Disclaimer

The work is part of an ongoing undergraduate thesis project; some of the data is not accessed and analyzed, so the corresponding sections are not finished.

Exploring the generalizability of visual search strategy in different settings

Undergraduate Research Thesis

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By Walden Li

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Project Advisor:

Professor Andrew Leber, Department of Psychology

Abstract

When searching our visual environment, we often have multiple strategies available (e.g., when looking for your favorite apples on a supermarket shelf, you can either look for the red ones or the round ones, or just serially search through all items). How do we choose a strategy? Recent research on this question has revealed substantial variation across individuals in attentional control strategies. Moreover, while attentional strategies have been found to be reliable within subjects, they have failed to generalize across different paradigms that assess various components of strategy use (Clarke et al., 2018). Thus, evidence for whether strategies generalize beyond a single paradigm remains scarce. While previous tests of generalizability used paradigms that vary in many ways, here, we foused on a single strategy component that could be preserved across tasks, while making several other changes. In two experiments, we assessed the correlation between individuals' strategies in the standard adaptive choice visual search (ACVS; Irons & Leber, 2018) and a modified novel visual search task, Spatial ACVS. In the Standard ACVS, participants seeking to perform optimally have to enumerate subsets of different colored squares and identify the smaller subset to choose a target from. Similarly, in the Spatial ACVS, participants seeking optimal performance have to enumerate spatially separate subsets of squares (one on the left and one on the right side of the display), choosing the target in the smaller subset. Participants finished both tasks in the same order in one experimental session. Results showed a positive correlation in optimal target choices between the two tasks, indicating similar strategy usage. Future studies can focus on what strategy components tend more to be generalized across tasks and whether an individual's strategy can generalize to tasks with a combination of several strategy components.

Keywords: visual search, attentional control, strategy, individual difference, numerosity

Introduction

Imagine you are in a stadium watching an exciting women's soccer championship final with your friends. It is a critical move, and the key player of your home team wants to pass the ball forward to the striker. What can she do? While the striker is surrounded by many defenders, she knows that she can either look for red shirts or blue shorts because that is what her team wears. But imagine when the opposing team wears shorts that closely resemble blue—maybe indigo. In this case, trying to search for blue shorts gives the player less of an advantage, since she needs to search through more potential targets to locate the striker. In this example, the strategy that the player uses is not a good one that will yield efficient search. While the optimal strategy often yields efficient search, people often abandon using it (Bacon & Egeth, 1994). Visual search is not limited to sports—many responsibilities, including airport baggage screening and radiological image reading, involve visual search.

One of the recent studies that have made a successful attempt on characterizing individual differences in visual search strategy introduces a new visual search paradigm—the adaptive choice visual search task (ACVS; Irons & Leber, 2016). The paradigm differs from traditional ones in that it allows subjects to choose freely from two target squares in each trail, where only one of the targets is the optimal choice. Researchers are able to access an individual's strategy use with two key measurements in the task: the proportion of optimal choices, which is the percentage of trials in which participants choose the optimal target, and the switch rate, the percentage of trials in which participants switch between two target types. Efficient searchers typically select more optimal targets and avoid unnecessary switches during the experiment, showing high proportion of optimal choices and lower switch rates. These two crucial parameters, then, grant the ACVS the ability to improve the current research of goal-directed attentional control by adding strategy measurements to the methodology toolbox beyond traditionally used reaction times and accuracy. Studies with the adaptive choice visual search task have shown a broad range of individual differences in the proportion of optimal choices and switch rates (Irons & Leber, 2016), both of which have also been proved to have good test-retest reliability, suggesting a trait-like behavior pattern. Further studies have shown that an individual's subjective perception of effort and performance adopting the strategies predicted their optimal target choice (Irons & Leber, 2018).

