# Statistical Learning Speeds Visual Search: More Efficient Selection, or Faster Response?

Sisi Wang[1,2], Stanislas Huynh Cong[3], and Geoffrey F. Woodman[2*]

[1] State Key Laboratory of Cognitive Neuroscience and Learning, Beijing Normal University

[2] Department of Psychology, Vanderbilt University

[3] Faculty of Psychology and Educational Sciences, University of Geneva

## Author Note

Portions of these findings were presented as a poster at the 2022 Vision Science Society conference, St. Pete Beach, Florida, United States.

We have no known conflict of interest to disclose.

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

## Abstract

Learning statistical regularities of target objects speeds visual search performance. However, we do not yet know whether this statistical learning effect is driven by biasing attentional selection at the early perceptual stage of processing, as theories of attention propose, or by improving the decision-making efficiency at a late response-related stage. Leveraging the high temporal resolution of the event-related potential (ERP) technique, we had sixteen human observers perform a visual search task where we inserted a fine-grained statistical regularity that the target shapes appeared in different colors with six unique probabilities. Observers unintentionally learned these regularities such that they were faster to report targets that appeared in more likely target colors. The observers' ERPs showed that this learning effect resulted in subjects making faster decisions about the target presence, and not by preferentially shifting attention to more rapidly select likely target colors, as is often assumed by the attentional selection account, supporting a post-selection account for statistical learning of the probabilistic regularities of target features. These results provide fundamental insights into the attentional control mechanisms of statistical learning.

*Keywords*: Statistical learning, Attentional selection, Decision-making, N2pc, LPC

## Public Significance Statement

Humans are able to learn regularities from the surrounding environment to increase their efficiency. However, the mechanisms underlying this statistical learning are not yet clear. Leveraging the high temporal resolution of human electrophysiology, we examined the attentional control mechanisms of statistical learning with a novel visual search paradigm. We used fine-grained statistical regularities that paired target shapes with different colors across trials. Our results demonstrated that observers could successfully learn the complex statistical regularities of the environment unintentionally. Contrary to theories of attentional selection, we found that this statistical learning effect was driven by more efficient decision-making, not biasing attention to select targets with prioritized features, helping solve the long-standing theoretical controversy regarding the cognitive control mechanisms underlying statistical learning.

When a human arrives in a new environment, it has an array of learning and memory mechanisms at its disposal to help it learn how to find and recognize objects that are critical for its survival (Turk-Browne et al., 2009; Turk-Browne, 2012; Goujon et al., 2015; Sha et al., 2017; Ferrante et al., 2018; Wang & Theeuwes, 2018; Batterink et al., 2019; Failing et al., 2019; Zhang et al., 2019; Conn et al., 2020; Kerzel et al., 2022). Theories propose that this learning allows the human brain to shift perceptual attention to objects that have target features, speeding behavioral reaction time (or RT, see reviews from Desimone & Duncan, 1995; Egeth & Yantis, 1997; Kastner & Ungerleider, 2000; Corbetta & Shulman, 2002). Although we know that learning speeds behavioral RTs, we do not yet know how the brain achieves this feat.

Although researchers have repeatedly confirmed the existence of statistical learning effects during visual search, they do not yet know how this might change attentional control. According to one view, past experiences bias attention to objects that contain target features (Awh et al., 2012; Wolfe & Horowitz, 2017; Theeuwes, 2019). However, faster RTs could also be due to more efficient post perceptual processing. That is, the repetition of the target features speed behavioral RTs by speeding a decision stage of processing (Huang et al., 2004). This alternative seems plausible given previous research suggesting that learning allows observers to make decisions faster after attention is shifted to a candidate target object (Huang et al., 2004; Huang & Pashler, 2005), and can increase the efficiency of a motor response (e.g., Cohen & Magen, 1999). Thus, our goal was to distinguish between these alternatives.

## Purpose of the Present Study

To examine the attentional and post-perceptual accounts of the locus of statistical learning benefits, we focused our measurements on two event-related potential (ERP) components. The N2pc (for a Negative going waveform, 200 ms following an array, with a posterior and contralateral distribution) and LPC (for Late Positive Complex) were measured while observers were learning a sophisticated pattern of statistical regularities in which the color of a target shape was manipulated across trials (e.g. targets were in red for 33% trials, in magenta for 26% trials, in yellow for 19% trials, in green for 12% trials, in blue for 5% trials, and in baseline colors for 5% trials). The N2pc emerges approximately 200ms following the search array onset and tracks the attentional selection of targets at early sensory-perception stage (Luck & Hillyard, 1994; Eimer, 1996; Woodman & Luck, 1999; Hopf et al., 2000). The LPC emerges approximately 500ms after stimulus onset and tracks post-perceptual decision-making (Friedman & Johnson, 2000; Rugg & Curran, 2007; Voss et al., 2010).

According to the attentional selection account, prioritized attention should be biased to targets with more predictable features, if this was the case, we should see larger amplitude N2pc for targets paired with high-probability colors. However, if differences in decision-making efficiency account for the statistical learning effect, we should observe that the LPC has a larger amplitude for targets paired with high-probability colors.

## Transparency and Openness

This experiment was not preregistered. Deidentified data and the data-analysis scripts are available at https://osf.io/f9p4r/.

## Materials and Methods

### Participants

Twenty-one undergraduates and graduate students from Vanderbilt University participated in the current experiment for gift card compensation ($15/hour). All participants self-reported normal or corrected-to-normal acuity, normal color vision, and received informed consent for procedures approved by the Vanderbilt University Institutional Review Board. Five participants were excluded from further data analysis due to excessive eye movements and muscular artifacts during EEG recording (see details in the EEG data preprocessing section), leaving 16 participants (11 females and 5 males, Mean age = 22.6 years, SD age = 2.0 years) in the final data set. All the gender and age information were self-reported by the participants with a free-response box.

### Sample Size Analysis

We estimated the necessary sample size for the present experiment using a multi-step procedure. First, we looked to the existing literature that has examined effects of statistical learning on attention for guidance (e.g., 12-24 participants across experiments in Sha et al., 2017; Cosman & Vecera, 2014). Second, we used approximately 4 times 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=16) using the G*Power analysis software (Faul et al., 2009). We took the effect size estimate ($\eta_p^2 = 0.269$) from the one-way repeated measures ANOVA of the RTs across target color probability ($F(5, 75) = 5.520$, $p = 0.001$, $\eta_p^2 = 0.269$; see Behavioral Results). 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 0.965 with the given sample size of 16, 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 CRT monitor contained in Faraday cage. Stimuli were presented on a white background (75.2 cd/m$^2$). Participants were seated approximately 75 cm from the screen.

**Figure 1A** shows example trials of the shape visual search task. Each trial began with a display containing a black fixation cross (1.2 cd/m$^2$, 0.4° of visual angle) in the center of the screen for 1000 ms, followed by a search array surrounding fixation containing one target box (box with an opening on the top edge or the bottom edge) and eleven distractor boxes (box with an opening on the left edge or the right edge). This display was visible until participants made a response on each trial. All boxes were unfilled squares (the square length*width, 0.7° *0.7° 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 at twelve fixed positions of the invisible circle (from 0 circle degrees to 330 degrees, in steps of 30 degrees). 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 as the response was made, a blank screen appeared with a variable inter-trial interval ranging from 1000 ms to 1500 ms. The "top" target and the "bottom" target trials were equally probable (50%) across 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=0.55, y=0.33), green (x=0.28, y=0.61), magenta (x=0.29, y=0.15), yellow (x=0.42, y=0.50), blue (x=0.11, y=0.07), cyan (x=0.20, y=0.29), black (1.2 cd/m$^2$), and orange (x=0.48, y=0.38). 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%, 5% for each color, with the remaining 5% of all trials randomly paired with the three remaining colors from the pool to form the baseline. In the test session, the targets were paired with each of the eight colors with a probability of 12.5% on a given trial. For each search array, the colors of the distractors were randomly chosen from the color pool, without repetition with the color of target, and with no more than two distractors appeared in the same color. It is worth noting that the colors paired with targets were not exclusive, they could be paired with distractors across the experiment. The probability-matching colors were randomized across participants to prevent confounds from stable color preferences across the sample (i.e., red was just as often as baseline or 5% color as it was the 33% color).

