

Intentional Learning Establishes Multiple Attentional Sets That Simultaneously Guide Attention

Sisi Wang^{1, 2} and Geoffrey F. Woodman¹

¹ Department of Psychology, Vanderbilt University

² Institute for Brain and Behavior Amsterdam, Department of Experimental and Applied Psychology, Vrije Universiteit Amsterdam

One of the key human cognitive capabilities is to extract regularities from the environment to guide behavior. An attentional set for a target feature can be established through statistical learning of probabilistic target associations; however, whether an array of attentional sets of predictive target features can be established during intentional learning, and how they might guide attention, is not known yet. To address these questions, we had human observers perform a visual search task where we instructed them to try to use color to find their target shape. We structured the task with a fine-grained statistical regularity such that the target shapes appeared in different colors with five unique probabilities (i.e., 33%, 26%, 19%, 12%, and 5%) while we recorded their electroencephalogram. Observers rapidly learned these regularities, evidenced by being faster to report targets that appeared in higher probability colors. These effects were not due to unequal sample sizes or simple feature priming. More importantly, equivalent speeding across a set of high-probability colors suggests that the brain was driving attention to multiple targets simultaneously. Our electrophysiological results showed larger amplitude N2 posterior contralateral component, indexing perceptual attention, and late positive complex (LPC) component, indexing postperceptual processes, for targets paired with high-probability colors. These electrophysiological data suggest that the learned attentional sets change both perceptual selection and how postperceptual decisions are made. In sum, we show that multiple attentional sets can be established during intentional learning that accompanies general task acquisition and that these attentional sets can simultaneously guide attention by enhancing both perceptual attention and postperceptual processes.

Public Significance Statement

It is yet unclear whether a single attentional set controls attentional selection or whether multiple attentional sets can simultaneously bias attention to different potential inputs. We recorded the electroencephalogram from human observers performing a visual search task where we inserted a fine-grained statistical regularity with the target shapes appearing in different colors with five unique probabilities (i.e., 33%, 26%, 19%, 12%, and 5%). Observers rapidly learned these regularities and showed speeded behavioral responses for targets paired with multiple high-probability colors. These behavioral benefits of intentional learning were accompanied by changes in brain activity related to perceptual attention and postperceptual processes. Thus, we show that humans can learn and simultaneously use multiple attentional sets of predictive target features at the same time, changing how information is handled across multiple stages of processing, with implications for our understanding of learning, memory, attentional control, and decision making.

Keywords: intentional learning, attentional set, attentional guidance, N2 posterior contralateral, late positive complex

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Sisi Wang  <https://orcid.org/0000-0002-9730-438X>

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Correspondence concerning this article should be addressed to Geoffrey F. Woodman, Department of Psychology, Vanderbilt University, 301 Wilson Hall, 111 21st Avenue South, Nashville, TN 37240, United States. Email: geoffrey.f.woodman@vanderbilt.edu

Humans prioritize stimuli that enable accurate predictions of future events (George & Pearce, 2012; Kruschke, 1992; Logan, 2002; Mackintosh, 1975). For example, learning that a target object appears in one color more frequently than in another color speeds observers' search (Conn et al., 2020; Cosman & Vecera, 2014; Sha et al., 2017). This learning effect demonstrates that the human brain extracts regularities from the environment across time and space to guide behavior (Batterink et al., 2019; Goujon et al., 2015; Turk-Browne, 2012). According to classic attentional guidance theories, this learning allows the human brain to shift perceptual attention to objects that have target features, speeding behavioral reaction time (or response time [i.e., RT]; see reviews from Corbetta & Shulman, 2002; Desimone & Duncan, 1995; Egeth & Yantis, 1997; Kastner & Ungerleider, 2000). Previous studies have demonstrated that simple *attentional sets*, consisting of a single target color, can be learned and bias early measures of attention (Cosman & Vecera, 2014; Feldmann-Wüstefeld et al., 2015). However, here we sought to study how our minds bias attention in more complex environments in which there are many possible targets that could appear in our field of view (S. Wang et al., 2023). When we drive a car on a roadway, we are trying to identify many possible targets at the same time, such as red brake lights, a truck looming in our rearview mirror, a child running out into the roadway, or any of a huge number of objects that require an action on our part. Given the powerful memory mechanisms constantly sampling our environment (Batterink et al., 2019; Batterink & Paller, 2017; Cowan, 2001; Karuza et al., 2014; Standing, 1973), it should be possible for multiple predictive target features to be learned and used to control how inputs are prioritized by attention and subsequent cognitive mechanisms.

There is a diversity of theoretical opinions about how many attentional sets can be operative in the human brain at one time. At one extreme is the view that we have only one attentional set that is operative at any one time to guide attention (Eimer & Kiss, 2010; Folk & Anderson, 2010; Houtkamp & Roelfsema, 2009; Huang & Pashler, 2007; Olivers, 2009). Alternatively, others proposed that we can have multiple attentional sets active at the same time and simultaneously guiding attention (Barrett & Zobay, 2014; Beck et al., 2012; Grubert & Eimer, 2013, 2015, 2016; Irons et al., 2012; Moore & Weissman, 2010). To distinguish between these theoretical perspectives, we developed a novel visual search task.

To investigate whether multiple attentional sets of predictive target features simultaneously guide attention or only a single attentional set can guide attention at a given time, we developed a visual search task with a graded target-feature probability structure. The probabilities of the target colors descend in small steps (i.e., 33%, 26%, 19%, 12%, 5%, and 5% baseline colors). In a previous study, we used a task like this to study incidental learning during search (S. Wang et al., 2023). Despite observers being unaware of the existence of target color regularities, they demonstrated speeded target discrimination across the three most probable colors. This suggests that multiple sets of target colors could concurrently guide visual search. However, our question here is focused on how explicitly trying to use the colors might maximize processing capacity, perhaps by changing the locus of selection compared with what we observed with incidental learning in previous work (S. Wang et al., 2023). To this end, we explicitly instructed participants that the target will appear in some colors more than others and they should use this to help themselves search for the

targets. Previous research has demonstrated that intentional learning has a greater impact on memory compared with incidental learning, as it involves a more effortful process that engages attentional and executive resources (Karrasch et al., 2010; Noldy et al., 1990; Popov & Dames, 2023; Vingerhoets et al., 2005). Consequently, we are interested in exploring whether, when harnessing all available cognitive resources, participants can effectively direct attention using a larger array of target features.

The finely graded percentages of target colors should allow us to determine the granularity of attentional control. If we can attend to a host of different object features with different attentional weights, then we should see a pattern of RTs and electrophysiology that mirrors the objective predictability of each target color. Alternatively, it is possible that we simply bias attention to the most likely possible target color, or cycle between possible target colors, and our task allows us to distinguish between these possibilities. A previous study has demonstrated that switching between target features takes about 250–300 milliseconds to complete (Dombrowe et al., 2011). Thus, if only one attentional set for a color can be active at a time, then observers should need to serially switch between searched-for targets, and we should see a clear ordering of RTs across the possible target color probabilities. Moreover, this should result in a staggering onset of the event-related potential (ERP) that we use as our marker of selection by perceptual attention.

