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Characterizing individual variation in the strategic use of attentional control

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Goal-directed attentional control can substantially aid visual search, but only if it is recruited in an effective manner. Previously we found that strategies chosen to control attention vary considerably across individuals, and we proposed that effort avoidance may lead some individuals to choose suboptimal strategies. Here we present a more thorough analysis of individual differences in attentional control strategies. We used the adaptive choice visual search (ACVS), which provides a method to quantify an individual's attentional control strategy in a dynamically changing, unconstrained environment. We found that individual's strategy choices are highly reliable across sessions, suggesting that attentional control strategies are stable and trait-like. In Experiment 2, we explored the extent to which strategy use was related to subjective evaluations of effort and performance. Results showed that the extent to which individuals found the optimal strategy to be effortful and effective predicted their likelihood of making optimal choices on a subsequent choice block. These results provide the first evidence for a relationship between effort and strategic attentional control, and they highlight the important and often neglected role of strategy in understanding attentional control.

Keywords: attentional control, visual search, strategy, individual differences

To intentionally prioritize task-relevant information while ignoring irrelevant information is among our most valuable attributes. It is made possible by goal-directed attentional control mechanisms, which selectively bias the processing of a desired target's known features, such that items possessing these features receive preferential processing (Desimone & Duncan, 1995; Folk, Remington & Johnston, 1992; Green & Anderson, 1956; Treisman & Sato, 1990; Wolfe, Cave & Franzel, 1990; Yantis, 2000). A classic example of goal-directed control is searching for a friend in a crowd: if we know this friend is wearing a red t-shirt, we can establish an *attentional control setting* for red, allowing us to narrow our search to red items. However, while examples like this are useful, they are simplistic because search targets are typically composed of many properties: our friend is wearing a red t-shirt *and* blue pants, and is tall and has dark hair. That is, the example omits that we must often choose among many possible features to prioritize – which may vary in their degree of effectiveness –

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when implementing goal-directed control. If our friend is surrounded by others who are mostly wearing red, then we should choose a control setting tuned not to their red shirt but instead to their height, hair color, or another feature.

This expanded example helps illustrate a fundamental distinction between two facets of goal-directed attentional control: *strategy,* which refers to the choice of which control setting to use vs. *ability* to implement the chosen control setting. The two facets are both necessary for successful behavioral outcomes; the ability to use a control setting can only go so far if that ability is not exercised appropriately. It is therefore vital to study both ability and strategy to form a complete understanding of the mechanisms of goal-directed attentional control in the real world.

Ability has been comprehensively studied over the past several decades, in which the experimenter typically instructs observers to search for something specific (e.g., the red thing) and then measures how well the observers can comply. This approach has spurred contentious debate over many years, centering on whether and in what situations goal-directed control is capable of overcoming bottom-up stimulus-driven factors (Folk et al., 1992; Theeuwes, 1991, 1992). The current consensus suggests that we are capable of precise tuning of attention to transient changes such as onsets, offsets, and movement (Atchley, Kramer & Hillstrom, 2000; Folk & Remington, 1998; Folk, Remington & Wright, 1994), and static features including color, shape, and size (Ansorge & Heumann, 2003; Becker, 2008, Folk & Anderson, 2010). Goal-directed control has also been demonstrated for some conjunctions of features (e.g. Becker, Harris, York & Choi, 2017) and category membership (Wyble, Folk & Potter, 2013), although control for these more complex appears to be limited (e.g., Treisman & Gelade, 1980; for a general review of attentional abilities, see Wolfe & Horowitz, 2017).

Studies of strategy, however, have lagged behind those of ability. This is possibly because experimental designs have tended to constrain strategic options during attentional tasks in order to reduce variability or prevent potential confounds. Furthermore, researchers may have assumed that observers are all *performance maximizers;* that is, they pursue options that yield the greatest benefit. In the realm of attentional control, this means choosing the strategy that brings the best performance metrics (i.e., accuracy, response time, and/or reward). The assumption of universal performance maximization might seem supported by the broader visual search literature, in which a number of studies have argued that visual search performance matches that of an ideal observer (e.g., Ma, Navalpakkam, Beck, Van Den Berg, & Pouget, 2011; Najemnic & Geisler, 2005; Navalpakkam & Itti, 2007; Scolari & Serences, 2009; Wolfe, 2013). If everyone is choosing the optimal strategy, little variation in such behavior should exist, and it is thus of little interest to investigate the influence of strategy choice on attentional control.

Nevertheless, several studies have highlighted non-optimal strategy selection. In a classic study, Bacon and Egeth (1994) showed that distraction by a salient, irrelevant feature singleton was not automatic, as had been previously argued (e.g., Theeuwes, 1992); rather, when coaxed to adopt a narrower "feature search mode" via experimental manipulations, individuals demonstrated an ability to override such distraction. Several others have reported conceptually similar results in which observers have used ineffective feature-based control, resulting in slower search latencies, poorer accuracy, and/or greater susceptibility to distraction (e.g., Leber & Egeth, 2006a, 2006b; Leber, Kawahara & Gabari, 2009; Kawahara, 2010; Proulx 2011; Rajsic, Wilson & Pratt, 2015; Rajsic, Taylor, & Pratt, 2017). Similar findings exist for the control for spatial attention. For example, observers often distribute their attention resources across different task components in an inefficient manner, an effect that can be mitigated through training in more effective strategies (Gopher, 1993; Gopher, Weil & Siegal, 1989). Additionally, several eye-movement studies have shown that observers do not always make fixations in a manner than maximizes information gain (Araujo, Kowler & Pavel, 2001; Boot, Becic & Kramer, 2009; Boot, Kramer, Becic, Wiegmann & Kubose, 2006; Clarke, Green, Chantler, & Hunt, 2016; Clarke & Hunt, 2016; Morvan & Maloney, 2012; Nowakowska, Clarke & Hunt, 2017; Williams, Pollatsek, Cave, & Stroud, 2009; Zelinsky, 1996). Taken together, it is evident that individuals use suboptimal strategies in a variety of attentional control tasks in the laboratory, and it seems likely that such suboptimal behavior extends to the less constrained environments encountered in the world outside the lab.

Why might individuals use such suboptimal strategies? Bacon and Egeth (1994) speculated that adopting a more optimal control setting required a greater investment of mental effort, which their participants at least somewhat avoided. To articulate this idea further, individuals may be *effort minimizers,* in which they seek to strategically conserve a limited cognitive resource (Fiske & Taylor, 1984; Kool, McGuire, Rosen & Botvinick, 2010). Decisions are made by weighing up the potential benefits against the effort costs to determine the value of a given strategy (Kool & Botvinick, 2014). In the realm of attentional control, multiple demands on effort exist. These including proactive monitoring of one's sensory environment to determine whether the current setting should be updated (Braver, 2012; Braver, Gray & Burgess, 2007; Chatham, Frank & Munakata, 2009; Locke & Braver, 2008), as well as task switching, or implementing the new task setting (Arrington & Logan, 2004; Monsell, 2003).

The Adaptive Control Visual Search (ACVS) Task

In seeking to learn how strategy choice is motivated (i.e., by factors such as performance maximization and effort minimization,) we recently devised the adaptive choice visual search (ACVS; Irons & Leber, 2016), which features three main components. First, individuals are free to choose one – and only one – of two targets on each trial. Second, the search environment is constructed in such a way that searching for one target is likely to be faster than the other (i.e., the optimal target). That is, using performance maximization would yield clear and robust behavioral benefits. Third, the search environment, and consequently the most optimal search target, changes frequently. Thus, maintaining optimal performance requires observers to continuously monitor the environment, decide when to update, and engage in task switching – all effortful activities that produce a tension between performance maximization and effort minimization.

In our first study (Irons & Leber, 2016), we found that, on average, search strategies were well below optimal, with participants choosing the non-optimal target on a substantial 40% of trials. Additionally, participants switched between the two targets much more frequently than necessary, incurring significant switch costs.

However, perhaps the most striking finding was vast individual differences on both the choice and switching measures. Some participants did search strategically for the optimal target on the majority of trials, updating their control settings as the environment changed. Others used strategies that were unaffected by the changing search environment, choosing the optimal target at chance levels (half of the trials). Of these, some avoided switching between targets and searched for the same target for extended periods, while others switched frequently and seemingly at random. Importantly, strategy use predicted overall performance, with high optimal choices and low switching rates corresponding to faster response times. There was also little evidence that the variation in strategy could be attributed to attentional control ability: we found no relationship between search strategy and working memory capacity or response time on a control visual search task (in which only one strategy was available).

The implications of these individual differences are potentially far reaching. While so much attentional control research has focused on ability, the relatively understudied component of strategy accounts for large variation in performance. In real-world search scenarios, where there are even fewer constraints on choice, a searcher's strategy may have just as much effect on their performance as ability, if not more. If each individual's strategy usage could be characterized, this would offer great promise in predicting the use of attentional control outside of the lab; for example, it could improve assessment and training in professions relying heavily on the optimal use of attentional strategies (e.g., airport baggage screening and radiological image interpretation), and it could provide a diagnostic marker for a variety of attention-related disorders (e.g., ADHD and frontal lobe damage). From a theoretical perspective, analysis of individual differences has great utility in illuminating the structure and interrelations between cognitive constructs (e.g., Cronbach, 1957; Vogel & Awh, 2008; Wilmer, 2008).

Here we present a study that seeks to advance the understanding of individual differences in attentional control strategy, using the vehicle of the ACVS. Our goal is twofold. First, we explore whether attentional control strategies are “trait-like” and stable over time. A general assumption of individual differences research is that a person’s behavior remains consistent across multiple measurements. While we observed clear individual variation in our previous work, it is unclear whether this reflects enduring, trait-like behavior. It may be that strategies are transient, chosen arbitrarily or driven by various temporary states (e.g. the individual’s level of fatigue). In Experiment 1, we explore this question by examining the reliability of attentional control strategies across testing sessions.

In Experiment 2, we turn to the factors underlying individual variation in attentional control strategies. As discussed previously, the failure to optimize attentional performance may be driven by a desire to minimize effort (Bacon & Egeth, 1994). In this second experiment, we examine the extent to which strategy choice is related to individuals’ subjective evaluations of effort and performance.