**Procedure**

**Figure 1C** illustrates the experimental design of a session with an individual observer. Each observer completed two learning sessions and a test session. The goal of the test session was to determine if the statistical learning effect survives interference from another task in which color is task relevant. With this goal, half of the observers completed the test session immediately after the learning session, while the other half of the observers completed a working memory task after the learning session, but before the test session. By comparing the influence of the learned statistical regularities on test session performance on these two groups, we could tell whether the statistical learning effect survived interference for the interposed task performance. The immediate-test group also completed the working memory task, but after the test session. Observers completed two learning sessions, each learning session includes five blocks of 200 trials with all target colors (33%, 26%, 19%, 12%, 5%, and 5% Baseline) and target shapes (upward, and downward) intermixed randomly. The test session includes two blocks of 80 trials with all eight colors from the color pool (12.5% for each color) and target shapes (upward, and downward) intermixed randomly.

To examine the relationship between WM capacity and statistical learning effect, a classic color change-detection task was used to estimate observers' WM capacity (Luck & Vogel, 1997; Vogel & Machizawa, 2004). In this task, participants were instructed to memorize the colors of a variable number of squares (3, 6, or 8, with width × height of 0.65° × 0.65° visual angle) that appeared in a memory array. During each trial, a memory array appeared on the screen for 100 ms, followed by a 900 ms delay period, before the appearance of the test array. The test array consisted one probe colored square presented at the location of a square in the memory array. On 50% of trials the color of the square in the test array would change to another color not previously seen in the memory array, and stays the same for the other 50% of trials. The locations of the colored squares in the test array stayed the same as it appeared in the memory arrays. Participants pressed "f" or "j" on the keyboard to indicate whether the color of the square in the test array had changed or stayed the same. The change versus no-change keys were counterbalanced across subjects.

The colors of the squares were chosen from the same pool of seven highly discriminable colors as the search items: red, green, magenta, yellow, blue, black, and white (same metrics as above). The colors of the squares in the sample array were randomly chosen from the color pool, with each color appearing no more than twice on a given trial. Each square was located in one of the 24 positions on three invisible circles (with eccentricities of 1.5°, 2.7°, and 3.9° visual angle, respectively). Each participant completed 48 trials at each set size (3, 6, and 8), and trials with different set sizes were intermixed within the block.

To examine whether observers were explicitly aware the mapping of color to target likelihood after learning, they completed a post-test questionnaire. In the questionnaire, they were asked if they thought that the target shape appeared more often in some colors than others. If they answered *yes*, they were further asked to write down the ranking for each color in terms of its relative frequency (rank the color that the target appeared in the most, the second most, the third most, etc.), and its corresponding approximate probability (they could at maximum rank all

8 colors, with 100% representing the highest probability). If they answered *no*, they were not required to answer further questions.

## EEG Acquisition

The electroencephalogram was recorded in an electrically shielded, soundproof booth from a 20-channel cap (Electro-cap International, OH) embedded with tin electrodes that make contact with 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, P7, P8, Fpz, Fz, Cz, Pz). Impedance values were kept below 4 kΩ. The reference electrodes were affixed with stickers to the left and right mastoids with the left mastoid operating as the online reference electrode, and a ground electrode placed 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 0.01-100 Hz and recorded with a 250 Hz sampling rate.

## Data Analyses

### *RT Analysis*

For the visual search task performance analysis, we analyzed reaction time (RT) for trials with targets paired with each color. To avoid contributions from outliers, only trials with RT faster than 3 seconds and trials with correct responses were included in the mean RT analyses.

### *Calculation of Working Memory Capacity*

Observers' working memory capacity was calculated from the averaged capacity of all three sample set sizes (3 vs. 6 vs. 8). The calculation of working memory capacity (K) for each set size in the change detection task followed the formula K = Set size* (Hit rate – False Alarm rate) (Rouder et al., 2011), where hit rate represents proportion of correct responses on change trials, and false alarm rate represents proportion of incorrect responses on no-change trials. As the correlations between performance of this task and the statistical learning task are not relevant for the accounts we are distinguishing between in this study, we report these in the Supplemental Materials (see **Figure S1**).

### *EEG Data Preprocessing*

A low-pass filter at 30 Hz was first applied to EEG data to remove high frequency activity caused by muscle and environmental noise. Data were then re-referenced offline to the average of the left and right mastoid reference. EEG epochs were then extracted from the re-referenced EEG signal. These epochs last for 1000 ms, beginning 200 ms prior to the search array onset, with the 200 ms pre-stimulus period serving as the baseline. Trials including artifacts due to blinks, amplifier saturation, or excessive noise that exceed -100μV to +100μV range were first rejected using a standard signal-rejection function from the EEGLAB Toolbox (eegthresh.m; Delorme & Makeig, 2004). A stricter threshold of -50μV and +50μV range was further conducted on the horizontal EOG signal (the difference voltage between horizontal EOG recorded from left and right eyes) and the vertical EOG signal, respectively, to remove trials contaminated by the horizontal and vertical eye movements. Five observers with fewer than 70% artifact-free trials remaining were excluded following the artifact rejection steps, with an average 82.3% (SD = 7.0%) of trials being kept for the remaining observers.

### *ERP Analysis*

**N2pc Analysis**: The N2pc component was analyzed as an electrophysiological marker of attentional selection of targets among distractors that operates at an early perceptual stage of processing (Woodman & Luck, 2003). The N2pc is a negativity that typically emerges between 180 and 200 msec after visual search array onset and is assumed to reflect the spatial of object representations in extrastriate visual cortex during early perceptual processing level (e.g., Luck

& Hillyard, 1994; Eimer, 1996; Woodman & Luck, 1999; Hopf et al., 2000). In current study, the N2pc amplitude was computed by subtracting the averaged activity from electrodes with target presented ipsilateral to its location from the activity of the electrodes contralateral to the target. Following precedent, we focused on the posterior-lateral electrode PO7/PO8 (Grubert et al., 2016). The time window for the N2pc analysis was 250-350 ms after the search array onset. The onset latency of the N2pc was calculated using the jackknife method in which we measured the latency at which the N2pc reached 50% of the area under the curve (Kiesel et al., 2008). Since only trials with targets presented laterally can be included in the N2pc analysis, we merged trials with targets in the low-probability colors (12%, 5%, and 5% baseline) to increase the signal-to-noise ratio of our N2pc analysis.

**LPC Analysis**: Following the N2pc, we measured a post-perceptual component known as the LPC (for late positive complex). The LPC is a relative positivity that emerges across the posterior scalp electrodes beginning about 500 ms after stimulus onset. Substantial evidence indicates that LPC potentials signal episodic retrieval from long-term memory (Friedman & Johnson, 2000; Rugg & Curran, 2007; Voss et al., 2010). Observers could store the probability of instances for targets paired with each color they saw from the search history in their long-term memory to extract the regularity and apply the regularity to guide their forthcoming search. Regularity extraction, target identification, and response decision-making requires comparison between the current features of target with the features stored in long-term memory. In the current experiment, the LPC amplitude was calculated by averaging signals across the parietal electrodes: P3/P4, P7/P8, PO3/PO4, PO7/PO8. The time window for the LPC analysis was 450-650 ms after the search array onset.

## Experimental Design and Statistical Analyses

To examine the influence of the target color probability on behavioral performance and the electrophysiological markers, one-way repeated-measures ANOVAs with the within-subjects factor of Target Color Probability (33%, 26%, 19%, 12%, 5%, and baseline) were performed on observers' mean RT and LPC amplitude. A 2 × 4 RMANOVA with within-subjects factors of Laterality (electrode contralateral vs. ipsilateral to target) and Target Color Probability (33% vs. 26% vs. 19% vs. 12%+5%+baseline) was applied to the N2pc analysis. Bonferroni corrections for multiple comparisons were applied to all paired-wise comparisons. All these statistical analyses were performed in Matlab and SPSS 19.0 (IBM Inc.).

