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Specificity and Persistence of Statistical Learning in Distractor Suppression

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Statistical regularities in distractor location trigger suppression of high-probability distractor locations during visual search. The degree to which such suppression reflects generalizable, persistent changes in a spatial priority map has not been examined. We demonstrate that suppression of high-probability distractor locations persists after location probabilities are equalized and likely reflects a genuine reshaping of the priority map rather than more transient effects of selection history. Statistically learned suppression generalizes across contexts within a task during learning but does not generalize between task paradigms using unrelated stimuli in identical spatial locations. These findings suggest that stimulus features do play a role in learned spatial suppression, potentially gating the weights applied to a spatial priority map. However, the binding of location to context during learning is not automatic, in contrast to the previously reported interaction of location-based statistical learning and stimulus features.

Public Significance Statement
With practice, people can learn to ignore locations in space that are likely to contain distracting information. We show that such learning has a persistent influence on attention that generalizes across context during learning but fails to generalize to new contexts not experienced during learning.

Keywords: statistical learning, distractor suppression, spatial attention, attentional capture, contextual learning

At any given moment, a plethora of irrelevant but physically salient visual stimuli compete for our limited attention. To prune the overwhelming variety of available input, observers must learn to prioritize some signals over others and subsequently filter out unwanted information. The priority map model of visual attention contends that objects in space are assigned priority signals based on salience, location, selection history, and the individual's goal state then weighted correspondingly for winner-take-all visual selection. Search efficiency is improved when targets are weighted substantially more heavily than nontargets (Zelinsky & Bisley, 2015); efficient downregulation of distractors and distractor-heavy regions of space therefore quickens search.

Spatial regularities in visual input, such as a target appearing more frequently in one region of visual space, are implicitly learned over repeated exposures (Schapiro & Turk-Browne, 2015); this learning, or spatial probability cueing, then translates into more-efficient stimulus prioritization (Geng & Behrmann, 2002). Statistical learning appears to regulate the intensity of representation in the spatial priority map such that high-frequency target locations are more heavily weighted for selection (Druker & Anderson, 2010; Ferrante et al., 2018; Geng & Behrmann, 2005; see Jiang, 2018 for a review). Rewarding participants for orienting to a particular region of space can similarly bias attention toward that region (Anderson & Kim, 2018a, 2018b; Chelazzi et al., 2014). The effects of spatial probability cueing on target selection have been well-characterized: Biased target selection persists for up to a week or hundreds of trials (Jiang, Swallow, & Rosenbaum, 2013; Jiang, Swallow, Rosenbaum, & Herzig, 2013) and is moderately generalizable between closely related tasks (Jiang, Swallow, Won, Cistera, & Rosenbaum, 2015; Salovich, Remington, & Jiang, 2018).

Recently a number of studies have demonstrated an apparently parallel effect by which high-frequency distractor locations are selectively suppressed, such that physically salient distractors in these locations capture attention relatively weakly (Failing, Feldmann-Wüstefeld, Wang, Olivers, & Theeuwes, 2019; Goschy, Bakos, Müller, & Zehetleitner, 2014; Sauter et al., 2019; Wang & Theeuwes, 2018a, 2018b, 2018c; Wang, Samara, & Theeuwes, 2019). This suppression is not the product of biased target selection (Failing, Wang, & Theeuwes, 2019). Instead, statistically learned distractor suppression and target selection appear to tap a common spatial priority map, such that manipulating target location probability affects distractor filtration efficiency and vice

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versa (Ferrante et al., 2018). Thus, it is possible that features of probability-cued target selection also manifest in distractor suppression. However, the degree to which location-based distractor suppression genuinely parallels target cueing is unknown.

From prior studies of learned spatial suppression, it is evident that stimulus features, such as target shape or distractor color, appear to bind to stimulus location during statistical learning, such that location-based distractor suppression is moderated by stimulus color (Failing et al., 2019). However, learned location-based distractor suppression has only been examined in a single task context in which the stimuli and location contingencies remain constant (e.g., Wang & Theeuwes, 2018a, 2018b, 2018c). The role of task context in the learning and expression of experience-dependent attentional biases has been examined with respect to value-based attention, search modes, and contextual cuing (e.g., Anderson, 2015; Brooks, Rasmussen, & Hollingworth, 2010; Cosman & Vecera, 2013) but has not been examined in the case of location-based distractor suppression. In the present study, we probed whether different high-probability distractor locations could be suppressed in a context-specific manner when the context predicted which location was likely to contain a distractor (Experiment 1) in addition to whether spatial suppression learned in one task context would generalize to stimulus processing in a novel task context (Experiment 3). To validate our experimental approach, we also confirmed that suppression of a high-probability distractor location reflects genuine attentional learning that persists into a period of extinction (Experiment 2).

Experiment 1

In addition to target and distractor location, contextual information appears to influence attentional learning during visual search such that the priority given to stimulus features depends on the background image against which the search display is presented (Anderson, 2015; Cosman & Vecera, 2013). Specifically, contextual information can gate learning-dependent biases in feature-based attention (Anderson, 2015; Cosman & Vecera, 2013), as well as gating which memory representations guide search in contextual cuing of target location (Brooks et al., 2010). However, in each of these cases, context is a perfect trial-by-trial predictor of the information that guides attention (e.g., which color is high-value, whether or not the target will be identifiable by a unique feature). It is presently unknown whether contextual information binds to location information during statistical learning of high-probability distractor locations, which is necessarily integrated over trials: Prior studies of spatial suppression (e.g., Wang & Theeuwes, 2018a, 2018b, 2018c) have presented their search displays within a single task context.

In Experiment 1, we examined statistical learning-based distractor suppression in context. Stimuli were superimposed on either of two background images, each of which was paired with a different high-probability distractor location. We assessed response speed when the distractor appeared in the context-matched high-probability distractor location versus the context-mismatched high-probability distractor location or a location in which the distractor appeared with low probability across both contexts. If statistical learning-based suppression is context-dependent, suppression should be specific to the high-probability location within a particular context; conversely, in the absence of context-dependent learning, both high-probability distractor locations should be similarly suppressed regardless of context.