Experiment 1

Experiment 1 was designed to assess the stability of attentional control strategies, using the adaptive choice visual search task. If an individual’s strategic control of attention reflects stable, trait-like behavior, they should use the same strategy across different sessions. To test this, we asked participants to perform the ACVS on two different days (spaced 1-10 days apart), and used test-retest reliability to assess the consistency of strategies across sessions. The ACVS task was based on that of Irons and Leber (2016), with some refinements. Each search display contained 54 colored squares containing a digit (see Figure 1). Two targets, a red and blue square containing a digit within a specific range (2-5), were embedded within every search display, and participants were free to search for either one on each trial. The other squares (distractors) were either red, blue, green or “variable” colored. Variable distractors changed color from trial to trial, moving between red and blue in color space. This change followed a “plateau-transition” pattern (see Figure 1b): red for five trials (red plateau), then incrementally transitioning from red to blue over the course of seven trials (red-to-blue transition), then blue for five trials (blue distractor plateau), and finally transitioning back to red over the course of seven trials (red-to-blue transition). In this way, the variable distractors determined the optimal target: when the variable distractors were red or close to red in color space, there were twice as many red/reddish distractors in the display and search for the blue target would generally proceed more quickly. Conversely, when the variable distractors were blue or close to blue, the red target was optimal. To maintain optimal performance, then, one must search for the target that is most different from the variable distractors, switching when the variable distractors reached the midpoint between red and blue.

We assessed each individual’s strategy using two parameters. First, we calculated *percent optimal,* or the percentage of trials in which the observer chose the optimal target color – i.e., the one belonging to the smaller color subset – on plateaus. We focused specifically on plateau trials because here the variable distractors fully matched one of the two targets, providing the clearest scenario in which one target is more optimal than the other target. Second, we assessed how frequently individuals updated their search properties using *switch rate,* the percentage of trials in the chosen target color on trial N was different from the chosen target color on trial N-1.

Method

Participants

Fifty individuals (20 male, 30 female) aged 19 to 40 (M = 22.37) were recruited from The Ohio State University. All participants had self-reported normal or corrected-to-normal visual acuity and normal color vision. With this sample size, we had a 90% chance of detecting Pearson r-values of 0.42 or greater in each of our critical test-retest reliability measures (percent optimal and switch rate). Participants came in for two separate hour-long sessions on different days, and were compensated $10 per session. Forty-seven participants returned for a third session to complete several additional cognitive tasks and surveys, as part of ongoing analyses of individual differences in attentional control strategies. Most of these measures were only added partway through the study and full data set was not collected, and consequently the data are not reported here.

General Procedure

All methods were approved by the Ohio State Institutional Review Board. Participants completed the ACVS task in both the first and the second session. The two sessions were separated by at least one day and no

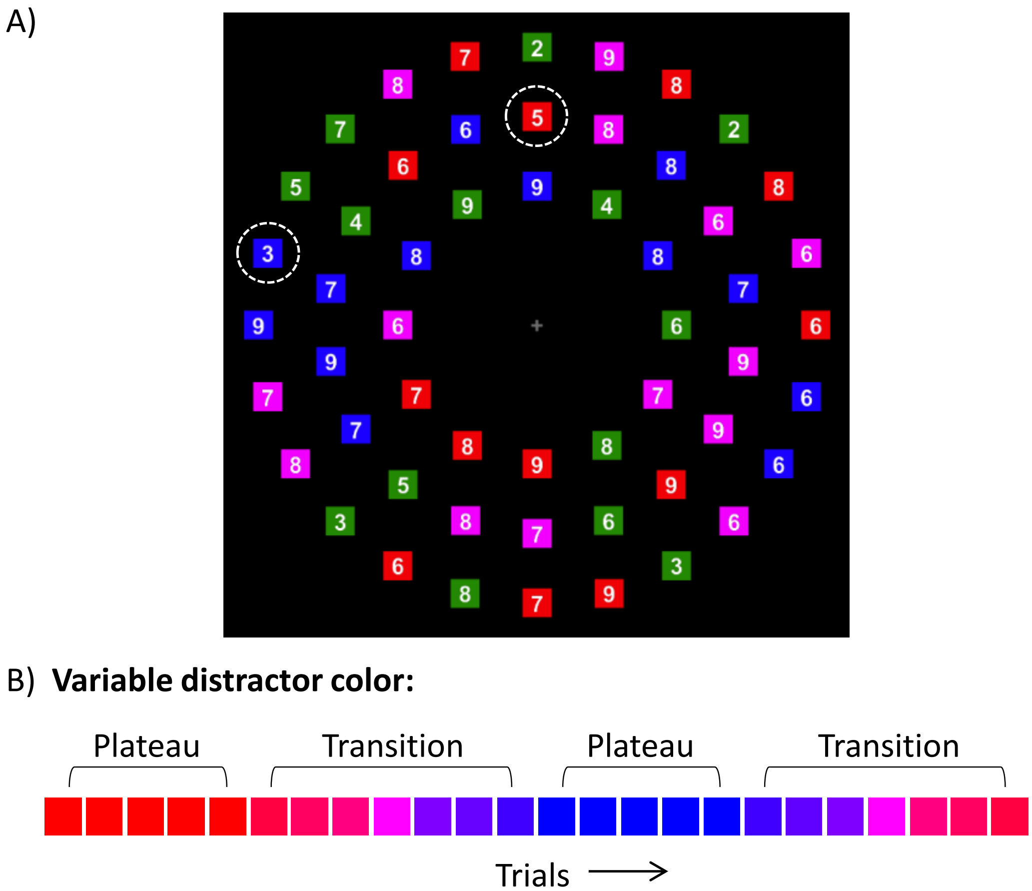

Figure 1. ACVS stimuli in Experiment 1. A) Example search display from a trial halfway through a transition with magenta-colored variable distractors. Targets (here circled) were a red and blue square with digit between 2 and 5. B) Cyclical progression of the variable distractor color across trials. Variable distractors were red for five trials, then transitioned from red to blue across seven trials, blue for five trials, and finally transitioned from blue to red across another 7 trials. This cycle was repeated throughout the experiment.

more than ten days (M = 3.1 days). The strategy self-report survey and the BIS-11 were completed at the end of session 2.

Adaptive Choice Visual Search (Sessions 1 and 2)

Stimuli. The adaptive choice task was based on the task used in Irons & Leber (2016), with some modifications. The search display was composed of 54 colored squares (sized 1 ° x 1 °) evenly spaced around three concentric rings centered on fixation. There were 12 squares in the inner ring (6.6 cm from fixation, or 6.3 ° at a 60cm viewing distance), 18 in the middle ring (9.9 cm or 9.4 ° from fixation), and 24 in the outer ring

(13.2cm or 12.4 ° from fixation). Thirteen squares were colored red, 13 were colored blue, 14 were colored green, and 14 were "variable distractors". The color of the variable distractors oscillated predictably between red and blue throughout the experiment. The distractors would be red for five trials (red plateau). Then, across seven trials, the distractor color would change from trial-to-trial from almost red through magenta to almost blue, in seven discrete "jumps" across color space (red-to-blue transition). The distractors would then be blue for five trials (blue plateau) and then transition back through magenta to red over seven trials (blue-to-red transition). The central color of the transition was halfway between red and blue (magenta), and the remaining transition colors were clustered towards either end of the transition, in order to highlight the changeover point between redder and bluer colors. That is, the three colors between red and magenta were clustered closer to red than to magenta, and the three colors between blue and magenta were clustered closer to blue (see Table 1 for color values.)

All squares contained a small digit between 2 and 9 in white font. Every display contained two targets: a red square with a digit from 2 to 5 inclusive, and a blue square with a digit from 2 to 5. The digits on the targets were chosen pseudo-randomly, with the restriction that they were always different from each other to enable us to determine which target was chosen. All other red and blue squares, as well as the variable distractors, contained digits between 6 and 9. The green squares could contain any digit from 2-9, to prevent participants from simply searching based on number and ignoring color entirely.

Table 1. ***Target and distractor RGB and CIE XYZ Color Values***

	RGB			CIE XYZ		
Red	255	0	0	42.24	21.26	1.93
Blue	0	0	255	18.05	7.22	95.05
Green	0	200	0	20.65	41.31	6.89
	255	0	63.75	42.16	21.63	6.77
	255	0	95.63	43.34	22.10	12.96
Variable distractors	255	0	127.50	45.11	22.81	22.27
	255	0	255	59.29	28.48	96.97
(red-to-blue transition)	127.50	0	255	26.87	11.77	95.44
	95.63	0	255	22.83	9.69	95.25
	63.75	0	255	20.14	8.30	95.13

Procedure. The experiment was completed in an individual light-controlled and sound attenuated testing room, on a Mac Mini computer with a 24-inch Dell monitor. Participants were seated at a viewing distance of approximately 60 cm. Stimulus presentation was controlled using Matlab (Mathworks, Natick, MA), with Psychophysics Toolbox extensions (Brainard, 1997; Pelli, 1997).

Participants were informed that each search display would contain both targets and that they could choose to search for either target on each trial. No instruction was given as to how they should choose targets. Participants responded by identifying the digit inside the target by pressing the V, B, N and M keys on the keyboard (corresponding to 2, 3, 4 and 5 respectively). Each trial began with a fixation cross for 1 s, followed by the presentation of the search display, which remained until a response was made and was then followed by a blank screen ITI of 1 s. The spatial arrangement of the targets and distractors within the display was randomized on each trial. Each block began at the start of the plateau (either the red or blue plateau, counterbalanced across participants) and contained 4 full cycles of the variable distractor color, resulting in a total of 96 trials per block. Participants completed five blocks (480 trials total) with self-paced breaks in between.

Strategy self-report questionnaire

At the end of the experiment, participants rated the approximate percentage of trials (0, 20, 40, 60, 80 or 100 percent) in which they used each of the following strategies: 1) Searched for the color that had the fewest squares in the display; 2) Searched for just one color for a long period of time (without switching to the other color); 3) Searched for the color than had the most squares in the display; 4) Searched for whichever color appeared first to them; and 5) Searched through squares of both colors for any that had a target number. Ratings were converted to percent of the total sum of ratings to standardize across participants. These ratings were used to classify the extent to which participants self-reported using one of three distinct strategies. Ratings on strategy 1) were taken as a measure of self-reported *optimal searching*. Ratings on strategy 2) were classified as the *repeated searching* (i.e., searching repeatedly for the same target color). Ratings on strategies 4) and 5) were added together to measure self-reported *random searching* (i.e., searching for either target at random).