We recorded multiple ERP components to determine at what stage of processing learning might be having its effect. Specifically, we measured the N2 posterior contralateral component (i.e., N2pc) and the late positive complex (i.e., LPC) to provide electrophysiological markers of early perceptual selection (the N2pc) and subsequent postperceptual processing (the LPC; N2pc: Eimer, 1996; Eimer & Kiss, 2008; Hopf et al., 2000; Lien et al., 2008; Luck & Hillyard, 1994; Woodman & Luck, 1999; LPC: Hillyard & Anllo-Vento, 1998; Luck, 1998; Luck & Hillyard, 1990). If multiple attentional sets simultaneously guide perceptual attention, then we should see similarly fast and large amplitude N2pc components elicited by target appearing in multiple colors across different trials (i.e., more than just the most likely target color). In contrast, if only a single attentional set at a time could be actively guiding attention, and the multiple attentional sets guide attention sequentially, we should observe a delayed N2pc latency for targets appearing in the lower probability colors compared with the highest probability color. If learning did not change how perceptual mechanisms are focused on objects in the array, then we would expect that the LPC, indexing the decision about the array and response selection, will exhibit a gradient of voltages suggesting that it is the source of the learning effect we observe. It is worth noting that in our recent incidental learning study (S. Wang et al., 2023), we observed a selective modulation of target color probability on the LPC, while a comparable N2pc was evident across different probability colors. This suggests that incidentally learned high-probability target features facilitate visual search by enhancing late response-related decision-making processes. Given that intentional learning engages more attentional and executive resources than incidental learning (Karrasch et al., 2010; Vingerhoets et al., 2005), we propose that the intentional learning used here could result in the use of both early and late selection to favor the high-probability colors, changing both the N2pc and the LPC components in the current experiment.

Finally, we sought to determine how enduring the guidance of these attentional sets might be. After finishing the learning session,

observers completed a test session in which the targets were paired with each color with an equal probability (i.e., 12.5% target probability for each color). This allowed us to determine how flexible and continuous this process of attentional sets learning might be. Specifically, it seems likely that after our cognitive system has become proficient at the visual search task, it would lock in the control settings and exploit its environment. This would predict no change when the probabilities shift in the unannounced test block. However, it is also possible that our minds continuously optimize these attentional control settings and as such are constantly updating attentional weights based on new information. If this is the case, then we should see the pattern of RTs shift to the rectangular distribution now present in the environment.

Materials and Method

Transparency and Openness

This experiment was not preregistered. Deidentified data and the data analysis scripts are publicly available and can be accessed at <https://osf.io/bk8ec/> (S. Wang & Woodman, 2024).

Participants

Participants were undergraduate students from Vanderbilt University. Twenty-six participated in the experiment for course credit. All participants self-reported normal or corrected-to-normal visual acuity and normal color vision, after providing informed consent. Seven participants were excluded from further data analysis due to excessive eye movements and muscular artifacts during their electroencephalogram (i.e., EEG) recording (see details in the EEG data preprocessing section), leaving 19 participants (8 females and 11 males, $M_{\text{age}} = 19.1$ years, $SD_{\text{age}} = 1.0$) in the final data set.

Sample Size Analysis

We estimated the necessary sample size for the present experiment using a multistep procedure. First, we looked at the existing literature that has examined the effects of statistical learning on attention for guidance (e.g., 12–24 participants across experiments in Cosman & Vecera, 2014; Sha et al., 2017). Second, we used approximately twice as many trials as the previous reports due to recording brain activity. Third, we performed a post hoc power analysis for our sample size ($N = 19$) using the G*Power analysis software (Faul et al., 2009). We took the effect size estimate ($\eta_p^2 = 0.388$) from the one-way repeated measures analysis of variance (ANOVA) of the RTs across target color probability, $F(5, 90) = 11.406$, $p < .001$, $\eta_p^2 = 0.388$; see the Behavioral Results section. Instead of setting a power threshold (e.g., 0.8) to estimate a suitable sample size, the post hoc power analysis outputs a power estimate with the input of a given sample size. An output power estimate larger than 0.8 implies a reasonable sample size. Our post hoc power analysis revealed an output power value of 0.999 with the given sample size of 19, demonstrating the statistical power available in the current experimental design.

Stimuli

Stimuli were presented using MATLAB (R2017b 9.3.0.; MathWorks) and the Psychophysics Toolbox (Version 3.0.12;

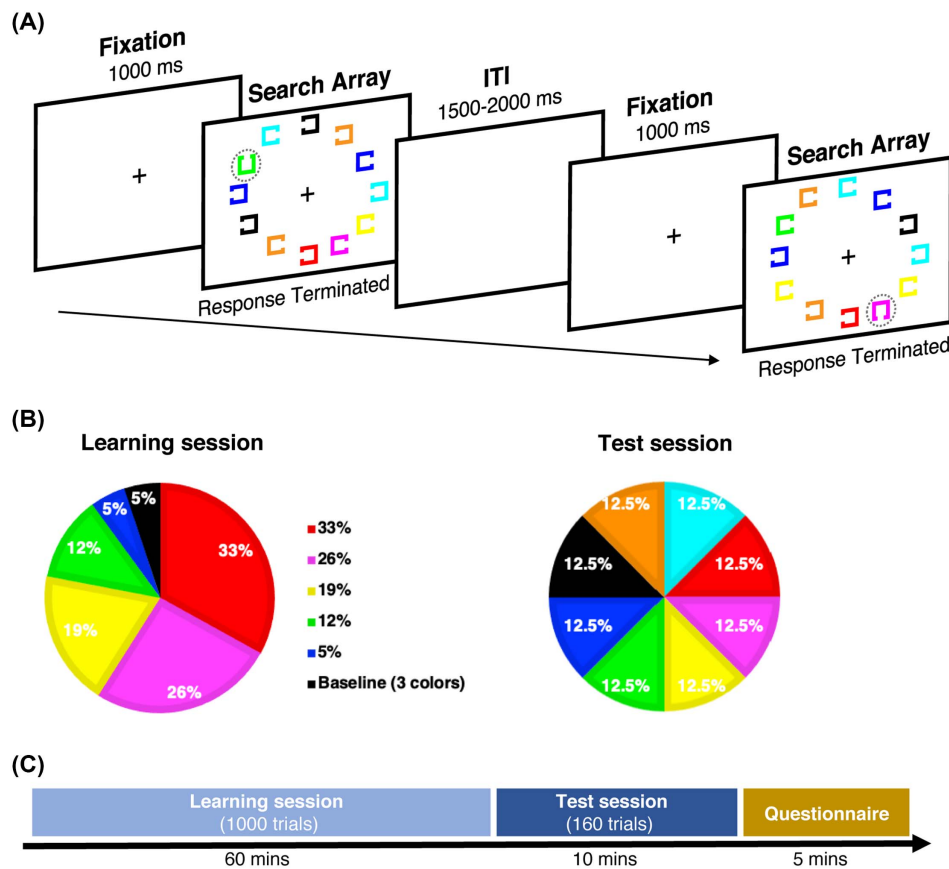
Brainard, 1997) on a cathode-ray tube monitor contained in a Faraday cage. Stimuli were presented on a white background (57 cd/m^2). Participants were seated approximately 75 cm from the screen.

Figure 1A shows two example trials from the shape visual search task. Each trial began with a display containing a black fixation cross ($>0.01 \text{ cd/m}^2$, 0.4° of visual angle) in the center of the screen for 1,000 ms, followed by a search array containing one target box (box with an opening on the top edge or the bottom edge) and 11 distractor boxes (box with an opening on the left edge or the right edge), until participants made a response on each trial. All boxes were unfilled squares (the square Length \times Width, $0.7^\circ \times 0.7^\circ$ visual angle, and the edge thickness, 0.1° visual angle) with an opening (the opening width, 0.5° visual angle) on one of the four edges and were evenly distributed on an invisible circle with the eccentricity of 4.4° visual angle. All boxes were randomly placed on the 12 stable positions of the invisible circle (from 0° to 330° with a step of 30°). Participants were instructed to use their peripheral vision to search for the target box while keeping their eyes fixed on the black fixation cross. They were also encouraged to make responses as fast and accurate as they could. After the search array disappeared upon response, a blank screen appeared with a variable intertrial interval ranging from 1,500 ms to 2,000 ms (randomly sampled from a rectangular distribution). The “top” target and the “bottom” target trials were each 50% across the experiment. Participants pressed “f” or “j” on the keyboard to indicate that they found a top or bottom target. The response keys were counterbalanced across subjects.

