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Statistical learning facilitates the strategic use of attentional control

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ABSTRACT

A growing body of research suggests that observers rely on a variety of suboptimal strategies when searching for objects. However, real-world environments contain a variety of statistical regularities that enable more efficient processing of information. In the present study, we examined whether statistical learning can influence the strategic use of attentional control using a modified version of the adaptive choice visual search task. Participants searched through an array of colored squares and identified a digit located within a red or blue target square. Each trial contained both a red and a blue target, and participants were free to choose which color to search for. On each trial, more squares were presented in one color than the other color. Thus, the optimal strategy was to search for the color with the fewest squares. Critically, one color was the optimal color on 75% of trials, while the other color was the optimal color on the remaining 25% of trials. Participants were faster to identify targets and made a larger proportion of optimal choices when the high-probability optimal color was optimal. Thus, statistical learning facilitated both search for the targets and the optimal choice of attentional control settings. These effects persisted when the color contingencies were equated, suggesting that these findings were not simply due to intertrial priming. Moreover, participants were not slower to identify targets when the high-probability optimal color appeared as a distractor, suggesting that these findings were not due to attentional capture by this color. Together, these findings suggest that statistical learning can facilitate the strategic use of attentional control by biasing which features observers choose to search for.

1. Introduction

A substantial body of research has been devoted to identifying which factors influence the control of attention. Early theories of attention distinguished between stimulus-driven and goal-directed forms of attentional control (e.g., Corbetta & Shulman, 2002; Theeuwes, 2010). For example, both visual salience (Theeuwes, 1992; Yantis & Jonides, 1984) and observers' task goals (Bacon & Egeth, 1994; Folk, Remington, & Johnston, 1992) have been found to influence the allocation of attention. However, more recent theories suggest that prior experience, or *selection history*, can also influence the control of attention (e.g., Anderson et al., 2021; Awh, Belopolsky, & Theeuwes, 2012). For example, intertrial priming (Maljkovic & Nakayama, 1994), statistical learning (Geng & Behrmann, 2005; Jiang, Swallow, Rosenbaum, & Herzig, 2013; Wang & Theeuwes, 2018a), reward learning (Anderson, Laurent, & Yantis, 2011; Della Libera & Chelazzi, 2006; Hickey, Chelazzi, & Theeuwes, 2010), and aversive conditioning (Anderson & Britton, 2020; Schmidt, Belopolsky, & Theeuwes, 2015) have all been found to influence the allocation of attention. Critically, these factors can influence attentional selection independently of visual salience or observers' task goals, suggesting that selection history represents a distinct form of attentional control (e.g., Anderson et al., 2021).

In many cases, visual salience and selection history compete with observers' task goals for the control of attention. To prioritize among these competing factors, many theories suggest that observers adopt an *attentional set*, or a set of features that is prioritized for attentional selection (e.g., Folk et al., 1992). For example, when observers search for a particular color, attention is biased toward objects that share this color. Previous evidence suggests that observers can adopt attentional sets for a variety of features, including color (Folk, Leber, & Egeth, 2002; Folk & Remington, 1998), abrupt onsets (Atchley, Kramer, & Hillstrom, 2000; Folk, Remington, & Wright, 1994), and apparent motion (Folk et al., 1994). There is also evidence that observers can adopt attentional sets for more abstract features, such as uniqueness (Bacon & Egeth, 1994) or relational information (Becker, Folk, & Remington, 2010). Lastly, there is some evidence that observers can adopt attentional sets for a particular category of objects (Lim, Clement, & Pratt, 2021; Wyble, Folk, & Potter, 2013). Together, these findings suggest that observers can

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prioritize a variety of features for attentional selection.

Typically, most studies have examined the goal-directed control of attention by instructing observers to search for a particular feature. This differs from many real-world situations, in which observers are free to choose which features to search for. For example, when searching for one's car in a crowded parking lot, observers can choose to search based on its color, shape, or other visual features. However, searching for one's car based on its color may be an inefficient strategy if other cars share similar colors. Previous evidence suggests that observers rely on a variety of strategies when searching for objects, some more efficient than others. For example, Bacon and Egeth (1994) found that observers can ignore salient distractors if they search for objects based on their specific visual features. However, observers often fail to use this strategy, instead searching for any unique object in the display. Several studies also suggest that observers often persist in using a particular strategy once it has been learned (Leber & Egeth, 2006a, 2006b; Leber, Kawahara, & Gabari, 2009; Liao, Britton, & Anderson, 2020) and can use different strategies in a context-specific manner (Cosman & Vecera, 2013). However, few studies have examined why observers choose to adopt different search strategies.

To examine the strategic use of attentional control, Irons and Leber (2016, 2018) recently developed the *adaptive choice visual search* (ACVS) task based on the finding that observers can restrict their search to a subset of stimuli (e.g., Bacon & Egeth, 1997; Egeth, Virzi, & Garbart, 1984). In this task, participants search through an array of colored squares and identify a digit located within a red or blue target square. Each trial contains both a red and a blue target, and participants are free to choose which color to search for. On each trial, more squares are presented in one color than the other color. Thus, the optimal strategy is to search for the color with the fewest squares (the *optimal color*). Critically, the optimal color unpredictably changes from trial to trial. Thus, using the optimal strategy requires participants to actively monitor the environment and update their attentional control settings accordingly. Irons and Leber (2016, 2018) found that participants make a relatively low proportion of optimal choices in this task. Participants also rely on a variety of suboptimal strategies, with some participants frequently switching colors and others repeatedly searching for the same color. Based on these findings, the researchers concluded that visual search behavior is often far from optimal (see also Nowakowska, Clarke, & Hunt, 2017).

In most ACVS studies, the optimal color unpredictably changes from trial to trial (Irons & Leber, 2016, 2018). However, real-world environments contain a variety of statistical regularities that enable more efficient processing of information. A large body of research suggests that observers can implicitly learn these statistical regularities, even in the absence of instructions or explicit awareness (Fiser & Aslin, 2001, 2002; Turk-Browne, Jungé, & Scholl, 2005). Moreover, this statistical learning process has been found to influence the allocation of attention. For example, observers are faster to identify targets when targets and distractors co-occur in specific spatial configurations (Chun & Jiang, 1998, 2003). Observers are also faster at identifying targets (Geng & Behrmann, 2002, 2005; Jiang et al., 2013) and are more efficient at suppressing salient distractors (Britton & Anderson, 2020; Wang & Theeuwes, 2018a, 2018b, 2018c) when these objects appear at high-probability locations. Lastly, there is some evidence that attention is automatically biased toward statistical regularities (Zhao, Al-Aidroos, & Turk-Browne, 2013). Together, these findings suggest that statistical learning plays an important role in the allocation of attention.

Although statistical learning can facilitate processes such as target selection and distractor suppression, it is unclear whether statistical learning can also influence the strategic use of attentional control. For example, can statistical learning bias which features observers choose to search for? Notably, there is some evidence that observers can adopt attentional sets based on statistical learning. For example, Cosman and Vecera (2014) had participants identify a red or green target that was preceded by a red or green peripheral cue. In an initial training phase, the target was presented in one color on 80% of trials and the other color on the remaining 20% of trials. In a subsequent test phase, these color contingencies were equated. Participants were faster to identify the target when it was preceded by a valid cue, suggesting that the cue captured attention. Moreover, the magnitude of this effect was greater when the cue was presented in the high-probability target color. These effects persisted when the color contingencies were equated, suggesting that these findings were not simply due to intertrial priming (Maljkovic & Nakayama, 1994). In the present study, we examined whether statistical learning can facilitate the strategic use of attentional control by biasing which features observers choose to search for.

