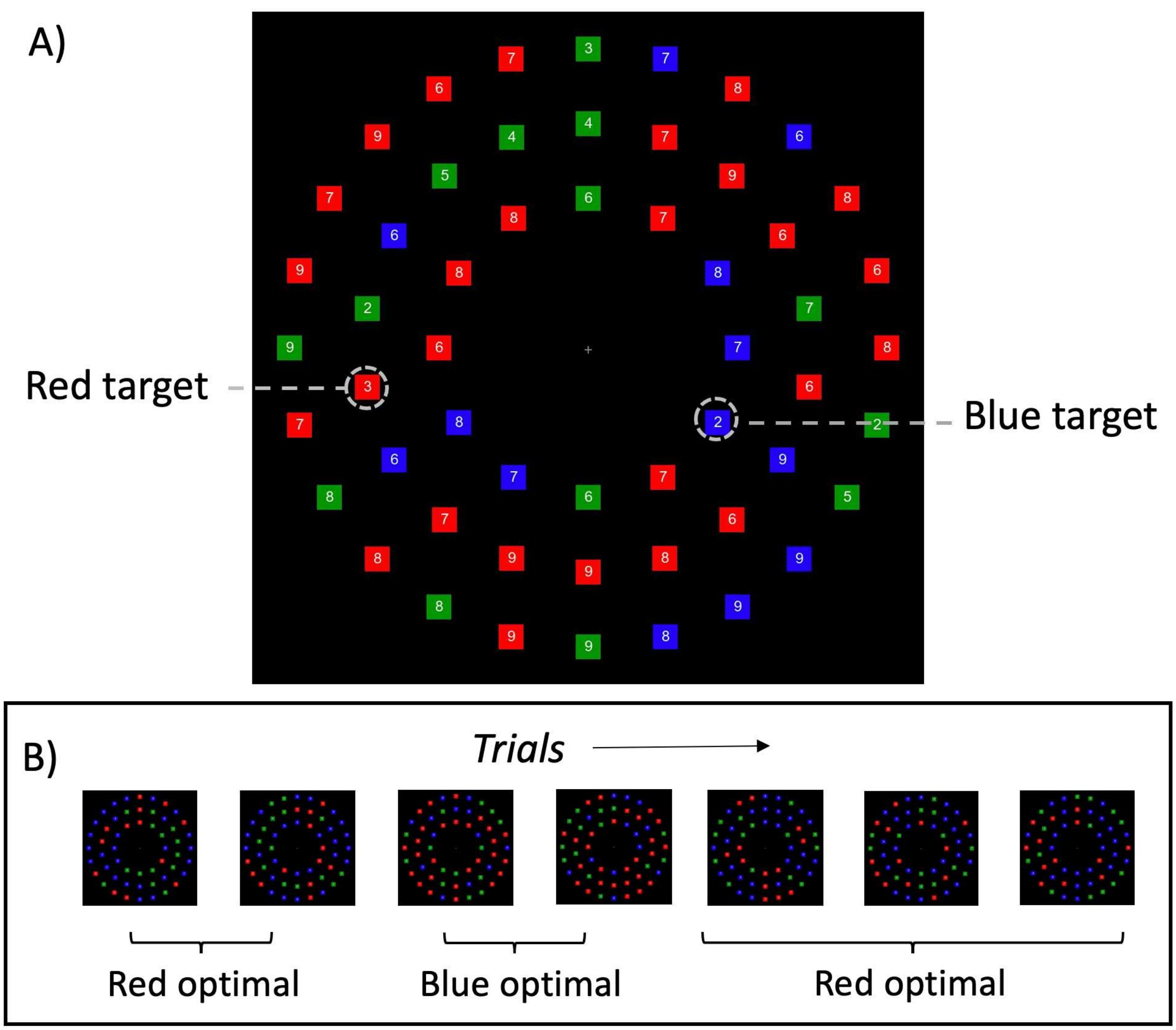

Figure 1. An example stimulus array (a) and series of trials (b) in the Standard Adaptive Choice Visual Search (ACVS). Each display contains a red target and a blue target, each defined as a 2, 3, 4, or 5.

Spatial ACVS In the Spatial ACVS, on every trial, 20 squares (non-optimal subset) appeared on one side (i.e., left or right) of the display and 10 squares (optimal subset) appeared on the other side, with each side containing the optimal subset on half of the trials. Every square was grey (RGB: 128, 128, 128) and positioned at one of the 54 locations where the squares in Standard ACVS appeared, except for the 6 locations closest to the vertical midline of the display. Two targets, one on each side, each had digits between 2 and 5. All other squares contained a digit between 6 and 9 (see Figure 2).

Three independent variables were factorially crossed: the optimal target side (left vs. right), the optimal target eccentricity (inner, middle, or outer ring), and the non-optimal target eccentricity (inner, middle, or outer ring). Then, the optimal target digit and non-optimal target digit combinations were balanced across each block. Finally, the presentation order of the trials was randomized, with the constraint that the number of consecutive trials of the same optimal target side was no more than three.

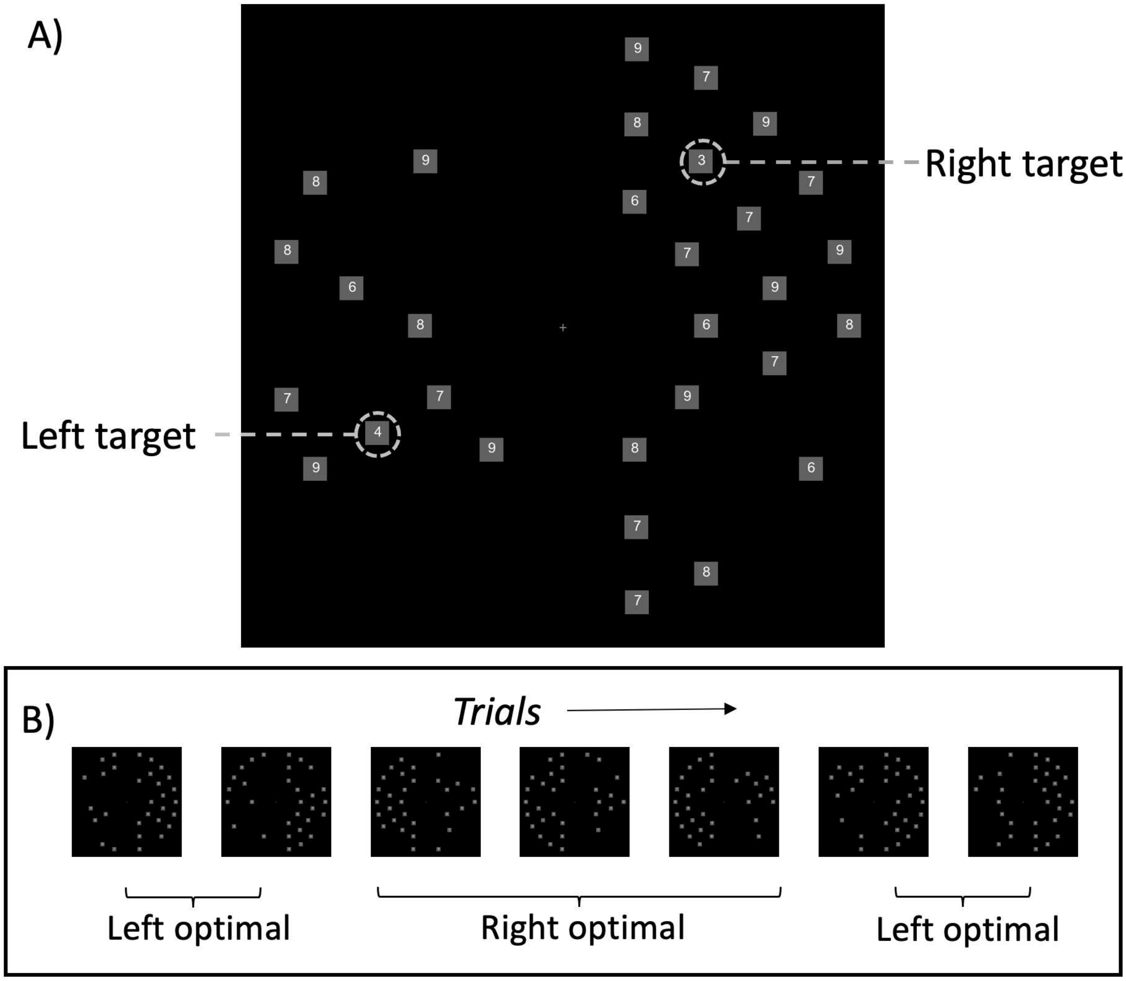

Figure 2. An example stimulus array (a) and trial sequence (b) in the Spatial ACVS. Each display contains two targets on both sides of the display. Target squares contained digits 2, 3, 4, or 5.

Procedure. In both tasks, each trial started with a fixation cross at the center of the screen for 1500 ms, followed by the stimulus array. The display was presented until the participant reported a target. If their response was correct, the task proceeded to the next trial; otherwise, a short beep (400 Hz for 150 ms) was played to indicate the error before proceeding.

Participants completed three blocks of Standard ACVS task followed by three blocks of Spatial ACVS. This order was preserved across all participants to minimize inter-subject variability driven by the design, for the purposes of individual differences analysis (Mollon et al., 2017).

For the Standard ACVS, participants were informed that a blue and a red target would be presented on every trial and that they were always free to search for either one. They were also told the ratio of red and blue objects could vary from trial to trial, but we did not explicitly tell them that it was optimal to search through the smaller subset. The targets contained a digit between 2 and 5, and participants responded using the keys V, B, N, and M corresponding to each of the possible target digits. The four response keys were each covered by a label indicating the corresponding digit. Participants completed ten practice trials followed by the three blocks, which were 84 trials each, with short breaks in between. At the end of these blocks, participants were told to notify the experimenter, and they were given the chance to take a short break.

Then, the experimenter explained the instructions for the Spatial ACVS. Participants were informed that all of the squares would be the same color, that they could always find one target on each side of the screen, and that they were always free to search for either one. They were also told the ratio of objects on the left and right side could vary, but we did not explicitly tell them that it was optimal to search through the smaller subset. The targets contained a digit between 2 and 5, and participants responded using the same keys as in the Standard ACVS (V, B, N, and M), corresponding to each of the possible target digits. Participants completed ten practice trials followed by three blocks of 72 trials.

Results and Discussion

Search accuracy was close to ceiling for both tasks (Standard ACVS: $M = 98.42\%$, Spatial ACVS: $M = 98.56\%$). In the following analyses, we excluded error trials and trials with search response times (RTs) less than 300 ms or more than three standard deviations above each participant's mean (3.03% of Standard ACVS trials, 2.69% of Spatial ACVS trials). For analyses involving bivariate correlations, we excluded outliers with a Mahalanobis distance of more than 13.82 ($p < .001$).

Descriptive Statistics.

Search Optimality There was a broad range of individual differences in the proportion of optimal choices in both tasks (Figure 3). For Standard ACVS, optimality ranged from .11 to .97 (*M* = .65, *SD* = .20). For Spatial ACVS, optimality ranged from .51 to .98 (*M* = .82, *SD* = .14).

Search Response Time For Standard ACVS, the mean RT was 3580 ms (range: 2176 – 5806, *SD* = 902), and for Spatial ACVS, the mean RT was 2006 ms (range: 1395 – 3236, *SD* = 364).

Frequency of Switching Switch tendency was assessed by the proportion of trials where participants made a switch in target type from last trial (e.g., red vs. blue or left vs. right). In Standard ACVS, the mean proportion of target switching was .31 (range .00 – .50, *SD* = .13) and in Spatial ACVS, .32 (range .00 – .61, *SD* = .10).