## Results

### Behavioral Results

#### ***Statistical Learning Speeds Visual Search for Targets in High-Probability Colors***

As shown in **Figure 2A**, our analyses on observers' RT for trials with targets appearing in different-probability colors demonstrated that behavior mirrored the probability structure that we imposed on the experimental environment.

The one-way repeated measures ANOVA revealed a significant main effect of Target Color Probability ($F(5, 75) = 5.520$, $p = 0.001$, $\eta_p^2 = 0.269$), with faster RT for targets paired with higher probability colors. Next, we performed pair-wise sample t-tests between RTs in each color probability against RTs when the target appeared in the baseline colors. These revealed a significant reduction in RT for targets appearing in the three highest-probability colors ($t(15) = 3.963, 3.297, 3.416$, $p = 0.019, 0.073, 0.058$ for 33%, 26%, and 19% colors, respectively), while no significant change in RT for targets appearing in the two lowest-probability colors ($t(15) = 2.158, 0.327$, $p = 0.713, 1.000$ for 12% and 5% colors, respectively). Moreover, there were no significant difference between RTs when the target appeared in the three highest-probability colors ($|t|\text{s} < 0.772$, $p\text{s} = 1.000$). In summary, the behavioral results demonstrate that subjects' learning reflected the regularities in the environment. We next examined whether these were task-specific representations that our observers acquired, or whether this kind of statistical learning survives a change in task context.

### *The Statistical Learning Effect is Short-Lived*

**Figure 2B** shows the duration of the learning effect as measured with performance in the test session. We calculated RT for targets in each color in the test session where targets were paired with equivalent probability colors, but binned according to their role in the previous learning sessions. Our results show that the learned target probability effects did not last into the test session in a robust enough form to determine observer's patterns of RT. Although a trend may seem visible in without interference, this pattern did not achieve significance, as we describe next.

The mean RTs during the test sessions were entered into a mixed-model two-way RMANOVA with the between-subjects factor of Group (immediate-test group vs. working-memory-task-interference-test group) and a within-subjects factor of Target Color Probability (33%, 26%, 19%, 12%, 5%, 5% baseline). The analysis revealed no significant group difference ($F(1, 13) = 0.208$, $p = 0.656$, $\eta_p^2 = 0.016$), no main effect of Target Color Probability ($F(5, 65) = 1.352$, $p = 0.266$, $\eta_p^2 = 0.094$), nor an interaction between these two factors ($F(5, 65) = 0.306$, $p = 0.907$, $\eta_p^2 = 0.023$). These null results suggest that the color priority settings acquired during learning were specific to the task in which they were acquired. This is consistent with other studies of statistical learning in which the representations of incidentally learned features are fragile and confined to the task (Sha et al., 2017; Ferrante et al., 2018; Conn et al., 2020).

### *Ruling Out Confounding Factors*

Because we paired different colors with the target shape, the learning effect could be driven by factors other than using the probability information to behave adaptively. 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 is confounded with color by design. As shown in **Figure 2A**, our control analyses rule out the contribution of several possible confounding factors to the statistical learning effects that we observed.

**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 some specific colors. For example, maybe the RT benefits for the 33% color are driven by the observers who were randomly assigned to have green as the most probably 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 100 trials) for targets in each color when observers had not yet learned 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 RMANOVAs with within-subjects factor of Target Color Probability (33%, 26%, 19%, 12%, 5%, and baseline) on observers' mean RT of the first 5% trials across all conditions revealed no significant main effect of Target Color Probability ($F(5, 75) = 1.381$, $p = 0.255$, $\eta_p^2 = 0.084$).

**Inequivalent Trial Number**: Within the learning session, observers saw more instances of targets paired with higher-probability colors. Therefore, it is possible that the faster RTs observed in these conditions were driven by greater statistical power for the high probability colors and more noisy samples at lower probability. To test this possibility, we randomly selected equivalent number of trials (5% of all trials for each condition) for targets in each probability color from all trials. This analysis confirmed a similar pattern of learning for targets paired with different probability colors as the original analysis ($F(5, 75) = 4.134$, $p = 0.007$, $\eta_p^2 = 0.216$), excluding the possibility that the learning effect was driven by uneven sampling.

**Priming**: Priming refers to the phenomenon that the search speed for target in the current trial is boosted if the target shares consistent features with target from a previous trial (Treisman, 1992; Maljkovic & Nakayama, 1994; 1996; see a review of Kristjánsson & Campana, 2010). In the current study, the odds that two adjacent trials would share the same color of target was higher for high-probability colors. Therefore, the larger learning effect for higher probabilities could purely be due to more trials benefitting from priming by the previous trial. To exclude this possibility, we analyzed trials without adjacent trial color priming by removing trial pairs with repetitive target colors (i.e., the target was red for two trials in a row), and our analysis confirmed a robust learning effect even with no trials containing target color repetitions from the previous trial ($F(5, 75) = 4.159$, $p = 0.007$, $\eta_p^2 = 0.217$), excluding the possibility that the learning effect was purely driven by priming effect.

### ***Post-Test Awareness***

We analyzed observers' responses in the post-test questionnaire to probe whether they became explicitly aware of the regularities of the target color probability matrix after learning. Our analyses demonstrated significant individual difference in observers' memory for the regularity after learning. The first question in the questionnaire was whether observers noticed the targets appearing in some colors more often than other colors. Most observers reported awareness of the probability difference of target color (13/16 observers answered *yes*), with the remainder reporting no perceived target color probability difference (3/16 observers answered *no*). Next, we analyzed their answers regarding the probability rank for each color (the rank ranges from 1 to 8, with 1 being the most probable color). The calculation of the recall accuracy of the probability rank for each color included two steps. First, we calculated the reported distance between the probability rank and the actual probability rank for each color. We used the absolute difference between observers' self-reported probability rank (ranges from 1 to 8) and the actual probability rank (ranges from 1 to 6) of this color. The calculated reported-actual probability rank distance runs from 0 to 7, with 0 representing correct recall. Second, we scored rank distance within 1 (i.e., values of 0 and 1) and above 1 (i.e., 2-7) as correct recall and incorrect recall, respectively. The total number of correct recalls were then counted within all observers for each color. Even though the awareness rate of the statistical regularity was high (i.e., 81.3%), observers were highly inaccurate in correctly reporting the probability rank of any of the colors, including the most likely possible target colors. Specifically, the number of observers out of 16 that correctly reported which color they saw in each probability bin was: 5/16, 7/16, 8/16, 8/16, 6/16, 5/16 observers for the color with a probability of 33%, 26%, 19%, 12%, 5%, and baseline, respectively. None of these values were significantly higher than the mean correct recall rates calculated from a Monte Carlo simulation with 10000 random draws for bin: 3.3/16, 4.9/16, 4.9/16, 4.9/16, 4.9/16, 4.9/16, respectively across the probability bins. These results suggest that even though most observers reported being aware of the regularity, their memory for which colors were actually more likely strikingly was imprecise.

## ERP Results

### *Attentional Selection Was Unbiased Following Statistical Learning*

Recall that the N2pc signal reflects the attentional selection of a target among distractors, with a larger N2pc amplitude indicating a more efficient attentional selection of the target (Grubert et al., 2016). If learning the statistical regularities of target color matrix biases attentional selection, then we should see a larger amplitude N2pc for targets in higher-probability colors than targets in lower-probability and baseline colors. However, our N2pc analysis revealed an equivalent N2pc amplitude contralateral to the target hemifield for targets paired with different probability colors, indicating that this perceptual attention mechanism operated the same on targets regardless of the color in which they appeared. This is verified by the following statistical analyses of the N2pc amplitudes.