2. Experiment 1

In Experiment 1, we examined whether statistical learning can facilitate the strategic use of attentional control using a modified version of the ACVS task (Irons & Leber, 2016, 2018). Participants searched through an array of colored squares and identified a digit located within a red or blue target square. Each trial contained both a red and a blue target, and participants were free to choose which color to search for. On each trial, more squares were presented in one color than the other color. Thus, the optimal strategy was to search for the color with the fewest squares. Critically, one color was the optimal color on 75% of trials, while the other color was the optimal color on the remaining 25% of trials. If statistical learning facilitates search for the targets, participants should be faster to identify targets when the high-probability optimal color is optimal. Moreover, if statistical learning facilitates the optimal choice of attentional control settings, participants should make a larger proportion of optimal choices when this color is optimal.

2.1. Methods

2.1.1. Participants

Assuming a small effect size ($f = 0.1$) and a moderate correlation between levels of our within-subjects variables ($\rho = 0.5$), an a priori power analysis conducted using G*Power 3 (Faul, Erdfelder, Lang, & Buchner, 2007) indicated that a sample size of 24 participants would be sufficient to detect a main effect of color at 80% statistical power. However, to account for the added variability of recruiting and testing participants online, we increased our sample size to 48 participants. As a result, a group of 70 participants from the Texas A&M community were recruited and tested online; however, 22 participants were excluded due to low accuracy (65% correct or less; $n = 17$) or because they made a low proportion of optimal choices (50% or less; $n = 14$). Participants could be excluded for multiple reasons. The remaining 48 participants (29 females; mean age = 19.4 years, $SD = 2.1$ years) were between the ages of 18 and 35 and reported normal or corrected-to-normal visual acuity and normal color vision. All participants received course credit for participating in the experiment.

2.1.2. Apparatus and stimuli

Stimuli consisted of 54 colored squares (each 4% of participants' screen height) arranged in three concentric rings around the center of the screen (see Fig. 1). The inner (radius 20% of participants' screen height), middle (radius 30% of participants' screen height), and outer rings (radius 40% of participants' screen height) consisted of 12, 18, and 24 squares, respectively. In addition to 14 green squares, the search display contained either 13 red squares and 27 blue squares (red optimal trials) or 27 red squares and 13 blue squares (blue optimal trials). Each square contained a white digit between 2 and 9 (3% of participants' screen height). One red target square and one blue target square contained a digit between 2 and 5. The two digits were always different so that the digit participants reported was diagnostic of which target they found. All other red or blue squares contained digits between 6 and 9. Green squares were task-irrelevant, and contained digits between 2 and 9 to prevent participants from searching based on digit identity alone.

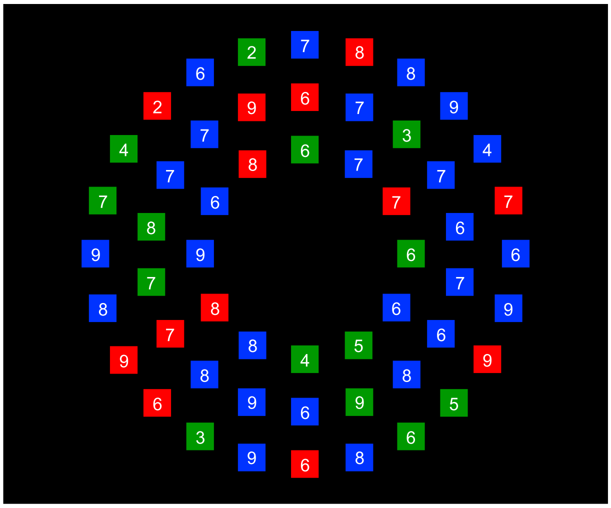

Fig. 1. Example search display in Experiment 1.

All stimuli were presented on a black background. The experiment was programmed and run using PsychoPy3 software (Peirce et al., 2019), and participants viewed the stimuli on their own computers.

2.1.3. Procedure and design

At the beginning of each trial, a white fixation cross (2% of participants' screen height) was presented in the center of the screen. After 1000 ms, a search display was presented on the screen. Participants were instructed to search for the red or blue target square and identify the digit located within this square. Participants were free to choose which color to search for. Participants pressed the "z", "x", "n", or "m" keys to identify whether the digit was a 2, 3, 4, or 5. A trial ended after 5000 ms or once participants made a response. Participants received an error message if they responded incorrectly or if their response times were <100 ms or >5000 ms.

Participants completed 24 practice trials followed by four blocks of 120 trials, for a total of 480 trials. One color (the *high-probability optimal color*) was the optimal color on 75% of trials while the other color (the *low-probability optimal color*) was the optimal color on the remaining 25% of trials. Which color served as the high-probability optimal color was counterbalanced across participants. Previous studies have found that participants make a relatively low proportion of optimal choices (~60% or less) when they are not informed of the optimal strategy (Irons & Leber, 2016). Thus, participants were instructed that the fastest way to perform the task was to search for the color with the fewest squares. Critically, this allowed us to maximize our chances of observing any statistical learning effects by ensuring that participants made a sufficiently large proportion of optimal choices (Kim, Lee, & Anderson, 2021). However, participants were not required to use the optimal strategy, and were free to choose which color to search for. Although participants were informed of the optimal strategy, they were not informed of the color contingencies.

2.1.4. Self-reported strategy ratings

After completing the experiment, participants were asked if they used any strategy when deciding which color to search for, and if so, whether they could explain this strategy. To further assess participants' awareness of their own search strategies, participants then rated the approximate proportion of trials (0%, 20%, 40%, 60%, 80%, or 100%) on which they searched for the red target without switching to the other color (the *red strategy*), searched for the blue target without switching to the other color (the *blue strategy*), switched between searching for the two colors (the *switch strategy*), randomly searched for either of the two colors (the *random strategy*), or attempted to search for both colors at the same time (the *simultaneous strategy*). Ratings for each strategy were standardized by dividing by the sum of all ratings for each participant (Irons & Leber, 2018). Ratings for the first two strategies were recoded to measure how often participants reported searching for the high-probability or low-probability optimal color (the *high-probability* and *low-probability strategy*, respectively).

2.1.5. Contingency awareness test

After providing ratings for each strategy, participants were asked if they noticed any difference between the two colors, and if so, whether they could explain this difference. Participants were coded as noticing the color contingencies if they correctly identified the high-probability optimal color. Participants then completed a short test to further assess their awareness of these contingencies. On each trial, participants viewed two search displays (one high-probability and one low-probability display) and were asked to indicate which display they thought was more likely to appear during the experiment. To prevent participants from recognizing individual displays, all displays were novel, and did not appear during the experiment. Participants completed a total of 24 trials, and the location of the two displays was counterbalanced across trials.

2.1.6. Data analysis

We measured whether participants selected the optimal color on each trial, as well as accuracy and response times. Accuracy was computed as the proportion of trials on which participants correctly responded to either target, while the proportion of optimal choices was computed as the proportion of trials on which participants correctly responded to the target in the optimal color. Incorrect responses and response times <100 ms and >5000 ms were excluded from analysis. All dependent variables were analyzed using paired samples *t*-tests. To assess the time course of any statistical learning effects, we also analyzed the proportion of optimal choices using a 2 (trial type: high-probability, low-probability) × 4 (block: 1, 2, 3, 4) repeated measures analysis of variance (ANOVA). Significant interactions were followed by simple effects tests comparing high-probability and low-probability trials for each block.