Method

Participants. Forty-two participants were recruited from the Texas A&M University community. All participants were between the ages of 18 and 35, and all reported normal or corrected-to-normal visual acuity and color vision. After excluding participants with low accuracy (see Analysis), the final sample size was 35 (21 female, mean age $= 18.9$, $SD = 1.5$). Participants were compensated with course credit. All procedures were approved by the Texas A&M University Institutional Review Board and conformed to the principles outlined in the Declaration of Helsinki. Given a target effect size estimated at $d = 0.602$, which was taken from the difference between color-matching and color-mismatching distractors appearing at a high-probability location (Failing et al., 2019), a sample size of at least 31 participants would yield $\beta > 0.90$ with α set to 0.05 (computed using G*Power 3.1); all reported experiments exceeded this minimal sample size.

Apparatus. Stimuli were generated using MATLAB 2017 (MathWorks, Natick, MA, U.S.A.) and Psychophysics Toolbox extensions (Brainard, 1997) then presented on a Dell P2717H monitor linked to a Dell OptiPlex 7040 (Dell, Round Rock, TX, U.S.A.). Participants viewed the monitor from a distance of approximately 70 cm in a dimly lit room. Responses were registered when the participant pressed the corresponding key on a standard keyboard.

Stimuli. On each trial a search display consisting of six shapes (each approximately 3.3° × 3.3°) was spaced regularly around an imaginary circle with a radius of 7.4° centered on a fixation cross. The target (a shape singleton) was a circle among five diamonds or vice versa (50% probability). On a subset of trials, a distractor was present. The distractor (a color singleton) was red while all other shapes were green, or vice versa (50% probability). Target shape was uncorrelated with distractor color, such that all possible combinations appeared equally often. Stimuli were not matched for luminance. The target shape contained a horizontal or vertical line segment (1.2 ° × 0.16°), whereas nontarget shapes contained a diagonal line segment oriented 45° to the left or right (1.6° × 0.16°).

Each search display was superimposed on a black-and-white photograph of a forest or a city (50% probability), henceforth the "context," as in Anderson (2015; see also Cosman & Vecera, 2013). Context was fully uncorrelated with target shape or (if present) distractor color. One photograph was used for each context and were the same photographs used in Anderson (2015; see Figure 1).

Design and procedure. Each trial began with the context photograph presented alone for 1000 ms. The fixation cross then appeared, followed after a 400–600 ms delay by the search array. The search array was then present for 1500 ms or until response (see Figure 1). Participants were instructed to search the display for the shape singleton and indicate the orientation of the corresponding line segment by pressing the "Z" key to indicate a vertical line and the "M" key to indicate a horizontal line as fast as possible. Incorrect or too-slow responses elicited written feedback (the words "Incorrect" and "Too slow," respectively, presented at

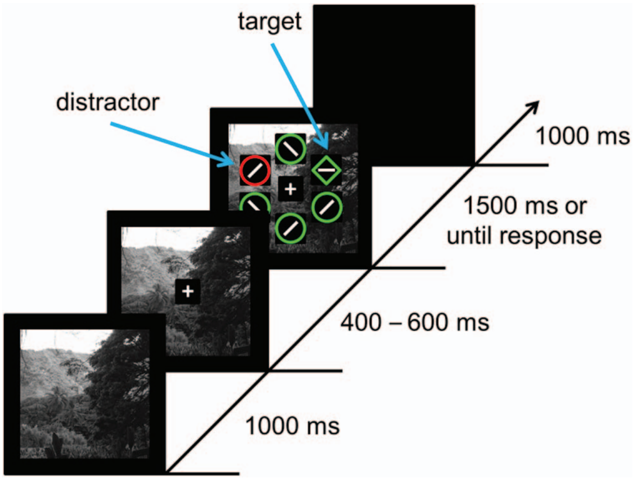

Figure 1. Sequence and time course of events for an example trial in Experiment 1. The target was defined as a shape singleton and the distractor as a color singleton. Participants identified the orientation of the line segment inside the target (vertical or horizontal). Each background scene was associated with a different high-probability distractor location. The forest image used in this figure was contributed by a coauthor (Brian A. Anderson) and differs from the corresponding photograph used in the experiment, which may be subject to copyright restrictions. See the online article for the color version of this figure.

the center of the screen) for 1000 ms before the 1000 ms intertrial interval (feedback was omitted following correct responses).

The study consisted of 784 trials following a 32-trial practice phase. A distractor was present on 66% of trials. For each context, one possible stimulus location was high-probability: the distractor appeared at this location on 62% of distractor-present trials, or approximately 8 times as often as the distractor appeared at any other location in that context (henceforth "low-probability locations"). The two contexts' high-probability locations were directly opposite one another and were counterbalanced between participants. On low-probability location trials, the distractor appeared at the remaining five locations equally often. The target location was unbiased, except insofar as the target never overlapped with the distractor and was thus less likely to appear at the high-probability location (7.7% vs. 18.5% for each low-probability distractor location on distractor-present trials, unbiased on distractor-absent trials). Participants were given a 30 s break every 100 trials, beginning at Trial 121.

Analysis. Seven participants were excluded for accuracy below 80%. We chose a threshold of 80% a priori to help ensure a robust estimate of mean RT on correct trials, given the frequency of low-probability distractor trials and targets appearing at the high-probability distractor location, although identical statistical conclusions are reached with a more liberal threshold such as 60%. Thirty-five participants are included in the following analyses. To control for intertrial priming effects, when the distractor appeared in the same location on two (or more) consecutive trials, the repeat trial was excluded from analysis (given that such repetitions are more frequent for trials in the high-probability distractor location condition; see Wang & Theeuwes, 2018a, 2018b, 2018c); this resulted in the removal of 11.5% of all trials. Incorrect responses were excluded from response time (RT) analysis, as were RTs shorter than 200 ms or more than three *SD*s above the mean of their condition (this resulted in the removal of <1% of all RTs, the proportion of which did not differ across experiment conditions: $p = .10$). Trials were categorized by distractor location (absent, low-probability, high-probability in the current trial's context; "context-matched", and high-probability in the other context; "context-mismatched") and RTs submitted to a repeated-measures ANOVA in IBM SPSS 25 (as in Anderson, 2015; Anderson & Britton, 2019; Cosman & Vecera, 2013). Due to violation of assumed sphericity, the Greenhouse-Geisser correction was applied, as $\varepsilon < 0.75$. A secondary analysis examined RT as a function of the location of the target. Where a null result was indicated, the Bayes Factor (BF) was computed to estimate the probability of the null hypothesis, with a $BF_{01} > 3$ interpreted as evidence in its favor (Rouder, Speckman, Sun, Morey, & Iverson, 2009). Across all experiments, there were either no effects in accuracy beyond a small cost associated with the presence of a distractor, or there was a small additional cost that mirrored the differences observed in RT; given this and the focus on RT in prior studies of location-based distractor suppression (e.g., Wang & Theeuwes, 2018a, 2018b, 2018c), subsequent analyses focus on RT.