The colors of the boxes were chosen from a pool of eight highly discriminable colors: red ($x = 0.616$, $y = 0.337$, in International Commission on Illumination color space, 14 cd/m^2), green ($x = 0.284$, $y = 0.958$, 44 cd/m^2), magenta ($x = 0.295$, $y = 0.153$, 19.2 cd/m^2), yellow ($x = 0.407$, $y = 0.504$, 54.4 cd/m^2), blue ($x = 0.146$, $y = 0.720$, 6.5 cd/m^2), cyan ($x = 0.432$, $y = 0.405$, 16.1 cd/m^2), black ($>0.01 \text{ cd/m}^2$), and orange ($x = 0.552$, $y = 0.397$, 24.2 cd/m^2). We manipulated target color probability differently for the learning session and the test session (Figure 1B). For the learning session, targets were paired with five out of the eight colors from the color pool with a probability distribution of 33%, 26%, 19%, 12%, and 5% for each color and with 5% of all trials pseudorandomly paired with the remaining three colors in the pool as baseline (with two of the remaining colors being selected for 2% of all trials and one of them being selected for 1%, so as not to leave a remainder). In the test session, the targets were paired with all the eight colors with a probability of 12.5% for each color.

The specific number of colors and their probabilities used were selected based on the following considerations. The number of possible target colors should be higher than typical working memory capacity estimates (i.e., more than four). We wanted to evenly spread the target features across probability space (a 7% difference between two adjacent percentages in the current experiment). The sum of the percentages must equal 100. Given these constraints, we used a distribution with the probabilities of 33-26-29-12-5-5%. However, we found similar results in a pilot experiment using a slightly different distribution (e.g., 30-25-20-15-5-5%). For each search array, the colors of distractors were randomly chosen from the color pool, all distinct from the target color, with no more than two distractors sharing the same color. The colors matched with different probabilities were randomized across participants. For example, for Participant 1, the colors red, green, blue, and magenta were paired with the target for 33%, 26%, 19%, and 12% of trials,

Figure 1
Illustration of the Experimental Paradigm and Procedure



Note. (A) An example of the shape visual search task from two trials with a “top” target and a “bottom” target, respectively, as is shown in the dashed circle, which is used for illustration only. The targets are paired with green and magenta for the example trials. ITI represents intertrial interval. (B) The probability distribution of colors paired with targets for the learning session (left) and the test session (right). (C) Experimental procedure for the entire session. See the online article for the color version of this figure.

respectively. Meanwhile, for Participant 2, the colors orange, black, red, and green were paired with the target for 33%, 26%, 19%, and 12% of trials, respectively.

Procedure

Figure 1C illustrates the experimental procedure. Participants completed a learning session and a test session. The learning session was composed of five blocks of 200 trials with all target colors (33%, 26%, 19%, 12%, 5%, and 5% baseline colors) and shapes of targets (upward and downward) intermixed randomly within each block. The test session was composed of two blocks of 80 trials with all eight colors from the color pool (12.5% targets appearing in each color) and shapes of targets (upward and downward) intermixed randomly.

Observers were briefly instructed about the fact that targets would appear in different colors across trials before the experiment began. They were told that the targets will appear in some colors more often than others and that they could use this to speed up their search for the target. Note that observers were only informed with this brief statement in the instructions to make them aware of the existence of

possible regularities relating target shape to its color; they were not made aware of the exact target color probability distribution, or which colors would be paired with the target shapes more frequently. Therefore, they still needed to learn the specific statistics themselves.

Posttest Questionnaire

To examine whether observers were explicitly aware of the regularities of target color probability distribution after learning, we had them complete a posttest questionnaire after the test session. In the questionnaire, they were first asked whether they noticed that the targets appeared in some colors more often than other colors. This question seems unnecessary because they have been told that the target might appear in some colors more often beforehand. However, given the fact that the color is not the defining feature of the target, participants could complete the shape search task without even processing the color of the shapes. Thus, we asked this question to first verify that participants were aware that the targets were paired with different colors with different probabilities. If they answered “Yes,” they were further asked to write down the

probability rank for each color and its corresponding approximate probability (the rank ranges from 1 to 8, with 1 representing the highest probability). If the answer was “No,” they did not need to answer subsequent questions.

Electroencephalogram Acquisition

The electroencephalogram was recorded from each individual in an electrically shielded, soundproof booth from a 20-channel cap (Electro-cap International, OH), embedded with tin electrodes that contact the skin through electrode gel. The 20 electrodes were positioned according to the International 10–20 system (F3, F4, C3, C4, P3, P4, PO3, PO4, O1, O2, PO7, PO8, T3, T4, T5, T6, Fz, Cz, Pz). Impedance values were kept below 4 k Ω . The reference electrodes were affixed with stickers to the left and right mastoids with the left mastoid being the online reference electrode. The ground electrode was placed in the elastic cap at Fpz. Electrooculogram (EOG) activity was recorded with two horizontal EOG electrodes placed ~1 cm lateral to the outer canthi of the two eyes, and one vertical EOG electrode was placed below the right eye to detect eye movements and blinks. All channels were bandpass filtered from 0.01 to 100 Hz and recorded with a 250 Hz sampling rate.

Data Analyses

Response Time Analysis

We analyzed RT for trials with targets paired with each probability color. Only trials with RTs faster than 3 s and trials with correct responses were included in the mean RT analysis for each condition. On average, 5.5% ($SD = 3.7\%$) of all trials were removed from further analyses for not satisfying these standards.

Electroencephalogram Data Preprocessing

Data were re-referenced offline to the average of the left and right mastoids. The EEG epochs were then extracted from the re-referenced EEG signal, which were 1,000 ms long, beginning 200 ms prior to the search array onset, to include the 200 ms prestimulus baseline. Trials including artifacts due to blinks, amplifier saturation, or excessive noise that exceed $-100\mu V$ to $+100\mu V$ were first rejected using a standard trial-rejection function from the EEGLAB Toolbox (eegthresh.m; Delorme & Makeig, 2004). A stricter threshold of $-50\mu V$ and $+50\mu V$ was further conducted on the horizontal electrooculogram signal (the difference voltage between horizontal EOG recorded from left and right eyes) and the vertical electrooculogram signal, respectively, to remove trials contaminated by the horizontal and vertical eye movements. Seven participants with fewer than 70% artifact-free trials remaining were excluded following the artifact rejection steps, with an average 79.3% ($SD = 6.7\%$) of trials being kept for the remaining subjects. A low-pass filter at 30 Hz was applied to EEG data to remove the high frequency noise caused by muscle artifacts or the recording environment. As in our behavioral analyses, only trials with correct responses and response times within 3 s were included in the ERP analyses.

Event-Related Potential Analysis

N2pc Analysis. The N2pc component was analyzed as an electrophysiological marker of selection by perceptual attention.

The N2pc is a negativity that typically emerges between 180 and 200 ms after the visual search array onset and is assumed to reflect early attentional selection during perceptual processing of the attended object in extrastriate visual cortex (e.g., Eimer, 1996; Eimer & Kiss, 2008; Hopf et al., 2000; Lien et al., 2008; Luck & Hillyard, 1994; Woodman & Luck, 1999). In the present study, the N2pc amplitude was computed by subtracting the activity of the electrodes ipsilateral to the target from the activity of the electrodes contralateral to the target over the posterior–lateral electrode pair: PO7, PO8 (Grubert et al., 2016), from trials with a target presented in the lateralized positions. The time window for the N2pc analysis was 250–350 ms after the search array onset. Only trials with targets presented laterally can be included in the N2pc analysis (we excluded trials with targets presented at the 12 and 6 o'clock positions). Due to the reduced number of general trials and the transient and variable nature of N2pc, which is a difference waveform, we merged trials with targets in those low-probability colors (12%, 5%, and 5% baseline) to increase the signal-to-noise ratio of our N2pc analysis, which leaves 241, 185, 135, and 158 clean trials (after artifact rejection) per condition for the N2pc analyses.