2.2. Results

2.2.1. Behavioral data

Accuracy was relatively high ($M = 89.65\%$, $SD = 7.27\%$), indicating that participants were correctly responding to the targets. Participants identified targets significantly faster on high-probability trials ($M = 2346$ ms, $SD = 240$ ms) compared to low-probability trials ($M = 2510$ ms, $SD = 237$ ms), $t\,(47) = -8.75$, $p < .001$, $\eta_p^2 = .620$. Participants also made a significantly larger proportion of optimal choices on high-probability trials ($M = 78.03\%$, $SD = 15.44\%$) compared to low-probability trials ($M = 60.39\%$, $SD = 20.25\%$), $t\,(47) = 5.44$, $p < .001$, $\eta_p^2 = .386$. Thus, statistical learning facilitated both search for the targets and the optimal choice of attentional control settings (see Fig. 2A & B). To assess the time course of these effects, we next analyzed the proportion of optimal choices as a function of block. Consistent with the previous results, the analysis revealed a significant main effect of trial type, $F\,(1, 47) = 28.85$, $p < .001$, $\eta_p^2 = .380$. However, there was neither a significant main effect of block, $F\,(3, 141) = 1.78$, $p = .155$, $\eta_p^2 = .036$, nor a significant interaction between trial type and block, $F\,(3, 141) = 0.81$, $p = .491$, $\eta_p^2 = .017$. Thus, while statistical learning facilitated the optimal choice of attentional control settings, this effect did not differ as a function of block (see Fig. 3).

2.2.2. Self-reported strategy ratings

To assess participants' awareness of their own search strategies, we analyzed ratings for the high-probability and low-probability strategies. A paired samples *t*-test revealed that ratings for the high-probability strategy ($M = 28.74\%$, $SD = 13.97\%$) were significantly greater than ratings for the low-probability strategy ($M = 20.47\%$, $SD = 8.60\%$), *t*

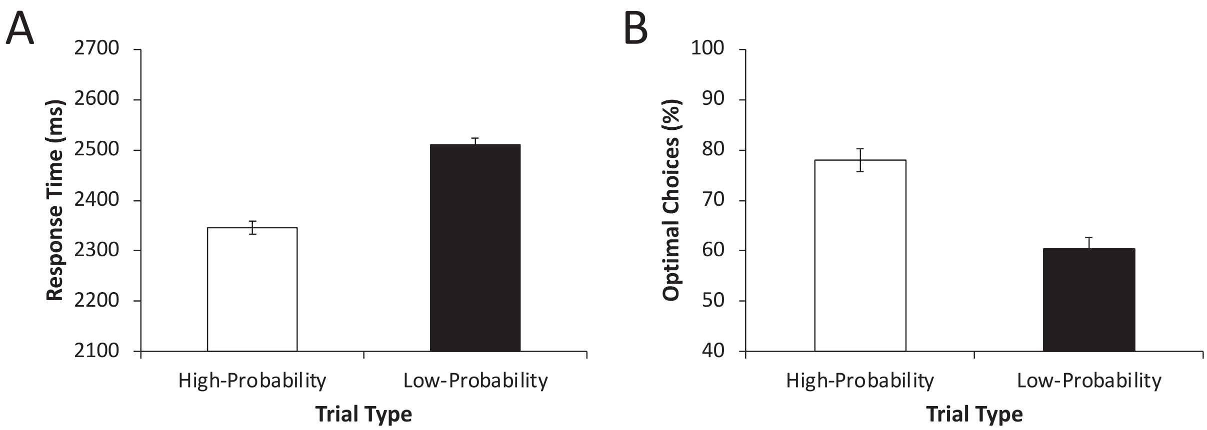

Fig. 2. (A) Average response times in Experiment 1. (B) The proportion of optimal choices in Experiment 1. Error bars reflect ±1 within-subjects standard error (Cousineau, 2005; Morey, 2008).

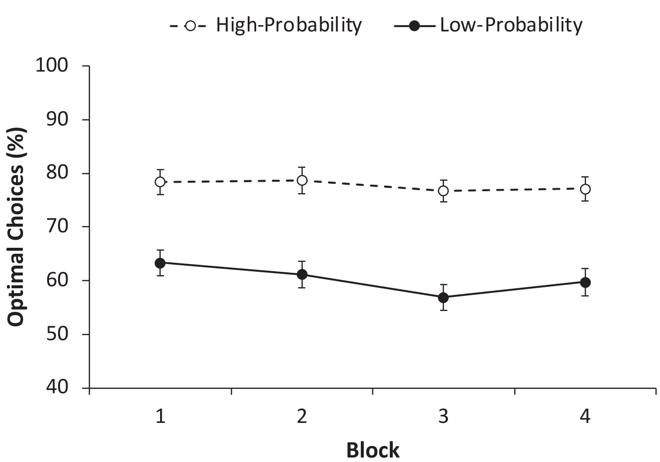

Fig. 3. The proportion of optimal choices as a function of block in Experiment 1. Error bars reflect ±1 within-subjects standard error (Cousineau, 2005; Morey, 2008).

(47) = 3.40, $p = .001$, $\eta_p^2 = .197$. Thus, participants reported searching for the high-probability optimal color more often than the low-probability optimal color. To further assess participants' awareness of their own search strategies, we correlated ratings for each strategy with the proportion of optimal choices on both high-probability and low-probability trials (see Table 1). Ratings for the high-probability strategy were positively correlated with the proportion of optimal choices on high-probability trials, $r = .309$, $p = .032$. Thus, participants who reported searching for the high-probability optimal color made a larger proportion of optimal choices when this color was optimal. Ratings for the simultaneous strategy were also negatively correlated with the proportion of optimal choices on low-probability trials, $r = -.387$, $p = .007$. Thus, participants who attempted to search for both colors at the same time made a smaller proportion of optimal choices when the low-probability optimal color was optimal. No other correlations were significant, all $ps \geq .080$. Together, these results suggest that participants were somewhat aware of their own search strategies.

Table 1
Correlations between ratings for each strategy and the proportion of optimal choices in Experiment 1.

Strategy	High-probability	Low-probability
High-probability strategy	.309*	−.005
Low-probability strategy	−.205	.255
Switch strategy	.035	−.008
Random strategy	−.152	.198
Simultaneous strategy	−.125	−.387**

Notes. Values represent Pearson's correlation coefficients. $^*p < .05$. $^{**}p < .01$.

2.2.3. Contingency awareness test

Only 12 of the 48 participants reported explicitly noticing the color contingencies. To further assess participants' awareness of these contingencies, we analyzed the proportion of trials on which participants indicated that a high-probability display was more likely to appear during the experiment. A one-sample *t*-test revealed that the proportion of these trials ($M = 54.51\%$, $SD = 23.20\%$) was not significantly different from chance, $t\,(47) = 1.35$, $p = .184$, $\eta_p^2 = .039$. Moreover, an independent samples *t*-test revealed that participants who noticed the color contingencies ($M = 57.64\%$, $SD = 29.24\%$) did not indicate that a high-probability display was more likely to appear during the experiment more often than participants who failed to notice these contingencies ($M = 53.47\%$, $SD = 21.21\%$), $t\,(46) = 0.54$, $p = .596$, $\eta_p^2 = .006$. Thus, participants did not appear to be aware of the color contingencies, and awareness was not higher for participants who reported explicitly noticing these contingencies. Lastly, to assess whether explicitly noticing the color contingencies modulated any of our effects, we re-ran all of our analyses with noticing entered as a between-subjects variable. There were no significant effects of noticing on response time, *ps* for all noticing effects $\geq .455$. There was also no significant main effect of noticing for the proportion of optimal choices, $F\,(1, 46) = 2.74$, $p = .104$, $\eta_p^2 = .056$. However, there was a trending interaction between trial type and noticing for the proportion of optimal choices, $F\,(1, 46) = 3.49$, $p = .068$, $\eta_p^2 = .070$. Simple effects tests revealed a significant main effect of trial type for participants who failed to notice the color contingencies, $F\,(1, 35) = 33.52$, $p < .001$, $\eta_p^2 = .489$. However, there was no significant main effect of trial type for participants who noticed the color contingencies, $F\,(1, 11) = 1.35$, $p = .270$, $\eta_p^2 = .109$. Thus, while explicitly noticing the color contingencies appeared to modulate our effects, these effects were strongest for participants who did not report noticing these contingencies.