Results

RT differed significantly between distractor locations, $F(1.99, 67.5) = 25.33$, $p < .001$, $\eta_p^2 = 0.76$ (see Figure 2). Post hoc *t* tests with Bonferroni correction indicated no reaction time (RT) difference between the context-matched and context-mismatched high-probability distractor locations, $t(34) = 0.34$, $p = .734$, $BF_{01} = 5.22$. Therefore, we pooled all high-probability distractor trials. Participants were slower in the low-probability condition than in the pooled high-probability condition, $t(34) = 6.63$, $p < .001$, $d = 1.12$, in the low-probability condition relative to the no-distractor condition, $t(34) = 10.43$, $p < .001$, $d = 1.76$, and in the pooled high-probability condition relative to the no-distractor condition, $t(34) = 6.75$, $p < .001$, $d = 1.14$.

By virtue of the task design, the target sometimes appeared at a high-probability distractor location, and location-based suppression would predict a slowing of target identification responses in

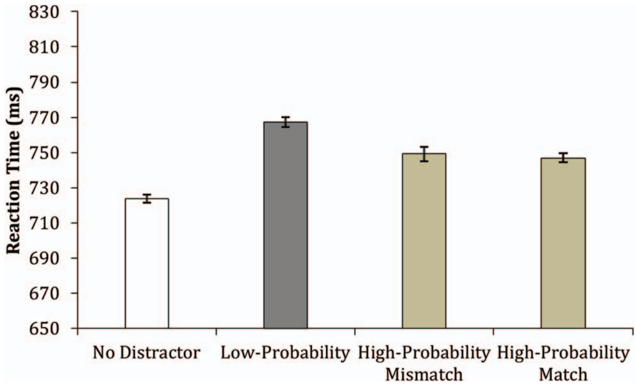

Figure 2. Mean RTs for Experiment 1. Error bars reflect within-subjects confidence intervals (Loftus & Masson, 1994). See the online article for the color version of this figure.

this case. Participants were significantly slower to report the target at both the context-matched ($M = 758$ ms, $SD = 91$ ms) and context-mismatched ($M = 762$ ms, $SD = 99$ ms) high-probability distractor locations compared to the low-probability locations ($M = 732$ ms, $SD = 81$ ms), $ts > 3.76$, $ps < 0.002$, $ds > 0.63$. RT did not differ between the context-matched and context-mismatched locations, $t(34) = 0.67$, $p = .509$, $BF_{01} = 4.48$, mirroring the pattern evident for distractor processing.

Discussion

Experiment 1 shows that statistically learned distractor suppression generalizes across contexts, such that high-probability distractor locations are suppressed regardless of the image against which they are presented. Our results replicate Wang and Theeuwes (2018a, 2018b, 2018c) in that both distractors and targets appearing in high-probability distractor locations were suppressed (even when accounting for trials in which the distractor location was immediately repeated). Notably, context did not impact participants' distractor filtration or target processing despite its substantial predictive power (the context-matched high-probability location was eight times more likely to contain the distractor). The results therefore suggest that statistical learning of high-probability distractor locations is tied predominantly to the location of the distractor regardless of the context in which the distractor appears, at least when the context is incidental to the task. This contrasts with feature-based associative reward learning (using the same background scene manipulation: Anderson, 2015; Cosman & Vecera, 2013) and statistical learning of the color of distractors appearing at particular high-probability locations (Failing et al., 2019), which does show evidence of context specificity even when the contextual information is incidental to the task. Potential implications of this difference are explored in the General Discussion.

It could be questioned whether participants processed contextual information in Experiment 1 sufficiently to support statistical learning. For several reasons, we think this objection is unlikely. First, we used the same scenes, positioning of the search array, and instructions concerning the role of the scenes as Anderson (2015), which demonstrated contextually dependent learning (see also Cosman & Vecera, 2013). The search array was embedded within the context scenes, requiring that participants look directly at these scenes to perform the task. Participants would therefore seem to have had ample opportunity to link contextual information to features of the search array (including distractor position). Furthermore, many contexts experienced in everyday life influence expectations without necessarily being salient or explicitly attended. That participants were unable to modulate spatial attention in a contextually specific manner in our experiment is therefore theoretically informative, although we cannot rule out the possibility that a more salient or explicit manipulation of task context could have produced a different pattern of results.

Experiment 2

Also of interest in the present study is the degree to which statistically learned spatial suppression transfers to the suppression of the same spatial location in a novel context. While the effects of some types of selection history, prominently reward learning, are known to transfer to novel stimuli and tasks (Anderson, Laurent, & Yantis, 2012; Mine & Saiki, 2015), spatial probability learning has so far been shown to generalize only to closely related tasks, and this generalization has been probed only in the context of target locations (Jiang et al., 2015; Salovich et al., 2018). We sought to examine whether a high-probability distractor location would be suppressed in a new task context. To address this question, however, it is necessary to first establish whether learned suppression of a distractor location persists more generally over time when the biased probabilities are no longer in place.

If distractor suppression can be meaningfully said to generalize between stimuli and tasks, it must be the product of genuine and persistent learning, rather than cross-trial inhibition, and thus resistant to extinction. Kabata, Matsumoto (2012) and Goschy et al. (2014) attribute probability cueing substantially, though not exclusively, to intertrial priming effects. While Wang and Theeuwes (2018a, 2018b, 2018c) exclude from analysis the second of two consecutive trials with identical distractor positions to control for intertrial priming effects, Maljkovic and Nakayama (1996) demonstrate that these effects can persist up to five to eight trials after the eliciting trial. Thus, trimming the second trial is insufficient to control for priming effects. Jiang et al. (2013) demonstrate that spatial probability learning of target location can persist up to a week after initial training, suggesting a longer-lasting effect consistent with genuine learning. Although using a different paradigm to the one used in the present study, Sauter et al. (2019) suggest that suppression of a high-probability distractor location may only persist into extinction when the target and distractor are defined in the same feature dimension, preventing (feature) dimension-based suppression.