LPC Analysis. The LPC is a positivity that is maximal at posterior parietal scalp electrodes and peaks around the time of subject's behavioral response. Substantial evidence indicates that the LPC provides a measure of postperceptual processes related to the decision making and response selection (Hillyard & Anllo-Vento, 1998; Luck, 1998; Luck & Hillyard, 1990). In the current experiment, the LPC amplitude was calculated by averaging signals across the parietal electrodes: P3 and P4, P7 and P8, PO3 and PO4, and PO7 and PO8. The time window for the LPC analysis was 450–650 ms after the search array onset (S. Wang et al., 2023). Given that the LPC is a large and relatively clean signal, the LPC amplitude in the three lowest probability conditions was not merged as we did in the N2pc amplitude analysis, which leaves 262, 206, 149, 96, 39, and 41 clean trials per condition for the LPC analyses.

Experimental Design and Statistical Analyses

To compare behavioral performance and electrophysiological markers across targets paired with different probability colors, one-way repeated measures ANOVAs with the within-subject factor of target color probability (33%, 26%, 19%, 12%, 5%, and baseline) were performed on observers' mean RT and LPC amplitude, respectively. A 2×4 repeated measures ANOVA with the within-subject factors of laterality (electrode contralateral vs. ipsilateral to the target) and target color probability (33% vs. 26% vs. 19% vs. 12% + 5% + baseline) was applied to the N2pc analysis. All reported F values for repeated measures ANOVAs were first checked for violations of sphericity. If the data satisfied Mauchly's test of sphericity ($p > .05$), the sphericity assumed that F values, p values, and effect size values were reported. If the data violated Mauchly's test of sphericity ($p \leq .05$), the Greenhouse–Geisser method-corrected F values, p values, and effect size values were reported. Bonferroni corrections for multiple comparisons were applied to all paired-wise comparisons for the tests of significant main effect or interactions. All these statistical analyses were performed in MATLAB and SPSS 19.0 (IBM Inc.).

Results

Behavioral Results

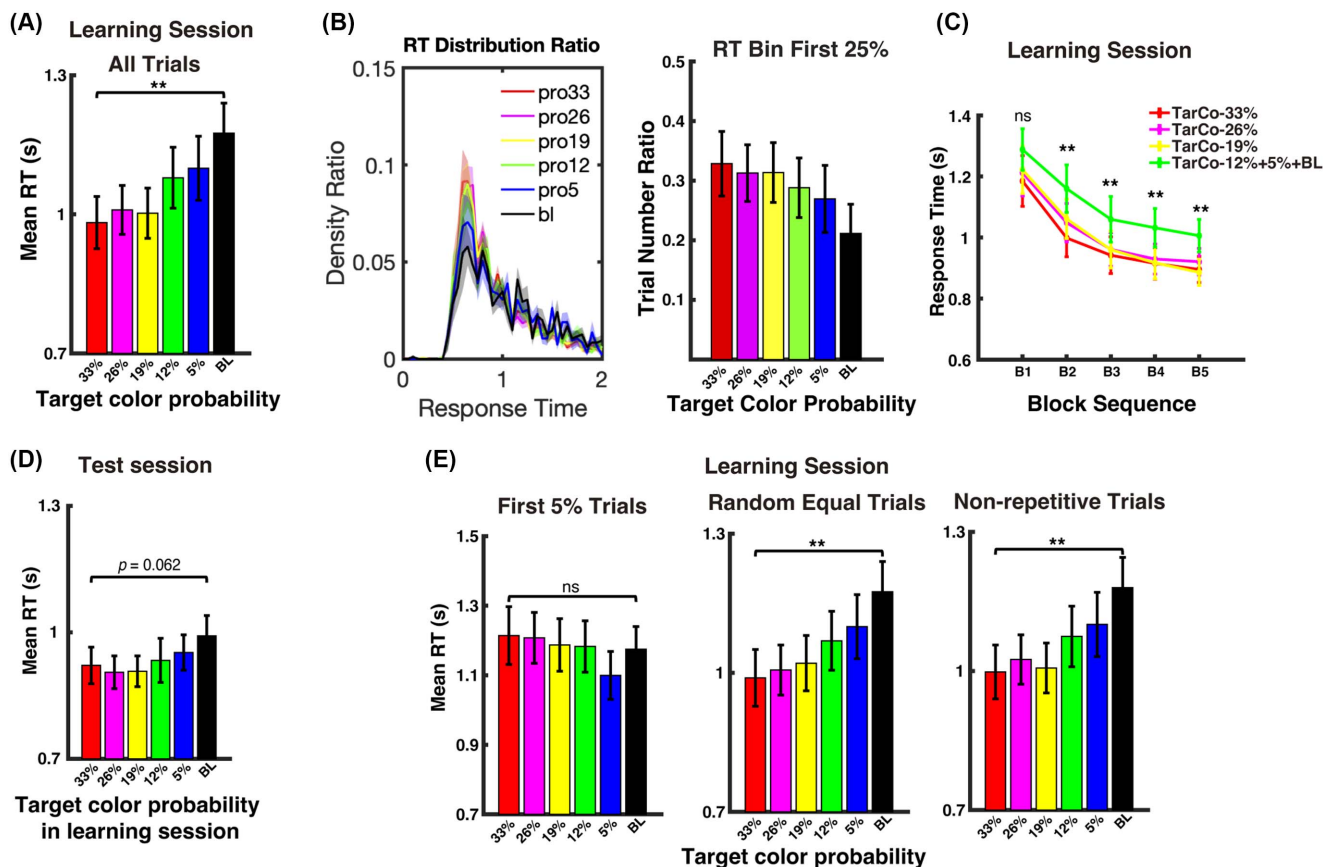
Multiple Attentional Sets Being Established During Learning

As shown in Figure 2A, our analyses of observers' RT showed a robust learning effect, with faster RTs for targets appearing in multiple high-probability colors relative to the low-probability baseline. Moreover, targets in these higher probability colors acquired approximately equivalent benefits, suggesting that multiple attentional sets of target-color associations may have been established and were guiding attentional selection. These observed patterns were verified with the following inferential statistics.

One-way repeated measures ANOVAs with the within-subject factor of target color probability (33%, 26%, 19%, 12%, 5%, and baseline) were applied to the mean RTs. The analyses revealed a significant main effect of target color probability, $F(5, 90) = 11.406$, $p < .001$, $\eta_p^2 = 0.388$, with faster RTs for targets paired with higher probability colors. Moreover, the paired-samples t tests between RTs from each color probability compared with the baseline RT revealed significant reductions in RT for targets in the three highest probability colors, $t(18) = 5.697, 4.217, 5.053$, $p = .000, .008, .001$, for 33%, 26%, and 19% colors, respectively, with no significant RT changes relative to the baseline for targets in the two lowest probability colors, $t(18) = 3.373, 2.897$, $p = .051, .144$, for 12% and 5% colors, respectively. In addition, the paired-samples t tests for each target-color association revealed no significant difference

Figure 2

Faster Responses for Targets Appearing in Multiple High-Probability Colors



Note. (A) The averaged response times (RTs) for targets appearing in different probability colors across all trials. (B) Left panel: the distribution of the ratio of trials with different RTs for targets appearing in different probability colors; right panel: the ratio of trials with the fastest RTs for targets appearing in different probability colors. (C) The averaged RTs for targets in different probability colors across blocks: each block includes 200 trials. Trials with targets paired with 12%, 5%, and 5% baseline colors are merged to increase statistical power for the block analysis. (D) The averaged RTs for targets in different colors in the test session: each color has equal probability (12.5%) in the test session. (E) Control analyses of the confounding factors. From the left to right panels: the averaged RTs for the first 5% trials for each target-color condition in the learning session, the averaged RTs for 5% of all trials that were randomly selected from each target-color condition, and the averaged RTs for targets appearing in different probability colors across the nontarget-color-repetitive trials. Labels in the x-axis represent target color probability in the learning session. The red, magenta, yellow, green, blue, and black bars represent 33%, 26%, 19%, 12%, 5%, and baseline colors, respectively. Error bars indicate the standard errors of the means. RT = response time; pro = probability; BL = baseline colors; TarCo = target color; ns = not significant. Asterisk indicates the significant main effect (** $p < .01$). See the online article for the color version of this figure.

between RTs for targets appeared in the three highest-probability colors ($lrls \leq 0.975$, $p = 1.000$). All reported p values were corrected for multiple comparisons using the Bonferroni method.