2.3. Discussion

In Experiment 1, we found that statistical learning facilitated the strategic use of attentional control. Participants were faster to identify targets and made a larger proportion of optimal choices when the high-probability optimal color was optimal. Thus, statistical learning facilitated both search for the targets and the optimal choice of attentional control settings. These effects emerged rapidly and did not diminish throughout the experiment. Interestingly, while participants were somewhat aware of their own search strategies, they displayed little awareness of the color contingencies. Moreover, while explicitly noticing the color contingencies appeared to modulate our effects, these effects were strongest for participants who did not report noticing these contingencies (see Grégoire & Anderson, 2019, for similar findings regarding the effects of awareness on value-driven attention). Thus, awareness did not appear to play a substantial role in the present findings. Together, these findings suggest that statistical learning facilitates the strategic use of attentional control.

3. Experiment 2

In Experiment 1, statistical learning appeared to facilitate the strategic use of attentional control. However, because the mostly optimal color was more likely to repeat from trial to trial, these findings may be due to the cumulative effects of intertrial priming rather than statistical learning (Maljkovic & Nakayama, 1994). Previous studies have attempted to address this issue by removing trials on which a statistically learned feature repeats (Wang & Theeuwes, 2018a; Wang & Theeuwes, 2018b; Wang & Theeuwes, 2018c) or by equating the statistical regularities in a test phase (Britton & Anderson, 2020; Cosman & Vecera, 2014; Jiang et al., 2013). In Experiment 2, we attempted to address this issue using a similar method. Participants completed the same task as in Experiment 1. In an initial training phase, one color was the optimal color on 75% of trials while the other color was the optimal color on the remaining 25% of trials. In a subsequent test phase, these color contingencies were equated. If the previous findings were due to statistical learning, we should observe similar effects in both the training and test phases. However, if the previous findings were due to intertrial priming, we should only observe these effects in the training phase.

3.1. Methods

3.1.1. Participants

A new group of 79 participants from the Texas A&M community were recruited and tested online; however, 31 participants were excluded due to low accuracy (65% correct or less; $n = 30$), because they made a low proportion of optimal choices (50% or less; $n = 17$), or because they reported being colorblind ($n = 1$). Participants could be excluded for multiple reasons. The remaining 48 participants (23 females; mean age = 19.5 years, $SD = 1.8$ years) were between the ages of 18 and 35 and reported normal or corrected-to-normal visual acuity and normal color vision. All participants received course credit for participating in the experiment.

3.1.2. Apparatus and stimuli

The apparatus and stimuli were identical to those in the previous experiment.

3.1.3. Procedure and design

The task was the same as in the previous experiment. In the first two blocks of the experiment (the *training phase*), one color was the optimal color on 75% of trials, while the other color was the optimal color on the remaining 25% of trials. In the last two blocks of the experiment (the *test phase*), the color contingencies were equated so that each color was the optimal color on 50% of trials. All other details of the experimental procedure were identical to those in the previous experiment.

3.1.4. Data analysis

The dependent variables were the same as in the previous experiment. However, all dependent variables were analyzed using 2 (phase: training, test) × 2 (trial type: high-probability, low-probability) repeated measures ANOVAs. Significant interactions were followed by simple effects tests comparing high-probability and low-probability trials for each phase. All other details of the analytical approach were identical to those in the previous experiment.

3.2. Results

3.2.1. Behavioral results

Accuracy was relatively high ($M = 88.20\%$, $SD = 8.03\%$), indicating that participants were correctly responding to the targets. To test whether statistical learning facilitated search for the targets, we first analyzed average response times. The analysis revealed a significant main effect of phase, $F(1, 47) = 45.07$, $p < .001$, $\eta_p^2 = .490$, with participants identifying targets faster in the test phase ($M = 2290$ ms, $SD = 212$ ms) compared to the training phase ($M = 2481$ ms, $SD = 292$ ms). There was also a significant main effect of trial type, $F(1, 47) = 17.36$, $p < .001$, $\eta_p^2 = .270$, with participants identifying targets faster on high-probability trials ($M = 2339$ ms, $SD = 256$ ms) compared to low-probability trials ($M = 2432$ ms, $SD = 240$ ms). Moreover, these effects were qualified by a significant interaction between phase and trial type, $F(1, 47) = 6.95$, $p = .011$, $\eta_p^2 = .129$. Simple effects tests revealed a significant main effect of trial type in the training phase, $F(1, 47) = 23.26$, $p < .001$, $\eta_p^2 = .331$, with participants identifying targets faster on high-probability trials ($M = 2419$ ms, $SD = 235$ ms) compared to low-probability trials ($M = 2544$ ms, $SD = 226$ ms). There was also a significant main effect of trial type in the test phase, $F(1, 47) = 6.01$, $p = .018$, $\eta_p^2 = .113$, with participants identifying targets faster on high-probability trials ($M = 2260$ ms, $SD = 320$ ms) compared to low-probability trials ($M = 2320$ ms, $SD = 288$ ms). However, this effect was smaller than the main effect of trial type in the training phase. Thus, while statistical learning facilitated search for the targets in both the training and test phases, this effect was reduced in the test phase (see Fig. 4A).

To test whether statistical learning facilitated the optimal choice of attentional control settings, we next analyzed the proportion of optimal choices. The analysis revealed a significant main effect of phase, $F(1, 47) = 5.35$, $p = .025$, $\eta_p^2 = .102$, with participants making a larger proportion of optimal choices in the training phase ($M = 73.23\%$, $SD = 17.96\%$) compared to the test phase ($M = 68.96\%$, $SD = 16.25\%$). There was also a significant main effect of trial type, $F(1, 47) = 5.17$, $p = .028$, $\eta_p^2 = .099$, with participants making a larger proportion of optimal choices on high-probability trials ($M = 74.37\%$, $SD = 18.12\%$) compared to low-probability trials ($M = 67.81\%$, $SD = 19.39\%$). However, there was no significant interaction between phase and trial type, $F(1, 47) = 0.40$, $p = .531$, $\eta_p^2 = .008$. Thus, statistical learning facilitated the optimal choice of attentional control settings in both the training and test phases (see Fig. 4B).

Lastly, to assess the time course of these effects, we analyzed the proportion of optimal choices as a function of block. Consistent with the previous results, the analysis revealed a significant main effect of trial type, $F(1, 47) = 5.09$, $p = .029$, $\eta_p^2 = .098$. There was also a significant main effect of block, $F(3, 141) = 5.04$, $p = .002$, $\eta_p^2 = .097$. Bonferroni-corrected pairwise comparisons revealed that participants made a significantly larger proportion of optimal choices in the first block ($M = 74.61\%$, $SD = 18.64\%$) compared to the last block ($M = 67.87\%$, $SD = 16.79\%$), $p = .024$. No other pairwise comparisons were significant, all $ps \geq .108$. Lastly, these effects were qualified by a significant interaction between trial type and block, $F(3, 141) = 3.76$, $p = .012$, $\eta_p^2 = .074$. Simple effects tests revealed a significant main effect of trial type in both the second, $F(1, 47) = 8.87$, $p = .005$, $\eta_p^2 = .159$, and third blocks, $F(1, 47) = 6.82$, $p = .012$, $\eta_p^2 = .127$. However, there was no significant main effect of trial type in either the first, $F(1, 47) = 2.68$, $p = .109$, $\eta_p^2 = .054$, or last blocks, $F(1, 47) = 0.07$, $p = .792$, $\eta_p^2 = .001$. Thus, while statistical learning facilitated the optimal choice of attentional control settings, this effect did not emerge until the second block and was no longer observed by the last block (see Fig. 5).

