

Explicit Attentional Goals Unlock Implicit Spatial Statistical Learning

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People can quickly learn spatial distributions of targets and direct attention to likely regions of targets. These implicitly learned spatial biases have been shown to be persistent, transferring to other similar visual search tasks. However, a persistent attentional bias is incompatible with frequently changing goals in our typical daily environment. We propose a flexible *goal-specific probability cueing* mechanism to address this discrepancy. We examined whether participants could learn and utilize target-specific spatial priority maps across five experiments (each $N = 24$). In Experiment 1, participants were faster to find the target at the target-specific high-probability location, in line with a goal-specific probability cueing effect. This demonstrated that separate spatial priorities derived from statistical learning can be flexibly activated based on the current goal. In Experiment 2, we ensured the results were not driven solely by intertrial priming. In Experiment 3, we ensured the results were driven by early attentional guidance effects. In Experiment 4, we extended our findings to a complex spatial distribution including four locations, supporting a sophisticated representation of target likelihood in the activated spatial priority maps. Finally, in Experiment 5, we confirmed that the effect was driven by the activation of an attentional template and not associative learning between the target cue and a spatial location. Our findings demonstrate a previously unrecognized mechanism for flexibility within statistical learning. The goal-specific probability cueing effect relies on coordination of feature-based and location-based attention, utilizing information that crosses traditional boundaries between top-down control and selection history.

Keywords: attention, visual search, statistical learning, probability cueing

Traditional theories of visual attention suggest two key drivers of the allocation of attention: top-down control and bottom-up salience. However, another class of internal attentional drivers, collectively called selection history, shows that attention is biased to prioritize items matching previous attention in a given context. Examples of selection history include intertrial priming (Kristjánsson & Driver, 2008; Maljkovic & Nakayama, 1994; Tipper, 1985), contextual cueing (Chun & Jiang, 1998), lingering effects of prior rewards (Andersen et al., 2011), and spatial statistical learning of likely locations of targets (Y. V. Jiang et al., 2013) and distractors (Wang & Theeuwes, 2018). In each of these selection history effects, attention is driven to items based on internal control settings that do not map on to traditional ideas of top-down control such as attentional

templates maintained in working memory (WM) (Hutchinson & Turk-Browne, 2012). Therefore, these effects do not fit well with many of the main theories of attention (Bundesen, 1990; Desimone & Duncan, 1995; Duncan & Humphreys, 1989; Wolfe, 1994) leading to the proposal that top-down, bottom-up, and selection history should be considered independent drivers of attention (Awh et al., 2012).

One well-studied aspect of selection history is a spatial statistical learning effect, called location probability cueing (Y. V. Jiang et al., 2013, 2014). In location probability cueing, targets are more likely to appear in one high-probability quadrant of the screen. For example, Y. V. Jiang et al. (2013, 2014) asked participants to search for a letter T among Ls. Unbeknownst to participants, the target T appeared at one high-probability quadrant for 50% of trials and at each of the other three low-probability quadrants for 17% of trials. Over experience performing searches under these conditions, participants' responses became faster when the target appeared in the high-probability quadrant compared to the lower-probability quadrants (Y. V. Jiang, 2018). Eye tracking measures have shown that participants were twice as likely to direct the first saccade to the high probability quadrant compared with sparse quadrants (Y. V. Jiang et al., 2014), demonstrating probability cueing is based on an early attentional effect. Importantly, these effects occur regardless of whether participants are aware of the spatial regularities (Y. V. Jiang et al., 2018). This indicates that location probability cueing is a form of selection history based on implicit memory in contrast to the explicit WM system used in top-down attentional control (Y. V. Jiang & Sisk, 2019).

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This study was pre-registered, and data is available at <https://osf.io/kztxn/>.

Nancy Carlisle served as lead for resources and supervision and served in a supporting role for project administration. Ziyao Zhang served as lead for data curation, formal analysis, investigation, project administration, and software. Nancy Carlisle and Ziyao Zhang contributed to conceptualization, validation, visualization, writing—original draft, writing—review and editing, and methodology equally.

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Once learned, the biases generated from location probability cueing are long-lasting. Y. V. Jiang et al. (2013) showed that the effects persisted for hundreds of trials after spatial regularities were removed and could still be observed after a week delay. They concluded that the persistence of these effects helps to distinguish this implicit learned spatial bias from goal-driven attention, which can change on a trial-by-trial basis. This separation from goal-driven attention was further supported by research showing the specific spatial priority maps learned while performing one location probability cueing task (find target T among Ls) transfer to tasks with a completely different target (find 2 among 5 s, or a difficult feature search) suggesting the effect can be persistent across changes in search targets (Y. V. Jiang et al., 2015). Similarly, Salovich et al. (2018) demonstrated that spatial bias learned in a letter search task could be transferred to a search task in scenes. However, the transfer effect of probability cueing might be constrained by the similarity of goal settings between tasks. The learned spatial bias does not transfer between a letter search task and a scene search task that had spatially overlapping displays (Addleman et al., 2019). The learned attentional bias does not facilitate discrimination performance (Sha et al., 2018) nor memory performance (Addleman et al., 2018) for stimuli at the biased region. Finally, a study by Y. Jiang and Leung (2005) suggested that spatial biases may be learned through mere exposure while a colored set of items is task irrelevant, but that learning can be expressed at a later time when the color of the learned items forms part of the currently active attentional set. However, a recent follow-up (Vadillo et al., 2020) did not replicate this finding. Overall, it is still under active debate when the learned spatial bias from one task can transfer to other tasks, but current results are generally consistent with the view that probability cueing results in an acquired habit during the attentional guidance stage, which is persistent and inflexible (Y. V. Jiang, 2018).