Participants also reported their motivations for using this chosen strategy from the following five options: 1) It required the least amount of effort; 2) It was the best strategy for getting fast response times and high accuracy; 3) It was the fastest way to finish the task; and 4) It was the least boring way to do the task; and/or 5) Other.

Barratt Impulsiveness Scale (BIS-11)

Finally, we administered the BIS-11, a well-established scale used to measure individual differences in trait impulsiveness (Patton, Stanford, & Barratt, 1995). In Irons & Leber (2016), we found a non-significant relationship between BIS-11 scores and increased random switching, and we speculated that unnecessary switching might be the consequence of an impulsiveness or novelty-seeking mechanism. We sought to test this hypothesis directly in the current study. The BIS-11 is composed of 30 items and individuals rate how much each statement is true of them on a scale from 1 to 4. Example questions include “I plan tasks carefully” and “I act on impulse”.

Results

ACVS: Group results

Error trials were excluded from RT analyses, along with trials with RTs less than 300ms or more than 3 standard deviations from the mean (1.8% of trials in session 1 and 1.4% in session 2). When multiple comparisons were conducted, we applied the Holm-Bonferroni method (Holm, 1979) to control false discovery rate (corrected p-values are denoted by p_{HB}). Accuracy on the ACVS was at ceiling for both sessions (session 1 M = 97.95%, session 2 M = 98.52%). Response time decreased significantly from session 1 (M = 2846 ms) to session 2 (M = 2540 ms; $t(49) = 8.86$, $p < .001$, $d = 1.26$), suggesting practice benefits.

We first analyzed the pattern of choices at each position in a run. A run extends from the start of the plateau until the end of the following transition. Data were combined for runs starting on a red plateau and runs starting on a blue plateau. Target choices were categorized as being either optimal at the start of the run (*start-optimal*) or optimal at the end of the run (*end-optimal*). For instance, in a run involving a red plateau followed by a red-to-blue transition, choosing a blue target would be start-optimal (optimal when the distractors are red or close to red) and choosing a red target would be end-optimal (optimal when the distractors have almost fully transitioned to blue). For best performance, participants should select the start-optimal target on all trials in the plateau and for the first half of the transition, and then select the end-optimal target for the second half of the transition.

As shown in Figure 2a, the data for the entire group replicated the pattern of choices found in Irons and Leber (2016). Choice data, combined across the two sessions, varied significantly as a function of the changing variable color, $F(11,539) = 29.13$, $p < .001$, $\eta_p^2 = .37$. At the start of the run, participants selected the start-optimal target more frequently than the end-optimal target (all $p_{HB} < .001$). Choices converged at position T5, one trial after the midpoint of the transition ($t(49) = 1.40$, $p_{HB} = .17$). By positions T6 and T7, participants were selecting the end-optimal target most frequently (all $p_{HB} < .004$). Choices across the run did change somewhat from session 1 to session 2 (significant session x run position interaction, $F(11, 539) = 2.11$, $p = .018$, $\eta_p^2 = .04$); there was a tendency for participants to make more optimal choices in session 2 (more start-optimal choices on plateaus and at the start of the transition, and more end-optimal choices at the end of the transition), and there was also a tendency for the switchover point to occur slightly earlier. However, the differences between sessions were numerically small and did not reach significance when averaged across the plateau trials ($p = .17$), or at any single position in the run (all $p_{HB} > .81$).

Next we examined switching frequency. A switch occurred when the target chosen on trial N was different from the target color chosen on trial N-1. Switches were costly, producing an averaging cost of 439 ms. Nevertheless, as with Irons & Leber (2016), participants switched on 24.8% of trials (approximately three times per run), significantly higher than the optimal rate (once per run, or 8.3% of trials, $t(49) = 8.94$, $p < .001$, $d = 1.90$). Switch rate varied significantly across position in the run, $F(11, 539) = 11.35$, $p < .001$, $\eta_p^2 = .19$ (see Figure 2b). The switch rate was highest at the optimal switching point, T5, one position after the middle of the transition. However, a substantial amount of switching still occurred at less optimal times, including on plateau trials where no switching should take place (22.7% switch rate).). The pattern of switches across the run differed significantly across sessions ($F(11, 539) = 1.97$, $p = .03$, $\eta_p^2 = .04$) and again this was due to a trend for performance to become slightly more optimal in session 2, with fewer switches made on plateaus and a larger peak at the position T5. However, the differences were small and did not reach significance on plateaus ($p = .27$) or at any individual position in the run ($ps_{HB} > .79$).

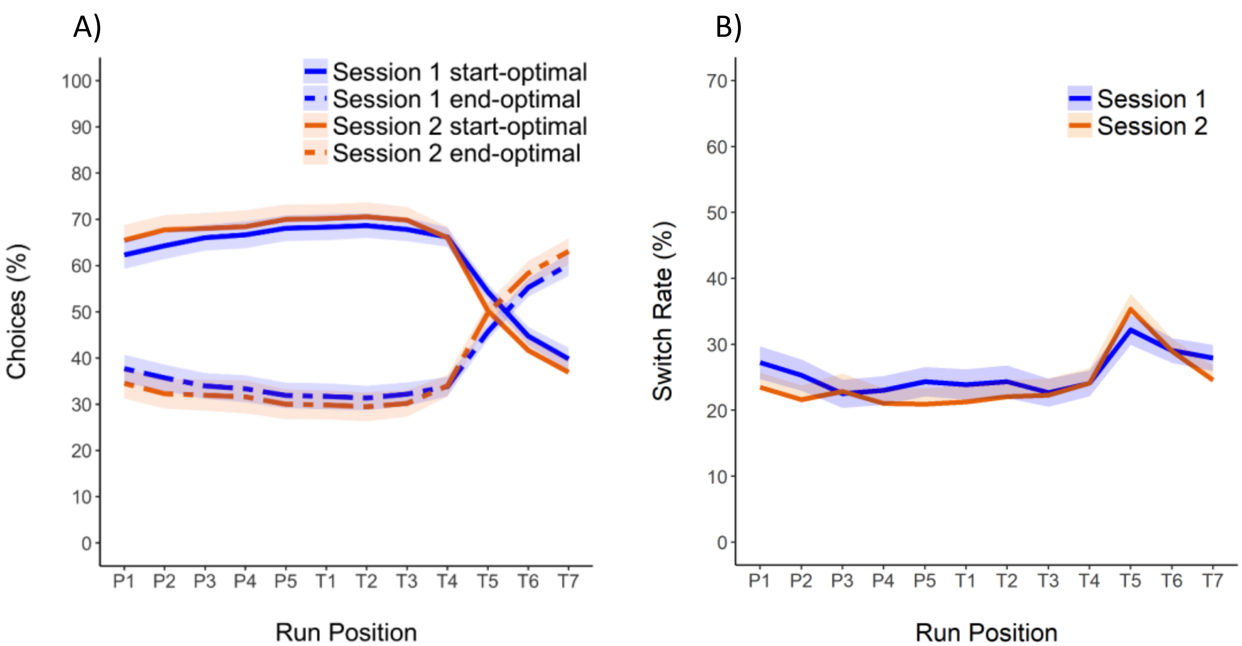

Figure 2. Results from Session 1 and 2 of Experiment 1. A) Percent of start-optimal and end-optimal choices across a run. Start-optimal refers to the target that is optimal at the start of the run, and end-optimal is the target that is optimal at the end of the run. B) Switch rate across a run. Error bands depict standard error of the mean.

Individual differences. All individual differences measures (percent optimal, switch rate switch rate, BIS-11 and self-report questionnaire measures) were screened for outliers. Cases in which outliers were detected are described in the text. Individuals were classified as univariate outliers if the *z*-score exceeded +/- 3.29 ($p < .001$). For correlations, multivariate outliers were based on a Mahalanobis distance exceeding 13.82 ($p < .001$).

ACVS measures. For each individual at each session, we extracted their percent of optimal choices on plateaus, and their switch rate across the entire run. Both measures showed considerable variation across individuals (see Figure 3a and 3b for histograms of scores across the two sessions). Percent of optimal choices varied from 36.8% to 99.5% (M = 66.7, SD = 20.25, averaged across both experimental sessions). The distribution appeared bimodal, with one peak centered on chance performance (50%) and another peak approaching fully optimal performance (100%). Internal consistency was estimated using split-half reliability with a Spearman-Brown correction, calculated and averaged over 50 random splits of the data (with the restriction that there was always an equal number of plateau and transition trials in each split half), following the method of Susilo et al. (2010). Average split-half reliability was very high (r = .97 for Session 1 and r = .98 for Session 2). Switch rate ranged from 0.9% to 47.4% (M = 24.8, SD = 13.0, averaged across both experimental sessions). Both measures correlated with overall search performance: slower search RT was correlated with fewer optimal choices (r = -.58, $t(48)$ = 4.87, $p < .001$) and higher switching rates (r = .50, $t(48)$ = 4.04, $p < .001$). Average split-half reliability was also very high for switch rate (r = .98 for both Session 1 and Session 2).

Note that to some extent, switch rate is constrained by the percent of optimal choices: the more frequently an observer chooses the optimal target, the closer their switch rate must be to the optimal number of switches (once per run). Consistent with this, the two measures were reasonably well correlated (r = -.57 in session 1 and -.65 in session 2, see Figure 3c). To derive an independent measure of switching after percent optimal is accounted for, regressions were performed with percent optimal as the predictor and switch rate as the dependent variable, separately for each session. The residuals after percent optimal was accounted for were retained as an independent switch measure. In general, the pattern of results was very similar to the results found for the non-independent switch rate, however for completeness we report results using both measures.