3.2.2. Self-reported strategy ratings

To assess participants' awareness of their own search strategies, we analyzed ratings for the high-probability and low-probability strategies. A paired samples *t*-test revealed that ratings for the high-probability

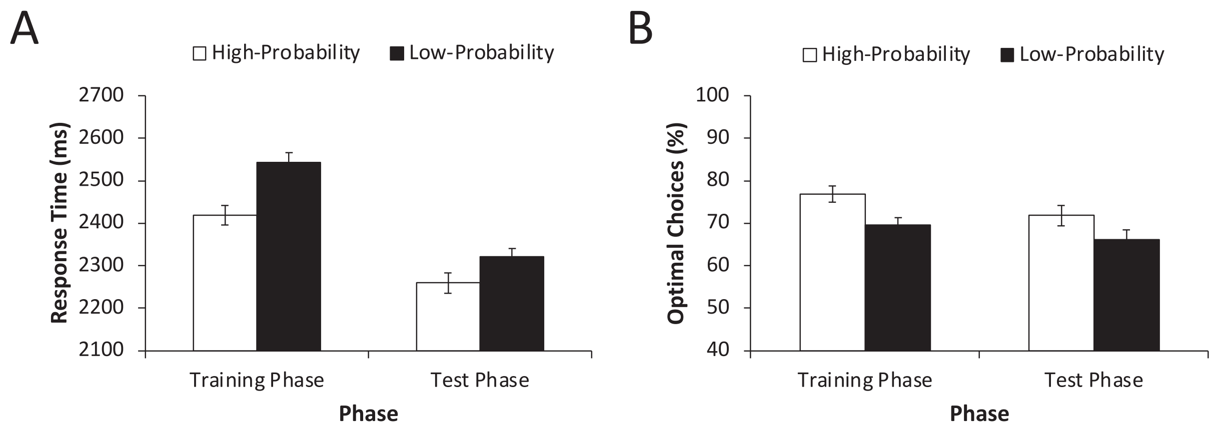

Fig. 4. (A) Average response times in Experiment 2. (B) The proportion of optimal choices in Experiment 2. Error bars in both panels reflect ±1 within-subjects standard error (Cousineau, 2005; Morey, 2008).

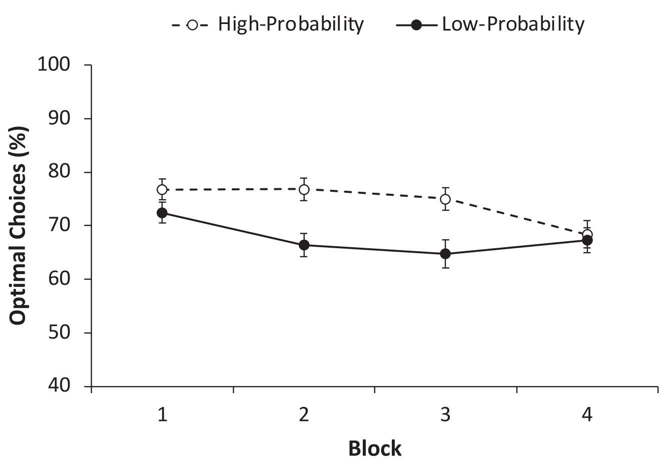

Fig. 5. The proportion of optimal choices as a function of block in Experiment 2. The training phase consisted of the first two blocks, while the test phase consisted of the last two blocks. Error bars reflect ±1 within-subjects standard error (Cousineau, 2005; Morey, 2008).

strategy (M = 27.65%, SD = 11.73%) were significantly greater than ratings for the low-probability strategy (M = 21.12%, SD = 8.82%), t (47) = 3.13, p = .003, η_p^2 = .172. Thus, participants reported searching for the high-probability optimal color more often than the low-probability optimal color. To further assess participants' awareness of their own search strategies, we correlated ratings for each strategy with the proportion of optimal choices on both high-probability and low-probability trials (see Table 2). Ratings for the high-probability strategy were positively correlated with the proportion of optimal choices on high-probability trials, r = .344, p = .017, and ratings for the low-probability strategy were positively correlated with the proportion of optimal choices on low-probability trials, r = .377, p = .008. Thus, participants who reported searching for either the high-probability or low-probability optimal color made a larger proportion of optimal choices when this color was optimal. Ratings for the simultaneous strategy were also negatively correlated with the proportion of optimal choices on both high-probability, r = −.435, p = .002, and low-probability trials, r = −.379, p = .008. Thus, participants who attempted to search for both colors at the same time made a smaller proportion of optimal choices overall. No other correlations were significant, all ps ≥ .348. Together, these results suggest that participants were generally aware of their own search strategies.

Table 2
Correlations between ratings for each strategy and the proportion of optimal choices in Experiment 2.

Strategy	High-probability	Low-probability
High-probability strategy	.344*	.094
Low-probability strategy	<.001	.377**
Switch strategy	−.050	.071
Random strategy	.067	−.138
Simultaneous strategy	−.435**	−.379**

Notes. Values represent Pearson's correlation coefficients. *p < .05. **p < .01.

3.2.3. Contingency awareness test

Only 4 of the 48 participants reported explicitly noticing the color contingencies. To further assess participants' awareness of these contingencies, we analyzed the proportion of trials on which participants indicated that a high-probability display was more likely to appear during the experiment. A one-sample t-test revealed that the proportion of these trials (M = 60.59%, SD = 23.20%) was significantly greater than chance, t (47) = 2.90, p = .006, η_p^2 = .152. Thus, participants appeared to be generally aware of the color contingencies. However, an independent samples t-test revealed that participants who noticed the color contingencies (M = 56.25%, SD = 5.38%) did not indicate that a high-probability display was more likely to appear during the experiment more often than participants who failed to notice these contingencies (M = 60.98%, SD = 26.42%), t (46) = −0.35, p = .725, η_p^2 = .003. Lastly, to assess whether explicitly noticing the color contingencies modulated any of our effects, we re-ran all of our analyses with noticing entered as a between-subjects variable. There were no significant effects of noticing, ps for all noticing effects ≥ .093. However, given the small number of participants who noticed the color contingencies, it is likely that our analyses were underpowered to observe any effects of noticing in this experiment.

3.3. Discussion

In Experiment 2, we again found that statistical learning facilitated the strategic use of attentional control. As in the previous experiments, participants were faster to identify targets and made a larger proportion of optimal choices when the high-probability optimal color was optimal. Thus, statistical learning facilitated both search for the targets and the optimal choice of attentional control settings. Moreover, these effects were observed in both the training and test phases. The magnitude of the response time effect was reduced in the test phase, suggesting that intertrial priming may have played a role in this effect. However, because this effect was not eliminated in the test phase, we think it cannot purely be due to intertrial priming. Moreover, because the magnitude of the optimal choice effect did not differ between the training and test phases, we think it unlikely that this effect was due to intertrial priming. Unlike the previous experiment, these effects did not emerge until the second block and were no longer observed by the last block. Thus, the effects of statistical learning emerged gradually and diminished when the color contingencies were equated. Lastly, while participants were generally aware of both their own search strategies and the color contingencies, our analyses were underpowered to observe any effects of noticing in this experiment. Together, these findings suggest that the previous findings were due to statistical learning rather than intertrial priming.