Experiment 2 addresses the issue of the persistence of spatial learning in distractor suppression by examining the robustness of such suppression during an extinction period. Participants completed an additional singleton training phase with a high-probability distractor location, then immediately completed an otherwise identical test phase with no high-probability location. Participants were not informed that the distractor location probabilities, or any other aspect of the task, had changed during the test phase. We assessed response speed when the distractor appeared in the formerly high-probability location. If distractor suppression is resistant to extinction, responses will continue to be facilitated when the distractor is in the formerly high-probability location.

Method

Participants. Fifty-four new participants were recruited from the Texas A&M University community. All participants were between the ages of 18 and 35, and all reported normal or corrected-to-normal visual acuity and color vision. After excluding participants with low accuracy (see Analysis), the final sample size was 43 (22 female, mean age = 19.5, $SD = 2.3$). Participants were compensated with course credit. All procedures were approved by the Texas A&M University Institutional Review Board and conformed to the principles outlined in the Declaration of Helsinki.

Apparatus. The apparatus used were identical to those used in Experiment 1.

Stimuli. The search display was identical to those presented in Experiment 1, except that the fixation cross and stimuli were superimposed on a uniform black background rather than a photograph.

Design and Procedure. The experiment consisted of two phases, preceded by 30 practice trials. During the 444-trial training phase, one location (counterbalanced between participants) was designated high-probability, such that the distractor appeared there on 66% of distractor-present trials (45% of total trials), as in Experiment 1. On the remaining distractor-present trials the distractor appeared equally often at the other 5 locations. On 33% of total trials, no distractor appeared (distractor-absent trials). Target location was again unbiased.

Each trial began with a central fixation cross for 400–600 ms, followed by the search display for 1500 ms or until a response was registered (see Figure 3). Participants were instructed to identify the line segment inside the shape singleton with a key press using the same stimulus-to-response mapping as Experiment 1. Incorrect or too-slow answers elicited written feedback as in Experiment 1. Participants were given a 30 s break every 111 trials.

After the final break, the 180-trial test phase began immediately. During this phase, the distractor was equally likely at all six locations. The distractor appeared on 66% of trials. Participants were not informed that the task contingencies had been altered, and the task was otherwise identical to the training phase.

Analysis. Eleven participants were excluded due to accuracy below 80%, leaving 43 participants for analysis. Data from the training phase were divided by distractor location (absent, high-probability, and low-probability) and submitted to a repeated measures ANOVA in IBM SPSS 25. To control for intertrial priming effects, when the distractor appeared in the same location on two (or more) consecutive trials, the repeat trial was excluded from analysis as in Experiment 1. High-probability distractor trials were excluded from the analysis comparing RT to targets appearing at the high- and low-probability distractor locations, as the target could by definition not appear at the high-probability distractor location on such trials.

To examine extinction over time, we broke the test phase into two 90-trial blocks (as distractors appeared at the formerly high-probability location on only 1/6 of distractor-present trials, further subdividing trials into smaller epochs would result in too few observations for this condition to draw meaningful conclusions). Data were subjected to a two-way repeated measures ANOVA in IBM SPSS 25, with block and distractor location (absent, previously high-probability location, previously low-probability location) entered as within-subjects variables. Due to violation of the assumption of sphericity, we applied the Huynh-Feldt correction, as $\varepsilon > 0.75$. For both the training phase and the test phase, incorrect responses were excluded from RT analysis, as were RTs shorter than 200 ms or more than three *SD*s above the mean of their condition.

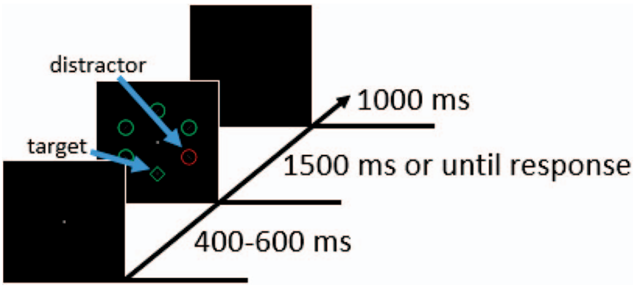

Figure 3. Sequence and time course of events for Experiment 2. As in Experiment 1, the target was defined as a shape singleton and the distractor as a color singleton. Participants identified the orientation of the line segment inside the target (vertical or horizontal). See the online article for the color version of this figure.

Results

Training phase. We observed a significant effect of distractor location, F(2, 84) = 98.49, p < .001, $\eta_p^2 = 0.84$ (Figure 4a). Post hoc *t* tests with Bonferroni correction indicated that participants were significantly faster on no-distractor trials than on low-probability distractor trials, *t*(42) = 14.37, *p* < .001, *d* = 2.19, on high-probability distractor trials compared to low-probability trials, *t*(42) = 6.22, *p* < .001, *d* = 0.95, and on high-probability distractor trials compared to no-distractor trials, *t*(42) = 7.78, *p* < .001, *d* = 1.19. Participants were slower to identify targets appearing at the high-probability distractor location (*M* = 798 ms, *SD* = 99 ms) compared to targets at the low-probability distractor locations (*M* = 737 ms, *SD* = 74 ms), *t*(42) = 8.23, *p* < .001, *d* = 1.26.

Test phase. A two-way repeated measures ANOVA showed no interaction between block and distractor location and no effect of block (*ps* > 0.13). There was a significant effect of distractor location, *F*(1, 42) = 35.86, *p* < .001, $\eta_p^2 = 0.46$ (Figure 4b). Thus trials were collapsed over both blocks and submitted to post hoc *t* tests with Bonferroni correction, which indicated that participants were faster on distractor-absent trials than on low-probability distractor trials, *t*(42) = 10.91, *p* < .001, *d* = 1.66, on high-probability distractor trials compared to low-probability trials, *t*(42) = 2.54, *p* = .015, *d* = 0.39, and on high-probability distractor trials compared to no-distractor trials, *t*(42) = 5.79, *p* < .001, *d* = 0.88. Participants were again slower to identify targets appearing at the high-probability distractor location (*M* = 751 ms, *SD* = 106 ms) compared to targets at the low-probability distractor locations (*M* = 722 ms, *SD* = 77 ms), *t*(42) = 3.22, *p* = .002, *d* = 0.49; the magnitude of this effect did not differ between blocks (41 ms in block 1 vs. 16 ms in block 2), *t*(42) = 1.78, *p* = .083, although there was a trend in the direction of extinction.