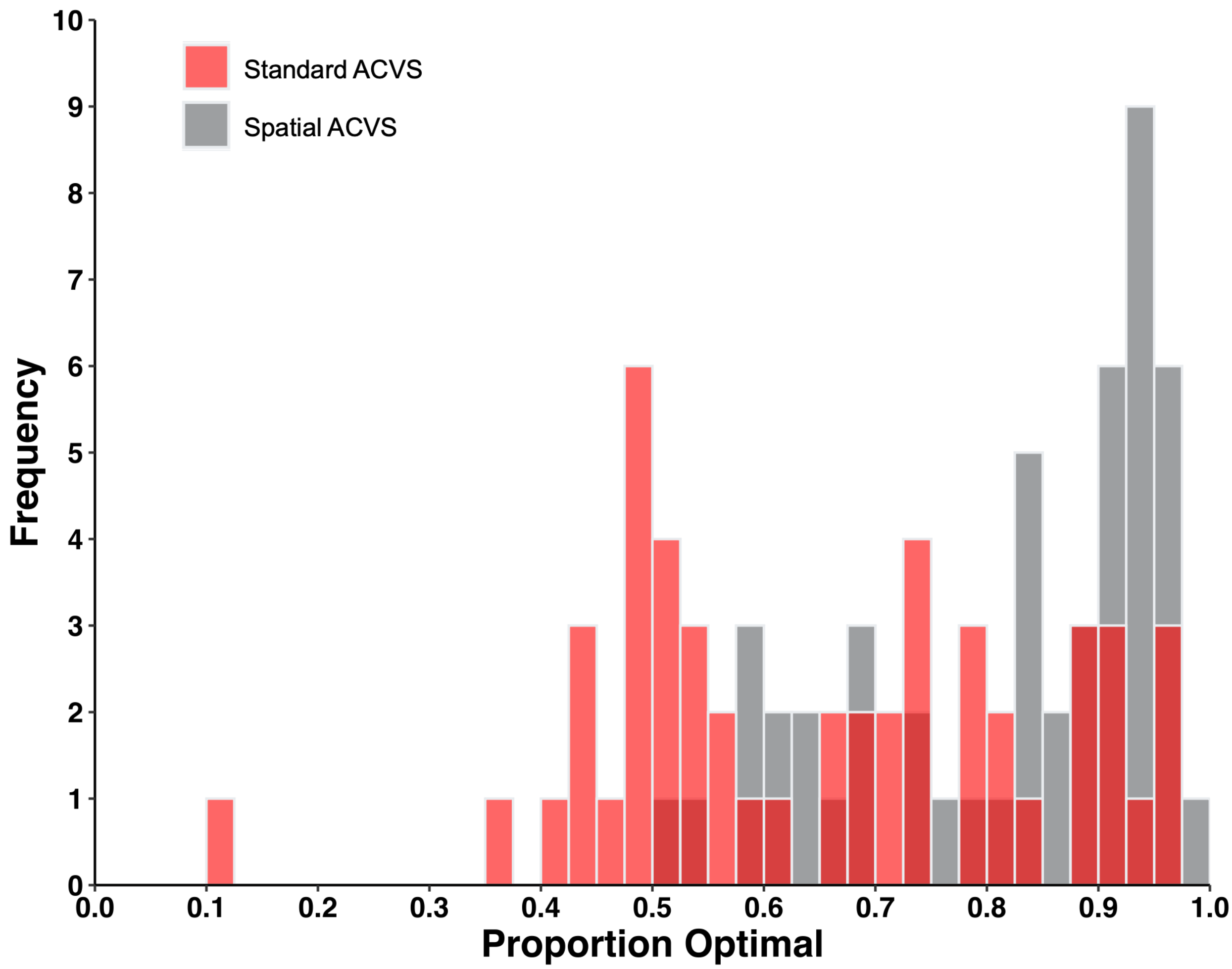

Figure 3. The distributions of mean proportion optimal in both the Standard ACVS and the Spatial ACVS.

Optimality – RT Correlation. The Optimality – RT correlation was tested to show how much benefit using the optimal strategy can have on search speed. As shown in Figure 4, in Standard ACVS, the proportion of optimal choices was negatively correlated with RTs (Standard ACVS: r = -.57, t(48) = -4.83, p < .001, 95% CI = [-.73, -.35]), replicating earlier work (e.g., Irons & Leber, 2018a). However, in Spatial ACVS, this correlation was not significant after removing one bivariate outlier (r = -.26, t(47) = -1.82, p = .08, 95% CI = [-.50, .03]). We suspected that the lack of such an effect was due to a restricted range of RT in Spatial ACVS, likely because Spatial ACVS was easier than Standard ACVS. A subsequent analysis not included in the pre-registration confirmed that participants took on average 1574 ms (SD = 689) longer to find a target in Standard ACVS than Spatial ACVS ($t(49) = 16.17$, $p < .001$, 95% CI = [1378, 1770], $d = 2.00$). While we did not manipulate display set size, we assume that the Spatial ACVS yields a shallower RT × set size slope than the Standard ACVS[1].

Correlation in Performance between Two Paradigms. The proportion of optimal choices in Standard ACVS was positively correlated with that in Spatial ACVS ($r = .38$, $t(48) = 2.83$, $p < .01$, 95% CI = [.11, .59]). Additionally, faster RT in the Standard ACVS predicted faster RT in Spatial ACVS ($r = .70$, $t(47) = 6.67$, $p < .001$, 95% CI = [.52, .82]). Finally, higher target switch rate in Standard ACVS was correlated with higher target switch rate in Spatial ACVS ($r = .29$, $t(48) = 2.08$, $p = .04$, 95% CI = [.01, .52]). These positive correlations—particularly the critical comparison of optimality—indicate that individuals were similar in adherence to the optimal strategy in tasks that do vs. do not involve feature-based attention (see Figure 5).

[1] It is possible to gain a rough approximation of slopes by comparing RT on trials in which targets in the small vs. large subsets were selected, if we assume that the searched set is equal to the number of items in the chosen subset. Specifically, we define slope as ($RT_{large\ subset} - RT_{small\ subset}$) / ($setsize_{large\ subset} / 2 - setsize_{small\ subset} / 2$). We present these estimates with great caution, however, as it is unlikely that all participants always confined their search solely within the reported target's color subset. Calculated slopes were 52 ms/item for Standard ACVS and 27 ms/item for Spatial ACVS.

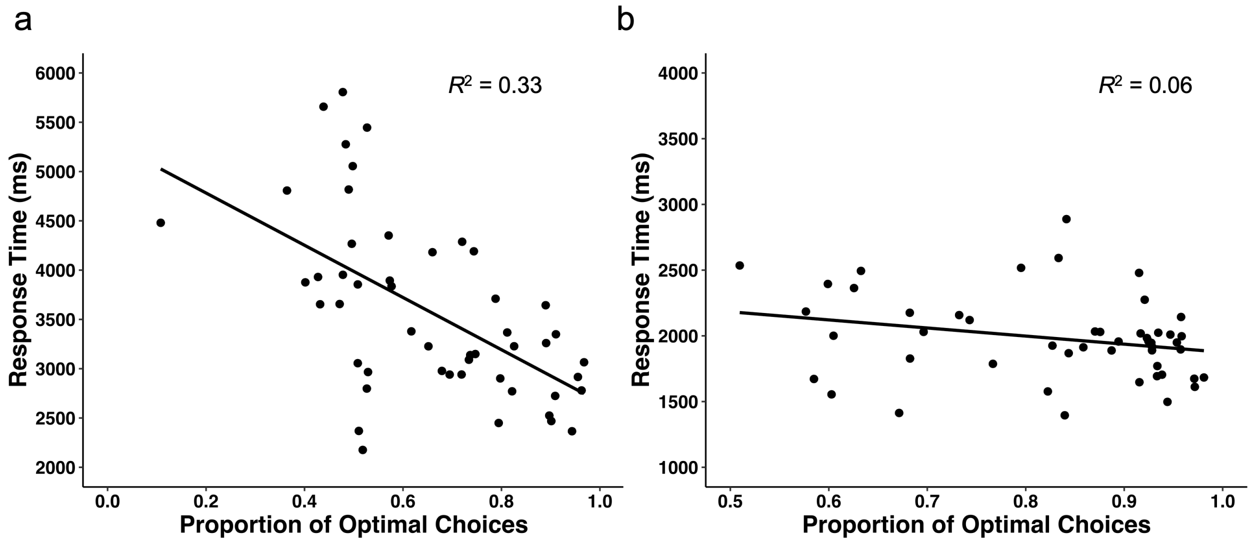

Figure 4. Scatterplots (with best-fitting regression lines) showing the correlation between proportion of optimal choice and response time in a) Standard ACVS and b) Spatial ACVS.

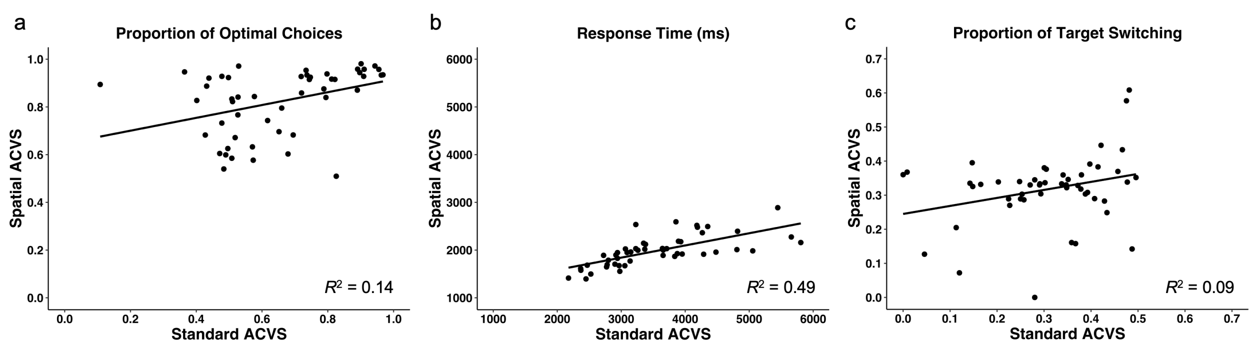

Figure 5. Scatterplots (with best-fitting regression lines) showing the correlation of a) proportion of optimal choices, b) response time, and c) proportion of target switching between Standard ACVS and Spatial ACVS.

The main finding from this study is some degree of generality in strategy optimization across two distinct tasks—the Standard ACVS and the Spatial ACVS—that share similar but distinct attentional components. Unlike the previous work of Clarke et al. (2022), which used more distinct tasks, we have produced evidence that strategy can correlate significantly across tasks. At the same time, the correlation (r = .38) was numerically weaker than our reported estimates of test-retest reliability in a previous version of the Standard ACVS (r = 0.83; Irons & Leber, 2018).

One possible concern with these results was that RT and optimality in the Spatial ACVS were not significantly correlated. This suggests the benefits of using the optimal strategy are not as strong as in the Standard ACVS, and it raises the concern that participants would not be properly incentivized to choose the optimal strategy. Nevertheless, the rate of choosing targets in the smaller subset was quite high and actually greater in the Spatial ACVS than in the Standard ACVS, mitigating such a concern. We will also address this point in Study 2, where a significant RT and optimality correlation was established.

Another limitation of this study is that we did not have a clear way to statistically compare the cross-task correlation in optimality with within-task reliability estimates. Having such estimates would allow us to better interpret the strength of cross-task correlations; does having slightly different attentional components (less shared components) lead to significantly less shared variance in strategy optimality?

One way to approach this is to compute split-half reliability within each task using existing data of three blocks, but such an approach is not ideal for two reasons. First, while reliability is not a task property but instead a property of obtained data (Vacha-Haase, 1998), we want to do our best to ensure that the way we compute reliability of scores from within a task matches how we do so across two tasks. Second, we were further concerned about small shifts in strategy optimality over time. While we have strong evidence that a stable trait-like variable determines individual differences in strategy (Irons & Leber, 2018), subtle changes could emerge within an individual over time. For example, a participant might become less willing to adopt the optimal strategy when the session gets longer (or, alternatively, they could grow more likely to use it). Therefore, having different session lengths could be problematic.

Despite these concerns, we did measure split-half reliability measures using odd vs. even trials, and they were considerably higher than the cross-task correlation in optimality (Standard ACVS $r = .97$, $p < .001$; Spatial ACVS $r = .94$, $p < .001$). Nevertheless, to fully address the limitations of these measures, Study 2 is designed to compute split-half correlations in essentially the same way as how the cross-task correlations are obtained.

Study 2: Enumeration vs. Cue Interpretation

Our aims in Study 2 were twofold. First, we investigated a new strategy component to seek converging evidence for the findings of Study 1. Specifically, we explored whether strategy optimization shows task generality across tasks that do vs. do not require enumeration. As we have seen in the previous two versions of the ACVS task, an individual will need to appraise the display and determine the smaller subset before choosing the optimal target on every trial. So, our question with this study was, what happens if the process of enumeration is no longer essential to determine the optimal strategy? To answer this question, we created a new task, the Color Cue ACVS, which tells subjects the optimal target on every trial via a central cue. In this task, there are three equal-sized subsets of squares with different colors, which are then organized into two differently sized groups. Specifically, two color subsets are combined to form a large group and one color subset constitutes the small group. Each group contains one target. A cue in the center of the display tells subjects the group membership of the squares. The optimal strategy is to search for the target in the smaller group (for an example of the task display and the cue, see Figure 6). Much like participants often do not choose the smaller subset in the Standard ACVS, we expected that some individuals would opt not to use the cue information to maximize their performance. Previous work has shown that individuals often ignore highly valid symbolic cues, even though those cues can facilitate their search (Pauszek & Gibson, 2018). To assess the strategy generality of the two tasks, we had participants complete the Standard ACVS and the Color Cue ACVS in one session, similar to how we designed Study 1.

Second, we also wanted to be better able to estimate the split-half reliability of optimality within each task. To do so, we included one group of participants who performed only the Standard ACVS for the full session and another group that only performed the Color Cue ACVS. This would allow us to compute split-half reliability based on the same exact number of trials as the critical cross-task comparison for the participants who performed both tasks.

Method

Transparency and Openness.