Does an individual who adopts an optimal strategy in the ACVS also search optimally in other visual search tasks? Stability in an individual's key measurements of their strategy seems to augur success in characterizing individual visual search strategy in a dynamically changing environment. In a recent study using three different established visual search tasks, the split-half line segment task (Nowakowska et al., 2017), conjunction foraging (Kristjánsson et al., 2014), and the ACVS, Clarke and colleagues (2018) found that individuals exhibited consistent optimality measurements within the three tasks. Surprisingly, however, neither the proportion of optimal choices nor even reaction times correlated across these tasks. This null result does not necessarily mean a failure in investigating the stability of individual search strategy. It is likely that the above mentioned visual search tasks involve different components that determine the frequency an individual adopts an optimal strategy. Just like a world-class runner or swimmer may not choose to actively engage in triathlon races, an individual who does not excel at all sub-components of a certain visual search task may fail to perform optimally overall. Real-world visual search scenarios involve even more complex components which may contribute to more confounds in characterizing an individual's strategy. Nevertheless, a full understanding of individual search strategy cannot be achieved without tackling these individual components.

The present study aims to start the exploration by testing the generalizability of the ACVS paradigm. Specifically, if we ask participants to complete a similar visual search task that keeps all the sub-components, will they behave as optimally as they do in the ACVS? If we remove or add some components to the task, will they still make optimal choices as frequently? What are the components that seem to be more "important" than others?

To make an optimal choice in an ACVS trial, participants should first extract statistical summary information by appraising the display. In specific, they need to know which color has more or fewer squares, or which color occupies more or less space, in the search array. Then, they need to deploy their attention to the smaller subset of colored squares, and search through the subset until one of the squares have a digit that belongs to the target digit set held in working memory. At least one of these stages has been shown to be critical in making optimal choices: by disrupting the appraisal phase with an irrelevant task, participants showed reduced optimality (Hansen, Irons, & Leber, 2019).

To create a novel visual search scenario while keeping these components, we modified the adaptive choice visual search paradigm so that color is no longer a defining feature of the targets which can serve as a guidance in search, but rather the spatially-dependent numerosity. We call this new paradigm the spatial ACVS. Similar to the original version, participants are free to choose either one of the two targets, and since choosing one target (the optimal target) requires searching through fewer squares than the other, a participant's overall response time correlates well with the frequency of selecting the optimal target. The configuration of each display, however, varies spatially. Specifically, the two targets are separated from each other the left side and right side of the display, surrounded by different number.

According to the classical theories of numerical cognition, human perception of numerosity involves separate systems for small and large numerosities (see Leibovich et al., 2016, for a recent review). When making numerosity comparisons beyond “subitizing” range (1 - 4), error rates change linearly with the contrast between two numerosities (Feigenson et al. 2004). In other words, participants find the comparison more and more difficult as the numerosity of two groups of items gets closer and closer. Given that subjective cognitive effort has been shown to negatively correlate with optimal strategy choice (Irons & Leber, 2018), we predict that the proportion of optimal choices will also correlate with the ratio between two groups of squares.

In Experiment 2, we tested the correlation between an individual’s strategy use in the spatial version and the original ACVS. Since an individual’s optimality reflects their subjective cognitive effort, we set the ratio of the two sides to be the one that best approximates the overall optimality of the original ACVS. Under this manipulation, adopting the optimal strategy in the spatial version should overall be perceived as effortful as Standard ACVS. If an individual’s visual search strategy is stable within tasks that involve the same sub-components and are perceived similarly effortful, the proportion of optimal choices should be well-correlated between these two tasks.

In Experiment 3, we moved on to assess if an individual who adopts a certain visual search strategy in Standard ACVS would use the same strategy in Spatial ACVS. If strategy use is consistent, then an individual’s proportion of optimal choices and target switch rate will be positively correlated.

Experiment 1

The goal of Experiment 1 was to create a novel visual search environment similar to the ACVS that could produce the same level of optimality across all individuals. Three key elements of the visual search environment should be taken into consideration. First, there are two targets, which can be easily separated into two categories, available for the participant to choose from in each display. Second, searching one target instead of the other should always take less effort. In each trial of the ACVS, there are red, blue, and green squares in the display. Targets are set to be one of the red squares and one of the blue squares, and green squares are distractors. Critically, the total number of red squares and blue squares are different in each display, which creates a discrepancy in the effort the participant must put into searching for the target (i.e., searching for a particular colored target requires going through fewer squares than the other target).