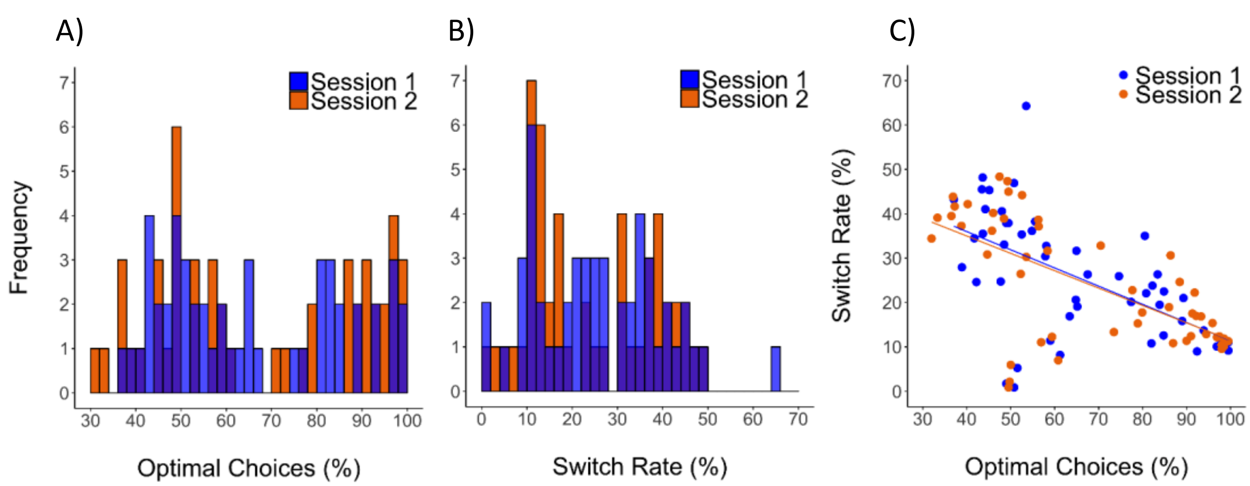

Figure 3. Individual differences data in Experiment 1. Histograms show individual scores in A) percent optimal choices and B) switch rate. C) Scatterplot of the relationship between percent optimal and switch rate.

Test-retest reliability. Figure 4 shows session 1 scores plotted against session 2 scores. Both percent optimal choices and switch rate produced good test-retest reliability. The correlation for percent of optimal choices across sessions was $r = .83$, significantly greater than zero, $t(48) = 10.48$, $p < .001$, 95% CI [.72, .90]). The disattenuated correlation, which estimates the correlation if internal consistency were perfect, was $r = .86$. This suggests that consistency is reduced somewhat across sessions (i.e., the correlation across sessions does not quite reach the level of the correlations within sessions), but nevertheless remains high. Test-retest reliability for switch rate was $r = .77$ (disattenuated $r = .80$), $t(48) = 8.46$, $p < .001$, 95% CI [.63, .87]. However, outlier screening identified one bivariate outlier (Mahalanobis distance = 14.69, $p < .001$), and removing this data point increased reliability to a small extent, $r = .82$, $t(47) = 9.69$, $p < .001$, 95% CI [.69, .89]. For independent switch rate after accounting for percent optimal, the correlation across sessions was $r = .77$ with outlier included ($t(48) = 8.29$, $p < .001$, 95% CI [.62, .86]), and $r = .77$ with outlier excluded ($t(47) = 8.14$, $p < .001$, 95% CI [.63, .87]). These findings indicate that both measures are reliable and stable indicators of individual attentional control strategies.

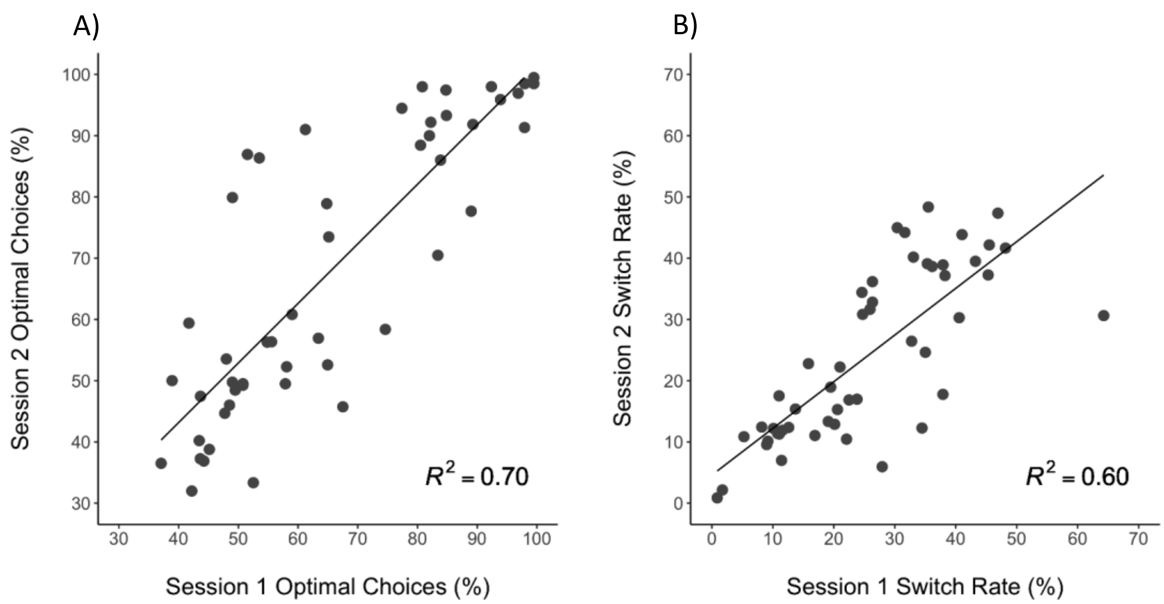

Figure 4. Test-retest reliability for A) percent optimal choices and B) switch rate in Experiment 1.

Strategy self-report questionnaire. Ratings on the strategy self-report survey were used to assess individuals' metacognitive insight into their strategy use. Scores on the survey were compiled to give self-reported estimates of how frequently each person engaged in optimal searching, repeated searching (repeatedly searching for one color) and random searching (searching for either color randomly). We correlated each of these self-report measures with percent optimal choices, switch rate, and independent switch rate (see Table 2). Overall, individuals' self-report data were highly consistent with their behavior. Those who self-reported higher rates of optimal searching chose the optimal target on a larger percentage of trials, $r = .67$, $t(48) = 6.53$, $p_{HB} < .001$. There was a trend for a high self-reported optimal strategy to also be associated with a lower switch rate ($r = -.35$, $t(48) = 2.55$, $p_{HB} = .056$), but this correlation disappeared after controlling for percent of optimal choices (correlation with independent switch rate, $p_{HB} = .48$). Self-reported repeated strategy did not correlate significantly with percent optimal (p_{HB} = .21), but higher ratings were associated with a lower switch rate (r = -.36, $t(48)$ = 2.71, p_{HB} = .047) and independent switch rate (r = -.64, $t(48)$ = 5.85, p_{HB} < .001). Note, however, that these correlations may have been partly driven by two univariate outliers on self-reported repeated strategy (both with z-scores of 3.36). When these datapoints were excluded, the correlation with switch rate was no longer significant (r = -.16, $t(46)$ = 1.10, p_{HB} = .83), although the correlation with independent switch rate remained (r = -.39, $t(46)$ = 2.91, p_{HB} = .034). Self-reported random searching correlated with a higher switch rate (r = .54, $t(48)$ = 4.43, p_{HB} < .001) and independent switch rate (r = .46, $t(48)$ = 3.54, p_{HB} = .005). The correlation with percent optimal did not reach significance, p_{HB} = .12.]

Table 2. ***Correlations between ACVS measures and strategy self-report questionnaire items.***

	ACVS Measures		
	Percent Optimal	Switch Rate	Ind. Switch Rate
	r [95% CI]	r [95% CI]	r [95% CI]
Experiment 1			
Self-reported Optimal Searching	.69 [.50, .81] **	-.35 [-.57, -.07] #	.10 [-.18, .37]
Self-reported Repeated Searching	-.23 [-.48, .05]	-.36 [-.58, -.10] *	-.64 [-.78, -.45] **
Excluding outliers	-.16 [-.42, .13]	-.16 [-.43, .13]	-.39 [-.61, -.12] *
Self-reported Random Searching	-.29 [-.53, -.01] #	.54 [.31, .71] **	.46 [.20, .65] *
Experiment 2			
Self-reported Optimal Searching	.77 [.63, .86] **	.07 [-.22, .34]	
Self-reported Repeated Searching	-.35 [-.57, -.08] *	-.52 [-.70, -.29] **	
Excluding outliers	-.29 [-.53, -.01] #	-.11 [-.39, .17]	
Self-reported Random Searching	-.47 [-.66, -.22] *	.28 [.01, .52] #	

* = p < .05, ** = p < .001 (Holm-Bonferroni corrected). # = p < .05 (uncorrected)

With regards to individuals' motivations for selecting their preferred strategy, thirty-four reported maximizing performance (either responding quickly and accurately, or completing the task in a timely manner) as their sole motivation. Four reported minimizing effort and two reported alleviating boredom as their sole motivations. The remaining 10 reported being motivated by both maximizing performance and minimizing effort, with one person reported also reporting a combination of all three motivating factors. Numerically, individuals who reported performance maximization as one of their motivations made more optimal choices

(68%) than those that did not (59%); however, given that almost all participants (44 out of 50) had maximizing performance as once of their motivations, we did not conduct formal analyses on these data.

Impulsiveness. Finally, we examined whether any ACVS measures correlated with scores on the BIS-11 impulsiveness scale, to more rigorously test our previous speculation that impulsiveness may be related to higher rates of random switching. Internal consistency on the BIS-11 was adequate (Cronbach's $\alpha = .77$) and in line with previous findings (e.g., Patton et al., 1995, found $\alpha = .82$ for undergraduates). Table 3 shows the correlations between BIS-11 scores and switch rate, independent switch rate and percent optimal. Because internal consistency estimates were available for independent switch rate and percent optimal, disattenuated correlations are also reported. Impulsiveness did not correlate significantly with any of the ACVS measures (*all* $p_{HB} > .72$).

Discussion

Experiment 1 verified and further articulated our previous finding of broad individual differences along the two measures, optimal choices and switch rate. Most importantly, it demonstrated that individual strategies were reliable across testing sessions, indicating stable behavior and suggesting individual trait characteristics. From a methodological standpoint, the results also provide evidence for the utility of the ACVS as a measurement tool. Key measures of internal consistency (split-half reliability) and test-retest reliability were high for both percent optimal and switch rate.