In sum, we observed a robust speeding of behavioral responses for targets appearing in the most likely colors, with RT changing systematically across probabilities. Thus, our behavioral evidence suggests that representations of more than just one or two colors are being used to control attention and processing during this visual search task. However, we next discuss additional analyses of these behavioral data, which provide an additional test of this idea.

Multiple Attentional Sets Established From Learning Simultaneously Guide Attention

Our preceding analyses have confirmed that targets appearing in multiple high-probability colors gain equivalent response speeding through learning. Intuitively, this equivalent speeding effect across multiple high-probability colors suggests that observers were holding multiple possible target color sets actively in their minds to guide attention simultaneously. However, it is also possible that observers only brought a single-color set into working memory at a given moment to guide attention and sequentially switched among the multiple high-possibility color sets until a target object was found. Although switching between attentional sets could be time-consuming, observers could prioritize different colors across trials and produce similar equivalent response speeding effect for targets appearing in multiple high-probability colors after averaging across all trials and subjects (Ort & Olivers, 2020). However, our next set of analyses favors the first possibility that observers use multiple attentional sets to simultaneously guide attention rather than holding a single active attentional set to guide attention at any one time.

If people were first searching for the most likely target color, then the second most likely, and so forth, then we should find that the fastest RTs are from those trials in which the target is the most likely color. In our next analyses, we analyzed the RT distributions to test for this predicted shift in the early tail of the RT distributions. We first binned the RT distributions extending from 0 to 2 s after the stimulus onset into 50 ms nonoverlapping bins and calculated the average ratio of trials for each color located in each time bin (Figure 2B). The ratio of trials was calculated by dividing the number of trials in the bin by the total trial numbers of targets in that color, controlling for the unbalanced trial numbers for targets in different colors. The serial search strategy predicts that the first RT bin should mostly be populated by trials with targets in the most likely color, fewer in the second most likely, and so forth.

With viewing the distribution of RTs for trials with different probability colors (Figure 2B left panel), our results show an equivalent ratio of trials for the three highest probability colors across the entire time range and all of them higher than the ratio of trials with targets paired with the lowest probability colors. To quantify this pattern, we extracted the ratio of trials for different probability colors within the fastest RT bins (the first 25% fastest RT trials: RT bins from 0 to 700 ms). Our analysis revealed that the fastest RT bin had the same ratio of trials from the three highest probability colors. Paired-samples t tests revealed no significant difference between the ratio of trials within the fastest RT bin for targets appearing in the three highest probability colors ($lrls \leq 0.806$, $p = 1.000$), and they were all significantly higher than the ratio of trials in baseline colors ($lrls \geq 4.367$, $p < .006$, Bonferroni corrected).

These findings are consistent with expectations of a system that uses three target representations to guide attention simultaneously, and we found no evidence for the sequential cycling through possible target colors that we would expect from a system with a single attentional set for one color.

Our next analysis focused on observers' postlearning recall of the target color probability. Observers reported in the postlearning questionnaire that they were clearly aware of the probability gradient across colors, with the mean reported probabilities descending from 30.7% to 4.2% (the mean reported probabilities are 30.7%, 20.6%, 15.6%, 12.4%, 9.9%, 8.0%, 5.6%, and 4.2% for all eight colors, respectively). Next, the accuracy of the recalled probabilities and their corresponding color was highly accurate, particularly for high-probability colors (10/19, 16/19, 14/19, 7/19, 8/19, 9/19 correct observers for 33%, 26%, 19%, 12%, 5%, and baseline colors, respectively), which is qualitatively different than a simulation of random guessing (sampled 10,000 times). So, we know they knew which colors to search first, and if we assume that subjects picked which color set to look for, then the most likely sequence of colors to pick would be from the highest to the lowest probability colors. Because switching attentional sets between target features takes over 200 milliseconds to complete (Dombrowe et al., 2011), the RT slowing should be more pronounced for lower probability colors since they are searched later. However, we found no evidence for this shift in the earliest RTs across the three highest probability colors.

The Rapid Establishment of Multiple Attentional Sets During Learning

In our preceding analyses, we confirmed that multiple attentional sets can be established from intentional learning, and they can simultaneously influence behavior during visual search. Next, we wondered how rapidly these attentional sets were established. As shown in Figure 2C, our analyses of observers' RTs for targets appearing in different probability colors across learning blocks demonstrate a rapid establishment of these attentional sets. The speeding of RT for targets appearing in high-probability colors was evident from the second block of learning onward (after 200 trials). These patterns were verified with the following inferential statistical analyses.

The learning session consisted of five 200-trial blocks with all probability colors intermixed within each block. To increase the statistical power of the block analysis, targets paired with the two lowest probability colors and the baseline colors were merged and averaged as the baseline RT for each block (i.e., 44 trials from the sum of the 12% color, the 5% color, and the baseline colors for each block). The mean RTs were then entered into a two-way repeated measures ANOVA with the within-subject factors of block (Blocks 1–5) and target color probability (33%, 26%, 19%, 12% + 5% + baseline). The analyses revealed a significant main effect of block, $F(4, 72) = 31.702$, $p < .001$, $\eta_p^2 = 0.638$, and target color probability, $F(3, 54) = 8.520$, $p < .001$, $\eta_p^2 = 0.321$. However, no significant interaction was found between these two factors, $F(12, 216) = 0.868$, $p = .580$, $\eta_p^2 = 0.046$, suggesting that observers acquired the attentional biases to high-probability colors sufficiently rapidly to be observable in the first block of the learning session. To further confirm this finding, one-way repeated measures ANOVAs of target color probability (33%, 26%, 19%, 12% + 5% + baseline) were

applied to each block separately. Observers started to robustly show a speeding effect for targets paired with the high-probability colors at the second block, $F(3, 54) = 2.728, 8.374, 5.319, 6.124, 7.459$; $p = .061, .000, .005, .002, .001$, for Blocks 1–5, respectively. These analyses demonstrate that our observers are learning the attentional sets within the first 200-trial block.

Long-Lasting Guidance of Previous Attentional Sets

As abovementioned, we saw that people rapidly learned the color mappings when they were explicitly told to do so. It is possible that once learned, subjects then exploit these control settings and stop sampling the statistics of the environment. However, it is also possible that our minds continuously sample the environment to keep our attentional control settings as current as possible. If the latter is the case, then we should see observers' behavior shift if the color probabilities shift during the experiment. To distinguish between these competing ideas, we included a test block of trials at the end of the experiment that had a rectangular distribution of probability across colors. If people exploit settings once established, then we should see the RT gradient maintained in the test session; however, if learning is continuous, then we should see RTs shift to approximate the new rectangular distribution.

Figure 2D shows the pattern of RTs from the test session. We observed a pattern consistent with continued sampling of the environment, as observers appear to be continuing to relearn even during the last block of trials, although the previously learned attentional sets also appear to have an enduring effect. The mean RTs for targets appearing in each color in the test session were entered into a one-way repeated measures ANOVA with the within-subject factor of target color probability (33%, 26%, 19%, 12%, 5%, 5% baseline), and the main effect approached significant, $F(5, 90) = 2.190, p = .062, \eta_p^2 = 0.108$. The preplanned contrast comparisons revealed significantly faster RTs for targets paired with the learning-stage high-probability colors than targets paired with the learning-stage baseline colors, $F(1, 18) = 8.328, 6.148, 8.891, \text{ and } 4.598, p = .010, .023, .008, \text{ and } 0.046, \eta_p^2 = 0.316, 0.255, 0.331, \text{ and } 0.203$ for the learning-stage 33%, 26%, 19%, and 12% color, respectively. On the contrary, no significant difference was found between the learning-stage 5% colors and the baseline colors, $F(1, 18) = 2.151, p = .160, \eta_p^2 = 0.107$. These results provide some suggestive evidence that the kind of learning we studied here might be a continuous process, in which the attentional priority of the features in the environment is updated with each new episode or event. However, we see this issue as one that we have only touched upon here and will need further study to understand more fully.