To create a visual search setting that retains these key elements of the previous task, we designed a new task in which the target feature was defined as spatial location. Participants need to search for a target square among many other distractor squares. There are two targets available in each display, grouped according to their spatial location—one of the targets is on the left side and the other is on the right side—and participants are free to choose either one. Importantly, the number of distractor squares is different on each side, with one side always having fewer squares than the other. Thus, similar to the previous task, searching for one target will be faster than searching for the other.

Since it will be increasingly difficult to identify the numerosity contrast when it gets smaller (Feigenson et al. 2004), we predicted that the proportion of optimal choices would increase as the numerosity contrast increases. However, there still should be individuals who reliably adopt the optimal strategy even for the Small contrast condition because it is larger than the just noticeable difference (Dehaene et al., 2008).

Method

Participants. Twenty-four individuals (10 male, 14 female) aged 18 to 26 (*M* = 18.63) were recruited from The Ohio State University. All participants had self-reported normal or corrected-to-normal visual acuity and normal color vision.

Apparatus. Participants completed the experiment in a dimly lit, sound-attenuated room. The experiment was programmed with Psychophysics Toolbox (Brainard, 1997; Pelli, 1997) implemented in MATLAB (Mathworks, Natick, MA, USA). Stimuli were presented using a Mac Mini computer and 24-inch LCD monitor. Participants were seated at a viewing distance of approximately 60 cm from the screen.

Stimuli. The stimuli were based on previous versions of the ACVS (Irons & Leber, 2016, 2018; Hansen, Irons, & Leber, 2019), with some spatial modifications. Different number of grey squares (sized 1° x 1°, RGB: 97, 97, 97) were placed at different sides (i.e., the left side and the right side) of each display on three concentric rings with 6.3°, 9.4°, and 12.4° eccentricity from the innermost to the outermost.

All squares had a small white digit between 2 and 9 was superimposed on the center. Each search array contained two targets, one on each side of the display. All target squares had digits between 2 and 5, and all distractor squares had digits between 6 and 9 superimposed on them. Target digits were chosen pseudorandomly such that each digit appeared equally often on both targets, and the two targets on each trial always contained different digits to enable us to determine which target was chosen by the participant.

Procedure. The experiment used a blocked design with three reference ratios of non-optimal versus optimal side number of squares: 1.17, 1.54, and 2.0, corresponding to Small, Medium, and Large contrast conditions. This gives three types of display, with the non-optimal side always having 20 squares, and the optimal side having 17, 13, and 10 squares, with respect to each contrast. All targets were generated in a pseudorandom manner that held the total target eccentricity constant for all participants. All distractors were generated at complete random. Two blocks of the same ratio were grouped together, making up a total of six blocks of 72 trials (432 total trials). The order of the ratios presented were completely counterbalanced across participants, with four participants completing each possible order. The number of times that optimal target appeared on each side were balanced for each participant, and no more than three times the optimal target appeared on the same side to avoid pattern suggesting.