Table 3. ***Correlations between ACVS measures and personality scales (disattenuated correlations in parentheses).***

	ACVS Measures					
	Percent Optimal		Switch Rate		Ind. Switch Rate	
	r (disatt. r)	[95% CI]	*r (disatt. r)*	[95% CI]	*r*	[95% CI]
Experiment 1						
BIS-11	.13 *(.15)*	[-.15, .40]	.05 *(.06)*	[-.23, .32]	.17	[-.12, .43]
Experiment 2						
IPIP Novelty-Seeking	.03 *(.03)*	[-.25, .31]	.17 *(.20)*	[-.12, .43]		
Need for Cognition	.08 *(.09)*	[-.20, .35]	-.40 *(-.46)* *	[-.61, -.14]		
Intolerance of Uncertainty	-.20 *(-.22)*	[-.46, .08]	.20 *(.22)*	[-.08, .45]		

* = $p < .05$ (Holm-Bonferroni corrected)

Experiment 2

Our goal in Experiment 2 was to examine the source of the observed individual differences. That is, are there theoretically important determinants of strategy use? We investigated this question in Experiment 2, by specifically focusing on the role of motivation in driving ACVS performance. As discussed earlier, one explanation for sub-optimal strategy use is effort avoidance (Araujo et al., 2001; Bacon & Egeth. 1994; Egeth, Leonard & Leber, 2010; Irons & Leber, 2016). The amount of effort an individual is willing to expend depends on their motivation to perform well. This effort-performance trade-off has been incorporated in models of decision-making (Bettmann, Johnson, & Payne, 1990; Hull, 1943; Johnson & Payne, 1985, Russo & Dosher, 1983) and cognitive control (Botvinick & Braver, 2015; Kool & Botvinick, 2014), and it may similarly apply to attentional control. In the ACVS, the optimal strategy requires individuals to maintain attention control settings in a proactive manner, monitor the search environment and their own performance, and update their strategy when the environment changes, all of which place additional cognitive demands on the observer (Arrington & Logan, 2004; Braver, 2012; Braver, Gray & Burgess, 2007; Chatham et al., 2009; Locke & Braver, 2008; Monsell, 2003). If an individual is not willing to expend this additional effort, they may revert to less effortful and less effective strategies.

Weighing up performance benefits against effort costs is a subjective process. A task that is highly effortful to one person may be less so for another. Likewise, a strategy may be considered more effective to one person than to another. Therefore, if strategy selection is driven by effort-performance trade-offs, then the relationship will be contingent on each individual's internal judgment of effort and performance for that strategy.

We test this in the current experiment, using a modified version of the ACVS. Before completing the original target choice version of the task, participants completed short "enforced strategy" blocks designed to simulate three distinct strategic approaches to performing the task. In each block, only one target appeared on each trial, and the target feature depended on the specific instructions for that block. In the *repeated strategy* condition, target color was blocked, red for the first half of trials and blue for the second half. Thus, the target was only optimal at chance levels, and only a single switch was required. Note that by "optimal," we mean that the target appears in the smaller subset (although technically, there is no option to choose an optimal vs. non-optimal strategy on enforced strategy blocks, as there is only one target). In the *random strategy block*, target color was mixed randomly within the block and cued via a word in the center of the display. Again, only half of the trials were optimal, but now switching was frequent (on average 50% of trials). Finally, in the *optimal strategy block*, the target was always the color of the smallest subset. As such, all targets were optimal, and a moderate amount of switching was required. To simplify the strategy instructions across the experiment, we decided to exclude the transition trials and use only plateau trials, with a variable plateau length between 1 and 6 to ensure that participants had to monitor the environment to determine the best target.

For each of these enforced strategy blocks, participants were asked to rate how effortful they found the block, and how fast they thought their performance to be. Our rationale was that individual differences in subjective effort and performance ratings on the three enforced strategy blocks would predict subsequent strategy use in the choice block. Specifically, the more effortful an individual finds an enforced strategy to be, the less likely that individual should be to later choose that strategy voluntarily. Likewise, the worse an individual rates their performance during an enforced strategy block, the less likely that individual should be to later choose that strategy. To preview the results, we found that this was indeed the case for subjective ratings on the enforced optimal strategy. That is, those who found the optimal strategy to be more effortful or less effective were less likely to adopt this strategy in the choice block.

Method

Participants

Fifty young adults (26 female and 24 male, age M = 19.25, SD = 1.71, range = 18-26) participated in return for Psychology course credit at The Ohio State University. An additional five participants completed the task but were excluded because their accuracy in at least one of the blocks was more than three standard deviations below the group mean. These participants were replaced to keep the sample size at 50. As with Experiment 1, we set the sample size at 50 to ensure a 90% chance of detecting Pearson r-values of approximately 0.4.

Stimuli and Equipment

The stimuli were based on the ACVS task in Experiment 1. However, the pattern of the variable distractor was altered in the current experiment. Transition trials were no longer included in this experiment, and the variable distractor instead jumped back and forth between red plateau and blue plateau. Transition trials were removed for two reasons. First, as percent optimal was based on plateau trials only, removing transition trials enabled us to increase the number of usable plateau trials per condition. Second, it made the explicit instructions for the enforced optimal strategy block easier to communicate to participants. To incentivize the monitoring of colors in each display, we now varied the length of each plateau unpredictably, such that they could be anywhere between one and six trials long (see Figure 5a). In the choice block, a red and a blue target appeared on every trial as before. In the enforced strategy blocks, only one target appeared on each trial, and the other target was replaced with a distractor of the same color.

The experiment was conducted on a Mac Mini computer and 24-inch ASUS monitor positioned 70cm from the viewer. Constant viewing distance was maintained using a chin-

rest. Although we do not report the data here, eye-tracking was performed for the duration of the experiment using an Eyelink 2000 eye-tracker running at 500Hz. The eye-tracker was calibrated at the beginning of each block, however we did not enforce fixation checks or recalibrate within blocks, out of concern that this may be disruptive to participants' strategies. We found that the accuracy of the eye-tracking data varied considerably across participants (i.e., estimates of eye-tracking accuracy based on the percent of trials in which the chosen target varied between 37% and 98%), and because we did not wish eye-tracking accuracy to confound analyses of individual differences, we chose not to report the eye-tracking results here.

Procedure

The experiment began with the three single-target, enforced strategy blocks (see Figure 5b) consisting of 84 trials each, 42 with a red target and 42 with a blue target. The order of the blocks was the same for all participants to minimize noise in the measurement of individual differences (see e.g., Mollon, Bosten, Peterzell & Webster, 2017). The color of the variable distractors on the first plateau was counter-balanced across participants. At the beginning of the experiment, participants were told that they would be searching for a red or blue square containing a digit between 2 and 5, and that each block would have different instructions for finding the target. They were told that some trials would have more red distractors and some would have more blue distractors. Informing participants about the relative proportions of distractors was necessary in order to explain the strategy in the optimal strategy block (see below).

Enforced strategy block 1: Repeated strategy. In the first block, the target was red for the first half of the block (42 trials) and then blue for the second half. Participants were informed of the target color at the start of the block and when the color changed to blue.

Enforced strategy block 2: Random strategy. To simulate frequent, unpredictable switching, red and blue target trials were mixed randomly within the block. Word cues "RED" and "BLUE" appeared in the center of the display to indicate the target color for each trial. The word cue appeared simultaneously with the search display, to prevent advance preparation.

Enforced strategy block 3: Optimal strategy. In the third block, participants were told that the target would always be the color with the fewest distractors in the display.

Choice block. Following the enforced strategy blocks, participants completed a block with the standard choice instructions, in which both targets appeared on every trial and participants were always free to search for either color. The block consisted of 252 trials, in three sub-blocks of 84, with breaks in between.

Subjective ratings and preferences. Subjective ratings were probed after each enforced strategy block and at the end of the choice block. First, participants were asked to rate how effortful each block was (with the additional prompt "In other words, how much of your mental resources did it take up, or how tiring did it feel?") on a rating scale from 0 ("least effort") to 10 ("most effort"). Participant made their response by using a mouse to select a response on an 11-point sliding scale. Next, they rated how fast they felt their responses were on a scale from 0 ("most slow") to 10 ("most fast"). Participants were encouraged to try to compare with their experience on previous blocks in making their ratings. At the end of the third enforced strategy block, participants were shown their ratings for the three enforced strategy blocks and were given the option to adjust any ratings in light of their subsequent experience.

At the end of the experiment, we also assessed strategy preferences, by leading participants to believe that there would be one more block to complete, and that this would be whichever of the four block types they most preferred. The four block types were listed on the screen ("Block 1: Search for the same color for a long time"; "Block 2: Search for the color written on the screen"; "Block 3: Search for the color with the fewest squares"; "Block 4: Choose either color on each trial"). For each, participants rated how much they preferred that block on a scale from 0 ("least preferred") to 10 ("most preferred"). Participants were asked to give a different rating to each block (i.e., no tied ratings). For their most preferred blocks, participants were asked why they preferred this block, by rating the extent to which they agreed with each of the following statements: "It requires the least effort", "It takes the least amount of time"," My performance is the best on this block"," It is the least boring block" (from 0 = "strongly disagree" to 10 = "strongly agree"). Finally, participants used a similar approach for

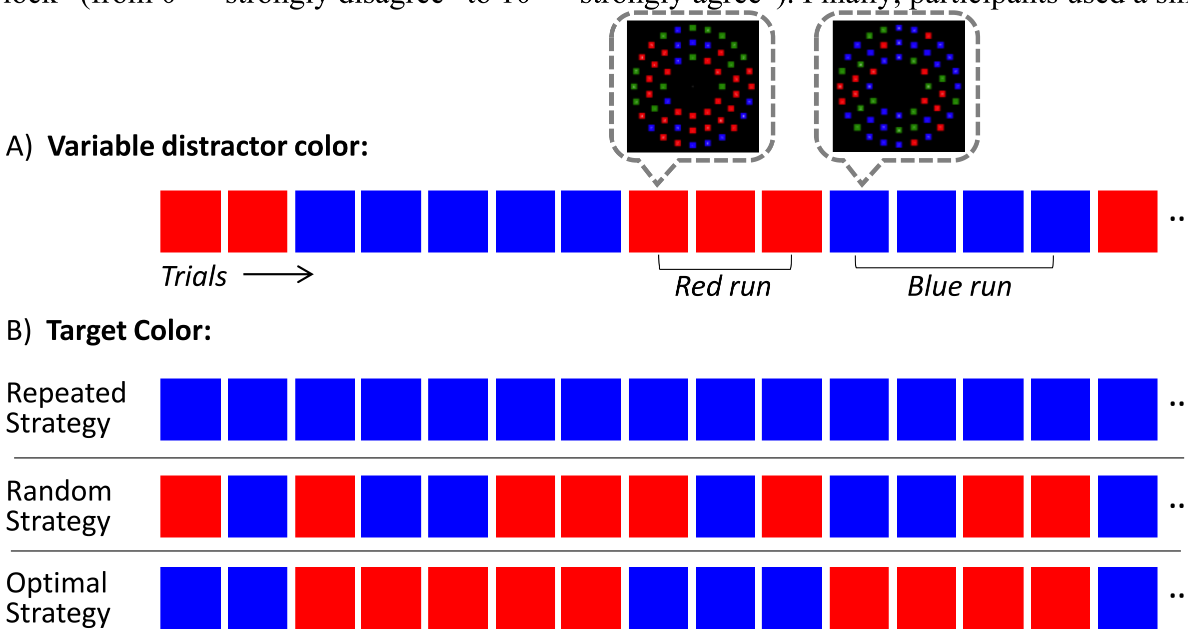

Figure 5. Examples of A) variable distractor color and B) corresponding target color across trials in the enforced strategy blocks. A) Variable distractor colors were organized into short runs of red or blue. B) In the Repeated Strategy block, target color was held constant, and in the Random Strategy block, target color was selected at random. In the Optimal Strategy block, the target was always the color with the fewest distractors.

their least preferred block, by rating their agreement with the following statements: "It requires the most effort", "It takes the most amount of time"," My performance is the worst on this block"," It is the most boring block". After they reported their preferences, participants were informed that they did not need to complete this additional block.