**Figure 3A** shows the ERP waveforms elicited by search displays from electrodes PO7/PO8 contralateral and ipsilateral to the side of target in the 800 ms interval following display onset. The ERPs are shown separately for targets paired with different probability colors (33%, 26%, 19%, and 12%+5%+baseline, note that trials with target color probability of 12%, and 5%, and baseline were merged together to increase the signal-to-noise ratio of the N2pc analysis), The corresponding contralateral-ipsilateral difference waveforms for these four conditions are shown in **Figure 3B**. Clear N2pc components were triggered by targets paired with each probability color (33%, 26%, 19%, 12%+5%+baseline), but these amplitudes did not differ across probability bins. Mean ERP amplitudes obtained 250–350 ms after search display onset were entered into a 2 × 4 RMANOVA with within-subjects factors of Laterality (electrode contralateral vs. ipsilateral to target) and Target Color Probability (33% vs. 26% vs. 19% vs. 12%+5%+baseline). The analysis revealed a significant main effect of Laterality ($F(1, 15) = 46.221$, $p < 0.001$, $\eta_p^2 = 0.755$), with the contralateral signal more negative than the ipsilateral signal. However, neither a significant main effect of Target Color Probability ($F(3, 45) = 0.402$, $p = 0.752$, $\eta_p^2 = 0.026$), nor a significant interaction between these two factors were found ($F(3, 45) = 1.290$, $p = 0.289$, $\eta_p^2 = 0.079$), suggesting the manipulation of the target color probability had no influence on attentional selection for shape-defined targets.

It is possible that the lack of an effect on the N2pc component was due to the fact that this ERP component is less reliable than the LPC. This might explain why the LPC amplitude shows clear effects of target color probability, whereas the N2pc amplitude does not. To address this, we also applied a Bayesian Repeated Measures ANOVA with the within-subjects factors of

Laterality (electrode contralateral vs. ipsilateral to target) and Target Color Probability (33% vs. 26% vs. 19% vs. 12%+5%+baseline) to the N2pc amplitude data to determine how much more likely the null hypothesis (that there was no difference between the N2pc amplitude across target color probabilities) was than the possibility that the N2pc amplitude actually did show a modulation by target color probability (JZS, Rouder et al., 2017). We found that for the effect of Target Color Probability on the N2pc amplitude, the null hypothesis was 15.9 times more likely than the hypothesis that a difference existed. Moreover, across all of the pair-wise comparisons of the N2pc amplitude across target color probabilities, the null hypothesis was on average 4.1 times (Bayes Factors range from 3.1 to 5.3, mean = 4.13, SD = 0.87) more likely than the hypothesis that a difference existed. These analyses demonstrate that our comparisons of the N2pc amplitude across target color probabilities were not simply limited by power, but instead there was a convincing null effect when measuring the N2pc amplitudes across targets appearing in different probability colors.

The next possibility that we addressed with regard to the N2pc component is the possibility that learning the target color probability leads to faster attentional selection for targets paired with higher-probability colors. If this happened reliably, we would observe this faster time course as an earlier onset latency of the N2pc in these conditions. To test this possibility, we 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). The analyses revealed no effect of target color probability on the N2pc onset latency ($F(3,45)_{\text{adjusted}} = 0.066$, $p_{\text{adjusted}} = 0.978$), ruling out the possibility that the RT facilitation effects established from statistical learning in the current paradigm is the result of faster attentional selection. Thus, the null effect of target color probability on both the

N2pc amplitude and onset latency together support a post-selection account for statistical learning in the current paradigm.

### ***The Statistical Learning Effect is Due to Differences in Post-Perceptual Processes***

If learning did not change how early perceptual attention was deployed, then the RT effects may be due to post-perceptual mechanisms that handle the objects differently depending on their surface features. For example, targets may be recognized faster when appearing in a target color, or subjects' decision-making may be more efficient for these items. Consistent with this view, our analyses revealed that the LPC amplitude linearly tracked the target color probability, with larger amplitude LPCs for targets paired with higher-probability colors, suggesting an essential role of post-perceptual cognitive control in realizing the benefits of statistical learning. These observations were verified by the following statistical analyses of LPC amplitudes.

**Figure 3C** shows the ERPs elicited by search displays averaged across the posterior electrodes (P3/P4, P7/P8, PO3/PO4, PO7/PO8) following display onset. The LPC amplitude monotonically increased with the target color probability and reached an asymptote after the 19% color. Mean ERP amplitudes averaged across the time window from 450–650 ms after search display onset were entered into one-way RMANOVAs with within-subjects factor of Target Color Probability (33% vs. 26% vs. 19% vs. 12% vs. 5% vs. baseline). The analyses revealed a significant main effect of Target Color Probability ($F(5, 75) = 4.174$, $p = 0.007$, $\eta_p^2 = 0.218$), with within-subjects contrasts revealing a linear increase from low to high probability colors ($F(1, 15) = 20.696$, $p < 0.001$, $\eta_p^2 = 0.580$ (*Linear*). Thus, this initial analysis suggests that the behavioral effects we observed were due to the most likely target colors benefitting from more efficient post-perceptual decision-making, not earlier shifts of attention as the N2pc would have evidenced.

In the N2pc analysis, trials with targets appearing in lower probability colors (12%+5%+BL) were binned to increase the signal-to-noise ratio of the N2pc. However, the LPC analysis was focused on 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%+BL) for the LPC analysis. A one-way RMANOVA on LPC amplitude across four probability conditions (33%, 26%, 19%, and 12%+5%+BL) again confirmed a significant main effect of Target Color Probability (F(3, 45) = 3.464, p = 0.024, $\eta_p^2 = 0.188$), with within-subjects contrasts revealing a linear increase from low to high probability colors (F(1, 15) = 6.363, p = 0.023, $\eta_p^2 = 0.298$ (Linear). These results demonstrate that the target probability effect on the LPC amplitude is sufficiently strong that it can be measured even when viewed with a courser resolution.

### ***LPC Amplitude Change Selectively Predicts Statistical Learning Effect***

We further examined the correlation between our ERP amplitude changes and the extent of the learning benefit across observers. As shown in **Figure 3D**, we found that the LPC amplitude change correlated with the RT benefit, but no such correlation between the N2pc and RT was found. These observations help bolster our inference that post-perceptual processing was the locus of the statistical learning benefits we measured.

The amplitude changes of N2pc and LPC were first calculated by subtracting ERP amplitudes in each probability bin from the baseline condition. The extent of the learning benefit was calculated by subtracting the mean RT for each probability bin from the baseline RT. Correlations between the amplitude change and the extent of learning benefit were then calculated for N2pc and LPC, respectively. Significant negative correlations were found between the LPC amplitude change and the RT changes for most probability conditions (*r* = -0.482, -

0.703, -0.579, -0.408, -0.685, $p = 0.059, 0.002, 0.019, 0.117, 0.003$ for the 33%, 26%, 19%, 12%, 5% color, respectively), with stronger LPC modulations accompanying a larger spread of RTs across colors, suggesting that the post-selection process indexed by LPC signal predicts the magnitude of the statistical learning effect for a given subject. No significant correlation was found between the N2pc amplitude changes and the RT changes ($|r|\text{s} < 0.380$, $p\text{s} > 0.147$).

## Discussion

Statistical learning is ubiquitous in our daily lives. However, exactly how this learning reshapes our cognitive architecture is not yet known. Here we show that observers could successfully learn the fine-grained statistical regularities of an incidental target feature, moving beyond previous work using color pairs (Sha et al., 2017; Conn et al., 2020). The most surprising results were that this learning did not result in observers differentially shifting attention to the likely target colors. Instead, the deployment of attentional selection to objects as indexed by the N2pc was unchanged in our experiment while the post-perceptual ERP components showed the effects of observers' learning history. Although the generality of these findings will be important to establish, it is possible that statistical learning typically shapes post-selection decision-making processes, and does not change patterns of performance by biasing attentional selection to targets with prioritized features.

We leveraged the high-temporal resolution of ERP measurements to provide novel evidence supporting a post-selection locus of statistical learning during attention demanding visual search. Specifically, our electrophysiological measures of brain activity across the course of information processing support an account in which learning the statistical regularities about target features enhances post-perceptual decision-making processes rather than biasing attentional selection. Our results speak to hypotheses long debated in the literatures on attention and learning. Previous studies of visual search proposed selection-based accounts in which repeating the target feature accelerates selection of the target either by increasing the target's relative salience (e.g., Maljkovic & Nakayama, 1996; Becker, 2008) or by speeding shifts of attention to such items (Yashar & Lamy, 2010). Contrary to these selection-based accounts, the post-selection accounts insist that learning speeds either a decision stage that occurs after a candidate target has been located (Huang et al., 2004; Huang & Pashler, 2005), or speeds response selection and execution (e.g., Cohen & Magen, 1999). We do note that this previous debate focused on tasks in which the color of the object was a task-relevant feature, while here we used incidental target features to track learning. However, the similarity of the hypothesized mechanisms is striking. Based on the episodic theory of priming in visual search (Huang et al., 2004), we assume 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 target instances stored in their episodic memory before proceeding to make the appropriate response. The confirmation process is faster if the color paired with the current target matches those high-probability colors retrieved from episodic memory. Otherwise, the system may need additional time to retrieve enough matching trials instances when the target shape appears in a rare color.