While this transfer of spatial biases across targets might make sense in the constraints of a cognitive psychology experiment, an inflexible and persistent spatial bias does not seem to make sense in the real world. Here is an example: Imagine that you repeatedly look for your keys and, most of the time, you find them on a hook in the hall. Spatial statistical learning would suggest that over time you would begin directing your attention to this high-probability location (HPL) when you are looking for your keys. This would certainly help you find your keys. However, what would happen if now your search target changes, and you are looking for your cat? If the spatial statistical biases developed during your key searches are persistent and inflexible, this suggests you would begin looking for your cat on the hall hooks as well! Persistent and inflexible biases do not make sense in the real world. Based on this observation, we predicted that selection history effects like location probability cueing may depend upon top down attentional goals. According to this view, instantiating an attentional template could activate a spatial priority map that is *specific to that search target*. This would mean you could activate a spatial priority map that highlights the hall hooks when you are looking for your keys, and another spatial priority map highlighting the cat bed by the radiator when you are looking for your cat.

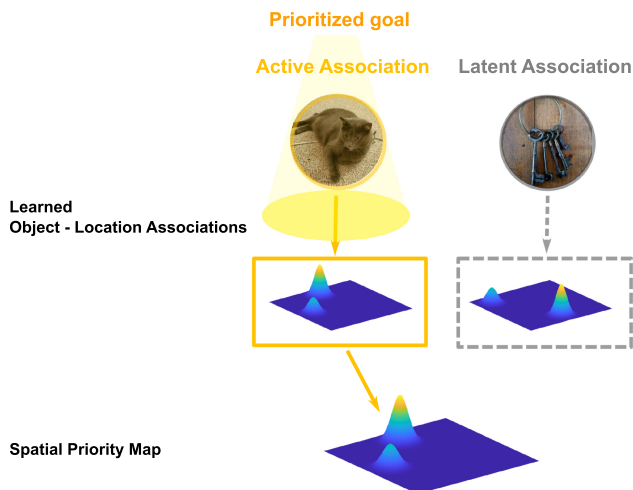
How would this relationship between our explicit attentional goals and implicit, inflexible statistical learning take place? In essence, current goals could serve as a context that is activating a *conditional automaticity* (Bargh, 1989) where an automatic behavior occurs, but only in a specific context. To gain benefits from probability cueing effects in complex real-world environments where our visual search

targets change frequently, a specific spatial bias could be associated with each search target (see Figure 1). When a particular object becomes the search target, this activates the specific spatial biases associated with that target. In this way, we predicted explicit search goals could unlock implicitly learned spatial biases. We will call this the *goal-specific probability cueing hypothesis*.

To test our hypothesis, we created a new paradigm combining probability cueing (Y. V. Jiang et al., 2013, 2014) and cued visual search (Treisman, 1985; Wolfe et al., 1989). On each trial, participants received a visual cue prior to search to indicate the goal-relevant object. Each target item was associated with a distinct spatial distribution. Specifically, in Experiments 1–3, each of the four target objects appeared at one location for 80% of trials (HPL) and appeared at another location for 20% of trials (low-probability locations [LPLs]). Importantly, the HPLs and LPLs were counterbalanced across the targets, so overall targets were evenly distributed across the four locations (see Figure 2b). Traditional probability cueing would predict no spatial biases should develop, as the overall target likelihood is equivalent at each quadrant. However, our goal-specific probability cueing hypothesis predicts learning occurs at the object level, so four different spatial biases should be learned for each of the four different search targets. This should lead to faster responses when the search target appears at the *target-specific HPL*.

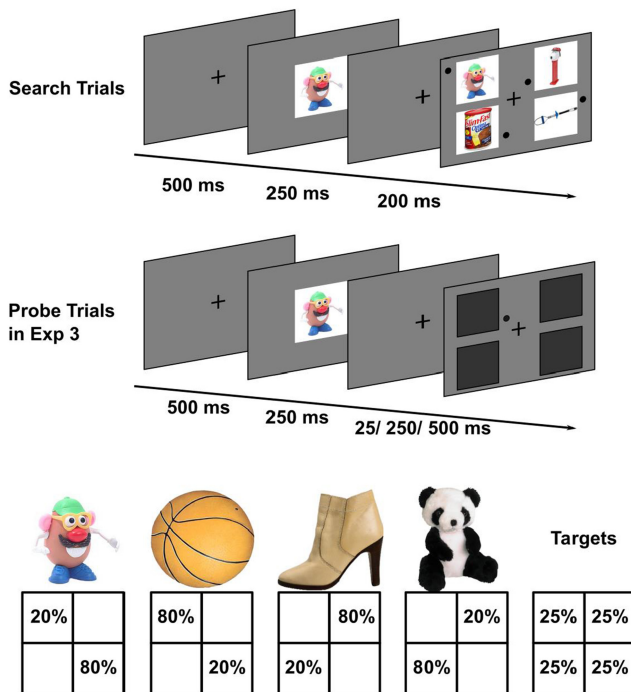
To preview our results, Experiment 1 demonstrated that participants were faster to respond to targets appearing at HPLs compared with LPLs, suggesting that different spatial biases were learned and employed for different targets on a trial-by-trial basis in line with the goal-specific probability cueing hypothesis. Experiment 2 ruled out the possibility that the effects were driven by intertrial priming by including a testing block where targets were evenly distributed across potential locations. Here, we found persistent biases to