Surveys

At the end of the experiment, participants completed the same strategy self-report questionnaire conducted in Experiment 1, to gauge self-reported awareness of strategy use in the Choice block. We also administered several personality scales, described below.

International Personality Item Pool (IPIP) Novelty Seeking Scale. We predicted that trait novelty-seeking, which is related to impulsiveness, may help to explain why some individuals engage in more random switching. We used a novelty-seeking scale based on items from the IPIP, a well-established pool of survey items available in the public domain (Goldberg, 1999; Goldberg et al., 2006; available at http://ipip.ori.org/).

The Novelty-Seeking scale (Goldberg et al., 2006) takes 34 items from the IPIP and is based to the novelty-seeking scale included in the Temperament & Character Inventory (Cloninger, Przybeck, Svrakic & Wetzel, 1994). Items are rates on a 5-point Likert Scale and include "I like to act on a whim" and "I think twice before doing something".

Need for Cognition Scale (short form). The Need for Cognition Scale (Cacioppo & Petty, 1982; Petty, Cacioppo & Kao, 1984) is a measure of an individual's willingness to engage in, and enjoyment of, cognitively demanding activities. The short form contains 18 items (e.g. "I would prefer complex to simple problems") that are rated on a 5-point Likert Scale. We predicted that individuals high on Need for Cognition would might be more willing to expend effort to maximize performance on the ACVS.

Intolerance of Uncertainty. Intolerance of Uncertainty measures an individual's ability to cope with ambiguity and desire to control the future (Buhr & Dugas, 2002; Freeston, Rheaume, Letarte, Dugas & Ladouceur, 1994). Scores on this scale have been linked to response strategy on complex search tasks (Muhl-Richardson et al., 2016). When performing the ACVS, participants are placed in a state of uncertainty with regards to which target they should choose and when they should switch. We speculated that those who have a higher Intolerance of Uncertainty would be more likely to limit this ambiguity by adopting a definitive strategy to complete the task (either the optimal strategy, or repeating the same color for extended periods), rather than searching in a random manner.

Results

Given the large number of analyses, the results section is ordered such that the analyses most pertinent to the primary research question – assessment of choice block performance and its association with subjective ratings – are reported first, before additional analyses are discussed.

Accuracy was uniformly high across all four blocks (M = 97.14%, no main effect of block, p = .71). As with Experiment 1, error trials and those with RTs less than 300ms or more than 3 SD above the means (2.3% of trials) were excluded from RT analyses. When multiple comparisons were conducted, the Holm-Bonferroni correction was applied. All continuous variables in correlational analyses (percent optimal, effort and performance ratings, preference ratings, personality scales and self-report questionnaire measures) were screened for univariate and multivariate outliers using the same procedures as in Experiment 1, and any cases in which outliers were detected are described in the text.

Choice performance

Recall that Experiment 2 only included plateau trials, and the length of each plateau varied unpredictably between 1 and 6. Consequently, percent optimal and switch rate are plotted at each position in the plateau (see Figure 6a and 6b).

On average, participants chose the optimal target on 70.04% of trials, although there was substantial variation across individuals (range 32.77 - 97.59%, SD = 17.83). Split-half reliability, averaged across 50 random splits, was high (r = .98). Percent of optimal choices was lowest on the first trial of the plateau and increased as the plateau progressed, $F(5, 245) = 12.70$, $p < .001$, $\eta_p^2 = .21$. Average switch rate was 32.54% (range 1.68% to 50.70%, SD = 9.64) and internal consistency was adequately high (average split-half reliability r = .90). This was significantly higher than the optimal switch rate of 27.71%, $t(49) = 3.55$, $p < .001$ (note that the optimal switch rate here was higher than in Experiment 1, due to the removal of transition trials). Switch rate was highest at the first position in the plateau and decreased substantial by the second position, $F(1, 49) = 63.03$ $p < .001$, $\eta_p^2 = .56$. Unlike Experiment 1, percent optimal and switch rate were not strongly correlated (r = -.17), mostly likely due to the higher optimal switch rate in Experiment 2 (compare Figure 6c to Figure 3c). For this reason, we did not calculate independent switch cost.

Subjective ratings on Enforced Strategy blocks

Individuals' ratings of effort and performance across the three enforced strategy blocks (Repeated Strategy, Random Strategy, Optimal Strategy) are shown in Figure 7a and b. Effort ratings varied significantly across block, $F(2, 98) = 11.93$, $p < .001$, $\eta_p^2 = .20$. The Random Strategy was considered more effortful than the Repeated Strategy ($t(49) = 5.88$, $p_{HB} < .001$, $d = .83$) and Optimal Strategy ($t(49) = 2.90$, $p_{HB} = .011$, $d = .47$).

The Repeated Strategy was numerically, but not significantly, less effortful than the Optimal Strategy (p_{HB} = .08). Likewise, subjective performance ratings varied significantly ($F(2, 98) = 6.97$, $p = .001$, $\eta_p^2 = .12$), and performance was rated lower on the Random Strategy block than the Repeated Strategy block ($t(49) = 4.44$, $p_{HB} < .001$, $d = .64$) and the Optimal Strategy block ($t(49) = 3.06$, $p_{HB} = .008$, $d = .44$). Repeated and Optimal blocks did not differ ($p_{HB} = .54$).

Predicting choice performance from subjective ratings

The key question was whether individuals' effort and performance ratings predicted choice performance (percent optimal and switch rate). Table 4 shows the correlations between these measures. For the Repeated and Random strategy blocks, subjective ratings were unrelated to either choice measure (all $p_{HB} = 1.00$). For the Optimal strategy, ratings were not correlated with switch rate ($p_{HB} = 1.00$), but critically, they were correlated with optimal choices: more optimal choices was associated with both lower effort ratings ($r = -.43$, $t(48) = 3.31$, $p_{HB} = .021$) and higher subjective performance ($r = .43$, $t(48) = 3.31$, $p_{HB} = .021$; see Figure 7).

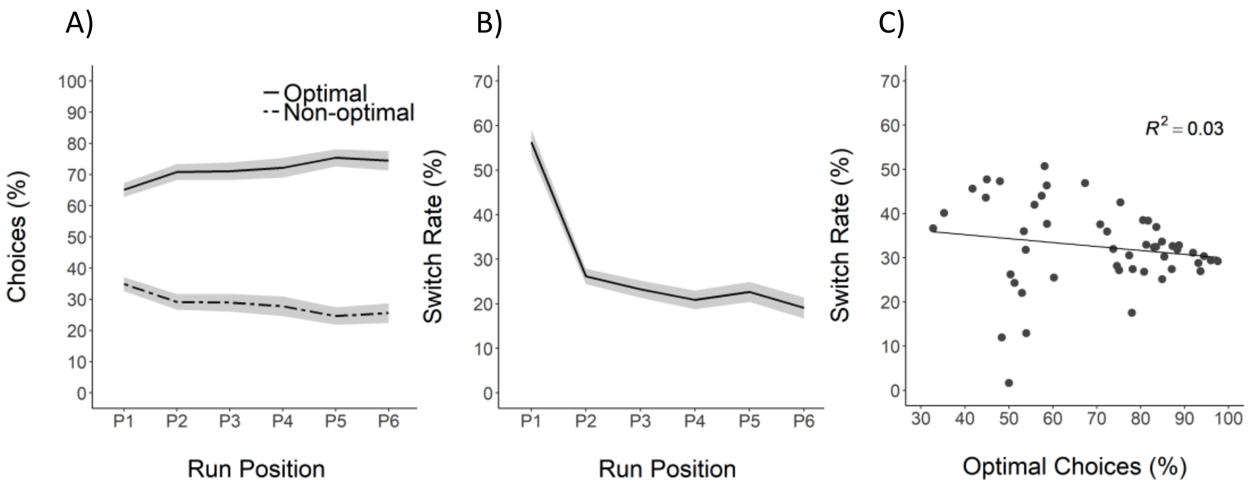

Figure 6. Experiment 2 Choice block results. A) Percent optimal and non-optimal choices and B) switch rate across run position. Error bands indicate standard error of the mean. C) Proportion optimal plotted against switch rate.

Given that both effort and performance were related to optimal choices, we next looked at the extent to which these two factors overlapped. Effort and performance ratings were correlated with each other ($r = -.38$), which may indicate multicollinearity. Moreover, both measures may be entirely dependent on *actual* performance. That is, participants who perform better on the optimal strategy block (i.e., faster RTs) may be more likely to rate their performance as high and the effort demand as low. To test this, we used hierarchical regression to predict optimal choices and entered RT on the Optimal Strategy block as the first predictor. Optimal strategy-block RT did account for a significant proportion of the variance in optimal choices ($R^2 = .08$, $F(1, 48) = 4.25$, $p = .04$), with faster RT during that block predicting more optimal choices. However, adding performance and effort ratings to the model significantly improved prediction ($R^2_{change} = .23$, $F(2, 46) = 7.55$, $p = .001$). This was largely driven by effort: effort ratings significantly predicted choice performance over and above the other two predictors ($R^2_{\text{change}} = .11$, $F(1, 46) = 7.42$, $p = .001$), but subjective performance did not ($R^2_{\text{change}} = .02$, $F(1, 46) = 1.41$, $p = .24$).