Discussion

Experiment 2 shows that statistically learned distractor suppression persists even after location probabilities are equalized. We again replicated the results of Wang and Theeuwes (2018a, 2018b, 2018c), observing a distractor suppression effect across both phases along with a corresponding location-specific suppression of target processing. Although we did not observe a significant difference in the magnitude of distractor suppression between the first and second halves of the test phase, the magnitude of the learned bias declined numerically and the difference was marginally significant for the effect on target reporting. The fact that distractor probabilities from the training phase reliably influenced performance in the test phase suggests that distractor suppression is the product of genuine statistical learning rather than a residual consequence of intertrial priming, which would have been expected to disappear after roughly five to eight trials of unbiased task con-

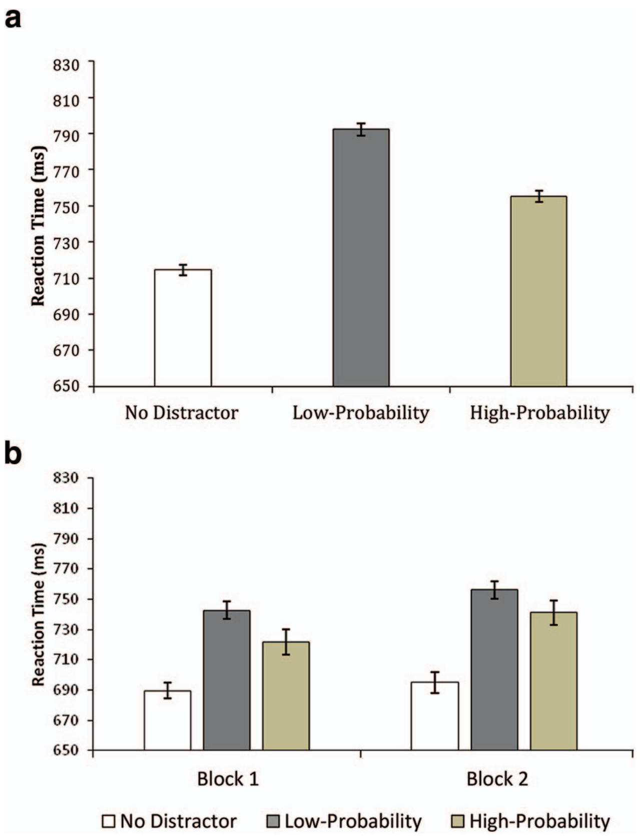

Figure 4. Mean RTs for Experiment 2. (a) Training phase. (b) Test phase. Error bars reflect within-subjects confidence intervals (Loftus & Masson, 1994). See the online article for the color version of this figure.

tingencies (Maljkovic & Nakayama, 1996). This finding is critical to Experiment 3, in which we examined the persistence of such learning outside the originally associated task.

Experiment 3

Having established that suppression of a high-probability distractor location indeed reflects a genuine learning effect that persists into extinction, we next examined whether this reshaping would influence attention allocation in a novel task, consistent with the generalization of learning as previously shown in the case of value-driven attention (Anderson et al., 2012; Mine & Saiki, 2015). Generalization of spatial inhibition would be consistent with a persistent biasing signal that is applied at the level of a spatial priority map without respect to feature-based influences, serving as an independent source of input. Conversely, a failure to generalize across stimuli and task would suggest that task context gates which spatial biases are applied to the priority map and/or that statistically learned distractor suppression reflects the confluence of location- and feature-based activation on the priority map and is therefore limited to particular eliciting stimuli (see Failing et al., 2019).

To adjudicate between these possibilities, Experiment 3 probed the effects of previously learned spatial inhibition in a novel task context using a variant of the modified spatial cueing paradigm of Folk, Remington, and Johnston (1992). In this paradigm, task-irrelevant uninformative cues appear briefly before search display onset; one cue shares stimulus features (typically color) with the target. Target identification is facilitated when the target appears at the colored cue's location, suggesting that attention is automatically directed to stimuli possessing a task-relevant feature. As in Experiment 2, participants completed an additional singleton training phase with a high-probability distractor location followed by a spatial cueing task. If learned distractor suppression generalizes to stimuli appearing at the same location in a novel task context, we should observe reduced capture by the colored cue when that cue appears in the previously suppressed location.

Method

Participants. Forty-four new participants were recruited from the Texas A&M University community. All participants were between the ages of 18 and 35, and all reported normal or corrected-to-normal visual acuity and color vision. After excluding participants with low accuracy (see Analysis), the final sample size was 33 (20 female, mean age = 19.6, *SD* = 2.4). Participants were compensated with course credit. All procedures were approved by the Texas A&M University Institutional Review Board and conformed to the principles outlined in the Declaration of Helsinki.

Apparatus. The apparatus used were identical to those used in Experiments 1 and 2.

Stimuli. Stimuli in the first phase of the experiment were identical to the stimuli in Experiment 2, save for white boxes surrounding all six stimuli. These boxes were approximately 3.3° in height and width. These boxes remained onscreen throughout each trial.

In the second phase of the experiment, six white boxes were drawn in the same positions used during training. During the cue display, four dots appeared, one per side, surrounding each box. One set of dots (the cue) was red; the others were white. During the target display, either an "X" or a "=" appeared in each box (50% probability). The "X" was approximately 2 × 2° in height and width, while the "=" was approximately 1.6° in length and 1.2° in height. One character (the target) was red; the others were white. Stimuli were not matched for luminance. The cue and target color matched one of the stimulus colors from the training task, potentially facilitating the transfer of learning. As the goal of the experiment was to examine the influence of prior learning on distractor suppression, rather than determine the degree to which distractor processing is contingent on task goals, we only presented a target-colored distractor that both goal-contingent (Folk et al., 1992) and stimulus-driven (Theeuwes, 1992) theories predict should capture attention in order to maximize our ability to detect modulations in attentional capture by stimulus location.