Citation: As in Study 1, while we do not use previously collected data by others, all code (e.g., libraries) and methods developed by others are cited.

Data, Analysis Methods (Code), and Research Materials: All data collected, the code used to analyze the data, and the code used to generate stimuli and record responses are publicly available, at https://osf.io/rx2c5.

Design and Analysis (Reporting Standards): We made our best effort to comply with the American Psychological Association's (APA) Journal Article Reporting Standards for Quantitative Research in Psychology (JARS-Quant; see Appelbaum et al., 2018).

Study and Analysis Plan Preregistration: The study was preregistered (https://osf.io/f6zaw) with all details of the sample size, design, and analyses. The preregistration was posted after the data collection of 12 participants but before any data were opened or analyzed. All methods were approved by The Ohio State University Institutional Review Board.

Participants. One hundred and sixty participants (69 female, 89 male, 2 chose not to answer) aged 18 – 28 (M = 19.13, SD = 1.73) from The Ohio State University participated in the study for course credit. Participants completed the study online, and they were instructed to use a personal computer with a physical keyboard attached. We chose this option due to limited in-person subject recruitment capacity during the COVID-19 pandemic. Participants were assigned to one of the three task groups. According to our pre-registration, we planned to include N = 50 for each group. This sample size would give us a power of .98 of finding a medium effect size (r = .50) for cross-task optimality correlation or within-task split-half reliability measures.

Note that, while we used the same rationale for sample size planning in this study as we did in Study 1, we recognize that we could have planned our sample size based on the observed effects of Study 1. Specifically, if the true cross-task correlation in optimality in Study 1 is ρ = .38 (estimated by the observed r = .38 in Study 1), then our power to detect that effect would have been 0.81. Had we considered this more carefully for the present study, we might have increased our sample size to obtain greater power. Nevertheless, our expected power to obtain a similar effect as in Study 1 is above 0.8.

We also planned to exclude participants with accuracy more than three standard deviations below the overall mean accuracy of their group; this led to the removal of 10 participants, whom we replaced in order to arrive at our planned sample size.

Stimuli and Design

Standard ACVS The task was the same as Standard ACVS in Study 1, but with the following differences. First, on every trial, a fixation cross appeared at the center of the screen for 400 ms. After the fixation cross and before showing the stimuli array, a "preview" display appeared for 1000 ms on the screen. The preview displays were otherwise identical to stimuli displays but without target digits on the squares. We chose to include previews in this study to boost overall optimality (Hansen et al., 2019); this was because previous online studies from our lab have shown poorer optimality than for in-lab studies (McKinney et al., 2020). Second, trial orders were randomized with the constraint that the number of consecutive trials of the same optimal target color was no more than three. Third, once the participant pressed a response key, the search array disappeared, and text feedback ("Correct" or "Incorrect") was shown at the center of the screen. The feedback text was shown in a 12 pt. white italic Arial font. If the response was incorrect, an auditory tone was played for 200 ms. The feedback was followed by a 1000 ms ITI, and the feedback text remained on the screen during the ITI. Finally, because the task was completed by participants using their own devices, we did not have precise visual angle estimates of the stimuli.

Color Cue ACVS The display contained 54 squares located in the same grid locations as in Standard ACVS. Potential target squares were colored magenta (RGB: 150, 0, 150), cyan (RGB: 0, 115, 115), and orange (RGB: 179, 107, 0), with 14 squares of each color. We chose a different color palette for this paradigm to discourage participants from associating it with the

Standard ACVS. These equal-sized subsets of squares were organized into two groups: one small group contained one subset and one large group contained the other two subsets. Two targets appeared in every display, one in each group. For example, in the trial shown in Figure 6, there was one target in the orange (single subset) group and one target shown in the cyan-magenta (two-subset) group. Each color was assigned to the single color/two color groups equally and trials were fully mixed. The targets contained a digit between 2 and 5, and magenta, cyan, and orange distractors contained a digit between 6 and 9. There were 12 irrelevant distractor squares in the display. These squares were colored grey (RGB: 98, 98, 98) and each of them had a 50% chance to contain a digit between 6 and 9 and a 50% chance to contain a target digit (between 2 and 5), although, as a reminder, these digits were irrelevant and only served to prevent a digit-based search. Participants responded using the keys V, B, N, and M corresponding to each of the possible target digits (2, 3, 4, and 5, respectively).

Each trial began with a 400 ms cue-only period, in which a circular “color cue” appeared at the center of the screen in place of a fixation cross. The cue consisted of an outline circle that was bisected horizontally, producing two semicircle regions. A single colored dot was presented in one region, indicating the color of the one-subset group that contained the optimal target. Two colored dots were presented in the other region, indicating the colors of the two-subset group containing the nonoptimal target. Next, for a 1000 ms preview period, the colored squares were added to the display without superimposed digits. After this, the digits were superimposed inside the squares, until a response was entered. The response was followed by feedback identical to that of the Standard ACVS. The feedback was followed by a 1000 ms ITI, during which the feedback word remained on the screen.

In generating trials of one block, the optimal target color and the non-optimal target color were selected equally often from magenta, cyan, and orange, with the constraint that the optimal target color was never the same as the non-optimal color. Both the optimal target and the non-optimal target were placed equally often in the inner ring, middle ring, and the outer ring. The optimal target digit was selected equally often for each target color, from the set of 2, 3, 4, and 5. The non-optimal target digit was similarly selected from the same set of 2, 3, 4, and 5, with the constraint that it was never the same as the optimal target digit. Each block contained 84 trials, and the presentation order of the trials was randomized with the constraint that no more than three consecutive trials had an optimal target of the same color.

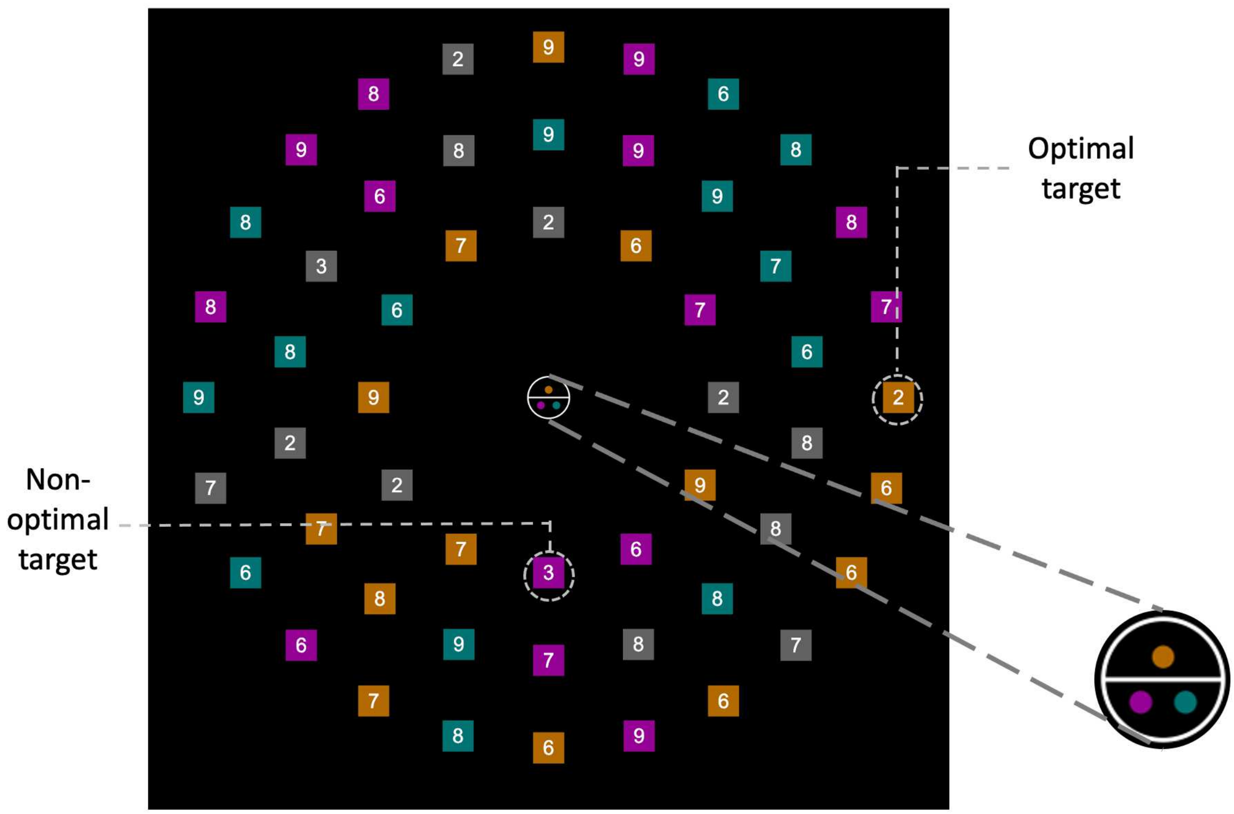

Figure 6. An example display of the Color Cue ACVS. The search array has three equal-sized task-relevant subsets of squares (14 items per subset) colored magenta, cyan, and orange, and one task-irrelevant subset of squares (12 items) colored grey. The three task-relevant subsets of squares are

organized into two groups such that one subset is assigned the small group and the remaining two subsets are combined to form the large group. The central cue indicates what the group arrangement is, such that each half of the circle contains the dot(s) representing the colored subset(s) in each group. In this example, the cue shows that the large group contains magenta and cyan squares, and the small group contains orange squares.

Procedure. Participants were assigned to three groups, *Standard ACVS-only*, *Color Cue ACVS-only*, and *both-task*. For the Standard ACVS-only group, the study consisted of six blocks of 84 trials of Standard ACVS. For the Color Cue ACVS-only group, the study contained six blocks of 84 trials of Color Cue ACVS. For the group that did both tasks, participants completed three blocks of Standard ACVS, followed by three blocks of Color Cue ACVS.

The study was run using a customized program hosted on our lab experiment server. The tasks were programmed in JavaScript with the use of jQuery (The jQuery Foundation, 2020) and D3.js library (Bostock et al., 2011) for stimulus rendering. PHP scripts were used to receive and write data to our server. All participants completed the task with their own computers that had a physical keyboard. At the start of each session, participants joined a virtual conference room with an experimenter (Zoom Video Communications, Inc., 2020). Participants were asked to use screen share to show the experimenter their browser windows with the task page opened. They were shown informed consent information before proceeding to task instructions. Participants read the task instruction pages by themselves, but they were free to ask questions about the task if there was any confusion. For the Standard ACVS, participants were told that there was one target in the red subset and one target in the blue subset, and for the Color Cue ACVS, participants were told that there was one target in the single subset group and one target in the two-subset group. However, in neither task did we explicitly inform participants what the optimal strategy was.

They then practiced the task for 10 trials and were given the chance to ask additional questions related to the task before the experimenter ended the virtual conference room. For the group that completed both tasks, participants were told in advance that they had to finish two tasks, and that after the first task they had to read the instructions and complete 10 practice trials before starting the second task. At the end of the session, the data were uploaded automatically to our lab experiment server.

Results and Discussion

Search accuracy was close to ceiling for all three groups (Standard ACVS-only M = 94.69%; Color Cue ACVS-only M = 96.29%; both-task M = 97.21% for Standard ACVS blocks and M = 95.87% for Color Cue ACVS blocks). The following analyses exclude incorrect trials and with RTs of less than 300ms or more than three standard deviations above the mean (3.12% of Standard ACVS-only trials, 2.38% of Color Cue ACVS-only trials, 2.02% of both-task trials). Although we did not anticipate it in our preregistration, our trial exclusion criteria necessitated that we had to exclude one more subject from the Standard ACVS-only group when reporting block-based data, because the exclusion left no trials for this subject in some blocks. For analyses involving bivariate correlations, we excluded outliers with a Mahalanobis distance of more than 13.82 ($p < .001$).