The dissociable pattern of the ERP components in the current study provides vital evidence supporting a response-selection account of selection history effects (Awh et al., 2012). The present results are consistent with experiments that measured search slopes across learning. These studies of contextual cuing and inter-trial priming illustrate robust speeding of responses for targets appearing in repetitive spatial locations or features compared to targets appearing in novel spatial locations or features (Chun & Jiang, 1998; Treisman, 1992; Maljkovic & Nakayama, 1994; 1996). However, this general speeding of search (i.e., a y-intercept effect) was accompanied by no change in the search slope relating RT to set size, as this is the canonical measure of how efficiently attention can shift between targets in an array (Lamy et al., 2006;

Kunar et al., 2007; Makovski & Jiang, 2010; Rausei et al., 2007; Wang et al., 2019; Harris & Remington, 2017). Thus, both the N2pc results and the lack of a change in search slope after statistical learning support an account in which this learning changes how efficiently decisions can be made, but without changing how efficiently attention can be shifted. In the future, we believe that it would be worth measuring both the N2pc and search slopes in the same experiment to verify that these effects co-occur.

One reason that a subsequent experiment would also be useful is to test a possibility that the N2pc effects in the current experiment were caused by the distractors that were present. For example, if distractors with high target probability colors were presented in the same hemifield as a target with low probable color, then the N2pc might be artificially inflated. If these same distractors were in the opposite hemifield from the target then the N2pc might be artificially reduced in amplitude. We randomized the object locations so that these possible effects would be balanced out, but the possible contamination of the target N2pc by the distractors that were also presented in possible-target colors deserves further attention in empirical studies. Future studies could use a task that allows for the precise estimation of the N2pc amplitude to objects in isolation, although doing so would inherently use a non-search task.

At the first glance, the statistical learning effect found in the current study looks similar to the well-studied feature priming effect. It has been shown in previous studies that repetition of the incidental features in adjacent trials speeds search performance for subsequent targets with feature matches (Huang et al., 2004; Sha et al., 2017; Conn et al., 2020). However, robust learning effect still existed in the current experiment with removal of the color-repetitive trial pairs. Moreover, if the speeding for targets paired with high-probability colors in the current experiment was resulted from feature priming, we should see the largest speeding for the highest-probability color given more color repetitions in this condition, which is also not the case in the current experiment because equivalent extent of speeding was found for three colors with different presence frequency (i.e., 33%, 26%, and 19% color). Thus, present work suggests that what our observers learned is distinct from simple feature priming although future study is needed.

Statistical learning is a complex process which could involve multiple dissociable cognitive mechanisms. Though theorists have different opinions about the details of the critical processes, they agree that the main sub-processes of statistical learning include pattern extraction, memory storage, and then retrieval and recognition (Karuza et al., 2014; Batterink & Paller, 2017; Batterink et al., 2019). As a critical neural circuit for both predictive pattern formation and memory establishment, the hippocampus has been shown to be involved in statistical learning (Turk-Browne et al., 2009; Bornstein & Daw, 2012; Schapiro et al., 2014; Schapiro et al., 2016). Moreover, computational models propose that statistical learning arises from a set of processes that are inherent in memory systems, including extraction of elements of the input into memory traces, and subsequent integration across those memory traces that emphasize consistent information (Thiessen et al., 2013; Thiessen, 2017). Thus, we can see the present findings as an additional piece of evidence supporting the view that the efficiency of memory retrieval may underlie a variety of statistical learning and selection history effects studied in the laboratory.

## Conclusion

The current study recorded the electrophysiological brain activity of observers as they searched for objects that could appear in different colors. We found that the probabilistic mapping of color to target changed how the brain performed post-perceptual processing of the target objects, not how early perceptual attention was deployed to the different colors in the array. These findings challenge the view that one of the primary functions of human statistical learning is to change how attention is deployed across our visual field, and bring broad inspiration to research focusing on statistical learning, attentional control, and decision-making.

## Acknowledgements

The study was funded by the National Institutes of Health to GFW (R01-EY019882, R01-MH110378, and P30-EY08126), the International Postdoctoral Exchange Fellowship Program (PC2021011) and the China Postdoctoral Science Foundation (2020M680421) to S.W. We thank Junchi Li, Maggie Xu, Seth Marx, and Yejin Jeong for helping with data collection.

## References

Awh, E., Belopolsky, A. V., & Theeuwes, J. (2012). Top-down versus bottom-up attentional control: A failed theoretical dichotomy. *Trends in Cognitive Sciences*. https://doi.org/10.1016/j.tics.2012.06.010

Batterink, L. J., & Paller, K. A. (2017). Online neural monitoring of statistical learning. *Cortex*, *90*. https://doi.org/10.1016/j.cortex.2017.02.004

Batterink, L. J., Paller, K. A., & Reber, P. J. (2019). Understanding the Neural Bases of Implicit and Statistical Learning. *Topics in Cognitive Science*. https://doi.org/10.1111/tops.12420

Becker, S. I. (2008). The mechanism of priming: Episodic retrieval or priming of pop-out? *Acta Psychologica*, *127*(2). https://doi.org/10.1016/j.actpsy.2007.07.005

Bornstein, A. M., & Daw, N. D. (2012). Dissociating hippocampal and striatal contributions to sequential prediction learning. *European Journal of Neuroscience*, *35*(7). https://doi.org/10.1111/j.1460-9568.2011.07920.x

Brainard, D. H. (1997). The Psychophysics Toolbox. *Spatial Vision*, *10*(4), 433–436. https://doi.org/10.1163/156856897X00357

Chun, M. M., & Jiang, Y. (1998). Contextual cueing: Implicit learning and memory of visual context guides spatial attention. Cognitive psychology, 36(1), 28-71. https://doi.org/10.1006/cogp.1998.0681

Cohen, A., & Magen, H. (1999). Intra- and cross-dimensional visual search for single-feature targets. *Perception and Psychophysics*, *61*(2). https://doi.org/10.3758/BF03206889

Conn, K. M., Becker, M. W., & Ravizza, S. M. (2020). Persistent guidance of attention in visual statistical learning. *Journal of Experimental Psychology: Human Perception and Performance*, *46*(7). https://doi.org/10.1037/xhp0000741

Corbetta, M., & Shulman, G. L. (2002). Control of goal-directed and stimulus-driven attention in the brain. *Nature Reviews Neuroscience*, *3*(3). https://doi.org/10.1038/nrn755

Cosman, J. D., & Vecera, S. P. (2014). Establishment of an attentional set via statistical learning. Journal of Experimental Psychology: Human Perception and Performance, 40(1), 1. https://doi.org/10.1037/a0034489

Delorme, A., & Makeig, S. (2004). EEGLAB: An open source toolbox for analysis of single-trial EEG dynamics including independent component analysis. *Journal of Neuroscience Methods*. https://doi.org/10.1016/j.jneumeth.2003.10.009

Desimone, R., & Duncan, J. (1995). *Neural mechanisms of selective visual attention*. *Annu. Rev. Neurosci* (Vol. 18). 10.1146/annurev.ne.18.030195.001205

Egeth, H. E., & Yantis, S. (1997). Visual Attention: Control, Representation, and Time Course. *Annual Review of Psychology*, *48*. https://doi.org/10.1146/annurev.psych.48.1.269

Eimer, M. (1996). The N2pc component as an indicator of attentional selectivity. *Electroencephalography and Clinical Neurophysiology*, *99*(3). https://doi.org/10.1016/0013-4694(96)95711-9