Design and procedure. The experiment consisted of two phases. The first phase was identical to the first phase of Experiment 2, except that all possible stimulus locations were marked by white boxes (Figure 5a). During the second phase, after 16 practice trials, participants completed 288 trials of a spatial cueing task (similar to Folk et al., 1992). Target and cue locations were counterbalanced within participants and fully uncorrelated, such that cue location predicted target location (i.e., the cue was valid) on only one sixth of trials. That is, cue location provided no information about target location.

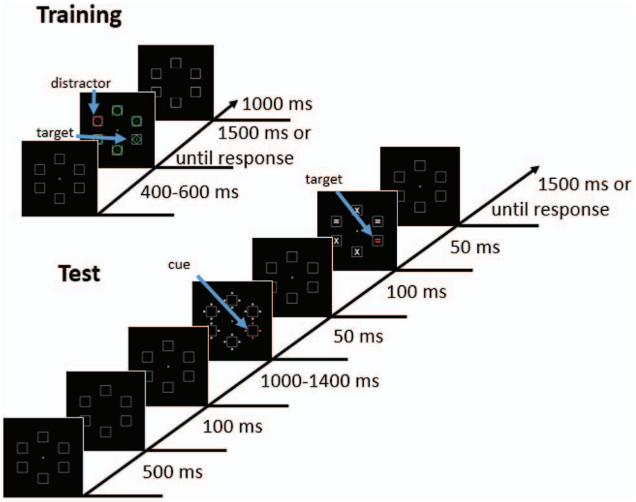

Figure 5. Sequence and time course of events for Experiment 3. The training phase was identical to Experiment 2 (see Figure 3) save for the addition of white boxes around each possible distractor location. In the test phase, white and red (dark gray) circles were flashed for 50 ms before target presentation. The target was defined as the red (dark gray) character and the cue as the red (dark gray) circles. Target and cue presentation were fully uncorrelated. See the online article for the color version of this figure.

Each trial began with a 500 ms fixation display, followed by the 100 ms disappearance of the fixation cross and its 1000–1400 ms reappearance. The cues were then flashed onscreen for 50 ms. After 100 ms, the target display was shown for 50 ms. The fixation display then remained onscreen for 1500 ms or until participants made a forced-choice response by pressing one of two keys corresponding to the identity of the target (the "Z" key for an "X" target and the "M" key for an "=" target; see Figure 5b). Incorrect or too-slow responses elicited written feedback.

Analysis. Eleven participants were excluded from analysis for accuracy below 80%, leaving 33 participants. Training data were analyzed as in Experiment 1. RTs from the test phase were entered into a two-way repeated measures ANOVA with cue location (formerly high-probability and formerly low-probability) and cue validity as within-subjects factors. Once again, incorrect responses were excluded from RT analysis, as were RTs shorter than 200 ms or more than three *SD*s above the mean of their condition.

Results

Train phase. A one-way repeated measures ANOVA indicated a significant effect of distractor location, F(2, 64) = 26.33, p < .001, $\eta_p^2 = 0.45$. Follow-up post hoc *t* tests with Bonferroni correction revealed that, as in Experiments 1 and 2, RTs were faster on distractor-absent trials than on low-probability distractor trials, *t*(32) = 7.26, *p* < .001, *d* = 1.26, faster on high-probability than on low-probability trials, *t*(32) = 3.14, *p* < .01, *d* = 0.55, and faster on distractor-absent trials than on high-probability trials, *t*(32) = 4.17, *p* < .001, *d* = 0.73 (Figure 6a). Concerning the location of the target, participants were slower to identify targets appearing at the high-probability distractor location (*M* = 823 ms, *SD* = 126 ms) compared to the low-probability distractor locations (*M* = 768 ms, *SD* = 87 ms), *t*(32) = 4.52, *p* < .001, *d* = 0.79, mirroring the results of prior experiments.

Test phase. A two-way repeated measures ANOVA revealed a significant main effect of validity, *F*(1, 32) = 30.73, *p* < .001, $\eta_p^2 = 0.490$, indicating attentional capture by the color cue. No main effect of cue location was observed, *F*(1, 32) = 0.20, *p* = .659, nor was any interaction between validity and location evident, *F*(1, 32) = 0.16, *p* = .695 (Figure 6b). A Bayesian ANOVA implemented in JASP (Version 0.9.0.1) indicated that a model containing a location factor and an interaction term was unlikely compared to a null model containing only validity (along with subject) as a factor, $BF_M = 0.09$. No reliable difference was observed between RT to targets appearing in the formerly high-probability distractor location (*M* = 602 ms, *SD* = 82 ms) compared to targets in the formerly low-probability distractor locations (*M* = 601 ms, *SD* = 75 ms), *t*(32) = 0.27, *p* = .789, $BF_{01} = 5.19$. Neither the interaction between validity and location (*F* < 1) nor the effect of location on target RTs (*p* = .88) were significant when restricting analyses to the first half of the test phase, suggesting that the previously reported statistics did not obscure a robust but rapidly extinguishing location bias.

Discussion

Experiment 3 indicates overall that statistically learned distractor suppression does not generalize between the additional singleton and spatial cueing paradigms. We observed a robust cuing

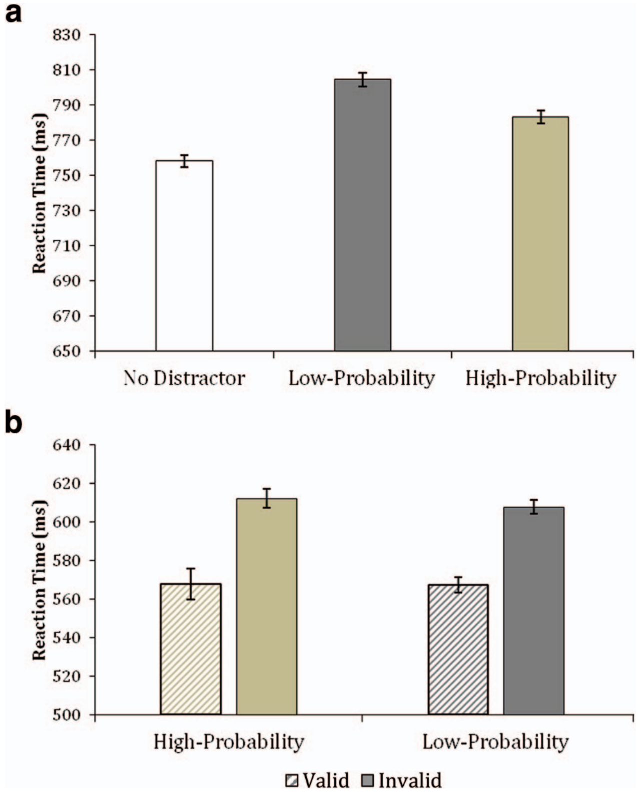

Figure 6. Mean RTs for Experiment 3. (a) Training phase. (b) Test phase. Error bars reflect within-subjects confidence intervals (Loftus & Masson, 1994). See the online article for the color version of this figure.