Ruling Out Confounding Factors

Because we paired different colors with the target shape, the RT effects could be driven by factors other than the establishment of attentional sets that guide attention. For example, our pattern of RTs could be due to observers' inherent preference for a specific color that may attract their attention due to experience outside the laboratory. Moreover, to manipulate the probability of targets appearing in different colors, the number of trials in each cell was unequal by design, such that we may just have more stable estimates of some of the means. As shown in Figure 2E, our control analyses rule out the contribution of multiple possible confounding factors.

Color Preference. Even though we randomized the color assignment across observers, it is still possible that the RT facilitation effect for the high-probability colors might be driven by participants' preference for certain specific colors. For example, it could be that the RT benefits for the 33% color are driven by the observers who were randomly assigned to have green as the most probable target color (e.g., associated with fast behaviors due to traffic light signals). To exclude this possibility, we analyzed the RTs for the first 5% trials (about 50 trials) for targets in each color when observers had yet to learn the regularities of the target color probability mapping. Our analysis confirmed no inherent preference for processing specific colors at the beginning of the learning session. One-way repeated measures ANOVA with the within-subject factor of target color probability (33%, 26%, 19%, 12%, 5%, and 5% baseline) on observers' mean RT of the first 5% trials across all conditions revealed no significant main effect of target color probability, $F(5, 90) = 1.995, p = .087, \eta_p^2 = 0.100$.

Uneven Sampling of the Feature Space With Different Trial Numbers. In the learning session, observers saw more instances of targets paired with higher probability colors. Larger numbers of trials with targets appearing in certain colors might cause us to have better estimates of those means, with the means using fewer trials being more variable. To rule out this explanation of our findings, we randomly selected an equal number of trials (50 trials) for targets paired with each probability color from all trials. Our analysis confirmed a similar pattern of RT speeding for targets paired with high-probability colors as in the original analysis, excluding the possibility that the learning effect is mainly driven by biased trial numbers. One-way repeated measures ANOVA with the within-subject factor of target color probability (33%, 26%, 19%, 12%, 5%, and baseline) on observers' mean RT with an equal number of trials across all conditions revealed a significant main effect of target color probability, $F(5, 90) = 7.441, p < .001, \eta_p^2 = 0.292$.

Perceptual Priming. We found a robust response speeding effect for trials with targets appearing in the high-probability colors. This speeding effect for targets appearing in the higher probability colors could be purely due to intertrial feature priming given that higher probability colors had higher odds of two adjacent trials sharing their target feature (Kristjánsson & Campana, 2010; Maljkovic & Nakayama, 1994, 1996; Treisman, 1992). If this was the case, we should observe a descending speeding effect from the high to lower probability colors because of intertrial feature repetitions. However, the paired-samples t tests between the mean RTs of targets appearing in the three highest probability colors revealed no significant difference between these colors ($|t|s \leq 0.975, p = 1.000$), which is difficult to account for by intertrial priming alone.

As a second way to address the potential priming explanation, we can also remove trials that were primed from our analysis. That is, here we discarded trials in which the target repeated colors on back-to-back trials. This does not entirely exclude the influence of the priming, as such affects can be tracked five to eight trials in the past (Maljkovic & Nakayama, 1994; Olivers & Humphreys, 2003), but the speeding effect should be dramatically attenuated if driven by priming. Our analysis confirmed a robust speeding effect even with the removal of all target-color repetitive trials. One-way repeated measures ANOVA with the within-subject factor of target color probability (33%, 26%, 19%, 12%, 5%, and baseline) on participants' RTs for the noncolor-repetitive trials revealed a significant main

effect, $F(5, 90) = 10.205$, $p < .001$, $\eta_p^2 = 0.362$. Despite a significant speeding for targets appearing in the three highest-probability colors compared with targets in the baseline colors ($l_t \geq 3.897$, $p < .016$), no significant difference was revealed between the RTs of these three colors ($l_t \leq 0.919$, $p = 1.000$).

These results confirm that the speeding effect for the high-probability target colors is not driven by the unintentional feature priming but instead is due to subjects being instructed to try to learn and use the mapping between color and target shape. Next, we turn to analyses of the observers' ERPs to determine the locus of these behavioral benefits due to learning the predictive target colors.

Event-Related Potential Results

Attentional Selection Was Equally Biased by Multiple Attentional Sets

Recall that the N2pc tracks whether attention selects a target from distractors in a visual search array, with an earlier N2pc onset and a more negative N2pc amplitude found when the attentional selection for a target is more efficient or stronger (Grubert et al., 2016). If multiple attentional sets established from learning guide attentional selection simultaneously, then we should observe N2pcs with similar onset and amplitude for targets appearing in multiple high-probability colors. Alternatively, if only a single attentional set can be actively guiding attention at a time, the N2pc latency should be delayed for the lower probability colors. Our analyses revealed a similar onset latency of N2pc across all target colors as well as a larger amplitude N2pc (more negative) for targets paired with high-probability colors compared with targets paired with lower probability colors. We verified these observations with the following inferential statistical analyses.

Figure 3A shows the ERP waveforms elicited by the search array onset at electrodes PO7/PO8 contralateral and ipsilateral to the side of the target. The ERPs are shown separately for targets paired with different probability colors, with the contralateral minus ipsilateral difference waveforms shown in Figure 3B. We first examined the onset latency of the N2pc across target color probability conditions using a jackknife approach in which we measured the latency at which N2pc reached 50% of the area under the curve (Kiesel et al., 2008). These analyses revealed no effect of target color probability on the N2pc onset latency, $F(3, 54)_{\text{adjusted}} = 0.027$, $p_{\text{adjusted}} = .994$, confirming that the attentional selection for targets appearing in different probability colors happens in an equally efficient way.

The analysis on the N2pc amplitude confirmed a selective emergence of the N2pc difference wave for targets paired with the two highest-probability colors (33% and 26% colors). During this same window, we did not observe an N2pc difference wave that was different from zero elicited by the low-probability colors (19% and 12% + 5% + baseline colors). These patterns were verified by a two-way repeated measures ANOVA with the within-subject factors of laterality (electrode contralateral vs. ipsilateral to the target) and target color probability (33% vs. 26% vs. 19% vs. 12% + 5% + baseline) on ERP waveforms in a time window of 250–350 ms after the search array onset. The analysis revealed a significant main effect of laterality, $F(1, 18) = 5.013$, $p = .038$, $\eta_p^2 = 0.218$, and a significant interaction between laterality and target color probability, $F(3, 54) = 3.934$, $p = .013$, $\eta_p^2 = 0.179$. Post hoc paired-samples t tests show that the interaction was driven by a more negative

contralateral amplitude than ipsilateral amplitude on trials with targets appearing in the high-probability colors, $t(18) = -2.481$, -3.060 , $p = .023$, $.007$, for 33% and 26% colors, respectively, which was not found for trials with targets appearing in the low-probability colors, $t(18) = -0.523$, -0.943 , $p = .608$, $.358$, for 19% and 12% + 5% + baseline colors, respectively.¹

These N2pc results indicate that the two most likely target colors benefitted from stronger shifts of perceptual attention than did targets appearing in other colors. These findings demonstrate that the intentional learning that observers used in the present study changed how they deployed early perceptual attention. Next, we will ask whether it also affected postperceptual mechanisms.