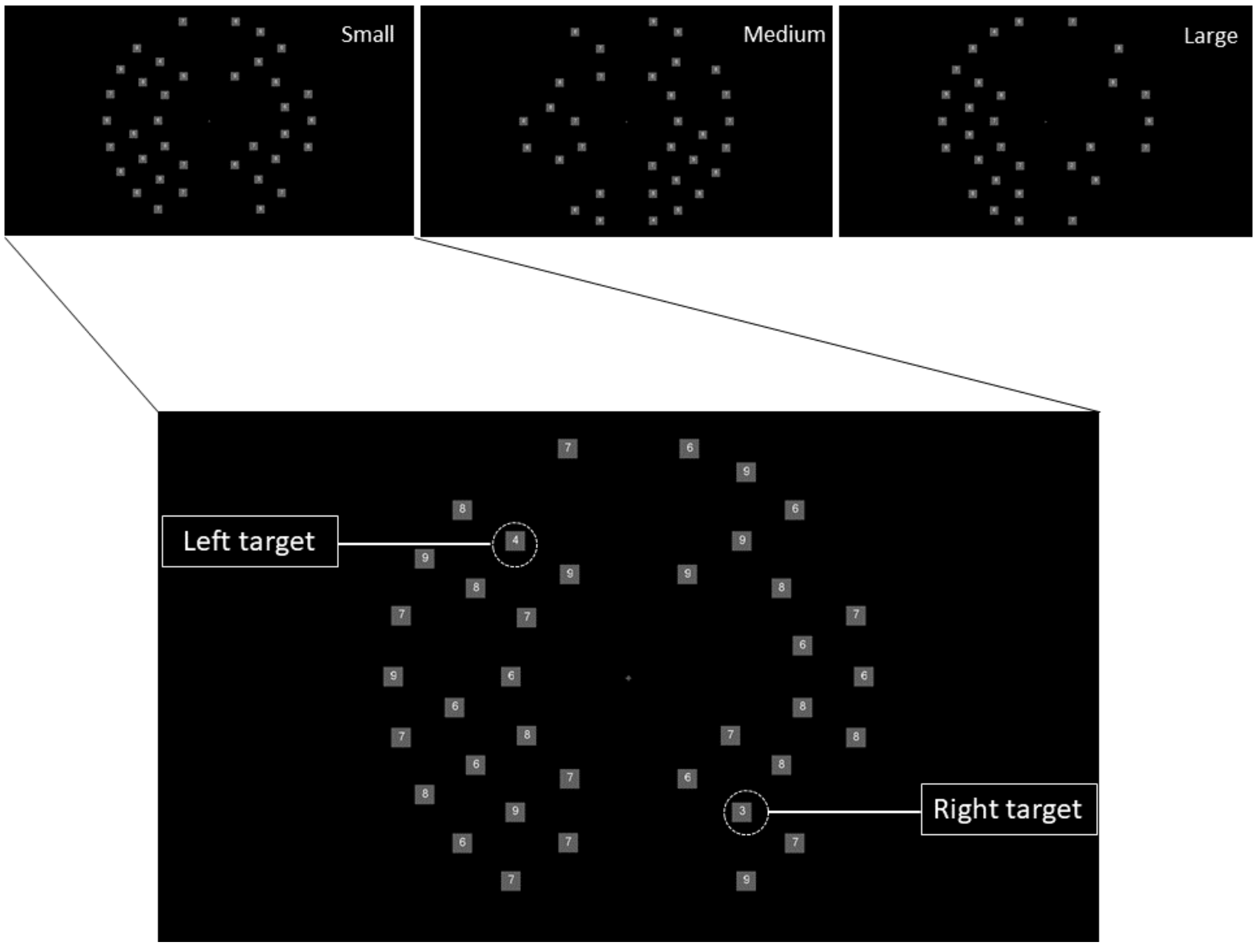

Figure 1. Sample displays with three different numerosity contrasts. The Small, Medium, and Large contrast displays have ratios 1.17:1, 1.54:1, and 2.00:1, respectively. In every display, there will be a left target and a right target. The side on which there are more squares is counterbalanced across trials.

Results

Data from one participant whose accuracy was more than three SD below the group mean was removed from analyses. Incorrect trials and trials in which participants responded in less than 300 ms or more than 3 SD above the participant's mean were removed from analyses. Overall, the accuracy of the task was close to ceiling (*M* = 97.93%).

Proportion Optimal increases with contrast: Small (Range 42.34% - 65.69%, *M* = 52.04%, *SD* = 5.273%), Medium (Range 51.77% - 86.23%, *M* = 60.12%, *SD* = 8.192%), and Large (Range 51.82% - 96.40%, *M* = 70.44%, *SD* = 12.75%).

In the Small contrast (i.e., the ratio 1.17) condition, participants' optimality were not different than chance ($t(23) = 1.899$, p = .070).