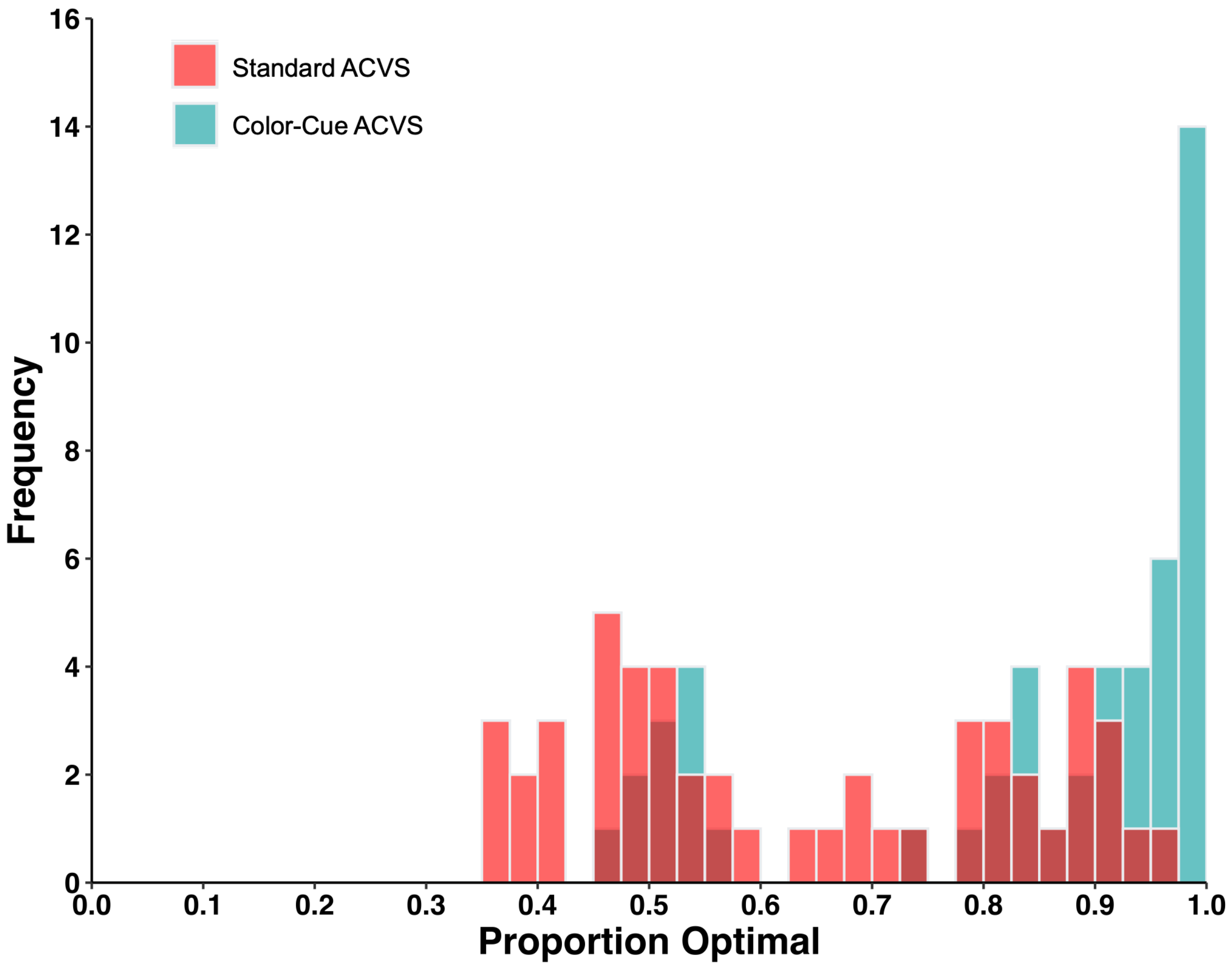

Figure 7. The distributions of mean proportion optimal in both the Standard ACVS and the Color Cue ACVS for the both-task group.

Descriptive Statistics. Search Optimality All three groups showed a wide range of individual differences in optimality measured by proportion of optimal choices. For the Standard ACVS-only group, proportion optimal ranged from .41 to .98 (*M* = .64, *SD* = .19) and for the Color Cue ACVS-only group, proportion optimal ranged from .43 to .99 (*M* = .74, *SD* = .21). For the both-task group, proportion optimal ranged from .36 to .96 (*M* = .64, *SD* = .19) in Standard ACVS and from .47 to 1.00 (*M* = .84, *SD* = .18) in Color Cue ACVS (Figure 7).

Search Response Times For the Standard ACVS-only group, the mean RT was 3076 ms (range 1610 – 5982, *SD* = 1015). For the Color Cue ACVS-only group, the mean RT was 3162 ms (range 1830 – 5294, *SD* = 826). For the both-task group, the mean RT was 3163 ms (range 1689 – 7436, *SD* = 1146) in Standard ACVS, and 2836 ms (range 1284 – 7257, *SD* = 1078) in Color Cue ACVS.

Frequency of Switching For the Standard ACVS-only group, the proportion of trials where subjects switched target types (from one color to the other) was .50 (range .11 – .67, *SD* = .10). For the Color Cue-ACVS-only group, the proportion of switched trials was 0.86 (range .76 – .93, *SD* = .03). For the both-task group, the proportion of switched trials was 0.48 (range .07 – .63, *SD* = .13) in Standard ACVS and .86 (range .71 – .97, *SD* = .05) in Color Cue ACVS. Note that in both groups, the frequency of switching in the Standard ACVS was greater in this study than in Study 1; this is likely due to the shorter run lengths of the optimal color in the present study, which meant that optimal choices necessitated more frequent switching.

Also, for the Color Cue ACVS, there was only a 2/3 probability that a chosen target color on one trial could also contain a target on the next trial (because on every trial, only two of the three sets of squares contained a target). This explains the higher switching rates compared to Standard ACVS, as well as a relatively restricted range across participants. This difference in task design may have affected correlation of switch frequency across tasks, though it was not of primary interest in our analyses.

Optimality – RT Correlation. We next tested whether higher optimality was associated with faster search speed. To do so, we calculated the correlation of optimality with RT in both Standard ACVS-only group and Color Cue ACVS-only group. As shown in Figure 8, for both paradigms, RTs were negatively correlated with proportion of optimal choices (Standard ACVS:

$r = -.70$, $t(48) = -6.72$, $p < .001$, 95% CI = [-.82, -.52]; Color Cue ACVS: $r = -.71$, $t(48) = -6.97$, $p < .001$, 95% CI = [-.82, -.54]), demonstrating that adopting the optimal strategy in both paradigms yielded faster search performance. Thus, unlike the Spatial ACVS in Study 1, we can be confident that participants experienced reliable advantages for choosing the optimal strategy in the Color Cue ACVS.

Correlation in Performance between the Two Paradigms. With the both-task group data, we were able to assess the correlation between individuals' performance on the two tasks in terms of their proportion of optimal choices, RT, and frequency of switching (see Figure 9). All three correlations were significant. Greater optimality in the Standard ACVS was associated with greater optimality in the Color Cue ACVS ($r = .33$, $t(48) = 2.46$, $p = .02$, 95% CI = [.06, .56]), faster RT in the Standard ACVS predicted faster RT in the Color Cue ACVS ($r = .64$, $t(46) = 5.70$, $p < .001$, 95% CI = [.44, .78]), and higher target switch rate in the Standard ACVS was associated with higher target switch rate in the Color Cue ACVS ($r = .30$, $t(47) = 2.18$, $p = .03$, 95% CI = [.02, .54]).

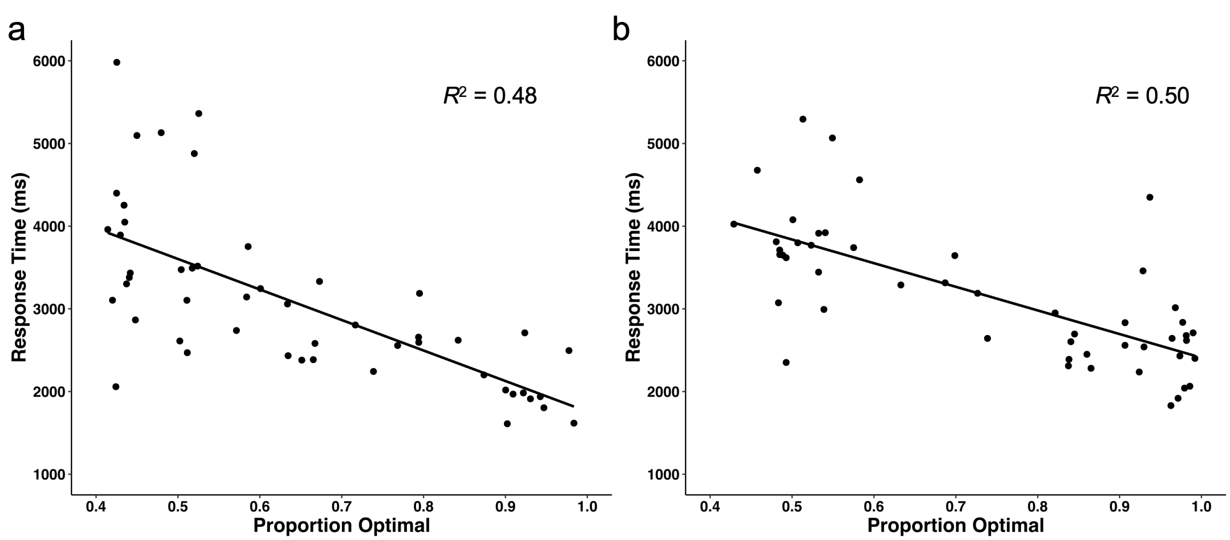

Figure 8. Scatterplots (with best-fitting regression lines) showing the correlation between proportion of optimal choice and response time for a) Standard ACVS-only group and b) Color Cue ACVS-only group.

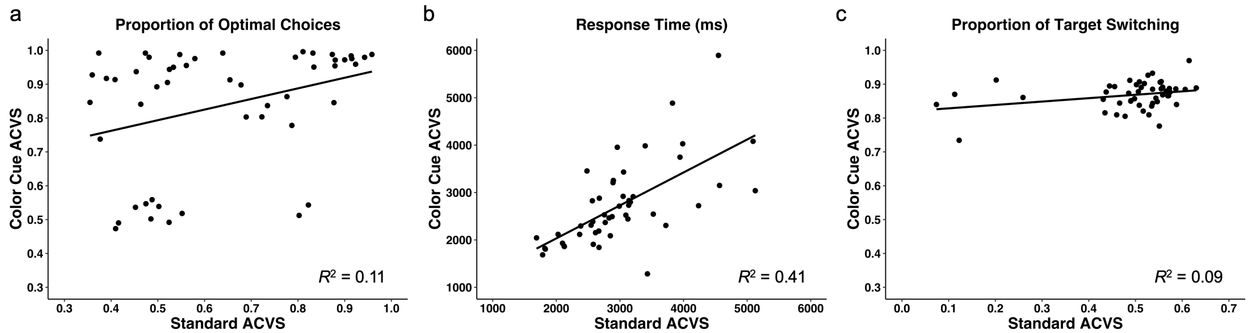

Figure 9. Scatterplots (with best-fitting regression lines) showing the correlation of a) proportion of optimal choices, b) response time, and c) proportion of target switching between Standard ACVS and Color Cue ACVS in both-task group.

Internal Consistency of Optimality. To estimate how similar the split-half reliability of the optimality measures in both paradigms is to the correlation between them, we calculated the Pearson correlation coefficients of proportion optimal between the first half of the task (Blocks 1 – 3) and the second half (Blocks 4 – 6) in Standard ACVS-only group and Color Cue ACVS-only group. Figure 10 shows the corresponding scatter plots. The split-half reliability of proportion optimal for Standard ACVS was r = .75 (t(48) = 7.92, p < .001, 95% CI = [.60, .85]). For Color Cue ACVS, it was r = .87 (t(48) = 12.26, p < .001, 95% CI = [.78, .93]). The observed split-half reliability and cross-task correlation may have been reduced by the somewhat restricted range of optimality in Color Cue ACVS by several participants with ceiling-level optimality.

The internal consistency measures of proportion optimal in both paradigms allowed us to then correct the cross-task correlation in the both-task group based on within-task variance, by calculating a disattenuated optimality correlation, r = .41, between Standard ACVS and Color Cue ACVS. Although, we should interpret this correction with caution because while we sampled our participants from the same population, we do not know how generalizable our reliability estimates are.

Although not included in our preregistration, we subsequently realized it was important to statistically test whether the cross-task optimality correlation was significantly different than our split-half reliability estimates of optimality from the single-task groups. That is, even though we have observed task generality in this study, it is important to assess the strength of the generality. Therefore, we statistically compared the cross-task correlation in strategy optimality with within-task correlation (i.e., split-half reliability) measures, using Fisher's (1925) z method and Holm-Bonferroni correction (Holm, 1979) to maintain a family-wise error rate of 0.05. We found that the cross-task correlation was significantly weaker than the split-half reliability of optimality in the Standard ACVS ($z = -3.07$, $p_{HB} = .004$) and the Color Cue ACVS($z = -4.80$, $p_{HB} < .0001$). This shows that, even with small changes in task, in which a measure of task generality can be detected, the generality is not strong.