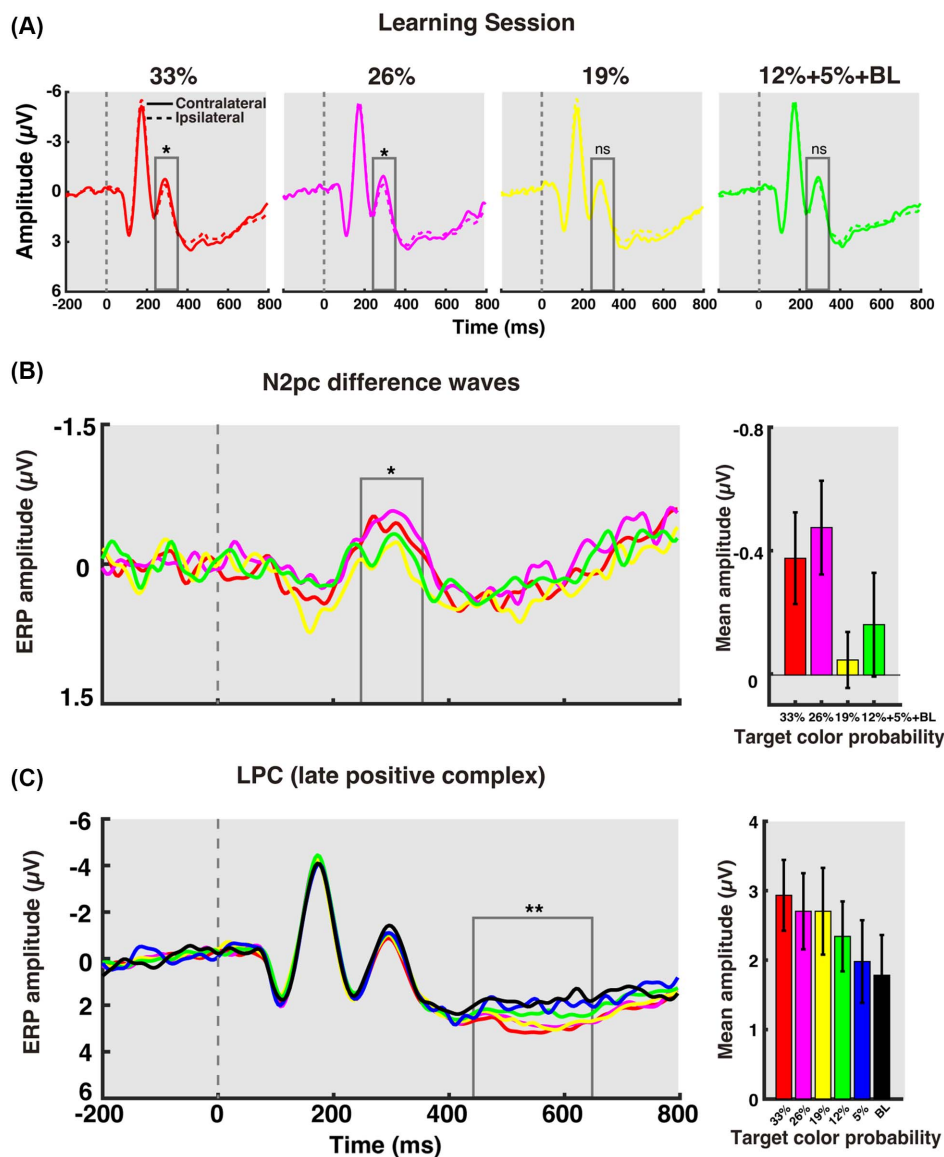
Processing Was Also Biased by Multiple Attentional Sets Postperceptually

As abovementioned we found evidence for changes in early selection by attention; however, this does not exclude the possibility that the intentional learning of these target features changes postperceptual processing as well. To this end, we analyzed the observers' LPC, which provides a measure of decision making and response selection.

Figure 3C shows the ERPs elicited by search displays averaged across the posterior electrodes (P3/4, P7/8, PO3/4, PO7/8) following the display onset. The LPC amplitude (measured during the window from 450 to 650 ms after the search array onset) was larger across target colors, with higher target color probabilities eliciting a more positive potential. The mean LPC amplitude was entered into one-way repeated measures ANOVA with the within-subject factor of target color probability (33% vs. 26% vs. 19% vs. 12% vs. 5% vs. baseline; note that the LPC amplitude in the three lowest probability conditions was not merged as we did in the N2pc amplitude analysis given that the LPC is a large and relatively clean signal; an analysis with similar trial grouping as used in the N2pc analysis is shown in the following paragraph). The analyses revealed a significant main effect of target color probability, $F(5, 90) = 5.408$, $p = .002$, $\eta_p^2 = 0.231$, with preplanned contrast comparisons revealing larger LPC amplitudes for targets paired with high-probability colors compared with the baseline colors, $F(1, 18) = 11.559$, 8.282 , and 6.805 , $p = .003$, $.010$, and 0.018 , $\eta_p^2 = 0.391$, 0.315 , and 0.274 , for 33%, 26%, and 19% color, respectively. The preplanned contrast comparisons revealed no significant LPC amplitude difference between targets paired with the low-probability colors versus the baseline colors, $F(1, 18) = 3.015$, 0.259 , $p = .100$, $.617$, $\eta_p^2 = 0.143$, 0.014 , for 12%, and 5% color, respectively. Consistent with the behavioral results, no significant difference was found among the LPC amplitudes of

¹ We verified that the same pattern of N2pc results are obtained when we analyze the difference waves themselves. A one-way repeated measures ANOVA with the within-subject factor of target color probability (33% vs. 26% vs. 19% vs. 12% + 5% + baseline) was applied to the N2pc difference amplitude (contralateral minus ipsilateral electrodes). The analysis revealed a significant main effect of target color probability, $F(3, 54) = 3.934$, $p = .013$, $\eta_p^2 = 0.179$. The preplanned contrast comparisons of the N2pc difference amplitude showed a null difference between the highest and the second rank probability colors, $F(1, 18) = 0.941$, $p = .345$, $\eta_p^2 = 0.050$; a significant decrease from the second to the third rank probability color, $F(1, 18) = 12.947$, $p = .002$, $\eta_p^2 = 0.418$; and a null difference between the third and the fourth rank probability color, $F(1, 18) = 0.463$, $p = .505$, $\eta_p^2 = 0.025$, confirming a stronger attentional selection indexed by N2pc amplitude for targets appearing in the high-probability colors.

Figure 3
N2pc and LPC Amplitude Changes With Target Color Probability



Note. (A) The waveforms of electrodes contralateral and ipsilateral to the target hemifield for targets in different probability colors, with panels representing the 33%, 26%, 19%, and the merged low-probability colors from the left to right, respectively. Solid and dashed lines represent contralateral and ipsilateral signals, respectively. Topographic map of the voltage distribution across all electrodes, with contralateral signal reflected in the left hemifield and ipsilateral signal reflected in the right hemifield. (B) Left panel: N2pc difference waveforms for targets in different probability colors at electrode pair of PO7/8; right panel: the mean N2pc amplitude over PO7/8 across 250–350 ms time window after the search array onset. (C) Left panel: LPC waveforms and topographic map for targets in different probability colors averaged over the posterior electrodes (P3/4, P7/8, PO3/4, PO7/8); right panel: the mean LPC amplitude over posterior electrodes across 450–650 ms time window after the search array onset. Error bars indicate the standard errors of the means. N2pc = N2 posterior contralateral component; LPC = late positive complex; ERP = event-related potential; BL = baseline colors; ns = not significant. Asterisk indicates the significant paired samples difference (A) or main effect (B and C; * $p < .05$. ** $p < .01$). See the online article for the color version of this figure.

targets in the three highest-probability colors ($F \leq 1.633$, $p \geq .218$). These results suggest that the multiple attentional sets established during learning change postperceptual processes, as well as early attentional selection, as indicated by the N2pc.