Figure 1
Hypothesized Model of Attention Guidance by Positional Regularities of Objects



Note. According to the goal-specific probability cueing hypothesis, the activation of a particular search target would also lead to the activation of the specific spatial statistical biases associated with that target item through prior probability cueing. The retrieved spatial associations would lead to changes in the spatial priority map during visual search. See the online article for the color version of the figure.

Figure 2
Example Trials and Target Distribution Manipulation



Note. Illustration of an example search trial and an example probe trial (a). An example target distribution manipulation in the Experiment (b). The overall target distribution is equal at each location. In this example, HPL and LPL are diagonally separated, but this was not the case for all participants. HPL = high-probability location; LPL = low-probability location. See the online article for the color version of the figure.

previously HPLs in the testing block, in line with a statistical learning explanation. Experiment 3 revealed that goal-specific probability cueing influenced early attentional selection by showing biases to HPLs in probe trials where only early attention selection was examined. In Experiment 4, we extended our finding to a more complex spatial distribution including all four search quadrants. We found participants could generate target-specific spatial priority maps that matched the complex distribution across spatial locations. Finally, to ensure that the activation of the spatial biases were dependent upon the attentional template, and not just based on associative learning of the cue and a target spatial location, we provided participants with a new search goal in the testing block while continuing to present the cues prior to search. We found that the probability cueing effects on RTs were not present when the search goal changed, in line with the goal-specific probability cueing hypothesis.

Our findings demonstrate an intricate linkage between explicit top-down control and implicit selection history in guiding visual attention. These results demonstrate attentional control depends on a coordination of control from separate memory systems (Batterink et al., 2019; Egner, 2014; Hutchinson & Turk-Browne, 2012), and unappreciated flexibility in selection history which is typically considered persistent and inflexible (Y. V. Jiang, 2018). This work challenges the existing notions that top-down control and selection history are independent and competing drivers of visual attention (Y. V. Jiang et al., 2013), and instead suggests that our attentional

templates may include a coordination of top-down information in explicit WM and activation of associated information from implicit long-term memory.

Experiment 1

Method

We report how we determined our sample size, all data exclusions (if any), all manipulations, and all measures in the study for this and the following experiments in our OSF registration: <https://osf.io/kztxn/>.

Participants

Twenty-four undergraduates ($M_{age} = 18.82$, $SD = 1.15$; 13 female, 11 male) from Lehigh University participated in this experiment for course credits. We chose the sample size to be larger than one of the original studies on location probability cueing (Y. V. Jiang et al., 2013), which had 8–16 participants in each experiment, and similar to previous behavioral studies from our lab (Experiment 2; Carlisle & Nitka, 2019). All participants reported normal or corrected-to-normal vision and normal color perception, and the procedures were approved by the Lehigh University IRB.

Stimuli

Stimuli were presented using PsychToolbox (Brainard, 1997) for Matlab and displayed on an Asus LCD monitor with gray background that was placed at a viewing distance of approximately 60 cm. Search items were randomly selected from a pool of 400 images of real-life objects (Brady et al., 2008). All image stimuli were presented in the same size (2.6° by 2.6°). Fixation cross consists of two perpendicular lines (length, 1.7° ; width, 0.4°). During the search phase, four object images were presented at vertices of a square that centered at the screen center (4.2° from the center). Four filled dots (0.5°) were presented at either the upper left, bottom left, upper right, or bottom right side of each object image, 1.9° from the image center.

Procedure

Participants were familiarized with the task with 10 practice trials. After the practice block, they completed 600 trials in the experimental block. Each trial began with a fixation point being presented for 500 ms. Next, an image cue indicating the target in the upcoming array was presented at the center of the screen for 250 ms. Cued object in each trial was randomly selected from four potential target objects. After a 200-ms delay period, the search display was presented. The search display stayed on the screen until participants responded or a maximum of 3,000 ms. Participants were instructed to find the cued object in the search display and report whether a dot was at the left or right side of the target as quickly and accurately as possible by pressing either left or right arrow key on the keyboard. Dot locations were randomized, so there were no associations between cued objects or locations and certain responses. Crucially, unbeknownst to participants, target locations followed a contingent probability distribution. For each potential target, one location was associated with high probability (80%; HPL), and another was associated with low probability (20%; LPL). The target never appeared at the remaining two locations. HPLs and LPLs of targets were

counterbalanced, so overall targets were evenly distributed at the four locations (see Figure 2b).

Preregistrations of the experiments and data are available at <https://osf.io/kztxn/>.