4. Experiment 3

In the previous experiments, statistical learning appeared to facilitate the strategic use of attentional control. However, because participants were more likely to search for the high-probability optimal color, these findings may be due to attentional capture by this color rather than the strategic use of attentional control. Indeed, previously task-relevant stimuli have been shown to capture attention when they appear as distractors in a test phase (Kyllingsbæk, Schneider, & Bundesen, 2001; Kyllingsbæk, Van Lommel, Sørenson, & Bundesen, 2014; Shiffrin & Schneider, 1977). In Experiment 3, we attempted to address this issue using a similar method. Participants completed the same task as in Experiment 1. In an initial training phase, participants searched for a red or blue target among green distractors. In a subsequent test phase, participants searched for a single green target among red or blue distractors. If the previous findings were due to attentional capture by the high-probability optimal color, participants should be slower to identify the target when this color appears as a distractor in the test phase. However, if the previous findings were due to the strategic use of attentional control, we should not observe these effects in the test phase.

4.1. Methods

4.1.1. Participants

A new group of 86 participants from the Texas A&M community were recruited and tested online; however, 38 participants were excluded due to low accuracy (65% correct or less; $n = 23$), because they made a low proportion of optimal choices (50% or less; $n = 24$), or because they reported being colorblind ($n = 1$). Participants could be excluded for multiple reasons. The remaining 48 participants (33 females; mean age = 18.7 years, *SD* = 0.9 years) were between the ages of 18 and 35 and reported normal or corrected-to-normal visual acuity and normal color vision. All participants received course credit for participating in the experiment.

4.1.2. Apparatus and stimuli

The apparatus and stimuli were the same as in the previous experiments. In the first two blocks of the experiment (the *training phase*), the search display contained 14 green squares and either 13 red squares and 27 blue squares (red optimal trials) or 27 red squares and 13 blue squares (blue optimal trials). However, in the last two blocks of the experiment (the *test phase*), the search display contained 27 green squares and either 27 red squares or 27 blue squares (see Fig. 6). One green target square contained a digit between 2 and 5. All other green squares contained digits between 6 and 9. Red and blue squares were task-irrelevant, and contained digits between 2 and 9 to prevent participants from searching based on digit identity alone. All other details of the apparatus and stimuli were identical to those in the previous experiments.

4.1.3. Procedure and design

The task was the same as in the previous experiments. In the training phase, participants were instructed to search for the red or blue target square and identify the digit located within this square. However, in test phase, participants were instructed to search for the green target square and identify the digit located within this square. Participants pressed the

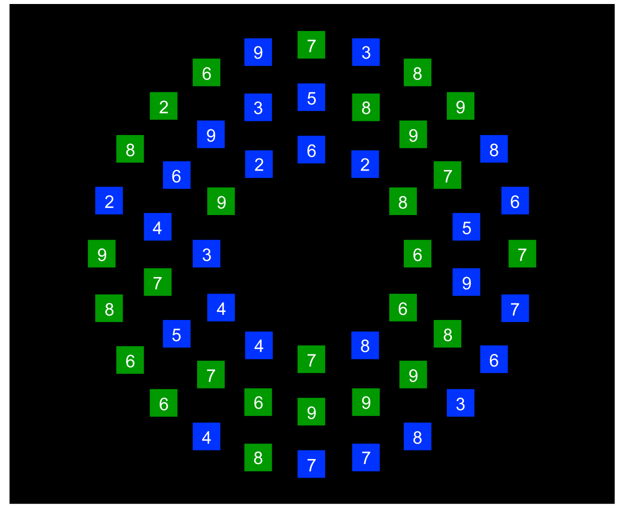

Fig. 6. Example search display in the test phase of Experiment 3.

"z," "x," "n," or "m" keys to identify whether this digit was a 2, 3, 4, or 5. A trial ended after 7000 ms or once participants made a response. Participants received an error message if they responded incorrectly or if their response times were <100 ms or >7000 ms. All other details of the experimental procedure were identical to those in the previous experiments.

4.1.4. Data analysis

The dependent variables were the same as in the previous experiments. However, because participants searched for a single green target in the test phase, the proportion of optimal choices was only analyzed in the training phase. Incorrect responses and response times <100 ms and >7000 ms were excluded from analysis in the test phase. All dependent variables in the training and test phases were analyzed using paired samples *t*-tests. To assess the time course of any statistical learning effects, we also analyzed the proportion of optimal choices using a 2 (trial type: high-probability, low-probability) x 2 (block: 1, 2) repeated measures ANOVA. All other details of the analytical approach were identical to those in the previous experiments.

4.2. Results

4.2.1. Behavioral results

Accuracy was relatively high ($M = 90.51\%$, $SD = 7.59\%$), indicating that participants were correctly responding to the targets. To test whether statistical learning facilitated search for the targets and the optimal choice of attentional control settings, we first analyzed average response times and the proportion of optimal choices in the training phase. Participants identified targets significantly faster on high-probability trials ($M = 2303$ ms, $SD = 261$ ms) compared to low-probability trials ($M = 2400$ ms, $SD = 270$ ms), $t\ (47) = -3.14$, $p = .003$, $\eta_p^2 = .174$. Participants also made a significantly larger proportion of optimal choices on high-probability trials ($M = 81.16\%$, $SD = 15.49\%$) compared to low-probability trials ($M = 67.48\%$, $SD = 25.86\%$), $t\ (47) = 3.51$, $p < .001$, $\eta_p^2 = .208$. Thus, statistical learning facilitated both search for the targets and the optimal choice of attentional control settings (see Fig. 7A & B). To assess the time course of these effects, we next analyzed the proportion of optimal choices in the training phase as a function of block. Consistent with the previous results, the analysis revealed a significant main effect of trial type, $F\ (1, 47) = 12.67$, $p < .001$, $\eta_p^2 = .212$. However, there was neither a significant main effect of block, $F\ (1, 47) = 0.38$, $p = .539$, $\eta_p^2 = .008$, nor a significant interaction between trial type and block, $F\ (1, 47) = 0.06$, $p = .810$, $\eta_p^2 = .001$. Thus, while statistical learning facilitated the optimal choice of attentional control settings, this effect did not differ as a

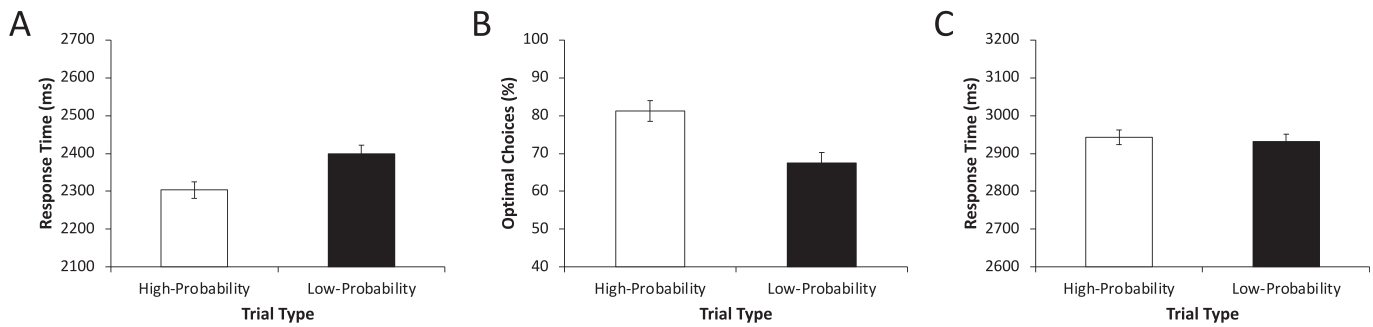

Fig. 7. (A) Average response times in the training phase of Experiment 3. (B) The proportion of optimal choices in the training phase of Experiment 3. (C) Average response times in the test phase of Experiment 3. Error bars in all panels reflect ±1 within-subjects standard error (Cousineau, 2005; Morey, 2008).

function of block (see Fig. 8).