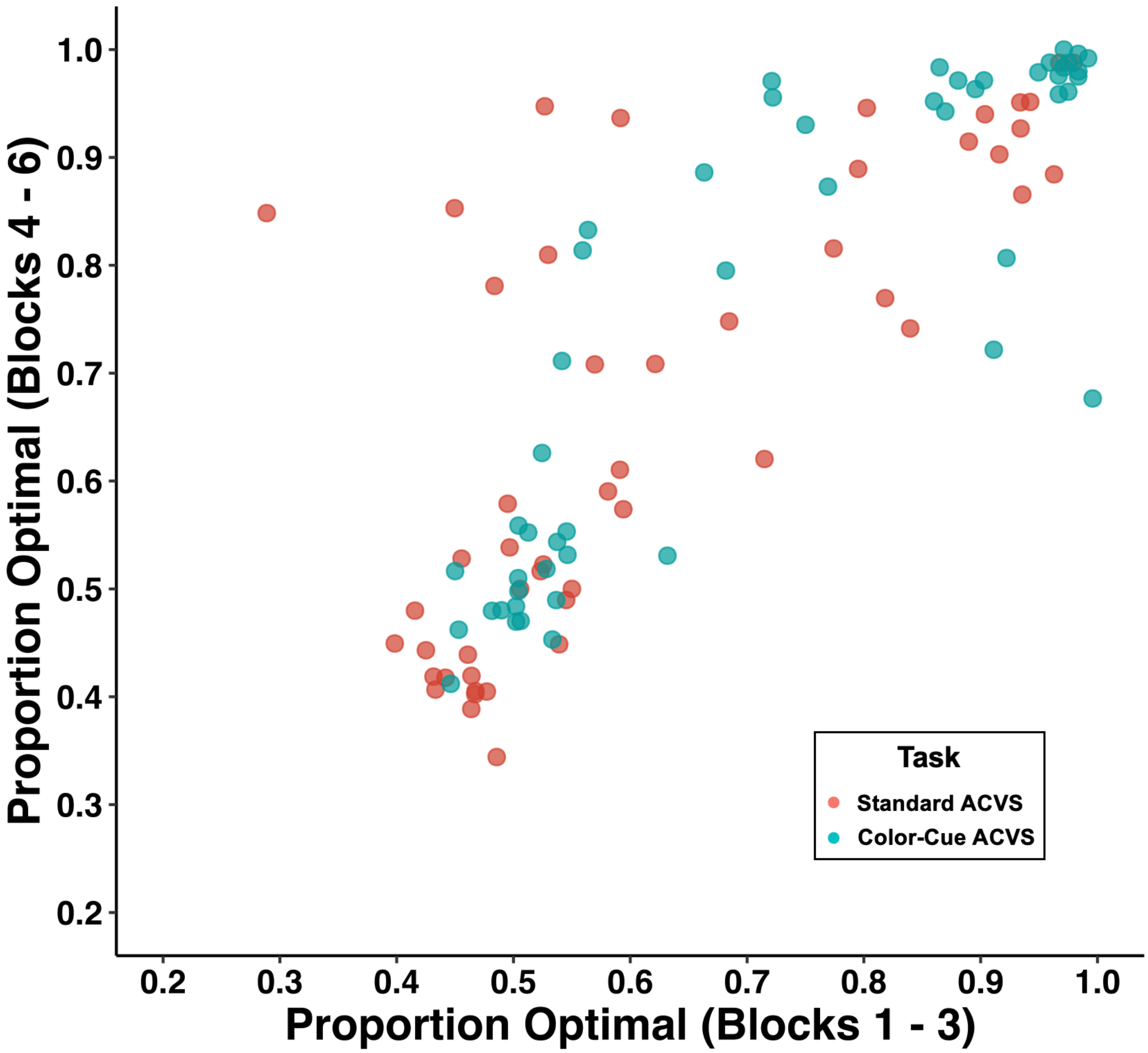

Figure 10. The scatterplot showing internal consistency of proportion optimal measured by split-half reliability between blocks 1 – 3 and blocks 4 – 6.

General Discussion

Understanding factors that control attention has been a mission for researchers over the past few decades. While existing research has largely focused on individuals' ability to exert goal-directed attentional control in visual search, another crucial factor—strategy—has been relatively overlooked despite the fact that it explains a significant source of variation in visual search performance. More recently, there has been an increased research interest in attentional control strategy using various paradigms and measurements (for a review, see Leber & Irons, 2019).

A complete understanding of individual differences in attentional control strategy, however, must take into consideration whether the tendency to optimize performance is task-general or task-specific (i.e., heterogeneous). The results of the present investigation offer an answer that can be viewed from two perspectives. First, the results support the notion that some degree of task generality exists, revealed via significant cross-task correlations in optimality for both studies.[2] Such findings had not been previously observed. At the same time, the results also show that people's strategy optimization is quite heterogeneous. Even with pairs of tasks that differed in only one substantive way, the cross-task correlations were quite low—and demonstrated in Study 2 to be significantly weaker than the robust within-task reliability estimates. This finding is quite consequential to our understanding of attentional strategy. In contrast to studies of attentional ability, in which many—if not most—ability metrics appear related to some degree (e.g., see Irons & Leber, 2020), strategy optimization across tasks is

[2] One alternative interpretation of our data is that that strategy optimization does not relate across tasks the way we have presumed. One can imagine that the data are comprised of two types of individuals. The first group consists of people who vary independently in how they optimize each of the two tasks. The second group is qualitatively different in that they do not even search by color (for Standard and Color Cue ACVS) or space (Spatial ACVS). Instead, they perform a random serial search on every trial and therefore score chance level optimality in both tasks. When these two groups of individuals are combined, a correlation in strategy optimization is realized. The first step in addressing such a concern is to remove all individuals plausibly belonging to the latter group, who have optimality scores centering around chance in both tasks. When we excluded participants whose proportion optimal were between .4 and .6 in both tasks, the cross-task correlation remained significant in Study 1, r (42) = 0.32, p = .03, but it was no longer significant in Study 2. Thus, for Study 2, we further examined whether those at chance-level optimality in both tasks (n = 9) were carrying out a search that ignored the color subsets. We found numerous signatures of a feature-based search in these individuals. In brief, all but one either a) showed a significantly biased level of switching between color subsets at a nonrandom rate, and/or b) demonstrated a significant bias toward searching within one color. Thus, we are confident that these individuals did make use of the color information in the displays, albeit in a consistently nonoptimal way across both tasks.

somewhat astonishingly heterogeneous. For researchers who seek to understand individual differences in the use of attentional strategy, this finding portends that much work lies ahead. That is, rather than obtaining a single measurement to establish trait variables for each individual, we may need to characterize several variables—and, perhaps even extensively map out a multidimensional space of all tasks—to fully characterize individual profiles of strategy optimization.

Related to this notion, it would be useful to know if the decline in generality of strategy optimization between tasks adheres to a *similarity gradient,* in which more similar tasks show greater correlations in strategy optimization. There is some qualitative support for this notion. Beginning with the present studies, we find significant cross-task correlations in optimization. In addition, other work with more disparate pairs of tasks failed to find significant cross-task correlations (Clarke et al., 2022; Li & Leber, 2021). Thus, in theory, it is plausible that cross-task correlations are weaker as pairs of tasks are more disparate. To properly test this idea, future research will need to systematically vary pairs of tasks in terms of their similarity and then determine if correlations do indeed vary along a similarity gradient.

Another issue worth consideration is how the degree of task generality relates to the generalizability of a learned strategy. When discussing task generality, we have presumed to be assessing individual's natural tendency to optimize performance on given tasks. However, it has previously been shown that strategy is malleable, via instructional manipulation (Bacon & Egeth, 1997; Irons & Leber, 2018b), or through past experience (Cosman & Vecera, 2013; Leber & Egeth, 2006). What remains unknown is whether the extent of strategy generality relates to the extent of learning generalizability of strategy. With respect to the latter, researchers have been interested for at least a century in whether improving one specific cognitive function via training can lead to the improvement of other cognitive functions (Woodworth & Thorndike, 1901). Whether there exists "far transfer," or skill generalization between domains that are loosely connected, has been a topic of heated debate (Anguera et al., 2013; Boot et al., 2011; Jaeggi et al., 2011; Morrison & Chein, 2011; Redick et al., 2013; Sala & Gobet, 2017; Schmiedek et al., 2010). Overall, evidence that strongly supports generalization of training-based improvement across tasks from different domains of cognitive abilities is scarce, making it difficult for cognitive training programs to generalize a specific training effect to a more general cognitive domain. Taken together with evidence from the present study, it is notable that not only is skill generalization not far, the generality of strategy optimization also does not extend "far" between tasks. However, it does remain unknown how far the learning of *strategy*, rather than skill, can generalize. Future research can explore this question.

Aside from the theoretical implications on the generality of strategy optimization, the present study introduces two paradigms that offer new ways to investigate attentional control strategies. A practical advantage for Spatial ACVS is that it allows easy eye tracking, thus enabling the test of hypotheses related to topics such as saccadic choice. Color Cue ACVS, on the other hand, incorporates cue usage that allows further research in how cue interpretation can be strategically used to attentional control and decision making.

Moreover, the Color Cue ACVS addresses one potential criticism of the Standard ACVS. Specifically, one can argue that the objects in the smaller subset—due to their lower numerosity and thus greater color contrast with their local neighbors (Nothdurft, 1993)—are each more salient than those in the larger subset. While the paradigm is designed to minimize the influence of this potential salience concern – via the inclusion of an irrelevant subset of green objects – it is plausible that individuals search the smaller subset due to salience rather than a drive to optimize performance. In the Color Cue ACVS, each of the colors has the same numerosity, thus preventing objects in the optimal group from being systematically more salient than those in the nonoptimal group. This paradigm is thus attractive to use in situations in which salience is a significant concern. Altogether, both new tasks add to a methodological toolbox offering varied ways for researchers to assess strategy optimality.

In conclusion, the present paper offers evidence that individuals' use of optimal strategies across visual search tasks with distinct attentional components does show some degree of task generality. The strength of such generality was notably small even between very similar tasks, underscoring the heterogeneity of strategy optimization. Overall, attentional control strategy seems neither completely unitary nor completely heterogeneous. Instead, strategy optimization is likely to be a complex construct with different subcomponents related to the stages of attentional processing in the task. Future research can continue to investigate the boundaries of the generality of strategy optimization across attentional tasks.

References

Anguera, J. A., Boccanfuso, J., Rintoul, J. L., Al-Hashimi, O., Faraji, F., Janowich, J., Kong, E., Larraburo, Y., Rolle, C., Johnston, E., & others. (2013). Video game training enhances cognitive control in older adults. *Nature*, *501*(7465), 97–101.

Appelbaum, M., Cooper, H., Kline, R. B., Mayo-Wilson, E., Nezu, A. M., & Rao, S. M. (2018). Journal article reporting standards for quantitative research in psychology: The APA Publications and Communications Board task force report. *American Psychologist*, *73*(1), 3.

Araujo, C., Kowler, E., & Pavel, M. (2001). Eye movements during visual search: The costs of choosing the optimal path. *Vision Research*, *41*(25–26), 3613–3625.

Bacon, W. F., & Egeth, H. E. (1994). Overriding stimulus-driven attentional capture. *Perception & Psychophysics*, *55*(5), 485–496.

Boot, W. R., Becic, E., & Kramer, A. F. (2009). Stable individual differences in search strategy?: The effect of task demands and motivational factors on scanning strategy in visual search. *Journal of Vision*, *9*(3), 7–7.

Boot, W. R., Blakely, D. P., & Simons, D. J. (2011). Do action video games improve perception and cognition? *Frontiers in Psychology*, *2*, 226.

Bostock, M., Ogievetsky, V., & Heer, J. (2011). D^3 data-driven documents. *IEEE Transactions on Visualization and Computer Graphics*, *17*(12), 2301–2309.

Brainard, D. H. (1997). The psychophysics toolbox. *Spatial Vision*, *10*(4), 433–436.

Clarke, A. D. F., Irons, J. L., James, W., Leber, A. B., & Hunt, A. R. (2022). Stable individual differences in strategies within, but not between, visual search tasks. *Quarterly Journal of Experimental Psychology*, *75*(2), 289–296. https://doi.org/10.1177/1747021820929190

Clarke, A. D., Green, P., Chantler, M. J., & Hunt, A. R. (2016). Human search for a target on a textured background is consistent with a stochastic model. *Journal of Vision*, *16*(7), 4–4.

Cosman, J. D., & Vecera, S. P. (2013). Context-dependent control over attentional capture. *Journal of Experimental Psychology: Human Perception and Performance*, *39*(3), 836.

Egeth, H. E., Leonard, C. J., & Leber, A. B. (2010). Why salience is not enough: Reflections on top-down selection in vision. *Acta Psychologica*, *135*(2), 130.

Egeth, H. E., Virzi, R. A., & Garbart, H. (1984). Searching for conjunctively defined targets. *Journal of Experimental Psychology: Human Perception and Performance*, *10*(1), 32.

Fisher, R. A. (1925). Statistical methods for research workers. Oliver and Boyd. *Edinburgh, Scotland*, *6*.

Folk, C. L., Remington, R. W., & Johnston, J. C. (1992). Involuntary covert orienting is contingent on attentional control settings. *Journal of Experimental Psychology: Human Perception and Performance*, *18*(4), 1030.

Green, B. F., & Anderson, L. K. (1956). Color coding in a visual search task. *Journal of Experimental Psychology*, *51*(1), 19.

Hansen, H. A., Irons, J. L., & Leber, A. B. (2019). Taking stock: The role of environmental appraisal in the strategic use of attentional control. *Attention, Perception, & Psychophysics*, *81*(8), 2673–2684.