Results and Discussion

Trials with an incorrect response (3.7%) were excluded from reaction time (RT) analysis. Additionally, trials with an RT less than 200 ms or greater than 2.5 deviations above the individual mean (0.1% of trials) were excluded from all analyses.

Search Accuracy

Paired *t*-test on accuracy was conducted with the factor of target location (HPL and LPL). Significant higher mean accuracy was found when targets appeared at HPLs (96.2%) compared to LPLs (94.5%), $t(23) = 10.23$, $p < .001$, $d = 2.54$.

Search RT

As expected, a paired *t*-test revealed that mean RT was faster when targets appeared at HPLs (520.92 ms) compared to LPLs, 586.45 ms, $t(23) = 13.27$, $p < .001$, $d = 2.91$ (Figure 3).

RT Learning Effect

To further assess the time course of learning, we separated the trials where targets appeared at the HPL into four time epochs. A repeated-measures analysis of variance (ANOVA) with the factor of epochs (1–4) was performed. We found a main effect of epochs, $F(3, 69) = 18.83$, $p < .001$, $\eta^2 = 0.45$. As shown in Figure 3, RTs linearly decreased as participants' search experience accumulated, epoch 1–epoch 2, $t(23) = 3.67$, $p = .008$, $d = 0.73$; epoch 1–epoch 3, $t(23) = 5.50$, $p < .001$, $d = 1.10$; epoch 1–epoch 4, $t(23) = 5.04$, $p < .001$, $d = 1.03$; epoch 2–epoch 3, $t(23) = 3.89$, $p = .004$, $d = 0.81$; epoch 2–epoch 4, $t(23) = 3.53$, $p = .011$, $d = 0.74$; epoch

3–epoch 4, $t(23) = 2.28$, $p = .178$. Critically, RTs at each HPL epoch were faster than the trials when the target appeared at the LPL, epoch 1, $t(23) = 7.681$, $p < .001$, $d = 1.56$; epoch 2, $t(23) = 10.09$, $p < .001$, $d = 2.12$; epoch 3, $t(23) = 12.99$, $p < .001$, $d = 2.62$; epoch 4, $t(23) = 10.13$, $p < .001$, $d = 2.07$, indicating that the benefits of probability cueing were present in all epochs.

Examining an Intertrial Priming Effect

An intertrial priming effect might explain the difference we found between HPLs and LPLs. It is possible that search benefits at HPLs were simply due to more target repetitions at HPLs compared with LPLs (Kristjánsson & Campana, 2010; Kristjánsson et al., 2002; Maljkovic & Nakayama, 1994, 1996). Although we could not fully eliminate the influence of intertrial priming in the current design, we could minimize its contribution by excluding trials that had repeated search targets. If the effect was largely driven by an intertrial priming effect, we would no longer find it after excluding target repeated search trials. However, analyses for non-repeated trials still showed the same pattern that mean RT was faster when targets were presented at HPLs compared to LPLs, $t(23) = 10.06$, $p < .001$, $d = 2.04$, although the attentional benefits in HPLs was smaller compared to the original effect, $t(23) = 6.39$, $p < .001$, $d = 1.34$. These results provide an initial support that intertrial priming does not fully explain the RT difference between HPLs and LPLs.

Faster visual search responses at target-specific HPLs in Experiment 1 provide preliminary evidence for the goal-specific probability cueing hypothesis. Additionally, our time epoch-based analysis showing increasing RT benefits at the HPL as participants gained more experience suggests that the effect is dependent upon learning. Overall, these results provide the first support for a goal-specific probability cueing effect.

Experiment 2

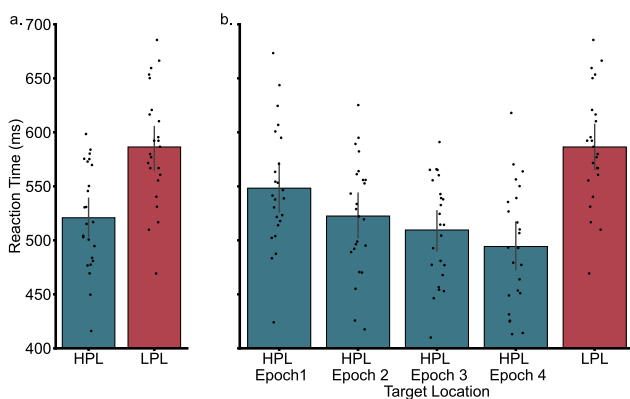
Although results from Experiment 1 were consistent with a goal-specific probability cueing effect based on statistical learning, we wanted to more firmly establish that the effect was not driven solely by intertrial priming. In Experiment 2, we added a testing block where targets were evenly distributed at previously occurring locations to prevent the intertrial priming effect (Y. V. Jiang, 2018; Y. V. Jiang et al., 2013, 2014). If the effect observed in Experiment 1 was mainly driven by an intertrial priming mechanism, it should be eliminated in the testing block as there were an equal number of target repetitions at the two target locations. In contrast, if the effect is mainly driven through a statistical learning mechanism, we should continue to find faster RTs at HPL compared to LPL in the testing block. Additionally, Experiment 1 was not designed to determine if the RT difference between HPL and LPL locations was driven by attentional enhancements of HPLs, attentional suppression of LPLs, or both. Therefore, we added control targets in which objects were always evenly distributed to provide a baseline for examining enhancement of HPLs and suppression of LPLs.