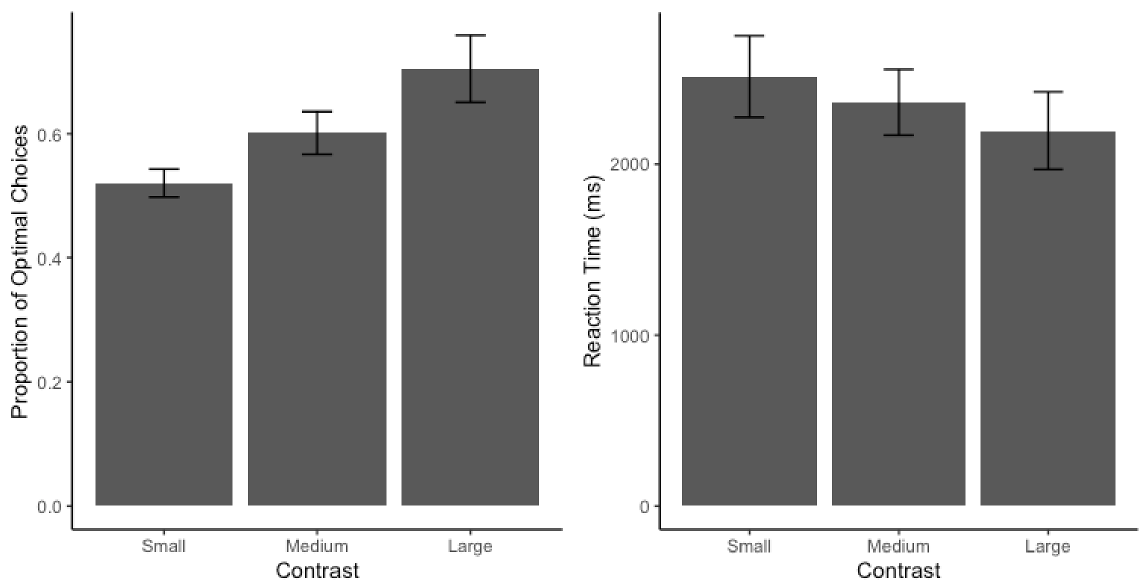

Figure 2. Proportion of optimal choices and reaction times under each of the contrast conditions. Error bars represent the 95% confidence interval.

A linear regression was calculated to predict proportion optimal based on ratio. A significant regression equation was found ($F(1, 70) = 47.7$, $p < .001$), with an R^2 of .405. Participants' predicted proportion optimal is equal to 25.806 + 22.310 (ratio) in percentage.

Discussion

As predicted, with increased stimuli numbers ratio, participants selected more optimal targets. However, we failed to establish a robust correlation between more optimal target choices and faster overall response times. In principle, such correlation should be present. While for every single trail, the target from the smaller subset may not necessarily take less time to find (e.g., when participants randomly fixate on a target closer to center), the overall search time cost for optimal targets should be lower than that of the nonoptimal targets. Failure to demonstrate this effect led us to examine the experimental procedure. We suspected that a change in the design might have contributed to this issue. In Standard ACVS, the feature of the optimal target was determined by intermixed “runs” of 1-6 (i.e., 1-6 successive optimal targets of the same feature). This requires the participant to switch on about 28.57% of the trials when they consistently select the optimal target. The design of the current task, however, did not control the optimal strategy switch rate in this sense. It turned out that, on average, participants needed to switch on 64.77% (*SD* = 1.72%) of the trials when choosing every optimal target throughout the task. The increase in switch demand might have cost participants who selected more optimal targets also more time to switch. Participants might also have been less optimal due to the switch demand. If this is indeed the case, then the slope of the current linear model might not be accurate. Thus, there is a need to carry out a further study that retains this key parameter of the original paradigm.

Experiment 2

Experiment 1 showed that proportion of optimal choices increased as the number of squares ratio increased. However, the failure to establish a correlation between optimal strategy and search speed led to the finding that the target switch frequency was not controlled to the same level as Standard ACVS. Since increased demand to switch might have influenced participants' proportion of optimal choices, we decided to control the switch rate required by the optimal strategy to the same level as Standard ACVS.

Method

Except for the logic of generating trial conditions, this experiment was a direct replication of Experiment 1. Fifteen individuals (5 male, 9 female, 1 binary) aged 18 to 22 (*M* = 19.00, *SD* = 1.31) were recruited from The Ohio State University. All participants had self-reported normal or corrected-to-normal visual acuity and normal color vision.

Results

Proportion Optimal increases with Ratio 1.2 (range 43.48% - 61.15%, M = 51.67%, SD = 5.35%), Ratio 1.5 (range 50.00% - 82.73%, M = 60.98%, SD = 10.07%), and Ratio 2.0 (range 50.71% - 93.66%, M = 68.02%, SD = 16.10%).