Lastly, to test whether the high-probability color captured attention when it appeared as a distractor, we analyzed average response times in the test phase. Participants were not significantly slower to identify the target on high-probability trials ($M = 2943$ ms, $SD = 367$ ms) compared to low-probability trials ($M = 2931$ ms, $SD = 353$ ms), $t\,(49) = 0.42$, $p = .678$, $\eta_p^2 = .004$. A Bayes factor analysis (Rouder, Speckman, Sun, Morey, & Iverson, 2009) indicated that the null hypothesis was 5.87 times more likely to account for the observed data than the alternative hypothesis that there was a significant difference between the mostly optimal and mostly non-optimal color, $BF_{10} = 0.17$. Thus, the high-probability optimal color did not appear to capture attention when it appeared as a distractor (see Fig. 7C).

4.2.2. *Self-reported strategy ratings*

To assess participants' awareness of their own search strategies, we analyzed ratings for the high-probability and low-probability strategies. A paired samples *t*-test revealed that ratings for the high-probability strategy ($M = 32.98\%$, $SD = 15.44\%$) were significantly greater than ratings for the low-probability strategy ($M = 19.16\%$, $SD = 10.32\%$), $t\,(47) = 4.88$, $p < .001$, $\eta_p^2 = .337$. Thus, participants reported searching for the high-probability optimal color more often than the low-probability optimal color. To further assess participants' awareness of their own search strategies, we correlated ratings for each strategy with the proportion of optimal choices on high-probability and low-probability trials (see Table 3). Ratings for the high-probability strategy were positively correlated with the proportion of optimal choices on high-probability trials, $r = .603$, $p < .001$, and negatively correlated with the proportion of optimal choices on low-probability trials, $r = -.288$, $p = .048$. Ratings for the low-probability strategy were also positively correlated with the proportion of optimal choices on low-probability trials, $r = .634$, $p < .001$. Thus, participants who reported searching for either the high-probability or low-probability optimal color made a larger proportion of optimal choices when this color was optimal. Moreover, participants who reported searching for the high-probability optimal color made a smaller proportion of optimal choices when the low-probability optimal color was optimal. Ratings for the simultaneous strategy were also negatively correlated with the proportion of optimal choices on high-probability trials, $r = -.435$, $p = .002$. Thus, participants who attempted to search for both colors at the same time made a smaller proportion of optimal choices when the high-probability optimal color was optimal. No other correlations were significant, all $ps \geq .348$. Together, these results suggest that participants were generally aware of their own search strategies.

Table 3
Correlations between ratings for each strategy and the proportion of optimal choices in Experiment 3.

Strategy	High-probability	Low-probability
High-probability strategy	.603***	−.288*
Low-probability strategy	.045	.634***
Switch strategy	−.277	.248
Random strategy	−.190	−.285
Simultaneous strategy	−.459**	−.087

Notes. Values represent Pearson's correlation coefficients. *$p < .05$. **$p < .01$, ***$p < .001$.

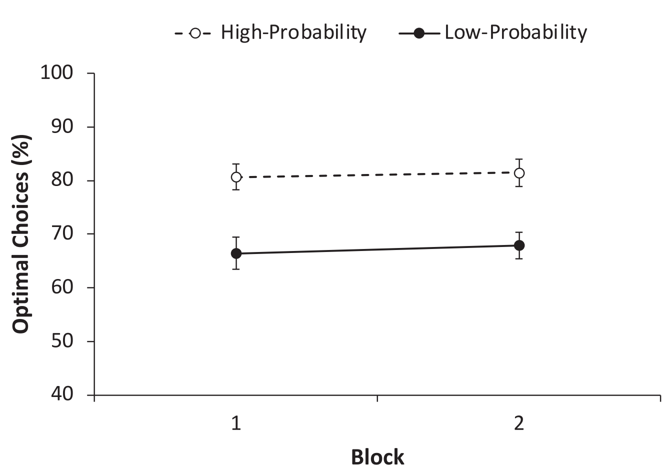

Fig. 8. The proportion of optimal choices as a function of block in the training phase of Experiment 3. Error bars reflect ±1 within-subjects standard error (Cousineau, 2005; Morey, 2008).

4.2.3. *Contingency awareness test*

Only 8 of the 48 participants reported explicitly noticing the color contingencies. To further assess participants' awareness of these contingencies, we analyzed the proportion of trials on which participants indicated that a high-probability display was more likely to appear during the experiment. A one-sample *t*-test revealed that the proportion of these trials ($M = 55.30\%$, $SD = 25.67\%$) was not significantly greater than chance, $t\,(47) = 1.43$, $p = .160$, $\eta_p^2 = .042$. Moreover, an independent samples *t*-test revealed that participants who noticed the color contingencies ($M = 66.67\%$, $SD = 22.16\%$) did not indicate that a high-probability display was more likely to appear during the experiment more often than participants who failed to notice these contingencies ($M = 53.02\%$, $SD = 25.96\%$), $t\,(46) = 1.39$, $p = .172$, $\eta_p^2 = .040$. Thus, participants did not appear to be aware of the color contingencies, and awareness was not higher for participants who reported explicitly noticing these contingencies. Lastly, to assess whether explicitly noticing the color contingencies modulated any of our effects, we re-ran all of our analyses with noticing entered as a between-subjects variable. There were no significant effects of noticing, *ps* for all noticing effects $\geq .154$. Thus, explicitly noticing the color contingencies did not appear to modulate any of our effects.

4.3. Discussion

In Experiment 3, we again found that statistical learning facilitated the strategic use of attentional control. As in the previous experiment, participants were faster to identify targets and made a larger proportion of optimal choices when the high-probability optimal color was optimal. Thus, statistical learning facilitated both search for the targets and the optimal choice of attentional control settings. These effects emerged rapidly and did not diminish throughout the experiment. However, participants were not slower to identify targets when the high-probability optimal color appeared as a distractor in the test phase. Lastly, while participants were generally aware of their own search strategies, they displayed little awareness of the color contingencies. Moreover, explicitly noticing the color contingencies did not appear to modulate any of our effects. Thus, as in the previous experiments, awareness did not appear to play a substantial role in the present findings. Together, these findings suggest that the previous findings were due to the strategic use of attentional control rather than attentional capture by the high-probability optimal color.

5. General discussion

A growing body of research suggests that observers rely on a variety of suboptimal strategies when searching for objects (Irons & Leber, 2016, 2018; see also Nowakowska et al., 2017). However, real-world environments contain a variety of statistical regularities that enable more efficient processing of information. In the present study, we examined whether statistical learning can facilitate the strategic use of attentional control using a modified version of the ACVS task. Participants were faster to identify targets and made a larger proportion of optimal choices when the high-probability optimal color was optimal. Thus, statistical learning facilitated both search for the targets and the optimal choice of attentional control settings. These effects persisted when the color contingencies were equated, suggesting that these findings were not simply due to intertrial priming (Maljkovic & Nakayama, 1994). Moreover, participants were not slower to identify targets when the high-probability optimal color appeared as a distractor, suggesting that these findings were not due to attentional capture by this color (Kyllingsbæk et al., 2001; Kyllingsbæk et al., 2014; Shiffrin & Schneider, 1977). Together, these findings suggest that statistical learning can facilitate the strategic use of attentional control by biasing which features observers choose to search for.