Method

Participants

Another group of 24 undergraduates ($M_{\text{age}} = 19.13$, $SD = 1.08$; seven females, 17 males) from Lehigh University participated in

Figure 3
Faster Searches for Targets Appeared in HPLs



Note. Mean RTs from Experiment 1 (a). Mean RTs of LPL condition and four time epochs in HPL condition, demonstrating the benefits of goal-specific probability cueing increase over time (b). Error bars indicate 95% confidence interval. HPL = high-probability location; LPL = low-probability location. See the online article for the color version of the figure.

this experiment. A power analysis based on the results in Experiment 1 indicated a sample size of four would be needed to achieve over 95% power to observe the RT difference between HPLs and LPLs in the learning phase. We maintained a sample size of 24 in this and subsequent experiments to match Experiment 1. All participants reported normal or corrected-to-normal vision and normal color perception, and procedures were approved by the Lehigh University IRB.

Stimuli

The stimuli were the same as Experiment 1.

Procedure

After 10 trials of practice, participants completed 480 learning trials, followed by 240 testing trials. Learning and testing were carried out continuously without further instructions. The learning block was the same as Experiment 1, except for the following changes. First, two of the four potential targets were evenly distributed at two locations, serving as controls. The probability manipulation was applied to the remaining two potential targets in the training block. Second, a testing block was added following the learning block. Items were evenly distributed at the two potential locations in the testing block, and comparisons were made between the previous HPL (PHPL) and the previous LPL (PLPL).

Results and Discussion

Trials with an incorrect response (5.1%) were excluded from RT analysis. Additionally, trials with an RT less than 200 ms or greater than 2.5 deviations above the individual mean (4.4% of trials) were excluded from all analyses.

Learning Block Accuracy

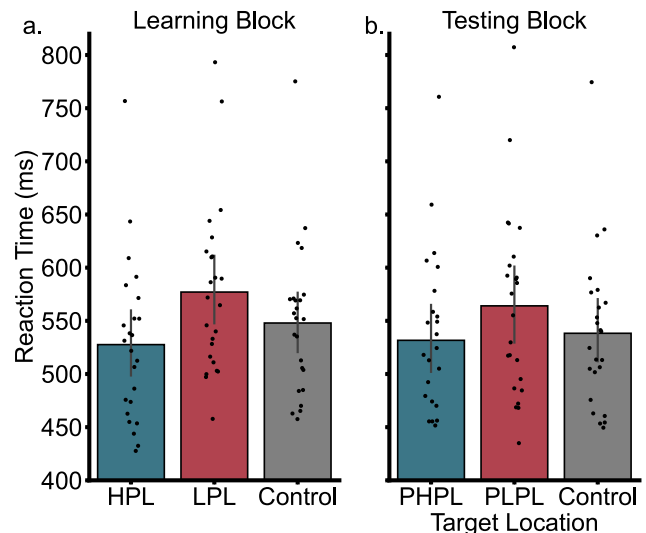
Significant higher mean accuracy was found when targets appeared at HPLs (96.9%) compared to LPLs (95.9%), $t(23) = 8.64$, $p < .001$, $d = 1.85$. To assess whether probability cueing led to benefits at HPLs as well as costs at LPLs, we ran a repeated-measures ANOVA to compare accuracy at HPLs, LPLs, and control locations. A main effect of location was found, $F(2, 46) = 51.26$, $p < .001$, $\eta_p^2 = 0.69$. Following-up t -tests revealed that accuracy at HPLs was higher than control locations (96.3%, 95% CI [95.9%–96.7%]) or LPLs, $t(23) = 7.35$, $p < .001$, $d = 1.50$; $t(23) = 8.64$, $p < .001$, $d = 1.76$. Accuracy at control locations was higher compared with LPLs, $t(23) = 3.92$, $p = .002$, $d = 0.80$, suggesting that both enhancement and suppression were occurring based on the target-specific statistical learning.

Learning Block RT

As shown in the Figure 4a, mean RT was faster when targets appeared at HPLs (527.64 ms, 95% CI [495.60–559.68 ms]) compared to LPLs (577.06 ms, 95% CI [543.13–611.00 ms]), $t(23) = -8.43$, $p < .001$, $d = 1.71$. A repeated-measures ANOVA was run to compare RTs at HPLs, LPLs, and control locations. A main effect was found, $F(2, 46) = 20.86$, $p < .001$, $\eta_p^2 = 0.48$. Following-up t -tests revealed that RTs at HPLs were faster than control locations (547.95 ms, 95% CI [518.11–577.79 ms]) or LPLs,

Figure 4

Goal-Specific Probability Cueing Persisted in the Testing Block



Note. Mean RTs at HPLs, LPLs, and two control conditions in the learning block of Experiment 2 (a). Mean RTs at PHPLs, PLPLs, and two control conditions in the testing block of Experiment 2 (b). Error bars indicate 95% confidence interval. HPL = high-probability location; LPL = low-probability location; PHPL = previous high-probability location; PLPL = previous low-probability location. See the online article for the color version of the figure.