effect in which response times were significantly faster when the cue predicted the location of the target sharing a stimulus feature. This cuing effect was not impacted by the prior learning from the training phase, nor was the speed with which targets were identified. The results suggest that spatial statistical learning does not transfer to novel stimuli in the same spatial locations, and by extension that the resulting spatial bias may be restricted to the task context in which it was learned. Although it could be argued that the absence of a reduced cuing effect at the formerly high-probability distractor location provides a strong test of relatively far transfer or that the strength of attentional capture by the cue overpowered any lingering location-specific suppression, no effect on target identification was observed when targets appeared in the previously high-probability distractor location, suggesting no evidence for even modest generalization. Although it is an empirical question whether more subtle changes in task context between training and test would have permitted transfer of a learned spatial bias, it is apparent from the present study that a purely spatial bias abstracted from the context in which it is learned is untenable.

General Discussion

Statistical learning is believed to impact target selection and distractor filtration by up- and downregulating representation intensity in the spatial priority map (Ferrante et al., 2018; Jiang, 2018; Wang & Theeuwes, 2018a, 2018b, 2018c). However, little is currently known about the linkage of nonspatial information to spatial locations during statistical learning and the degree to which such nonspatial information modulates the learning and expression of location-based spatial suppression. The present study examined the formation of context-spatial associations during statistical learning and the degree to which statistically learned distractor suppression persists and generalizes across tasks, with the greater aim of investigating potential commonalities with statistically learned target selection and with other types of selection history.

Statistically learned suppression is predominantly tied to the stimulus's location in space and secondarily modulated by associated stimulus features. The color of stimuli is incorporated into priority weighting alongside learning from spatial regularities (Stilwell, Bahle, & Vecera, 2019). Failing et al. (2019) demonstrated that suppression can occur at multiple high-probability locations, as in Experiment 1 of the present study. However, when one color distractor appears more frequently at one high-probability location and a different color distractor at another high-probability location, distractor suppression at these two high-probability locations is further modulated by the color of the distractor (Failing et al., 2019). To this characterization, our Experiment 1 adds evidence that contextual information is not likewise bound to stimulus location during statistical learning, although it was similarly incidental to the performance of the task. That is, where color-location mismatches attenuate the suppression effect, context-location mismatches do not.

Of note in Experiment 1, contextual information was strategically useful as a predictor of distractor location. Moreover, in other paradigms, participants do appear able to integrate similarly incidental contextual information into their spatial representations during statistical learning, speeding target detection. Naturalistic background scenes appear to bind to stimulus locations in contextual cuing paradigms (Brockmole, Castelhano, & Henderson, 2006; Brooks et al., 2010), in which part or all of the search display is repeated on some trials: Target selection is speeded for repeated search arrays only when the global context matches the array. Thus, it is unclear why participants in Experiment 1 were unable to integrate contextual information. Several explanations for this disconnect are conceivable. Distractor suppression, compared to target selection, may tap separate mechanisms of spatial bias less reliant on guidance from global contextual representations. Alternately, the nature of the search arrays in Experiment 1, in which distractor position varies across trials and must be statistically integrated over trials, may reflect relationships that are more difficult to associate with context. This latter interpretation would be consistent with the observation by Brooks et al. (2010) that minor changes to the search array prevented array-context associations and with prior studies linking context to subsequent attentional capture when context was a perfect trial-by-trial predictor of the associated task contingency (Anderson, 2015; Cosman & Vecera, 2013).

Contextual information is known to bias some types of predominantly feature-based visual search (Anderson, 2015; Cosman & Vecera, 2013). We have previously shown that contextual information is acquired during reward learning, such that reward-associated colors do not capture attention outside of the context in which they predict reward even though participants are unaware of the contextual contingencies (Anderson, 2015). Participants can also learn to engage different search strategies in different contexts based on context-specific target-nontarget relations (Cosman & Vecera, 2013). Conversely, when the same context manipulation predicts the color of the target, former target colors gain attentional priority regardless of the context in which they appeared (Anderson & Britton, 2019); this pattern parallels the results evident in the present study, potentially reflecting a distinction between associative learning and selection history-driven learning whereby contextual information gates the prediction errors that shape attentional priority only in reward-based associative learning (Sali, Anderson, & Yantis, 2014).

In Experiment 2, we show that statistically learned location suppression persists well after location probabilities are equalized. In combination with evidence that target-centered probability learning persists after several hundred trials (Jiang et al., 2013) and that estimated intertrial repetition priming is insufficient to account for speeded processing in high-probability locations (Jiang, Sha, & Remington, 2015), our findings in Experiment 2 are inconsistent with the intertrial priming account of probability cueing. Rather, selection history tied to distractors shapes the attentional priority map in an enduring way.

Though maintained for later use, statistically learned priority representations appear not to be accessed outside the original task in which they were acquired. In Experiment 3 we observed no learning transfer from the additional singleton paradigm to the spatial cueing paradigm: The high-probability distractor locations from the first task were not suppressed in the second, although the spatial aspects of the first task's search display were retained. This finding is consistent with prior reports that statistically learned target prioritization can be limited in its generalization to a different task, particularly when the task demands of search change (Jiang et al., 2015).