In the N2pc analysis, trials with targets appearing in lower probability colors (12% + 5% + baseline colors) were binned to increase the signal-to-noise ratio of the N2pc. However, the LPC analyses used all six target color probabilities. To further verify that

the effect of LPC modulation by target color probability is not due to our analyses of this component having more probability conditions, we also binned trials with targets appearing in lower probabilities (12% + 5% + baseline colors) for the LPC analysis. A one-way repeated measures ANOVA on the LPC amplitude across four probability conditions (33%, 26%, 19%, and 12% + 5% + baseline colors) again confirmed a significant main effect of target color probability, $F(3, 54) = 5.877, p = .002, \eta_p^2 = 0.246$, with preplanned contrast comparisons revealing larger LPC amplitude for targets paired with high-probability colors compared with targets paired with the combined low-probability colors, $F(1, 18) = 19.345, 11.150, \text{ and } 7.011, p = .000, .001, \text{ and } 0.016, \eta_p^2 = 0.518, 0.383, \text{ and } 0.280$, for 33%, 26%, and 19% color compared with the 12% + 5% + baseline colors, respectively. These results suggest that the target probability effect on the LPC amplitude is sufficiently strong that it can be measured even when viewed with a coarser resolution.

Discussion

Summary of the Main Findings

Previous studies have demonstrated that an attentional set for target-defining features can be established from learning probabilistic target features. However, these studies were limited to examining a contrast of just two feature values (Conn et al., 2020; Cosman & Vecera, 2014; Sha et al., 2017; others focused on attentional capture for distractors with a critical feature: Failing et al., 2019, 2019b; Ferrante et al., 2018; Goschy et al., 2014; Kerzel et al., 2022; Reder et al., 2003; Sauter et al., 2019; Stilwell et al., 2019; B. Wang et al., 2019; B. Wang & Theeuwes, 2018; Zhang et al., 2019). Here, we show that people can rapidly intentionally learn a finely grained set of predictable target features and use 2–3 of these object features to simultaneously bias attentional selection.

Multiple Attentional Sets Simultaneously Guide Attention

The key question the present study intended to answer was how multiple attentional sets guide attention after being explicitly learned. The controversy as to whether a single attentional template or multiple attentional templates can be held in working memory to guide attention at any given moment has been a recent focus in the study of attention (Barrett & Zobay, 2014; Beck et al., 2012; Dombrowe et al., 2011; Grubert & Eimer, 2013, 2015, 2016; Houtkamp & Roelfsema, 2009; Irons et al., 2012; Kerzel & Grubert, 2022; Moore & Weissman, 2010; Olivers et al., 2011). Our results provide multiple pieces of evidence supporting the later proposal that multiple attentional sets can be held in an active state to simultaneously guide attention.

Our study supports the notion that intentional learning can establish multiple attentional sets (around two or three colors) simultaneously guiding visual search, consistent with prior research showing that multiple target templates simultaneously guiding attention (Grubert et al., 2016; Grubert & Eimer, 2013, 2015, 2016; Kerzel & Grubert, 2022). While some studies propose a capacity for three simultaneous target sets (Grubert et al., 2016), others suggest a maximum of two (Kerzel & Grubert, 2022). In the present study, behavioral and LPC results indicate that three attentional sets (corresponding to the three colors with the highest probabilities)

could simultaneously guide visual search. However, N2pc results suggest that only the first two highest probability colors bias attention, indicating that two or three attentional sets could simultaneously guide attention. Considering the constraint that the sum of all possibilities must be 100%, and that working memory typically holds around three to four items, determining the precise capacity of attentional sets guiding visual search is challenging. Future studies could explore this further by presenting more high-probability colors (e.g., six colors with 15% probability, one 5% low-probability color, and 5% baseline colors) to investigate whether more than three to four colors demonstrate speeding benefits and attentional bias, as observed in our study, thereby elucidating the capacity of learned attentional sets.

An interesting finding of the current experiment is that the number of target colors showing an equivalent speeding benefit is 2–3, which is clearly similar to the capacity of visual working memory estimated at about three to four items (Luck & Vogel, 1997; Vogel & Machizawa, 2004). If we assume that representations need to be in working memory to bias perceptual attention, then our findings suggest that observers may fill working memory with features that can all concurrently guide attention. Alternatively, it is possible that active long-term memory representations can be used to perform search (Woodman et al., 2007), and that the similarity in capacity estimates is spurious. The fact that the number of simultaneous attentional sets estimated from the current intentional learning experiment is similar to the one measured in our recent incidental learning experiment (S. Wang et al., 2023) might support the first explanation, which suggests that the number of simultaneous attentional sets is limited by working memory capacity, regardless of whether the learning process is intentional or incidental. We believe that future work will be well positioned to distinguish between these competing explanations.

Target-Feature Learning Enhances Both Perceptual Selection and Postperceptual Processes

Our ERP results showed that the learning effect changed neural activity across multiple stages of processing. Specifically, we found a larger amplitude N2pc and LPC components for targets in high-probability colors. This is particularly notable because the closest previous study to the present one had subjects learn target colors regularly incidentally (S. Wang et al., 2023), without the benefit of the instructions that the present observers enjoyed. With that difference, the previous study found no evidence for changes in how early perceptual attention was deployed to different colors. Despite a larger amplitude LPC found for targets in high-probability colors, an equivalent amplitude N2pc was found for targets in both high- and low-probability colors in our previous study of implicit learning. Thus, it appears that subjects need to be intentionally trying to learn and use the color information to see the early attention effects that we report here.

The N2pc results support proposals that learning and selection history guides perceptual attention to select features (e.g., colors) that are task relevant (Conn et al., 2020; Cosman & Vecera, 2014; Sha et al., 2017). At the perceptual selection stage, attention is biased by multiple attentional sets of high-probability colors that either by increasing the target's relative salience (e.g., Becker, 2008; Maljkovic & Nakayama, 1996) or by making attentional shifts more stereotyped (Yashar & Lamy, 2010), thus eliciting a larger

amplitude N2pc for targets in high-probability colors while weaker N2pc for targets in low-probability colors.

Our LPC results provide additional information about how learning target features can reconfigure cognitive processing. These findings suggest that learning the target features was either able to speed a decision stage that occurs after a candidate target has been located (Huang et al., 2004; Huang & Pashler, 2005) or to speed response selection and motor execution (e.g., Cohen & Magen, 1999). For example, perhaps the larger amplitude LPC for targets paired with multiple high-probability colors suggest that when a candidate target has been selected, the system seeks to verify that this element is indeed the target by comparing the current potential target with the target instances stored in memory. The confirmation process is faster if the color paired with the current target matches those high-probability colors retrieved from memory (Logan, 2002). Otherwise, the system may need extra episodic retrieval time to check the status of the target when paired with a rare color in which fewer instances can be retrieved per unit of time.

Constraints on Generality

The present study shows that statistical regularity learning can establish multiple attentional sets for target features, particularly through a finely tuned target-color probability distribution. However, it remains to be seen whether this phenomenon extends to other statistical learning paradigms. For instance, future research could explore the effects of introducing distractors at varying locations with different probabilities, as seen in the classic singleton task (Failing, Feldmann-Wüstefeld, et al., 2019), or presenting targets at multiple locations with distinct probabilities (Kerzel et al., 2022). In this study, we specifically manipulated one of the incidental features of targets—color. Yet, in real-world contexts, statistical regularity may involve multiple target features, such as color and location, or color and shape. Thus, while confirming the generalizability of our findings to the learning of regularities involving multiple features is crucial, our study offers valuable insights for future investigations into more complex and ecologically valid statistical learning scenarios.

Conclusion

The present study demonstrates that multiple attentional sets of target features with relatively high probability can be established rapidly during task learning and that these attentional sets can simultaneously guide attention. Our ERP results show that this attentional guidance is achieved by enhancing both the perceptual selection and the postperceptual processes. Together, these results imply that multiple attentional sets can be learned and guide attention at the same time, reshaping the course of information processing throughout the brain.

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