Failing, M., Feldmann-Wüstefeld, T., Wang, B., Olivers, C., & Theeuwes, J. (2019). Statistical regularities induce spatial as well as feature-specific suppression. *Journal of Experimental Psychology: Human Perception and Performance*, *45*(10). https://doi.org/10.1037/xhp0000660

Faul, F., Erdfelder, E., Lang, A. G., & Buchner, A. (2007). G*Power 3: A flexible statistical power analysis program for the social, behavioral, and biomedical sciences. In *Behavior Research Methods*. https://doi.org/10.3758/BF03193146

Ferrante, O., Patacca, A., Di Caro, V., Della Libera, C., Santandrea, E., & Chelazzi, L. (2018). Altering spatial priority maps via statistical learning of target selection and distractor filtering. *Cortex*, *102*. https://doi.org/10.1016/j.cortex.2017.09.027

Friedman, D., & Johnson, R. (2000). Event-related potential (ERP) studies of memory encoding and retrieval: A selective review. *Microscopy Research and Technique*. https://doi.org/10.1002/1097-0029(20001001)51:1<6::AID-JEMT2>3.0.CO;2-R

Goujon, A., Didierjean, A., & Thorpe, S. (2015). Investigating implicit statistical learning mechanisms through contextual cueing. *Trends in Cognitive Sciences*. https://doi.org/10.1016/j.tics.2015.07.009

Grubert, A., Carlisle, N. B., & Eimer, M. (2016). The control of single-color and multiple-color visual search by attentional templates in working memory and in long-term memory. *Journal of Cognitive Neuroscience*, *28*(12). https://doi.org/10.1162/jocn_a_01020

Harris, A. M., & Remington, R. W. (2017). Contextual cueing improves attentional guidance, even when guidance is supposedly optimal. Journal of Experimental Psychology: Human Perception and Performance, 43(5), 926–940. https://doi.org/10.1037/xhp0000394

Hopf, J. M., Luck, S. J., Girelli, M., Hagner, T., Mangun, G. R., Scheich, H., & Heinze, H. J. (2000). Neural sources of focused attention in visual search. *Cerebral Cortex*, *10*(12). https://doi.org/10.1093/cercor/10.12.1233

Huang, L., Holcombe, A. O., & Pashler, H. (2004). Repetition priming in visual search: Episodic retrieval, not feature priming. *Memory and Cognition*, *32*(1). https://doi.org/10.3758/BF03195816

Huang, L., & Pashler, H. (2005). Attention capacity and task difficulty in visual search. *Cognition*, *94*(3). https://doi.org/10.1016/j.cognition.2004.06.006

Karuza, E. A., Emberson, L. L., & Aslin, R. N. (2014). Combining fMRI and behavioral measures to examine the process of human learning. *Neurobiology of Learning and Memory*. https://doi.org/10.1016/j.nlm.2013.09.012

Kastner, S., & Ungerleider, L. G. (2000). Mechanisms of visual attention in the human cortex. *Annual Review of Neuroscience*. https://doi.org/10.1146/annurev.neuro.23.1.315

Kerzel, D., Balbiani, C., Rosa, S., & Huynh Cong, S. (2022). Statistical learning in visual search reflects distractor rarity, not only attentional suppression. *Psychonomic Bulletin and Review*. https://doi.org/10.3758/s13423-022-02097-x

Kiesel, A., Miller, J., Jolicœur, P., & Brisson, B. (2008). Measurement of ERP latency differences: A comparison of single-participant and jackknife-based scoring methods. Psychophysiology, 45(2), 250-274. https://doi.org/10.1111/j.1469-8986.2007.00618.x

Kristjánsson, Á., & Campana, G. (2010). Where perception meets memory: A review of repetition priming in visual search tasks. *Attention, Perception, and Psychophysics*. https://doi.org/10.3758/APP.72.1.5

Kruijne, W., & Meeter, M. (2016). Implicit short- and long-term memory direct our gaze in visual search. *Attention, Perception, and Psychophysics*, *78*(3). https://doi.org/10.3758/s13414-015-1021-3

Kunar, M. A., Flusberg, S., Horowitz, T. S., & Wolfe, J. M. (2007). Does contextual cuing guide the deployment of attention? Journal of Experimental Psychology: Human Perception and Performance, 33(4), 816–828. https://doi.org/10.1037/0096-1523.33.4.816

Lamy, D., Carmel, T., Egeth, H. E., & Leber, A. B. (2006). Effects of search mode and intertrial priming on singleton search. Perception & psychophysics, 68(6), 919-932. https://doi.org/10.3758/BF03193355

Luck, S. J., & Vogel, E. (1997). The capacity of visual working memory for features and conjunctions. *Nature*, *390*(6657), 279–281. https://doi.org/10.1038/36846

Luck, S. J., & Hillyard, S. A. (1994). Spatial Filtering During Visual Search: Evidence From Human Electrophysiology. *Journal of Experimental Psychology: Human Perception and Performance*, *20*(5). https://doi.org/10.1037/0096-1523.20.5.1000

Makovski, T., & Jiang, Y. V. (2010). Contextual cost: When a visual-search target is not where it should be. Quarterly Journal of Experimental Psychology, 63(2), 216-225. https://doi.org/10.1080/17470210903281590

Maljkovic, V., & Nakayama, K. (1994). Priming of pop-out: I. Role of features. *Memory & Cognition*, *22*(6). https://doi.org/10.3758/BF03209251

Maljkovic, V., & Nakayama, K. (1996). Priming of pop-out: II. The role of position. *Perception and Psychophysics*, *58*(7). https://doi.org/10.3758/BF03206826

Rausei, V., Makovski, T., & Jiang, Y. V. (2007). Attention dependency in implicit learning of repeated search context. Quarterly Journal of Experimental Psychology, 60(10), 1321-1328. https://doi.org/10.1080/17470210701515744

Rouder, J. N., Morey, R. D., Morey, C. C., & Cowan, N. (2011). How to measure working memory capacity in the change detection paradigm. *Psychonomic Bulletin & Review*, *18*(2), 324–330. https://doi.org/10.3758/s13423-011-0055-3

Rouder, J. N., Morey, R. D., Verhagen, J., Swagman, A. R., & Wagenmakers, E. J. (2017). Bayesian analysis of factorial designs. Psychological Methods, 22(2), 304. https://doi.org/10.1037/met0000057

Rugg, M. D., & Curran, T. (2007). Event-related potentials and recognition memory. *Trends in Cognitive Sciences*, *11*(6), 251–257. https://doi.org/10.1016/j.tics.2007.04.004

Schapiro, A. C., Gregory, E., Landau, B., McCloskey, M., & Turk-Browne, N. B. (2014). The Necessity of the Medial Temporal Lobe for Statistical Learning. *Journal of Cognitive Neuroscience*, *26*(8). https://doi.org/10.1162/jocn_a_00578

Schapiro, A. C., Turk-Browne, N. B., Norman, K. A., & Botvinick, M. M. (2016). Statistical learning of temporal community structure in the hippocampus. *Hippocampus*, *26*(1). https://doi.org/10.1002/hipo.22523

Sha, L. Z., Remington, R. W., & Jiang, Y. V. (2017). Short-term and long-term attentional biases to frequently encountered target features. *Attention, Perception, and Psychophysics*, *79*(5). https://doi.org/10.3758/s13414-017-1317-6

Theeuwes, J. (2019). Goal-driven, stimulus-driven, and history-driven selection. *Current Opinion in Psychology*. https://doi.org/10.1016/j.copsyc.2018.12.024

Thiessen, E. D. (2017). What's statistical about learning? Insights from modelling statistical learning as a set of memory processes. *Philosophical Transactions of the Royal Society B: Biological Sciences*. https://doi.org/10.1098/rstb.2016.0056

Thiessen, E. D., Kronstein, A. T., & Hufnagle, D. G. (2013). The extraction and integration framework: A two-process account of statistical learning. *Psychological Bulletin*, *139*(4). https://doi.org/10.1037/a0030801

Treisman, A. (1992). Perceiving and re-perceiving objects. *American Psychologist*, *47*(7). https://doi.org/10.1037/0003-066X.47.7.862