Overall, the present findings provide important evidence regarding the strategic use of attentional control. Previous studies have largely focused on individual differences in attentional control strategy (see Irons & Leber, 2020, for a review). For example, Irons and Leber (2016, 2018) found that participants rely on a variety of suboptimal strategies, with some participants repeatedly searching for the same color and others frequently switching between colors. These strategies appear to be stable within individuals, and can be observed across multiple testing sessions (Irons & Leber, 2018). However, these strategies do not appear to be correlated with participants' cognitive abilities (Irons & Leber, 2016, 2018) or performance in other visual search tasks (Clarke, Irons, James, Leber, & Hunt, 2022). Thus, it is unclear why observers choose to adopt different search strategies. In the present study, we found that statistical learning facilitated the optimal choice of attentional control settings. These findings suggest that statistical learning plays an important role in the strategic use of attentional control, regardless of individual differences in attentional control strategy.

Notably, the present findings also provide important evidence regarding the effects of selection history on attention. While selection history has largely been studied by examining involuntary attentional biases for task-irrelevant stimuli (e.g., Anderson et al., 2021), the goal-directed control of attention has largely been studied by examining the voluntary allocation of attention to task-relevant stimuli (e.g., Corbetta & Shulman, 2002). However, few studies have examined the effects of selection history on the goal-directed control of attention. In the present study, we found that statistical learning facilitated both search for the targets and the optimal choice of attentional control settings. These findings add to a growing body of research suggesting that selection history can influence the goal-directed control of attention. For example, recent evidence suggests that reward learning can also influence the optimal choice of attentional control settings (Lee, Kim, & Anderson, 2022). Along with the present findings, these findings suggest that selection history plays an important role in determining which features observers choose to search for.

In addition to these findings, the present findings provide new evidence regarding the effects of statistical learning on attention. Previous evidence suggests that statistical learning plays an important role in the allocation of attention. For example, observers are faster at identifying targets (Geng & Behrmann, 2002, 2005; Jiang et al., 2013) and are more efficient at suppressing salient distractors (Britton & Anderson, 2020; Wang & Theeuwes, 2018a, 2018b, 2018c) when these objects appear at high-probability locations. Observers are also faster to identify targets when they appear at locations that contain statistical regularities, suggesting that attention is automatically biased toward these regularities (Zhao et al., 2013). However, it is unclear whether statistical learning can influence the strategic use of attentional control. In the present study, we found that statistical learning facilitated both search for the targets and the optimal choice of attentional control settings. These findings not only provide converging evidence for the effects of statistical learning on attention, but also suggest that statistical learning plays an important role in determining which features observers choose to search for (see also Cosman & Vecera, 2014).

Notably, the present findings differ from some previous studies, which suggest that the effects of statistical learning are often independent of observers' task goals. For example, Wang and Theeuwes (2018a) found that participants were more efficient at suppressing salient distractors when these objects appeared at high-probability locations. Critically, these effects were observed regardless of participants' search strategies, suggesting that statistical learning influenced attention independently of observers' task goals (Wang & Theeuwes, 2018b, 2018c). However, the salient distractor in these studies was always irrelevant to observers' task. Notably, there is some evidence that statistical learning can influence the goal-directed control of attention when a statistically learned feature is task-relevant. For example, Cosman and Vecera (2014) found that participants were faster to identify a target when it was preceded by a valid cue. Critically, the magnitude of this effect was larger when the cue was presented in a high-probability target color, suggesting that observers adopted an attentional set based on statistical learning. In the present study, the optimal color was always relevant to observers' task. Thus, consistent with previous evidence, statistical learning can influence the goal-directed control of attention when a statistically learned feature is task-relevant.

In the present study, we assume that statistical learning biased which features observers choose to search for. However, it is also possible that statistical learning influenced attention at an earlier stage of processing. Previous evidence suggests that the ability to actively monitor, or *appraise,* the environment plays an important role in the strategic use of attentional control. For example, Hansen, Irons, and Leber (2019) had participants complete a modified version of the ACVS task in which they viewed a colored preview of the display on each trial. Critically, participants made a relatively large proportion of optimal choices in this task, suggesting that providing a colored preview facilitated observers' ability to appraise the environment. However, the magnitude of this effect was reduced when participants completed a secondary task during the preview period, suggesting that this task interfered with the environmental appraisal process. It is possible that statistical learning may also influence observers' ability to appraise the environment, allowing them to make a larger proportion of optimal choices in the high-probability optimal color. While the present study was not designed to address this possibility, future work should attempt to clarify the role of environmental appraisal in the present findings.

Although statistical learning facilitated the optimal choice of attentional control settings, the time course of these effects differed across our experiments. In Experiments 1 and 3, these effects emerged rapidly and did not diminish throughout the experiment. However, in Experiment 2, these effects emerged gradually and diminished when the color contingencies were equated. Previous evidence suggests that the effects of statistical learning often diminish when the statistical regularities are equated, suggesting that observers gradually readjust to the changing regularities (Cosman & Vecera, 2014). This likely explains why the effects of statistical learning diminished when the color contingencies were equated in Experiment 2. However, it is unclear why these effects emerged at different rates across our experiments. It is likely that there are individual differences in the time course of these effects, and that we randomly sampled a group of participants who were slower to learn the color contingencies in Experiment 2. Previous evidence suggests that the effects of statistical learning often emerge gradually (Chun & Jiang, 1998, 2003; Jiang et al., 2013), although there is some evidence that these effects can emerge rapidly under certain conditions (Wang & Theeuwes, 2018a). Thus, there is at least some variation in the time course of these effects. Nonetheless, future work should attempt to clarify why the time course of these effects differed across our experiments.

Lastly, it is worth noting that participants in the present study appeared to be generally aware of their own search strategies. This is consistent with previous evidence, which suggests that observers' self-reported strategy ratings often correlate with their own search behavior (Irons & Leber, 2018). However, while participants were generally aware of their own search strategies, they displayed little awareness of the color contingencies. What can account for this apparent discrepancy in findings? Critically, although participants were generally aware of their own search strategies, this does not mean that these strategies were driven by explicit awareness of the color contingencies. Indeed, while explicitly noticing the color contingencies modulated some of our effects, these effects were strongest for participants who did not report noticing these contingencies. Previous evidence suggests that the effects of statistical learning are often implicit, and can be observed in the absence of explicit awareness (Chun & Jiang, 1998, 2003; Jiang et al., 2013; Wang & Theeuwes, 2018a). Thus, it is unlikely that awareness played a substantial role in the present findings. Nonetheless, future work should attempt to clarify the role of awareness in the present findings, as well as the relationship between awareness and selection history in general (see also Anderson et al., 2021).

In summary, we found that statistical learning facilitated the strategic use of attentional control. Participants were faster to identify targets and made a larger proportion of optimal choices when the high-probability optimal color was optimal. Thus, statistical learning facilitated both search for the targets and the optimal choice of attentional control settings. These effects persisted when the color contingencies were equated, suggesting that these findings were not simply due to intertrial priming. Moreover, participants were not slower to identify targets when the high-probability optimal color appeared as a distractor, suggesting that these findings were not due to attentional capture by this color. Together, these findings suggest that statistical learning can facilitate the strategic use of attentional control, and provide important evidence regarding the effects of selection history on attention. Specifically, selection history can not only produce involuntary attentional biases for task-irrelevant stimuli, but can also bias which features observers choose to search for. Thus, selection history provides one possible explanation for why observers choose to adopt different search strategies.

Declaration of interest

None.

CRediT authorship contribution statement

Andrew Clement: Conceptualization, Methodology, Software, Formal analysis, Investigation, Writing – original draft. **Brian A. Anderson:** Conceptualization, Supervision, Writing – review & editing.

Data availability

The materials, analyses, and data from all of our experiments are available on the Open Science Framework (https://osf.io/wpf4u/).

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