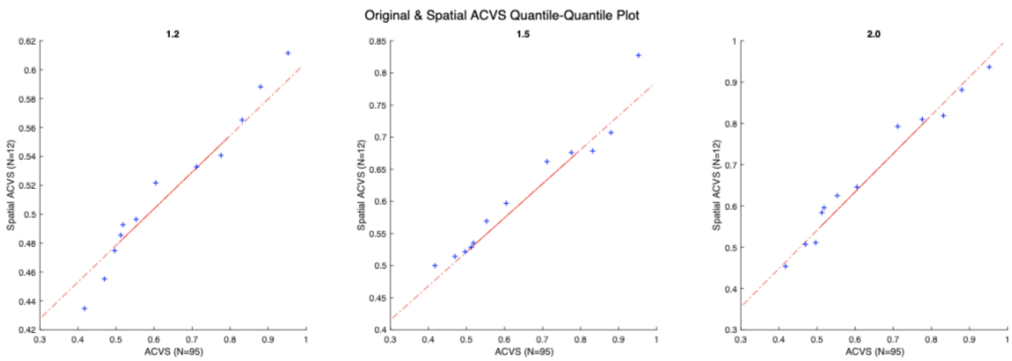

Figure 3. The distribution of optimality was also compared to Standard ACVS by a quantile-quantile plot.

Cross-Experiment Analyses Since this experiment was run with only one parameter different from the last one, we did *post hoc* analyses on how target switch influence optimality. For the overall proportion optimal collapsed across ratios, the two tasks did not differ ($t(34) = 0.23$, $p = .82$). The proportion optimal under none of the three ratios differed as well. Similarly, the overall switch rate of the two tasks did not differ ($t(34) = 0.29$, $p = .77$).

Discussion

The result shows that incorrectly manipulated high target switch demand did not influence participants' proportion of optimal choices, indicating that the linear model used in Experiment 1 still validly captures the relation between the ratio and optimality.

The cross-experiment analysis of Experiment 1 and Experiment 2 suggests that decreasing the switch rate required by following the optimal strategy did not affect participants' optimality. The possible explanation is that switching between two parts in space is perceived as less effortful than switching between two features. Indeed, a significant optimality decrease was found when the optimal strategy required more switch between color-defined subsets (red and blue; unpublished data). We will come back to this point later in the general discussion.

Experiment 3

Experiment 3 was preregistered (osf.io/rx2c5). We asked participants to do the Standard ACVS task (Irons & Leber, 2018; McKinney et al., 2019), followed by the Spatial ACVS task with the established 2:1 spatial ratio.

Method

Participants. 57 individuals (28 male, 29 female) aged 18 to 32 (M = 19.23) participated in this study. All participants had self-reported normal or corrected-to-normal visual acuity and normal color vision. Data from one participant was excluded because she completed the two tasks with a different order than predetermined. 7 participants whose overall accuracy was 3 standard deviations lower than average were excluded from analysis. The final sample included 50 participants, specified in the preregistration, which would give us a power of .98 of finding a medium effect size (r = .50).

Equipment. Participants sat in a dimly lit, sound attenuated room without restraint approximately 60 cm from the display. The stimuli were presented using Psychophysics Toolbox (Brainard, 1997; Pelli, 1997) implemented in MATLAB (Mathworks, Natick, MA, USA) and were displayed on a 24-inch LCD monitor with a 60 Hz refresh rate.

Stimuli. The Standard ACVS used displays that were based on Irons & Leber (2018). Each search display contains 54 squares (13 red, 13 blue, 14 green and 14 “variable”). On every trial, the targets are a red and a blue square containing a digit between 2-5 (all other red, blue and variable squares contain digits 6-9). On half of the trials, the variable distractors are red and on the other half the variable distractors are blue. Short runs of 1-6 trials with red variable distractors are interleaved with short runs of 1-6 trials with blue variable distractors. For Spatial ACVS, on every trial, 20 squares appear on one side (i.e., left or right) of the display and 10 squares appear on the other side, with every square positioning at one of the 54 locations where the squares in Standard ACVS appear, except for the 6 locations closest to the vertical midline of the display. All squares are colored grey and contain a digit between 2-9. Two targets, one on each side, each have digits between 2-5. On half of the trials, more squares will appear on the left side and on the other half, more squares will appear on the right side. Short runs of 1-6 trials with more squares on the left side are interspersed with short runs of 1-6 trials with more squares on the right side.