Turk-Browne, N. B. (2012). Statistical learning and its consequences. *Nebraska Symposium on Motivation*. https://doi.org/10.1007/978-1-4614-4794-8_6

Turk-Browne, N. B., Scholl, B. J., Chun, M. M., & Johnson, M. K. (2009). Neural evidence of statistical learning: Efficient detection of visual regularities without awareness. *Journal of Cognitive Neuroscience*, *21*(10). https://doi.org/10.1162/jocn.2009.21131

Vogel, E. K., Vogel, E. K., Machizawa, M. G., & Machizawa, M. G. (2004). Neural activity predicts individual differences in visual working memory capacity. *Nature*, *428*(April), 748–751. https://doi.org/10.1038/nature02447

Voss, J. L., Schendan, H. E., & Paller, K. A. (2010). Finding meaning in novel geometric shapes influences electrophysiological correlates of repetition and dissociates perceptual and conceptual priming. *NeuroImage*, *49*(3). https://doi.org/10.1016/j.neuroimage.2009.09.012

Wang, C., Haponenko, H., Liu, X., Sun, H., & Zhao, G. (2019). How Attentional Guidance and Response Selection Boost Contextual Learning: Evidence from Eye Movement. Advances in Cognitive Psychology, 15(4), 265. https://doi.org/10.5709/acp-0274-2

Wang, B., & Theeuwes, J. (2018). Statistical Regularities Modulate Attentional Capture. *Journal of Experimental Psychology: Human Perception and Performance*, *44*(1). https://doi.org/10.1037/xhp0000472

Wolfe, J. M., & Horowitz, T. S. (2017). Five factors that guide attention in visual search. *Nature Human Behaviour*, *1*(3). https://doi.org/10.1038/s41562-017-0058

Woodman, G. F., & Luck, S. J. (1999). Electrophysiological measurement of rapid shifts of attention during visual search. *Nature*, *400*(6747). https://doi.org/10.1038/23698

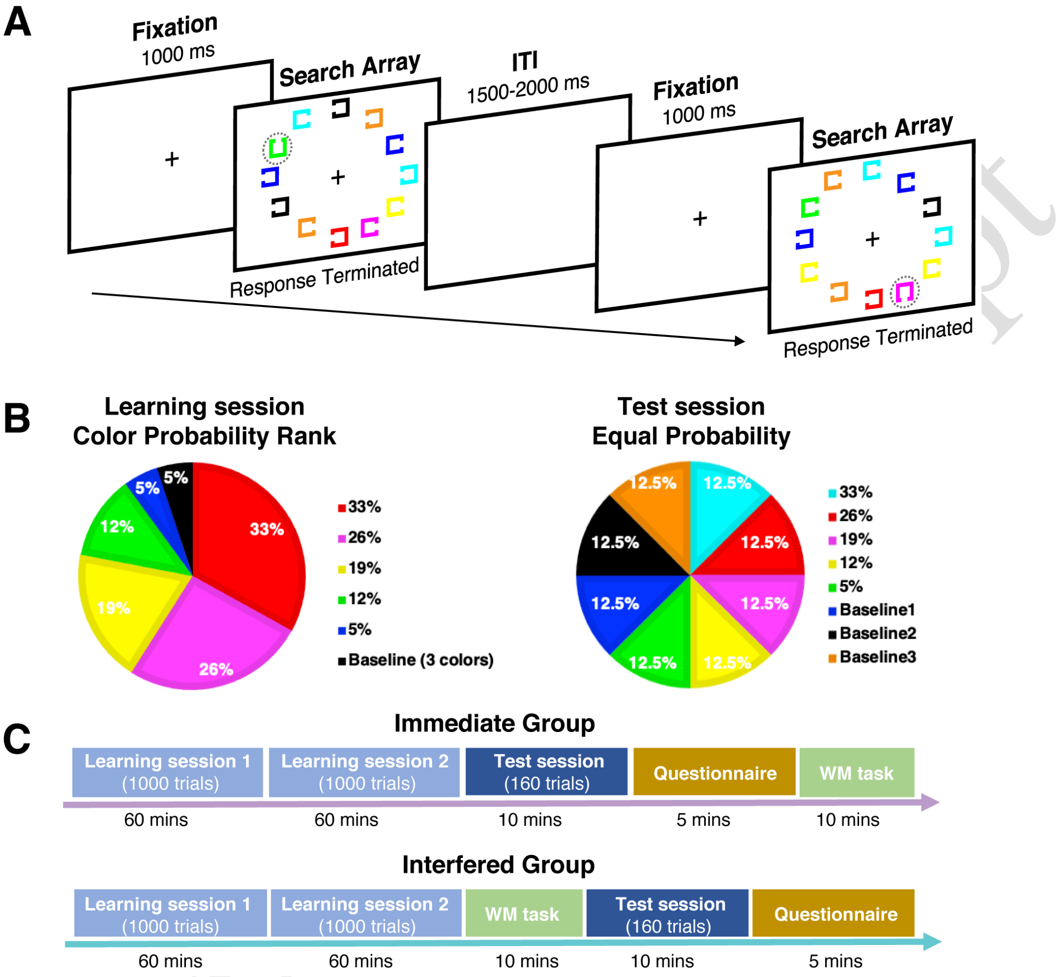
Woodman, G. F., & Luck, S. J. (2003). Dissociations among attention, perception, and awareness during object-substitution masking. *Psychological Science*, *14*(6). https://doi.org/10.1046/j.0956-7976.2003.psci_1472.x

Yashar, A., & Lamy, D. (2010). Intertrial repetition affects perception: the role of focused attention. *Journal of Vision*, *10*(14). https://doi.org/10.1167/10.14.3

Zhang, B., Allenmark, F., Liesefeld, H. R., Shi, Z., & Müller, H. J. (2019). Probability cueing of singleton-distractor locations in visual search: Priority-map- versus dimension-based inhibition? *Journal of Experimental Psychology: Human Perception and Performance*, *45*(9). https://doi.org/10.1037/xhp0000652

**Figure 1**

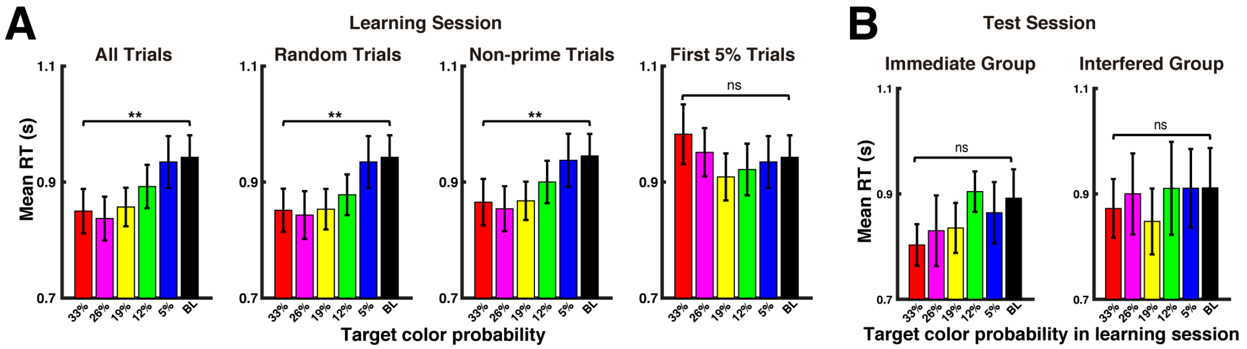
*Illustration of the Experimental Paradigm and Procedure.*



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. B. The probability distribution of colors paired with targets for the learning session (left) and the test session (right). C. Experimental procedure.