Hogeboom, M., & van Leeuwen, C. (1997). Visual search strategy and perceptual organization covary with individual preference and structural complexity. *Acta Psychologica*, *95*(2), 141–164.

Holm, S. (1979). A simple sequentially rejective multiple test procedure. *Scandinavian Journal of Statistics*, 65–70.

Irons, J. L., & Leber, A. B. (2016). Choosing attentional control settings in a dynamically changing environment. *Attention, Perception, & Psychophysics*, *78*(7), 2031–2048. https://doi.org/10.3758/s13414-016-1125-4

Irons, J. L., & Leber, A. B. (2018a). Characterizing individual variation in the strategic use of attentional control. *Journal of Experimental Psychology: Human Perception and Performance*, *44*(10), 1637–1654. https://doi.org/10.1037/xhp0000560

Irons, J. L., & Leber, A. B. (2018b). Ignorance vs. Laziness: Why do people use suboptimal attentional control strategies? *Journal of Vision*, *18*(10), 630–630.

Irons, J. L., & Leber, A. B. (2020). Developing an individual profile of attentional control strategy. *Current Directions in Psychological Science*, *29*(4), 364–371.

Jaeggi, S. M., Buschkuehl, M., Jonides, J., & Shah, P. (2011). Short-and long-term benefits of cognitive training. *Proceedings of the National Academy of Sciences*, *108*(25), 10081–10086.

Kleiner, M., Brainard, D., & Pelli, D. (2007). *What's new in Psychtoolbox-3?*

Kristjánsson, Á., Jóhannesson, Ó. I., & Thornton, I. M. (2014). Common attentional constraints in visual foraging. *PloS One*, *9*(6), e100752.

Li, W. Y., & Leber, A. B. (2021, November). Attentional strategy use in a combined target choice and foraging task. Poster presented at the 29th Annual Object Perception, Attention, and Memory (OPAM) Workshop. https://doi.org/10.17605/osf.io/ghm9u.

Leber, A. B., & Egeth, H. E. (2006). It's under control: Top-down search strategies can override attentional capture. *Psychonomic Bulletin & Review*, 13(1), 132-138.

Leber, A. B., & Irons, J. L. (2019). A methodological toolbox for investigating attentional strategy. *Current Opinion in Psychology*, *29*, 274–281.

McKinney, M. R., Irons, J. L., & Leber, A. B. (2020). Monetary reward motivates the adoption of optimal attentional control strategies. *Journal of Vision*, *20*(11), 1671–1671.

Mollon, J. D., Bosten, J. M., Peterzell, D. H., & Webster, M. A. (2017). Individual differences in visual science: What can be learned and what is good experimental practice? *Vision Research*, *141*, 4–15.

Morrison, A. B., & Chein, J. M. (2011). Does working memory training work? The promise and challenges of enhancing cognition by training working memory. *Psychonomic Bulletin & Review*, *18*(1), 46–60.

Morvan, C., & Maloney, L. T. (2012). Human visual search does not maximize the post-saccadic probability of identifying targets. *PLoS Comput Biol*, *8*(2), e1002342.

Muhl-Richardson, A., Godwin, H. J., Garner, M., Hadwin, J. A., Liversedge, S. P., & Donnelly, N. (2018). Individual differences in search and monitoring for color targets in dynamic visual displays. *Journal of Experimental Psychology: Applied*, *24*(4), 564.

Nosek, B. A., Alter, G., Banks, G. C., Borsboom, D., Bowman, S. D., Breckler, S. J., Buck, S., Chambers, C. D., Chin, G., Christensen, G., & others. (2015). Promoting an open research culture. *Science*, *348*(6242), 1422–1425.

Nothdurft, H. C. (1993). Saliency effects across dimensions in visual search. *Vision Research*. *33*(5-6), 839-844.

Nowakowska, A., Clarke, A. D., & Hunt, A. R. (2017). Human visual search behaviour is far from ideal. *Proceedings of the Royal Society B: Biological Sciences*, *284*(1849), 20162767.

Pauszek, J. R., & Gibson, B. S. (2018). The Least Costs Hypothesis: A rational analysis approach to the voluntary symbolic control of attention. *Journal of Experimental Psychology: Human Perception and Performance*, *44*(8), 1199.

Pelli, D. G. (1997). The VideoToolbox software for visual psychophysics: Transforming numbers into movies. *Spatial Vision*, *10*, 437–442.

Redick, T. S., Shipstead, Z., Harrison, T. L., Hicks, K. L., Fried, D. E., Hambrick, D. Z., Kane, M. J., & Engle, R. W. (2013). No evidence of intelligence improvement after working memory training: A randomized, placebo-controlled study. *Journal of Experimental Psychology: General*, *142*(2), 359.

Sala, G., & Gobet, F. (2017). Does Far Transfer Exist? Negative Evidence From Chess, Music, and Working Memory Training. *Current Directions in Psychological Science*, *26*(6), 515–520.

Schmiedek, F., Lövdén, M., & Lindenberger, U. (2010). Hundred days of cognitive training enhance broad cognitive abilities in adulthood: Findings from the COGITO study. *Frontiers in Aging Neuroscience*, *2*, 27.

Vacha-Haase, T. (1998). Reliability generalization: Exploring variance in measurement error affecting score reliability across studies. *Educational and Psychological Measurement*, *58*(1), 6–20.

Von Mühlenen, A., & Lleras, A. (2004). Spatial context and top-down strategies in visual search. *Spatial Vision*, *17*(4), 465–482.

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

Woodworth, R. S., & Thorndike, E. L. (1901). The influence of improvement in one mental function upon the efficiency of other functions. *Psychological Review*, *8*(3), 247.

Zohary, E., & Hochstein, S. (1989). How serial is serial processing in vision? *Perception*, *18*(2), 191–200.

Figures and Captions

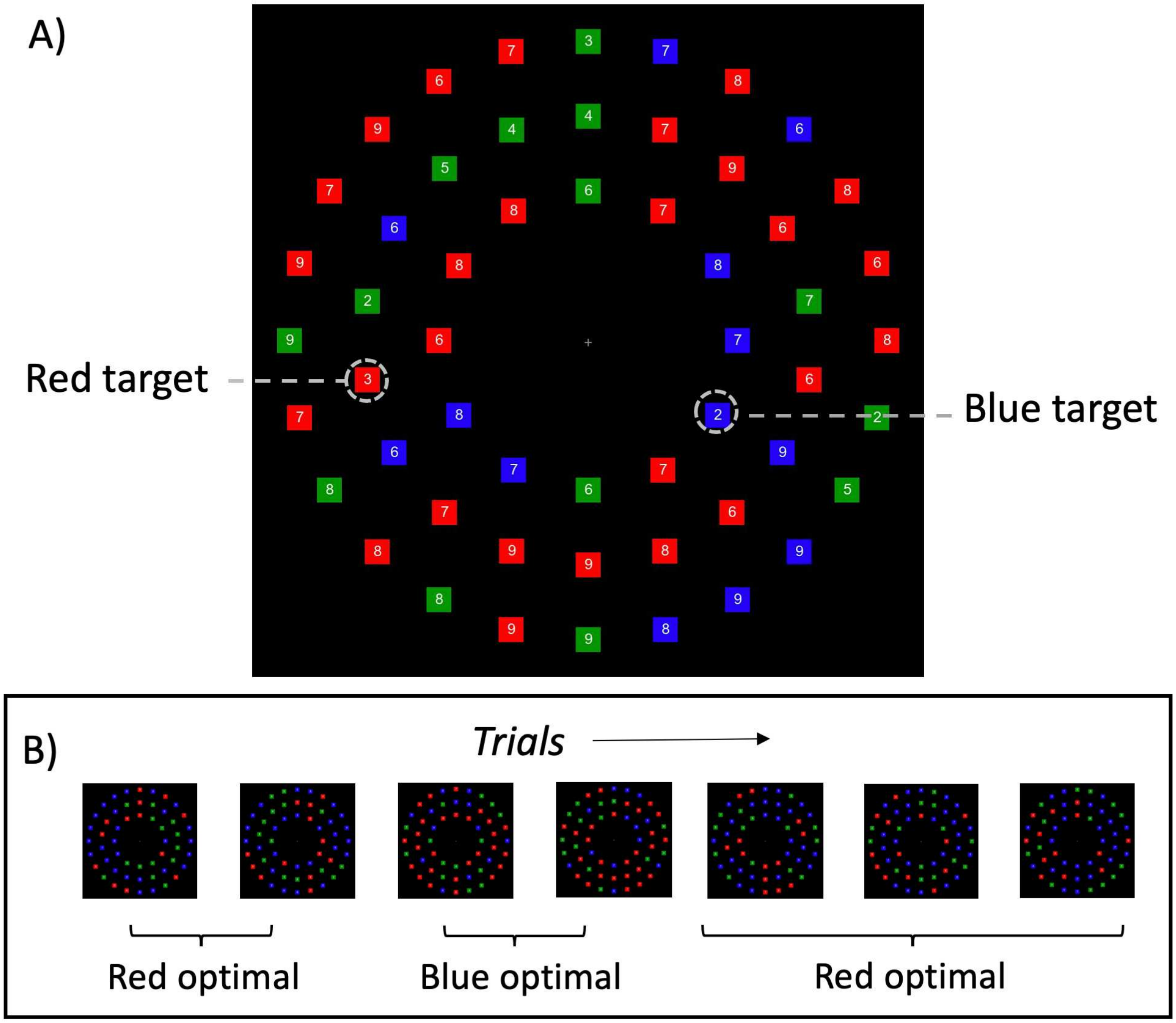

Figure 1. An example stimulus array (a) and series of trials (b) in the Adaptive Choice Visual Search (ACVS). Each display contains a red target and a blue target, each defined as a 2, 3, 4, or 5.

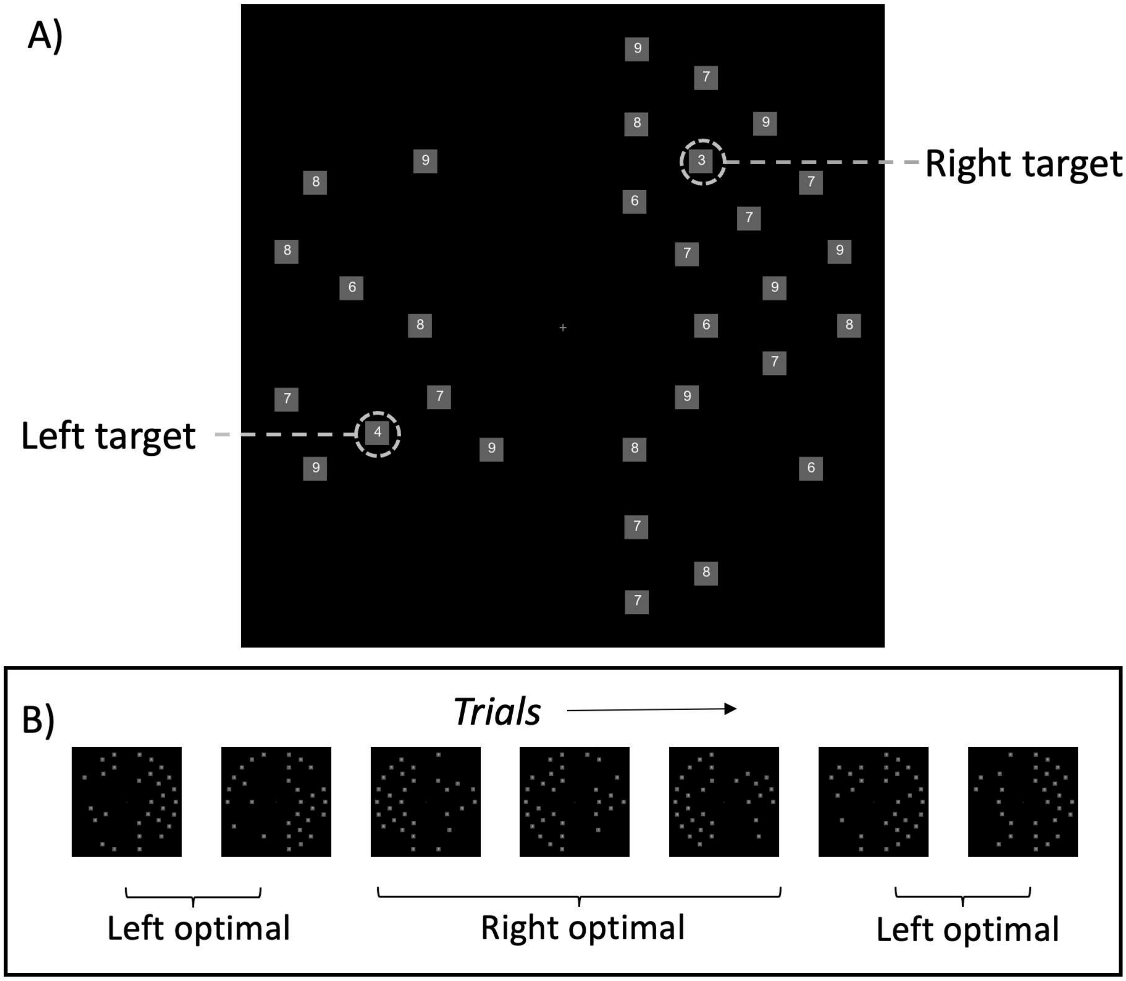

Figure 2. An example stimulus array (a) and trial sequence (b) in the Spatial ACVS. Each display contains two targets on both sides of the display. Target squares contained digits 2, 3, 4, or 5.