$t(23) = -2.87$, $p = .026$, $d = 0.59$; $t(23) = -8.43$, $p < .001$, $d = 1.72$. RTs at control locations were faster compared with LPLs, $t(23) = -3.02$, $p = .018$, $d = 0.62$, suggesting that both enhancement and suppression were occurring based on the target-specific statistical learning. The control condition is important for interpreting the RT effects at HPLs and LPLs. If the slower RTs at the LPL were an indirect consequence of enhancement of the HPL, we would expect to see similar RTs at control locations and LPLs. However, the slower RTs at the LPLs than the control locations indicate an attentional bias away from the LPLs, suggesting a suppression of attention to the LPL in addition to enhancement of attention to the HPLs.

Testing Block Accuracy

Significant higher mean accuracy was found when targets appeared at PHPLs (96.5%) compared to PLPLs (94.7%), $t(23) = 8.84$, $p < .001$, $d = 1.74$. A repeated-measures ANOVA was conducted to compare accuracy among PHPLs, control locations, and PLPLs. A main effect was found, $F(2, 46) = 59.68$, $p < .001$, $\eta_p^2 = .72$. Accuracy at PHPLs was higher than control locations (94.8%) or PLPLs, $t(23) = 9.69$, $p < .001$, $d = 1.98$; $t(23) = 8.84$, $p < .001$, $d = 1.80$. No difference was found between control condition and PLPLs, $t(23) = 0.56$, $p = .926$.

Testing Block RT

As shown in the Figure 4b, mean RT was faster when targets appeared at PHPLs (531.68 ms) compared to PLPLs (564.08 ms), $t(23) = -6.23$, $p < .001$, $d = 1.25$. A repeated-measures ANOVA

was conducted to compare RTs among PHPLs, PLPLs, and control locations. A main effect was found, $F(2, 46) = 11.22, p < .001, \eta_p^2 = 0.33$. RTs at PHPLs were faster than PLPLs, $t(23) = -6.23, p < .001, d = 1.27$. RTs at control locations (538.30 ms) were faster than PLPLs, $t(23) = -2.85, p = .027, d = 0.58$. Although RTs at PHPLs were numerically faster than control locations, that comparison was not significant, $t(23) = -0.96, p = .721$.

Our results are consistent with a statistical learning hypothesis by showing persistent biases toward PHPLs of cued objects in the testing block, where all targets were evenly distributed. By comparing HPLs and LPLs to control locations, the current experiment further showed that the goal-specific probability cueing effect led to both benefits at HPLs and costs at LPLs during the learning block. Although the overall pattern within the testing block matched the pattern benefits at PHPLs and costs at PLPLs, post hoc comparisons showed only benefits remained significant in accuracy, while only costs remained significant in RTs. Overall, our persistent effects after the removal of the spatial biases in Experiment 2 confirm the effects of target-specific probability cueing are driven by statistical learning and not intertrial priming (Y. V. Jiang et al., 2013).

Experiment 3

Although Experiments 1 and 2 consistently found faster responses when targets appeared at HPLs, it remains unclear which stage of processing during visual search is leading to the goal-specific probability cueing effect. Multiple stages of processing are required before response in a visual search task, including attentional guidance toward the target as well as target identification (Ghorashi et al., 2010). Based on previous probability cueing studies, we would expect to see attentional bias toward HPLs as a result of learning (Y. V. Jiang et al., 2013, 2014). However, probability cueing might also lead to an object recognition benefit for objects appearing at HPLs. Previous object recognition research has shown objects appearing at typical locations lead to faster object recognition compared with objects appearing at atypical locations (Kaiser & Cichy, 2018a, 2018b; Kaiser et al., 2019; Kravitz et al., 2008). To confirm that our results are driven mainly by shifts in attentional processing, not shifts in object recognition, in Experiment 3, we included probe trials to examine early spatial attentional effects. On these probe trials, only a single dot probe was presented around placeholder boxes, which ensured to remove any object identification components. As the probes were presented randomly on a minority of trials, we expected participants would prepare to perform the visual search task after receiving the cue on each trial. If our results are driven by spatial attention toward the HPL, we would expect to find faster responses to the probes at the target-specific HPL compared to LPL. If instead the results are driven by facilitated object recognition at the target-specific HPL, we would expect to find faster RT at HPL on typical search trials and no difference between HPL and LPL locations on probe trials.

Method

Participants

Another group of 24 undergraduates ($M_{\text{age}} = 18.54, SD = 0.78$; 15 females, nine males) from Lehigh University participated in this experiment. All participants reported normal or corrected-to-normal

vision and normal color perception, and procedures were approved by Lehigh University IRB.

Stimuli

The stimuli were the same as Experiment 1.