Failing et al. (2019) and Wang, van Driel, Ort, and Theeuwes (2019) construct a two-stage model of spatial suppression, in which a location in the priority map is preemptively suppressed prior to search display onset; this suppression is then modulated by a feature-specific response to the presence or absence of a distractor. Had the hypothesized preemptive, purely spatial suppression been entirely independent of information about stimulus features, we might have expected suppression at the previously high probability location regardless of the visual search task performed. Instead we observed no suppression effect at all when the visual search task changed from singleton search to feature-based orienting in Experiment 3. This finding is consistent with evidence that spatial attentional biases favoring high-probability target locations in one task do not extend to stimulus processing in a different task when the two tasks are randomly intermixed, suggesting task and stimulus specificity (Addleman, Schmidt, Remington, & Jiang, 2019; see also Addleman, Tao, Remington, & Jiang, 2018). Thus, any purely spatial suppression must be reliant on features of the originally learned stimulus context, at least in its ability to instantiate an overall set of context-specific spatial priority weights. Similarly, distractor suppression may be tied to a specific attentional strategy for localizing the target, which varied between a shape singleton and a color-defined target in Experiment 3. An alternative possibility would be that statistically learned suppression is at least partially contingent on a combination of feature and spatial inputs, with novel stimuli matching the trained input insufficiently to activate suppressive mechanisms. Perhaps related to these latter two possibilities, Sauter et al. (2019) demonstrate, using a different task that promotes feature-based attentional guidance, that frequent distractor locations are persistently inhibited only when the distractor is defined in the same feature dimension as the target. From these data it cannot be determined whether preemptive suppression occurs but is immediately overwritten by the processing of an untrained stimulus or whether the associated spatial priority representations are never activated at all in the novel task. To differentiate these possibilities, pretrial electrophysiological recordings could be informative (see Wang et al., 2019).

The location-based suppression observed in the present study can be contrasted with feature-based suppression of physically salient color singletons (e.g., Gaspar & McDonald, 2014; Gaspelin & Luck, 2018a, 2018b; Gaspelin, Leonard, & Luck, 2015, 2017; Sawaki & Luck, 2010; Vatterott & Vecera, 2012). Under certain task conditions, while searching for a specific feature-defined target (i.e., feature search mode), processing of color singleton distractors can be substantially reduced, even below that of other nontarget stimuli (e.g., Gaspelin & Luck, 2018a; Gaspelin et al., 2015, 2017). The extent to which such suppression differs mechanistically from the suppression observed in the present study is unclear, although given that feature-based suppression is contingent upon goal-state (feature search mode) and the color singleton distractor is always task-irrelevant, feature-based suppression is often characterized as an explicitly top-down control mechanism (e.g., Gaspelin & Luck, 2018b; Gaspelin et al., 2015; Sawaki & Luck, 2010) whereas implicit statistical learning may underlie the observed location-based suppression (Wang & Theeuwes, 2018a, 2018b, 2018c). Both in the present study and in prior demonstrations of the phenomenon (e.g., Wang & Theeuwes, 2018a, 2018b, 2018c), attentional capture was reduced but not completely prevented at the high-probability distractor location; such incomplete suppression may be a product of the fact that targets could still appear at this location on some trials, requiring that some attention be directed to it in order to perform the task accurately.

Awareness of the high-probability distractor location was not measured in the present study (see also, Wang & Theeuwes, 2018a, 2018c). However, evidence from multiple investigations of the phenomenon suggest that the learned suppression is implicit and robust in individuals who report no awareness of the contingencies (Failing et al. 2019; Wang et al., 2019; Wang & Theeuwes, 2018b). A similar lack of explicit awareness of task contingencies was demonstrated in the context-dependent modulation of value-driven attention (Anderson, 2015) and search mode (Cosman & Vecera, 2013), making it unlikely that differences in awareness of the underlying task contingencies would explain the difference between the findings of those two prior studies and the present study. However, this possibility cannot be explicitly ruled with our data. Whether participants become explicitly aware of the distractor-location contingencies or not, our data show that participants fail to learn trial-by-trial context contingencies during training. Our data additionally indicate that the influence of biased location probabilities persists well after contingencies are equalized (and so reflects genuine learning rather than more remote effects of repetition priming), but this persistence is no longer evident when the stimuli and task are changed.

Statistical learning has recently been described using two competing models of selection history. Theeuwes (2018, 2019) contends that top-down goals, bottom-up physical salience, and selection history collectively weight a common spatial priority map (see also Awh, Belopolsky, & Theeuwes, 2012), and that statistical learning is rapid and flexible. Conversely, Jiang (2018) characterizes statistical learning as habitual and relatively inflexible—hence its persistence into similar tasks—and slow to readjust, distinct from goal-driven attention; in this framework, selection history and top-down goal-driven attention do not necessarily reflect parallel and potentially competing input into a common priority map, and statistical learning is dependent upon the former. We have previously noted that selection history is not a unitary construct and that its constituent learning experiences may tap quite different attentional mechanisms (Anderson, Chiu, DiBartolo, & Leal, 2017; Kim & Anderson, 2019a, 2019b). For instance, attentional bias arising from reward history (value-driven attention) is context-sensitive (Anderson, 2015), whereas as noted above, attentional bias arising from history as a frequent target of visual search is not (Anderson & Britton, 2019). Additionally, value-driven attentional biases transfer between unrelated tasks (Anderson et al., 2012). Experiments 1 and 3 in the present study therefore suggest that statistical spatial learning is more analogous to the role of frequent target features in selection history, which we characterize as a habit-like effect contingent on the repetition of past orienting behavior and driven primarily by reinforcement learning mechanisms (Anderson et al., 2017; Kim & Anderson, 2019a, 2019b). In contrast, the influence of learned value on feature-based attention is explicitly associative (e.g., Bucker & Theeuwes, 2017; Kim & Anderson, 2019a; Le Pelley, Pearson, Griffiths, & Beesley, 2015) and may therefore more readily incorporate contextual information.

In sum, statistically learned distractor suppression is persistent, generalizes across contexts experienced during learning, and is limited in its transference to different visual search tasks. In these ways, statistically learned distractor suppression differs from value-driven attention, which is learned in a context-specific manner (Anderson, 2015) and generalizes to novel visual tasks (Anderson et al., 2012), suggesting different learning systems in contrast to a unitary model of selection history (Awh et al., 2012; Theeuwes, 2018, 2019). Our findings raise further questions about the degree to which distractor suppression generalizes between more closely related tasks, the possible preemptive suppression of high-probability distractor locations absent features of the original stimuli, and the degree to which statistically learned priority is maintained free from retroactive interference by subsequent tasks.

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