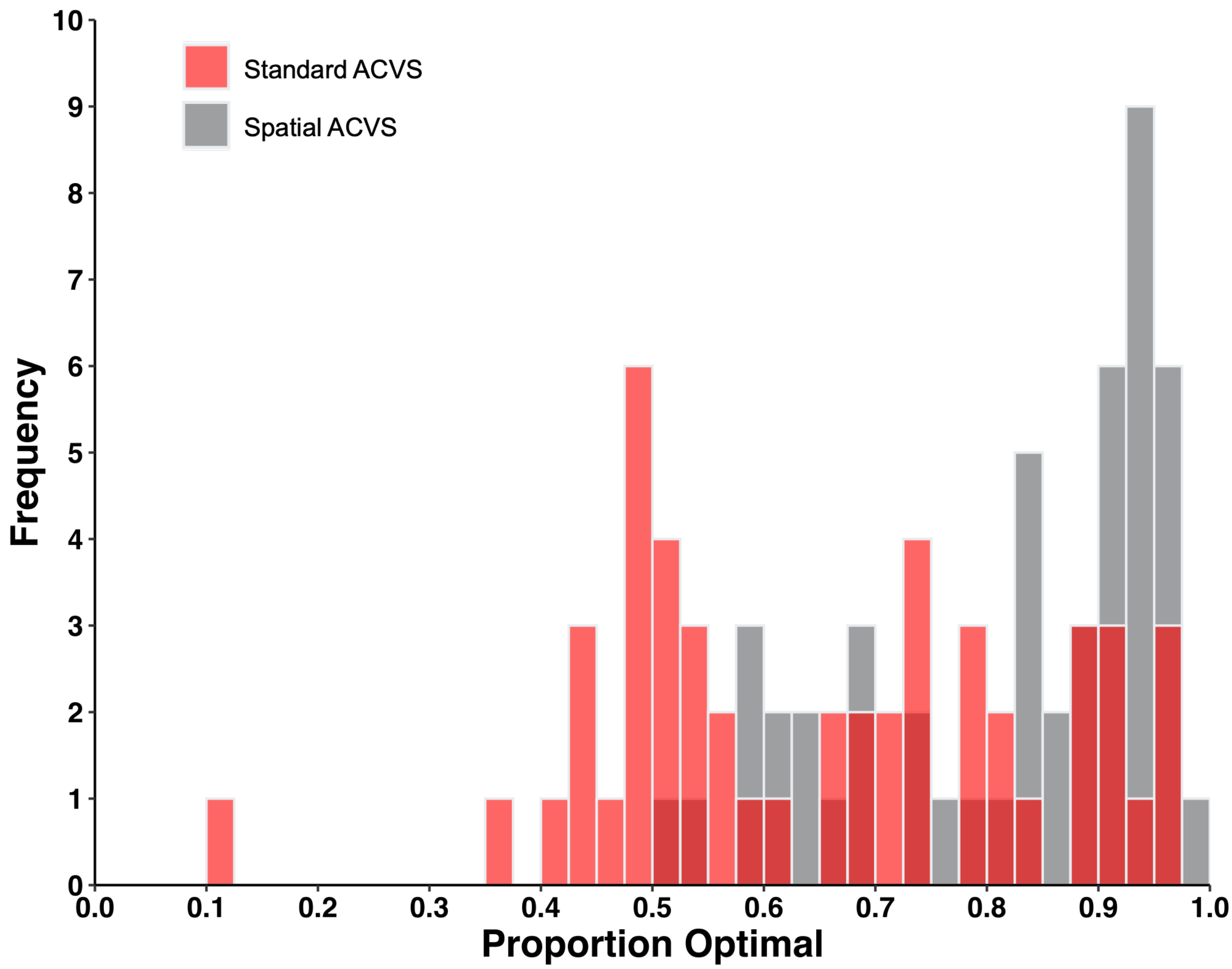

Figure 3. The distributions of mean proportion optimal in both the Standard ACVS and the Spatial ACVS.

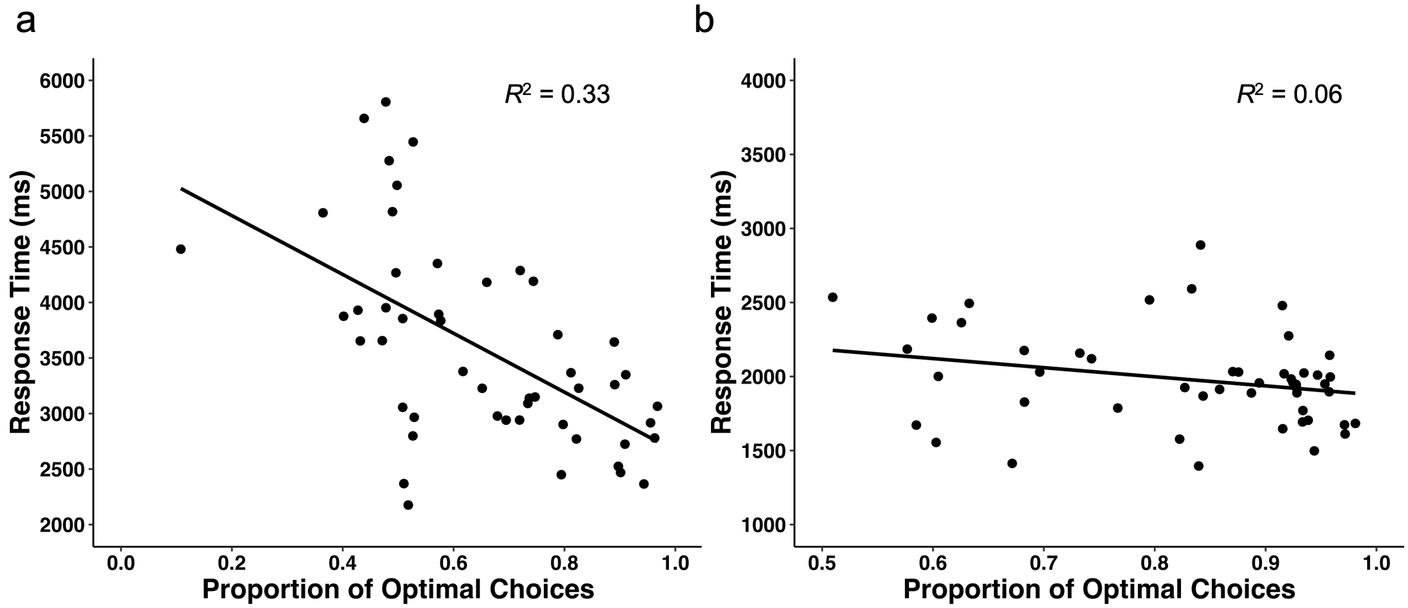

Figure 4. Scatterplots (with best-fitting regression lines) showing the correlation between proportion of optimal choice and response time in a) Standard ACVS and b) Spatial ACVS.

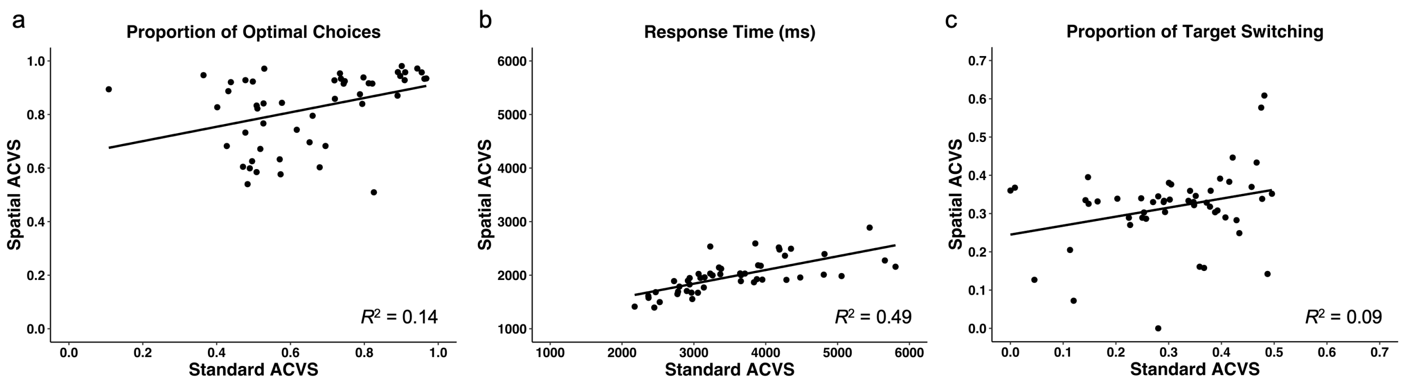

Figure 5. Scatterplots (with best-fitting regression lines) showing the correlation of a) proportion of optimal choices, b) response time, and c) proportion of target switching between Standard ACVS and Spatial ACVS.

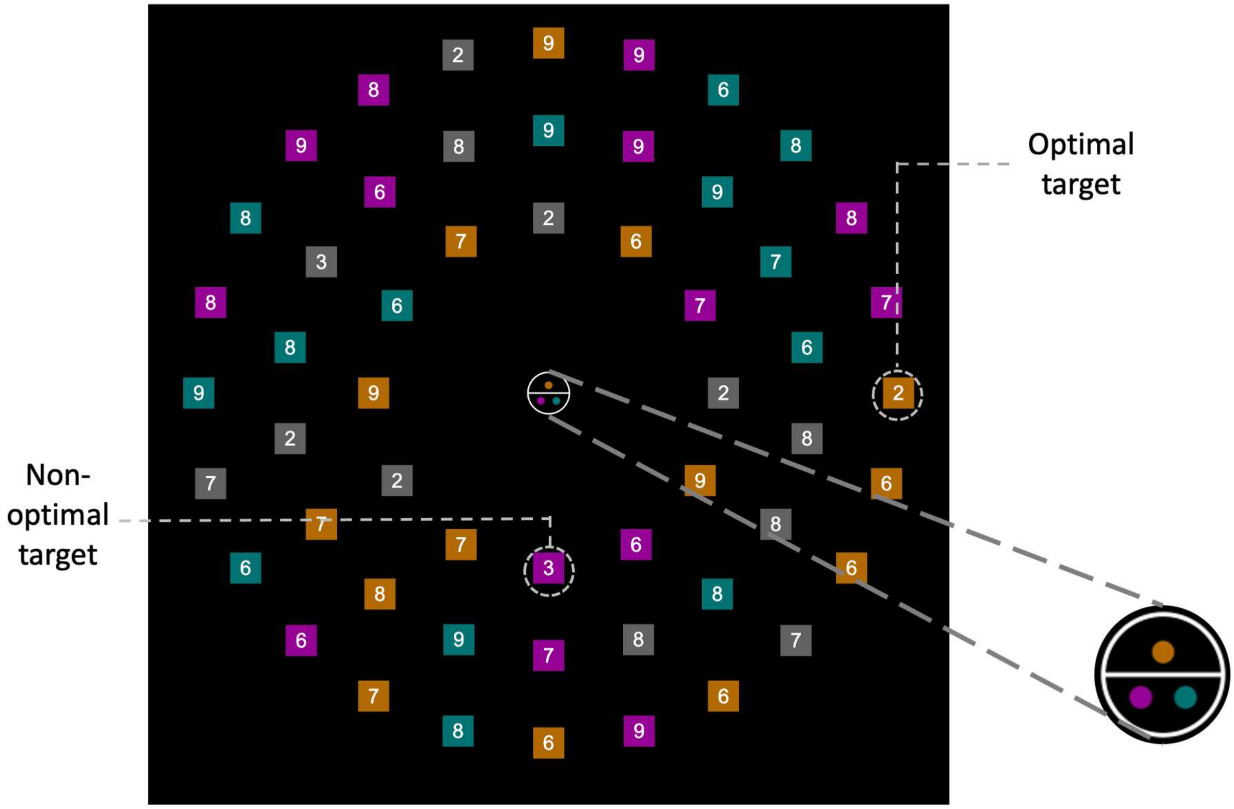

Figure 6. An example display of the Color Cue ACVS. The search array has three equal-sized task-relevant subsets of squares (14 items per subset) colored magenta, cyan, and orange, and one task-irrelevant subset of squares (12 items) colored grey. The three task-relevant subsets of squares are organized into two groups such that one subset is assigned the small group and the remaining two subsets are combined to form the large group. The central cue indicates what the group arrangement is, such that each half of the circle contains the dot(s) representing the colored subset(s) in each group. In this example, the cue shows that the large group contains magenta and cyan squares, and the small group contains orange squares.