Additional individual differences analyses

Subjective ratings on the Choice block. While our main focus was on subjective ratings on the enforced strategy blocks, we also looked at ratings on the Choice block and their relationship to choice performance. The Choice block was considered more effortful than the Repeated Strategy block ($t(49) = 3.11$, $p_{HB} = .009$, $d = .45$), but of equal effort to the Random or Optimal Strategies (both $p_{HB} > .39$). Choice performance ratings did not differ significantly from any other block (all $p_{HB} > .17$).

Correlations between subjective ratings and percent optimal or switch rate were not significant when correcting for family-wise error rate (see Table 4); uncorrected, two correlations were significant: participants with higher switch rates rated the Choice block as more effortful (r = .30, t(48) = 2.17, p = .035) and their performance as lower (r = -.33, t(48) = 2.45, p = .018).

Table 4. ***Correlations between ACVS measures and subjective ratings in Experiment 2.***

	ACVS Measures	
	Percent Optimal	Switch Rate
	r [95% CI]	*r* [95% CI]
Repeated Strategy		
Subjective Effort	-.18 [-.34, .10]	.13 [-.16, .39]
Subjective Performance	.14 [-.14, .40]	-.13 [-.40, .15]
Random Strategy		
Subjective Effort	-.21 [-.46, .07]	-.14 [-.41, .14]
Subjective Performance	.16 [-.12, .42]	-.01 [-.28, .28]
Optimal Strategy		
Subjective Effort	-.43 [-.63, .17] *	.03 [-.25, .30]
Subjective Performance	.43 [.17, .63] *	-.18 [-.44, .10]
Choice block		
Subjective Effort	-.21 [-.46, .07]	.30 [.02, .53] #
Subjective Performance	.26 [-.02, .50]	-.33 [-.56, -.06] #

* = p < .05 (Holm-Bonferroni corrected). # = p < .05 (uncorrected)

Preference ratings. At the end of the experiment, participants rated their preferences for each of the four blocks. Preference ratings varied significantly across blocks, $F(3, 147) = 6.16$, $p < .001$, $\eta_p^2 = .11$. The Random Strategy, which was rated as most effortful and least effective, was also the least preferred, lower than the Repeated Strategy block ($t(49) = 3.60$, $p_{HB} = .004$, $d = .51$), Optimal Strategy block ($t(49) = 4.11$, $p_{HB} < .001$, $d = .58$), and the Choice block ($t(49) = 2.94$, $p_{HB} = .02$, $d = .42$). The other three blocks did not differ.

Preference ratings were largely uncorrelated with choice performance. Only one relationship was significant: individuals with a higher switch rate also showed a higher preference for the Random Strategy block relative to those with a lower switch rate, $r = .41$, $t(48) = 3.11$, $p_{HB} = .025$. There was also a trend for those with a higher switch rate to have a lower preference for the Choice block, r = -.37, $t(48) = 2.72$, p_{HB} = .064. No other correlations were significant (all $p_{HB} > .12$).

Finally, we looked at the motivations underlying each individual's most and least preferred strategy. Four motivating factors were rated, emphasizing performance, effort, time or boredom. A 2-way mixed ANOVA revealed a significant interaction between most preferred strategy (between-subjects) and motivating factor, $F(9, 138) = 2.36$, $p = .017$, $\eta_p^2 = .13$. Motivation ratings varied significantly for individuals who chose the Repeated Strategy block as their preferred strategy ($N = 15$; $F(3, 42) = 9.19$, $p < .001$, $\eta_p^2 = .40$), with effort minimization rated as highest motivating factors and boredom alleviation as the lowest. For the remaining participants, there were no differences across motivating factor (ps > .46). Least preferred strategy also interacted with motivating factor, $F(9, 138) = 3.95$, $p < .001$, $\eta_p^2 = .21$. Participants for whom the Repeated

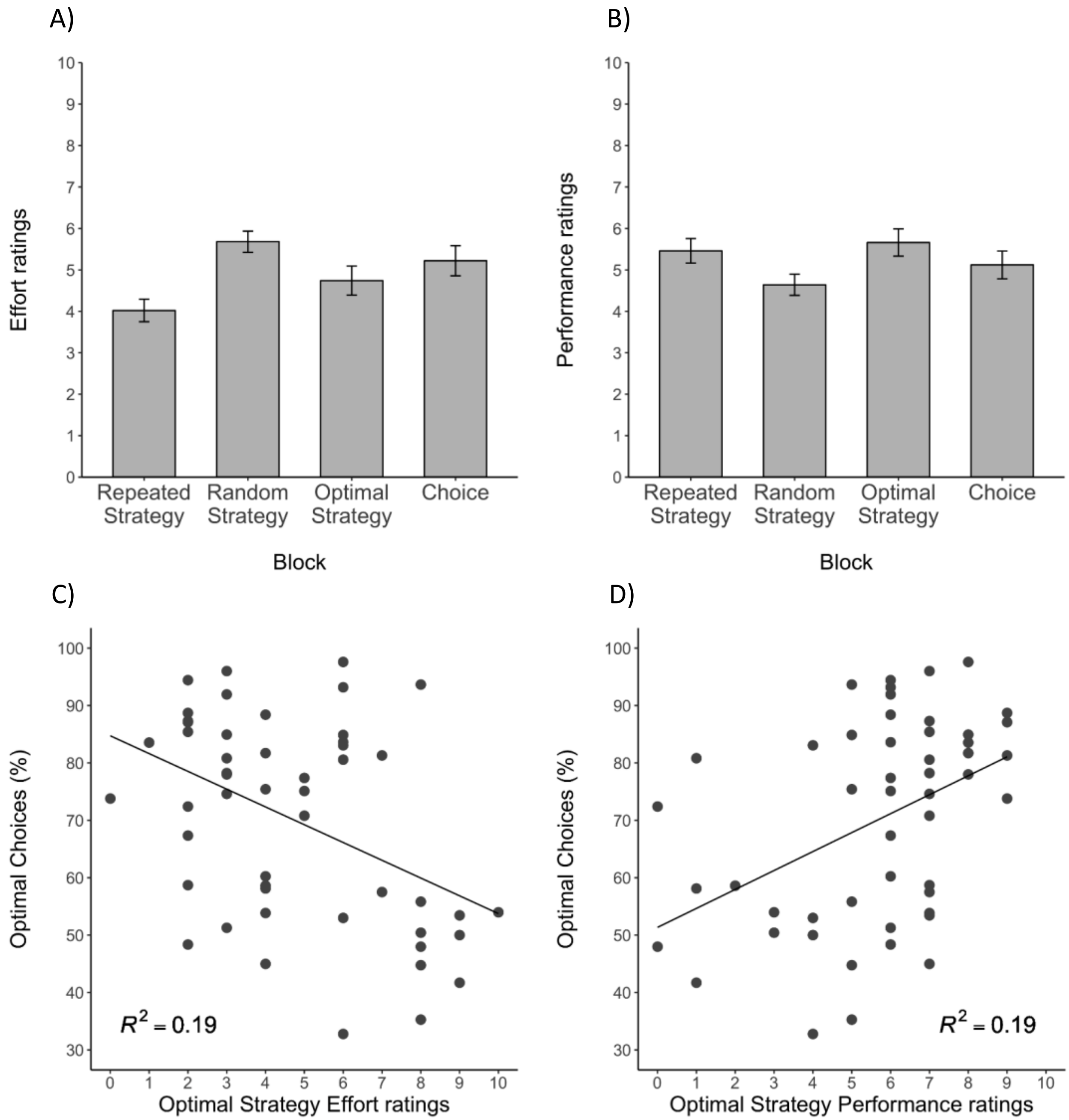

Figure 7. A) Subjective effort and B) performance ratings on each block in Experiment 1. Error bars show standard error of the mean. C) –D) Scatterplots showing Choice block percent optimal choices as a function of C) effort ratings and D) performance ratings on the Optimal Strategy block.

Strategy was their least preferred option (N = 10) rated boredom as the main reason they disliked this block, $F(3, 27) = 3.13$, $p = .04$, $\eta_p^2 = .26$. Participants who selected the Choice block as their least preferred (N = 15) were more likely to cite effort as the reason to avoid this block, and least like to cite boredom, $F(3, 42) = 6.83$, $p = .001$, $\eta_p^2 = .33$. Motivations did not vary for those who selected the Random Strategy as their least preferred ($p = .11$), and were not analyzed for those selecting the Optimal Strategy as their least preferred (as only 4 people fell in this group).

Strategy self-report questionnaire. As with Experiment 1, responses to the strategy self-report questionnaire showed that participants had good insight into their strategy on the Choice block (see Table 2). Self-reported optimal searching was positively correlated with optimal choices ($r = .77$, $t(48) = 8.42$, $p_{HB} < .001$), but unrelated to switch rate ($p_{HB} = .65$). Self-reported repeated searching was negatively correlated with both optimal choices ($r = -.35$, $t(48) = 2.59$, $p_{HB} = .038$) and switch rate ($r = -.52$, $t(48) = 4.25$, $p_{HB} < .001$). However, these latter two correlations appeared to be driven by two outliers with high self-reported repeated searching scores (z-scores = 4.58 and 3.53), and neither correlation reached significance when these outliers were removed ($p_{HB} > .19$). Self-reporting random searching was associated with fewer optimal choices ($r = -.47$, $t(48) = 3.67$, $p_{HB} = .002$) and a higher switch rate, although this latter correlation did not reach significance when corrected ($p_{HB} = .098$).

Again, participants indicated the motivating factors underling their strategy choice. Twenty-nine participants reported that the sole motivation for their chosen strategy was to maximize their performance. Seven selected effort minimizing as their only motivation, and two selected boredom alleviation only. The remaining participants reported multiple motivations: Eleven selected both performance maximization and effort minimization, and one person chose all three motivations. Because participants were able to select multiple options, and because most (41 out of 50) participants selected performance maximizing as one of their options, we did not formally analyze the data. We note, however, that the nine individuals who did not choose performance maximization as a motivation (choosing only either effort minimization or boredom alleviation) all rated self-reported random searching as their more frequently used strategy, and made fewer optimal choices (58%) than those who were motivated to maximize performance (73%).