Procedure

Participants received instructions about the search task first and practiced on 10 search trials. They then received instructions about the probe trials and completed an additional 10 trials of mixed search and probe trials. Participants then completed the experimental trials. The experimental session started with 130 search trials to facilitate the formation of object location associations. Then, there were 310 search trials intermixed with 204 probe trials. Search trials were matched to previous experiments, except for the following changes: First, cue presentation duration was reduced to 100 ms. Second, the delay period between cue display and search array display was increased to 500 ms. Probe trials started just like search trials (see Figure 2). However, after a delay of either 25, 250, or 500 ms, four gray placeholders were presented. A small dot was randomly displayed at one side of the placeholder at either the HPL or LPL of the cued item. Participants were asked to report whether the dot appeared at the left or right side of the nearest placeholder, and had a maximum of 3,000 ms to make their response. The probe dot appeared at HPL and LPL of the cued item with the same probability (50%). On probe trials, no object recognition was required. Therefore, if goal-specific probability cueing led to attentional bias to HPLs of cued objects, we expected to find faster RTs when probe dots appeared at HPLs of cued objects on probe trials. However, if the goal-specific probability cueing effect was driven by faster object recognition at HPLs, we should find no difference in RT between HPL and LPL on probe trials, while still showing a significant difference on typical visual search trials.

Results and Discussion

Trials with an incorrect response (2.8% of search trials, 4.8% of probe trials) were excluded from RT analysis. Additionally, trials with an RT less than 200 ms or greater than 2.5 deviations above the individual mean (0.2% of search trials, 0.1% of probe trials) were excluded from all analyses.

Search Trial Accuracy

Replicating Experiments 1 and 2, significant higher mean accuracy was found at HPLs (96.7%) compared to LPLs (95.9%), $t(23) = 7.39, p < .001, d = 1.51$.

Search Trial RT

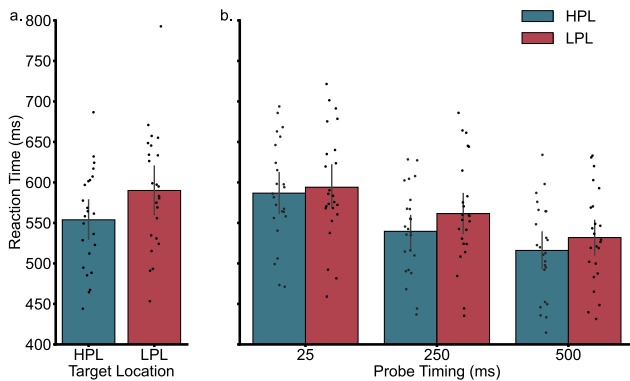
Mean RT was faster when targets appeared at HPLs (553.86 ms) compared to LPLs (590.06 ms; Figure 5a), $t(23) = -6.52, p < .001, d = 1.33$.

Probe Trial Accuracy

A repeated-measures ANOVA with factors of probe time (25, 250, and 500 ms) and probe locations (HPLs and LPLs) was conducted on accuracy from probe trials. Accuracies were higher when probe

Figure 5

Goal-Specific Probability Cueing Led to Attentional Benefits at HPLs Over LPLs



Note. Mean RTs in search trials at HPLs, LPLs of Experiment 3 (a). Mean RTs in probe trials at varied probe timing (b). Error bars indicate 95% confidence interval. HPL = high-probability location; LPL = low-probability location. See the online article for the color version of the figure.

dot appeared at HPLs of the cued item compared with LPLs, $F(1, 23) = 4.78$, $p = .040$, $\eta_p^2 = 0.17$. No other significant effects were found (Table 1).

Probe Trial RT

As expected, mean RT was faster when probe dot appeared at HPLs (547.48 ms) compared with LPLs (562.53 ms; Figure 5b), $F(1, 23) = 22.07$, $p < .001$, $\eta_p^2 = 0.14$. Mean RT linearly decreased from the 25-ms condition (590.44 ms) to the 250-ms condition (550.59 ms), and from the 250-ms condition to the 500-ms condition (523.99 ms), leading to a main effect of probe time, $F(2, 46) = 90.47$, $p < .001$, $\eta_p^2 = 0.80$. No significant interaction was found. To examine the time course of the attentional bias effect, we ran paired t -tests to directly compare RTs at HPLs with LPLs for varied probe time. Mean RT was significantly faster at HPLs compared with LPLs when probe dot appeared 250 or 500 ms following the cue presentation, 250 ms, $t(23) = -4.40$, $p < .001$, $d = 0.90$; 500 ms, $t(23) = -4.00$, $p = .001$, $d = 0.82$. No significant difference was found between the locations when probed at 25 ms, $t(23) = -1.17$, $p = .266$.

Our results revealed an attentional bias effect of goal-specific probability cueing by showing faster probe detection at HPLs of cued objects compared to LPLs. Additionally, such an attentional bias was only found when probe dots appeared 250 or 500 ms

following the cue presentation, suggesting that spatial priorities from goal-specific probability cueing take some time to be set up.

Experiment 4

Experiments 1–3 demonstrated the goal-specific probability cueing effect under a relatively simple task setting where each potential target appeared at only two locations. In the real world, spatial distributions of objects can be much more complex. Objects might appear at multiple locations with different probabilities. Therefore, it remains unclear whether the goal-specific probability cueing would also occur for more complex spatial distributions. Here, we examine spatial priority spread across all four locations. While this does not begin to replicate the complexity of real-world search, it takes a step toward the higher complexity in real scenes. Recent studies suggested that spatial priority maps including priorities of multiple locations can be created via reward learning (Chelazzi et al., 2014). Here we examine whether complex spatial priority maps can be created as well via goal-specific probability cueing.