Procedure. Participants completed three blocks of Standard ACVS task followed by three blocks of Spatial ACVS task. This order was preserved across all participants to minimize intersubject variability driven by the design, for the purposes of individual differences analysis (cf. Irons & Leber, 2018). Participants are informed that a blue and a red target will be presented on every trial, and that they are always free to search for either one. The targets contain a digit between 2 and 5, and participants respond using the keys V, B, N, and M corresponding to each of the possible target digits. The four response keys are covered by four stickers with handwritten corresponding digits. Participants complete ten practice trials followed by three blocks of 84 trials, with short breaks in between. At the end of these blocks, participants are told to notify the experimenter, and they are given the chance to take a short break.Participants are informed that all the squares will be of the same color from now on, that they can always find one target on each side of the screen, and that they are always free to search for either one. The targets contain a digit between 2 and 5, and participants respond using the keys V, B, N, and M corresponding to each of the possible target digits. The four response keys are covered by four stickers with handwritten corresponding digits. Participants complete ten practice trials followed by three blocks of 72 trials.

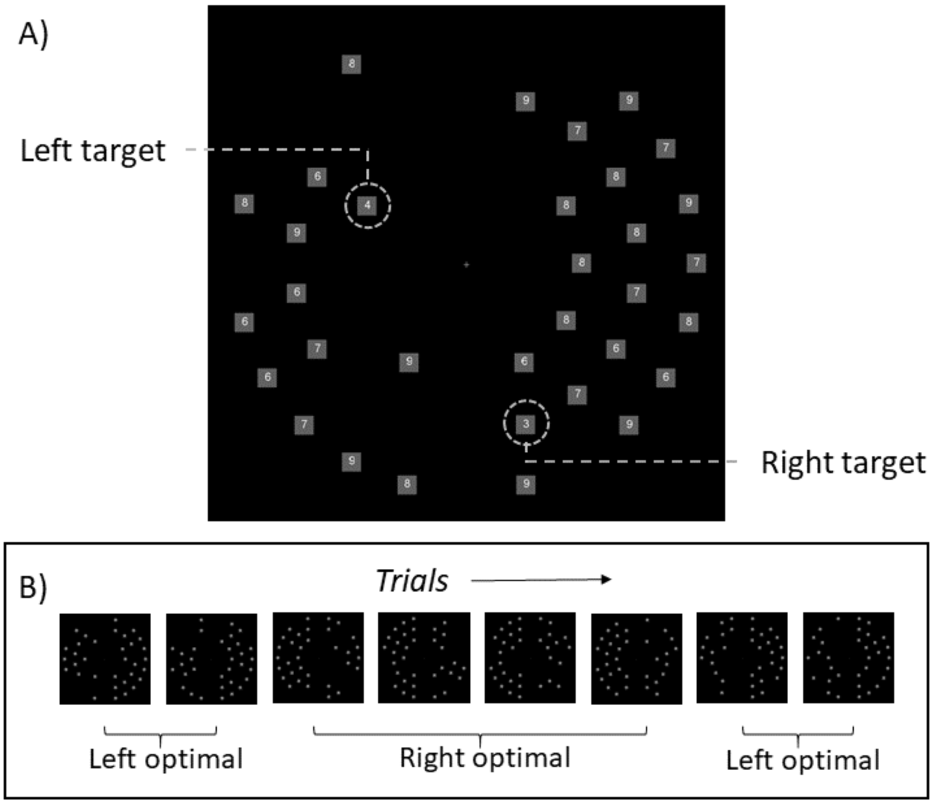

Figure 1. A) Example search display from the Spatial ACVS task. Each display contains a left and a right target, with a digit (2, 3, 4, or 5) on them. There is always an “optimal” target which is located on the side with fewer squares. B) Example sequence of trials. All sequences in the task contained runs of 1-6 trials with fewer squares on the left and fewer squares on the right.

Results

General Discussion

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