Correlations with personality scales. Correlations between ACVS scores and IPIP novelty-seeking, need for cognition and intolerance of uncertainty are shown in Table 3. One participant's score on the IPIP was identified as a univariate outlier (z-score = 3.94) and multivariate outlier (Mahalanobis distance > 13.82 for correlations with both percent optimal and switch rate), and this data point was excluded from analyses. Internal consistency, measured using Cronbach's alpha, was adequate for all scales (IPIP novelty-seeking $\alpha = .80$; intolerance of uncertainty $\alpha = .90$; need for cognition $\alpha = .84$). Results showed that individuals higher on need for cognition had a lower switch rate, $r = -.40$ (disattenuated $r = -.46$), $t(48) = 3.06$, $p_{HB} = .022$, which may indicate that these individuals are more likely to discern that unnecessary switching is costly to performance. No other correlations were significant (all $p_{HB} > .75$).

Response time analyses

Enforced strategy blocks. Mean response time varied significantly across blocks ($F(9, 98) = 17.30$, $p < .001$, $\eta_p^2 = .26$). Responses were fastest in the Optimal Strategy block (M = 3037ms), followed by the Repeated Strategy block (M = 3302ms), and slowest in the Random Strategy block (M = 3563ms). This pattern is consistent with the predicted costs associated with each strategy: relative to the Optimal Strategy, RT on the Repeated and Random block should be slowed by the presence of non-optimal trials, and the addition of frequent switch trials should slow RTs even further on the Random block. However, because the blocks were not counter-balanced, practice may have also contributed to the faster responses in the Optimal Strategy block. Analysis within blocks confirmed that RTs were faster on optimal trials than non-optimal trials, and the size of the cost was similar on the Repeated Strategy block (non-optimal cost = 1015ms, t(49) = 13.40, $p < .001$, d = 1.53) and the Random Strategy (non-optimal cost = 1080ms, $t(49) = 18.12$, $p < .001$, $d = 2.93$). Additionally, we found a significant switch cost in both blocks containing switches: the Random Strategy block (switch cost = 340ms, t(49) = 3.76, $p < .001$, $d = .65$) and the Optimal Strategy block (switch cost = 358ms, t(49) = 5.90, $p < .001$, $d = .84$).

Choice block. Mean RT in the Choice block was 2921ms (significantly faster than the Repeated and Random blocks, $p_{HB} < .001$, but not faster than the Optimal block, $p_{HB} = .16$). Unlike in the enforced strategy blocks, non-optimal choices were not slower than optimal choices, $t(49) = .29$, $p = .77$. This might seem surprising at first glance, but there was still solid evidence that the performance maximizing strategy was most effective: overall RT correlated significantly with the percent of optimal choices ($r = -.48$, $t(48) = 3.79$, p <.001), which could not be explained by visual search ability (there was no correlation between optimal choices during the choice block and RT on the Random strategy or Repeated strategy blocks, $r = .10$ and $r = .06$ respectively). We speculate that the apparent lack of cost for non-optimal trials is driven by different factors depending on an individual's strategy. For those who primarily use the optimal strategy, non-optimal trials – which only represented a small proportion of trials – were relatively quite fast, and these may represent the occasional, opportunistic cases in which individuals happened to fixate the non-optimal targets incidentally. In support of this, we found that chosen non-optimal targets were more often located closer to fixation than optimal targets (t(49) = 2.74, $p = .008$), suggesting that they were more likely to have been found opportunistically. This effect was larger for those who used the optimal strategy more often ($r = .35$, $p = .012$). In contrast, for individuals with low percent optimal and high switch rate, we found that both optimal and non-optimal trials were quite slow. We suspect that many trials may have involved searching through items of both colors, and hence whether the optimal target or the non-optimal target was found first would make no difference to RT.

Discussion

Experiment 2 shed light on the motivational factors underlying attentional control strategies. Despite the fact that all observers had the opportunity to try out the optimal strategy, many used suboptimal strategies when given the choice. Importantly, the extent to which individuals chose the optimal strategy depended on how effortful and how effective they found that strategy to be. Moreover, performance and effort were shown to be separate contributing factors. Subjective performance ratings no longer predicted choice when optimal strategy RT was accounted for, implying that subjective ratings track well with actual performance. Effort, on the other hand, independently predicted choice after accounting for performance. This finding suggests that in strategy selection, effort and performance are weighted independently.

General Discussion

A complete understanding of attentional control in everyday life must take into account not only the capabilities of the attentional control system, but also strategic factors. Here we show that there are stable and predictable individual differences in the strategies used to control attention. We used a novel paradigm, the ACVS, to assess two measures of individual variation in attentional control strategy: how frequently an individual chooses the optimal control setting, and how frequently they switch between settings. In Experiment 1, we found that both measures correlated with overall performance on the task (search RT), replicating our previous results (Irons & Leber, 2016). Additionally, we showed that that both measures, which varied considerably across individuals, were reliable across different testing sessions, suggesting that variation in attentional control strategy reflects stable individual behavior.

In Experiment 2, we went on to explore the factors underlying strategy choice, by testing whether strategy choice was related to subjective evaluations of effort and performance. If, as we predicted, strategy choice emerges as the result of an internal comparison of performance gains against effort costs, then subjective evaluations of the optimal strategy in particular should predict choice performance. This was indeed supported by the data: participants who rated the optimal strategy as less effortful, or as more effective, were more likely to use this strategy when placed in a choice context. The results suggest that performance-effort trade-offs form a meaningful basis for strategy selection. Moreover, it is the *experience* of effort, not just the willingness to expend effort, that drives strategy choice. In other words, it is not necessarily the case that those who used the optimal strategy were more willing to expend effort than those who did not. Rather, they did so because they found it to be less effortful and more effective than others did.

Although subjective evaluations played a role in choice behavior, they did not account for all the variance, and it seems likely that other factors also contribute to attentional control strategies. The notion that unexplained variance in behavior exists in this task is something we previously discussed (Irons and Leber, 2016); there, we observed that the two factors of effort minimization and performance maximization alone could not easily account for the tendency for participants to switch between target colors more than necessary, given that switching is both effortful and costly to performance (Kool et al., 2010; Rogers & Monsell, 1995). In the previous study, we speculated that a novelty-seeking mechanism influences choice behavior, driving individuals to actively explore new information in their environment even when this runs counter to the task goal. If this were true, however, we would expect ACVS performance to correlate with indices of trait novelty-seeking or impulsiveness, and the present study showed that this was not the case. Thus, the other factors that contribute to attentional control strategy remain the target of future research.

This study adds to the existing literature on individual differences in attentional control, by highlighting the substantial effect of strategy on attentional control performance. While individual differences in attentional control have been well studied, such work has focused primarily on abilities rather than strategy (e.g. Gopher & Kahneman, 1971; Lansman, Poltrock & Hunt, 1983; Hunt, Pellegrino & Yee, 1989; Miyake et al., 2000; Fan et al., 2002; Engle, 2002; Kane & Engle, 2003). This research has enabled the development of detailed models encompassing multiple facets of attentional control (e.g. Fan et al., 2002; Miyake et al., 2000; Miyake & Friedman, 2012), and has demonstrated links between attentional control and a variety of important dimensions such as working memory capacity (Engle, 2002; Kane & Engle, 2003; Shimi, Kuo, Astle, Nobre & Scerif, 2014; Fukuda & Vogel, 2009; 2011; Gaspar, Christie, Prime, Jolicoeur, & McDonald, 2016), IQ (Friedman et al., 2006; Kane & Engle, 2002), impulse control (Hofmann, Friese & Roefs, 2009), and emotion regulation (Schmeichel, Volokhov & Demaree, 2008). In contrast, only a handful of studies to date have reported on individual differences in attentional control or visual search strategies (e.g. Hogeboom & van Leeuwen, 1997; Irons & Leber, 2016; Kristhansson, Johannesson, & Thornton, 2014; Lleras & von Mühlenen, 2004; Nowakowska et al., 2017), and usually as post hoc observations rather than as a priori goals. A more comprehensive analysis was conducted by Boot and colleagues (Boot et al., 2006, 2009), who identified individual differences in the use of covert (searching without eye movements) versus overt (searching with eye movements) search strategies. These studies demonstrated that strategy use generalized across different tasks, and, importantly, accounted for most of the variation across individuals on an attention task (change blindness), providing further evidence for the need to understand strategy choices. The current study adds to this work by offering a new way to interpret individual differences in strategy, within the framework of an effort-performance trade-off. Such an approach may explain existing findings. For example, in Nowakowska et al.'s (2017) task, the optimal visual search strategy involved preferentially fixating informative, heterogeneous regions of a search display. While some observers used this strategy, others showed a bias away from these regions and towards more homogenous parts of the display. This bias towards regions of the display where search would be easier (pop-out) may be driven by a desire to minimize the effort associated with difficult, heterogeneous search.

These results also highlight the potential of the ACVS as a methodological tool. A common limitation in using standard cognitive tasks in individual differences designs is that they tend to have low reliability. For example, a recent study assessing a variety of commonly used attention capture measures found that internal consistency ranged between 0 and .56 (Roque, Wright & Boot, 2016). This may be the result of a number of different factors. Hedge, Powell and Sumner (2017) argue that low reliability is a natural consequence of designing cognitive tasks to minimize between-subject variability, which improves sensitivity to changes across groups or conditions, but reduces the amount of measurable individual variation in relation to noise. Additionally, many cognitive tasks rely on difference scores (e.g., the magnitude of attentional capture as measured by the difference between distractor present and distractor absent trials), and differences scores are known to be unreliable (Johns, 1981). The ACVS does not have either of these concerns, and has very high internal consistency (.9 or higher for both measures in both experiments) and good test-retest reliability (.83 for percent optimal and .77 switch rate, considered by many to be acceptable for individual differences, e.g. Barch & Carter, 2008; Hedge et al., 2017). Thus, the ACVS may offer a stable option for researchers contemplating studying individual differences in attentional control.

We note, however, that the reliability of this task has only thus far been measured in a specific version of the task performed under the same experimental context. Further research is required to examine whether an individual's strategy remains stable across state-based changes. Preliminary evidence in our lab suggests that this might be the case – individuals' scores appear to be robust to changes in search configuration and task contexts.

In summary, this study provides evidence for stable individual differences in strategies for controlling attention, and a relationship between strategy use and subjective evaluations of effort and performance. The results reaffirm previous work showing that understanding strategy is essential for fully understanding attentional control (e.g., Bacon & Egeth, 1994; Leber & Egeth, 2006a). Additionally, these finding lay the groundwork for developing a more detailed profile of how an individual uses attentional control, which may have broad applied and clinical uses.

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