**Figure 2**

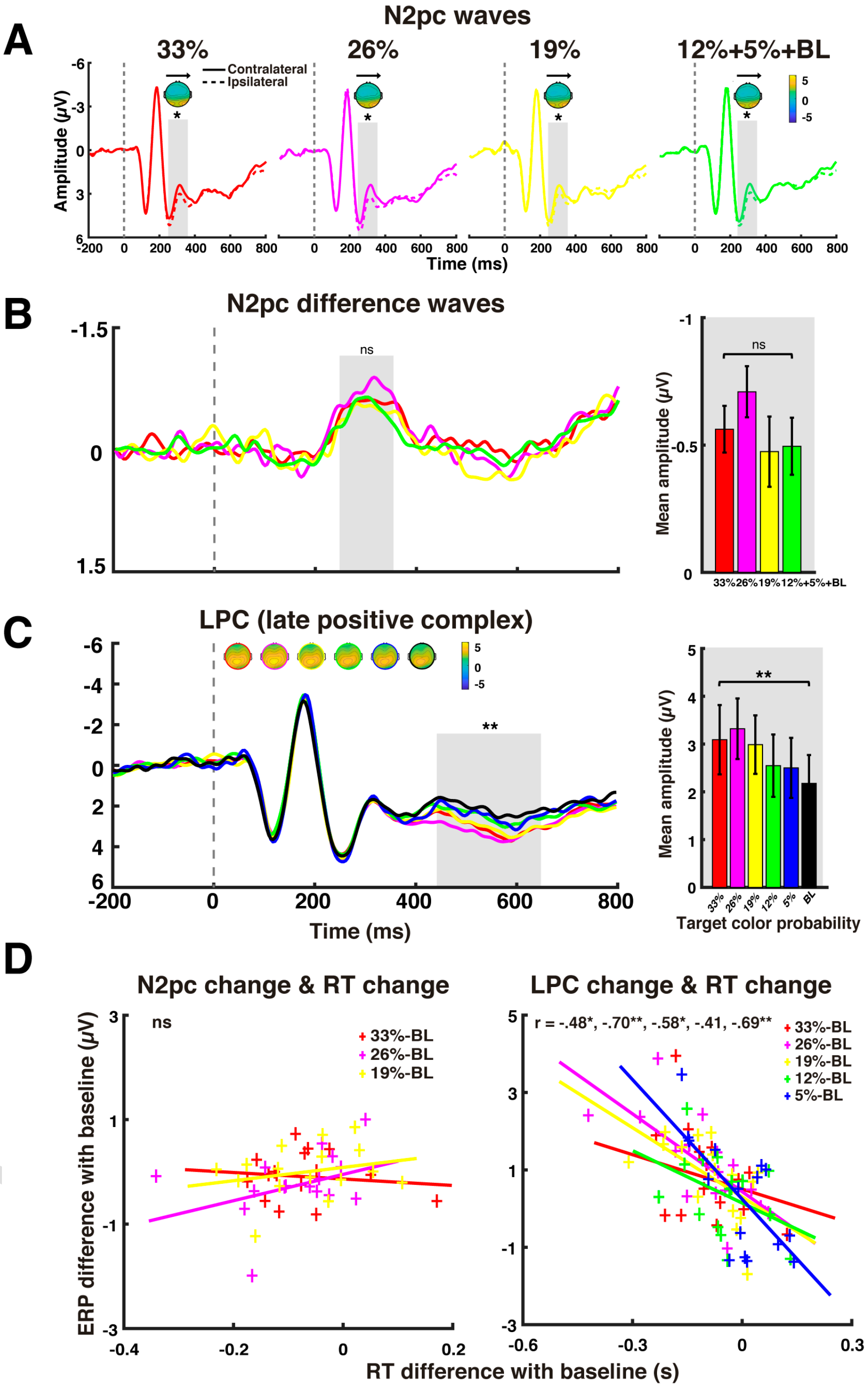
*The Behavioral Results.*



A. The mean RT for targets in different probability colors across all trials, randomly selected equal number trials, non-color-repetitive trials, and the first 5% trials in the learning session of Experiment 1, from left panel to right panel. B. The mean RT for targets in different equal-probability colors in the test sessions. Error bars indicate the standard errors of the means (SEMs). Asterisk indicates the significant main effect (** indicates significant difference with *p*<0.01, ns represents null significant difference).

**Figure 3**

*ERP Results.*

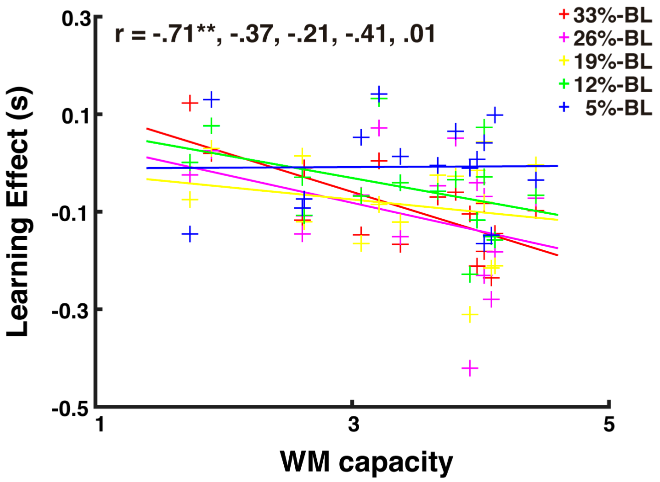


A. The waveforms of electrodes contralateral and ipsilateral to the target hemifield for targets in different probability colors, with panels represents 33%, 26%, 19%, and the merged low-probability condition from left to right, respectively. Solid and dashed lines represent contralateral and ipsilateral signal, 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. N2pc difference waveforms for targets in different probability colors at electrode pair of PO7/8, and the mean N2pc amplitude over PO7/8 across 250-350 ms time window after search array onset. Red, magenta, yellow, and green line and bar represents 33%, 26%, 19%, and the merged low-probability colors (12%+5%+baseline colors), respectively. C. LPC waveforms and topographic map for targets in different probability colors averaged over posterior electrodes (P3/4, P7/8, PO3/4, PO7/8), and the mean LPC amplitude over posterior electrodes across 450-650 ms time window after search array onset. D. Correlations between the N2pc amplitude difference and RT difference (left), and correlations between the LPC amplitude difference and RT difference (right). Each cross represents each subject in a corresponding condition. Error bars indicate the standard errors of the means (SEMs). Asterisk indicates the significant pair-wised difference (A), main effect (B and C), or correlation (D) (*, ** indicate significant difference or correlation with $p<0.05$, $p<0.01$, respectively).

## Supplemental Materials

### Figure S1

*Correlations Between the Statistical Learning Effect and Working Memory Capacity.*



The correlation between observers' working memory capacity estimate and their statistical learning effect calculated from subtracting RTs for targets in each probability color from the baseline RT. Error bars indicate the standard errors of the means (SEMs). Asterisk indicates the significant correlation (** indicates significant difference with *p*<0.01).

### Statistical Learning Effect is Predicted by Working Memory Capacity

A recent study suggested that statistical learning is only observed when the items that need to be learned can be encoded and maintained in working memory (Hall et al., 2015). To probe this relationship in our current study, we also measured observers' working memory capacity. If maintaining target features in working memory is critical for statistical learning, then observers with higher working memory capacity should be able to represent more task relevant information and exhibit larger learning benefits. To test this relationship, we performed a correlation between the size of the statistical learning benefit and working memory capacity for each individual subject. As shown in **Figure S1**, Pearson correlations revealed a significant negative correlation in the highest-probability color (33% color: *r* = -0.710, *p* = 0.002), with larger response speed increase for observers with higher working memory capacity. Although they did not reach significance, negative correlations were found in the other probability colors (*r* = -0.371, -0.213, -0.414, *p* = 0.157, 0.429, 0.111, for 26%, 19%, 12% color, respectively), except for the lowest-probability (the 5% color: *r* = 0.011, *p* = 0.968). The correlation remained significant after we merged the RT benefits across the four highest color frequency conditions (*r* = -0.515, *p* = 0.041). These results are consistent with previous work suggesting that working memory plays an important role in realizing the benefits of statistical learning (Hall et al., 2015).

## Reference

Hall, M. G., Mattingley, J. B., & Dux, P. E. (2015). Distinct contributions of attention and working memory to visual statistical learning and ensemble processing. *Journal of Experimental Psychology: Human Perception and Performance*, *41*(4), 1112–1123. https://doi.org/10.1037/xhp0000069