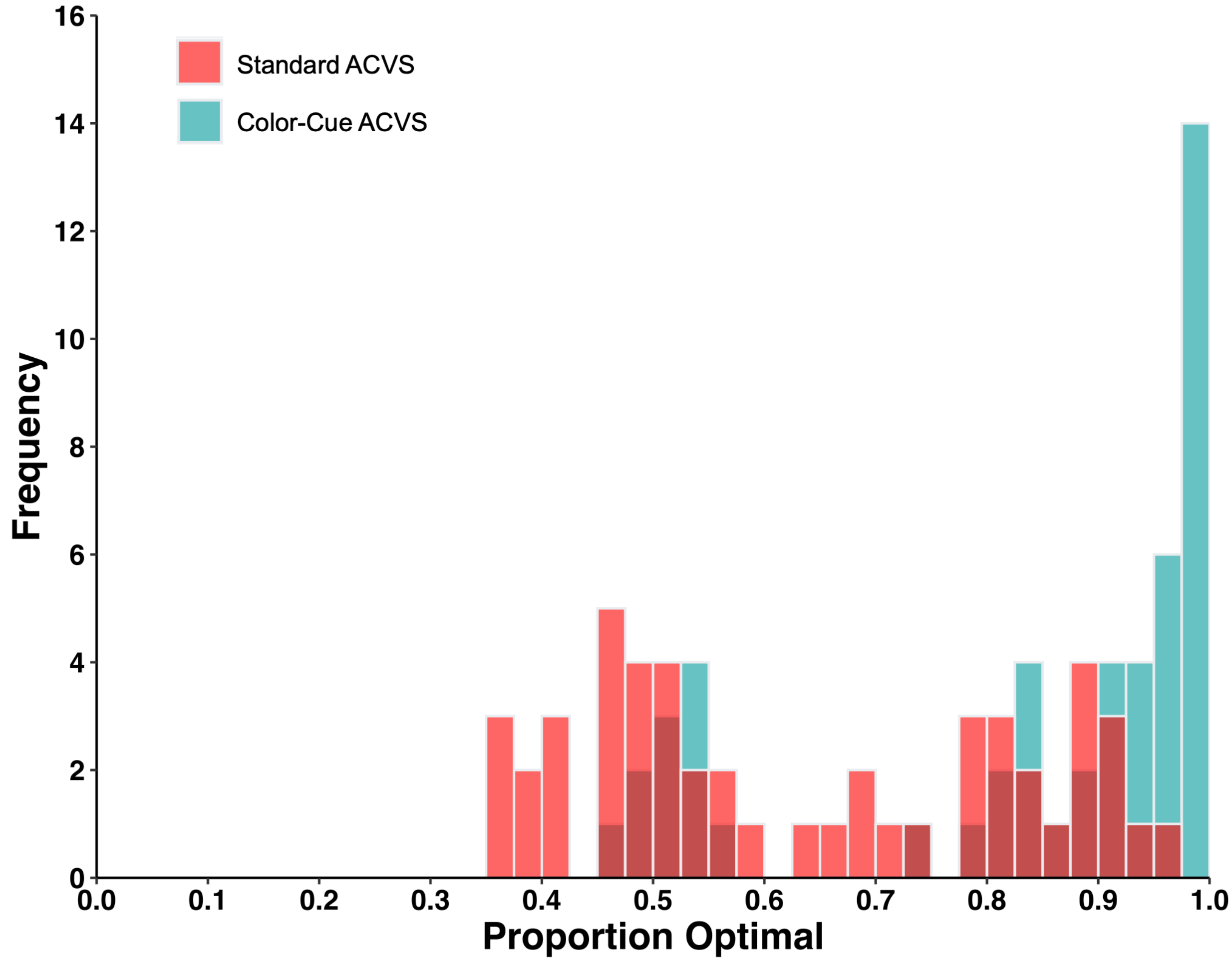

Figure 7. The distributions of mean proportion optimal in both the Standard ACVS and the Color Cue ACVS for the both-task group.

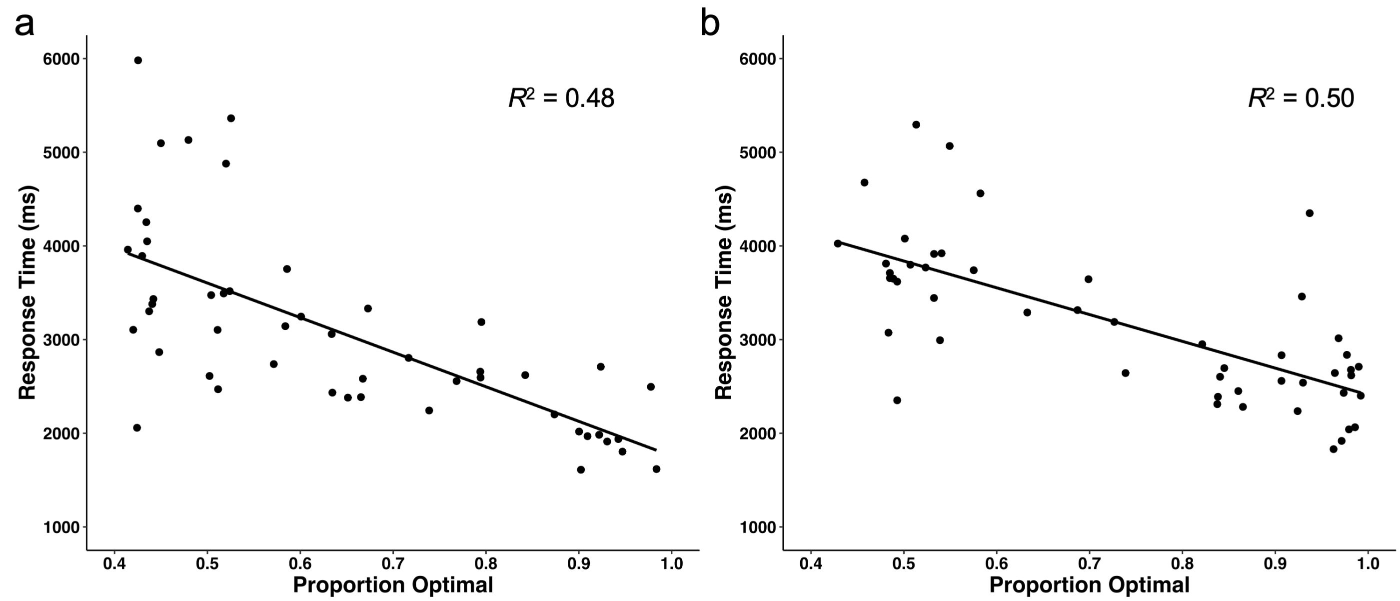

Figure 8. Scatterplots (with best-fitting regression lines) showing the correlation between proportion of optimal choice and response time for a) Standard ACVS-only group and b) Color Cue ACVS-only group.

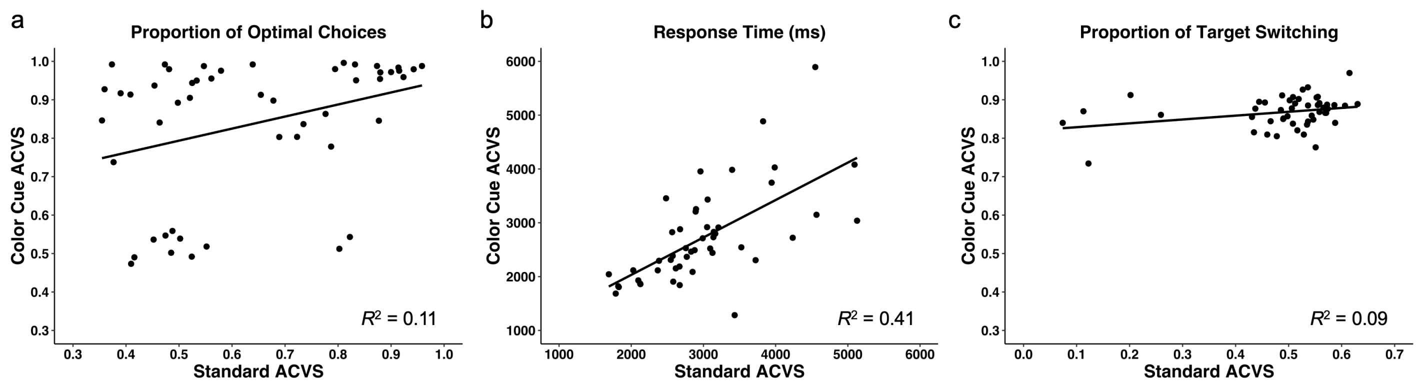

Figure 9. Scatterplots (with best-fitting regression lines) showing the correlation of a) proportion of optimal choices, b) response time, and c) proportion of target switching between Standard ACVS and Color Cue ACVS in both-task group.

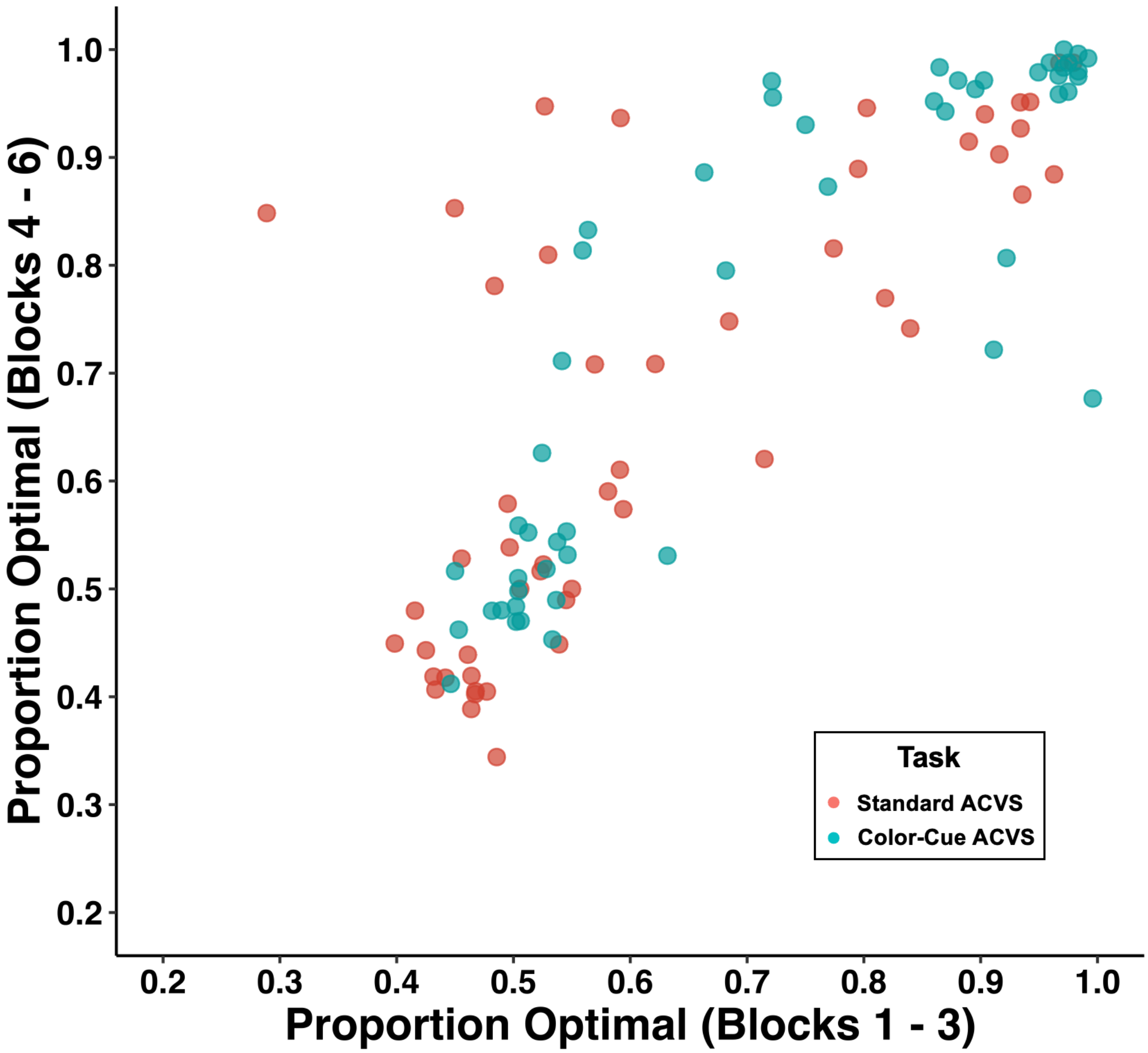

Figure 10. The scatterplot showing internal consistency of proportion optimal measured by split-half reliability between blocks 1 – 3 and blocks 4 – 6.