Previous statistical learning studies suggested that regularities in the environment were learned implicitly (Turk-Browne et al., 2005, 2009), suggesting statistical learning could influence attention even when participants were unaware of the learning. To address the question of whether the goal-specific probability cueing influences attention implicitly or explicitly, we added an awareness test at the end of the search task, in which participants were asked to indicate the HPL and LPL for each target object.

Method

Participants

Another group of 24 undergraduates ($M_{\text{age}} = 18.70$, $SD = 0.86$, 15 females, nine males) from Lehigh University participated in this experiment. All participants reported normal or corrected-to-normal vision and normal color perception.

Stimuli

The stimuli were the same as Experiment 1.

Procedure

The experimental procedure was similar to Experiment 1, except for the following changes. Firstly, in the current experiment, targets were unevenly distributed at four locations. For each potential target, one location was associated with high probability (40%; HPL), another was associated with low probability (10%; LPL); and the remaining two locations were associated with medium probability (25%; medium probable locations, MPLs). HPLs and LPLs were counterbalanced, so overall targets were evenly distributed. Participants completed 720 search trials in the experimental block. After the search task, participants completed an awareness test, in which they were asked to indicate the HPL and LPL of each target.

Results and Discussion

Trials with an incorrect response (5.0%) were excluded from RT analysis. Additionally, trials with an RT less than 200 ms or greater than 2.5 deviations above the individual mean (2.3% of trials) were excluded from all analyses.

Table 1

Accuracy and RT From Probe Trials in Experiment 3

Probe time	25 ms	250 ms	500 ms
HPL accuracy	96.9%	95.8%	95.5%
HPL RT	586.78 ms	539.60 ms	516.03 ms
LPL accuracy	95.3%	94.3%	93.6%
LPL RT	594.10 ms	561.55 ms	531.95 ms

Note. HPL = high-probability location; LPL = low-probability location; RT = reaction time.

Accuracy

A repeated-measures ANOVA with a factor of target location (HPL, MPL, and LPL) was conducted. A significant main effect was found, $F(2, 46) = 27.69$, $p < .001$, $\eta_p^2 = 0.55$. Accuracy was higher at HPLs (96.4%) compared with MPLs (95.8%), $t(23) = 8.74$, $p < .001$, $d = 1.78$, or LPLs (95.6%), $t(23) = 7.72$, $p < .001$, $d = 1.58$. No significant difference was found between MPLs and LPLs, $t(23) = 1.32$, $p = .489$.

RT

As shown in Figure 6, RTs linearly decreased as target probability at a location increased. A repeated-measures ANOVA revealed a significant main effect of target location, $F(2, 46) = 28.62$, $p < .001$, $\eta_p^2 = 0.55$. RTs were faster when targets appeared at HPLs (596.85 ms) compared with MPLs (610.33 ms) and LPLs (630.53 ms), $t(23) = -4.82$, $p < .001$, $d = 0.98$; $t(23) = -6.67$, $p < .001$, $d = 1.36$. RTs were faster when targets appeared at MPLs compared with LPLs, $t(23) = -3.90$, $p = .002$, $d = 0.79$.

Awareness Test

Twelve out of 24 participants achieved an accuracy higher than the chance level (0.25) in the awareness test. However, only one participant correctly identified HPLs and LPLs of all four targets. To determine whether awareness of the spatial distribution of targets is required in the goal-specific probability cueing, we separated our data on target objects into two sets based on whether participants successfully identified the HPL and LPL of a target. If participants failed to indicate the HPL and the LPL of a target object, we took this to mean that participants were unaware of that object's spatial distribution. RT data were then averaged for the two target sets (Aware, Unaware) at three locations (HPL, MPL, and LPL). Among our participants, 17 were aware of some objects' distribution but were unaware of other objects' distributions. We utilized the data from

these 17 individuals to determine if awareness of the spatial distributions were necessary for the goal-specific probability cueing effect. A repeated-measures ANOVA was conducted with factors of target location (HPL, MPL, and LPL) and awareness (Aware, Unaware). A significant main effect of target location was found, $F(2, 32) = 30.73$, $p < .001$, $\eta_p^2 = 0.66$. More importantly, neither the main effect of awareness nor the interaction was found, $F(2, 32) = 0.06$, $p = .816$; $F(2, 32) = 0.06$, $p = .944$. This suggested awareness did not modulate the goal-specific probability cueing effect.

To further confirm the probability cueing effect was present when learning was implicit, we ran paired t -tests to directly compare RTs at different locations only for the unaware data. Utilizing only this data based on implicit learning (Figure 6b), RTs were faster when targets appeared at HPLs (587.82 ms) compared with MPLs (601.49 ms) and LPLs (619.12 ms), HPL–MPL: $t(16) = -2.16$, $p = .046$, $d = 0.52$; HPL–LPL: $t(16) = -3.04$, $p = .008$, $d = 0.74$. RTs were faster when targets appeared at MPLs than LPLs, $t(16) = -2.28$, $p = .031$, $d = 0.55$. These results provided additional support that the goal-specific probability cueing effect is based on implicit learning.

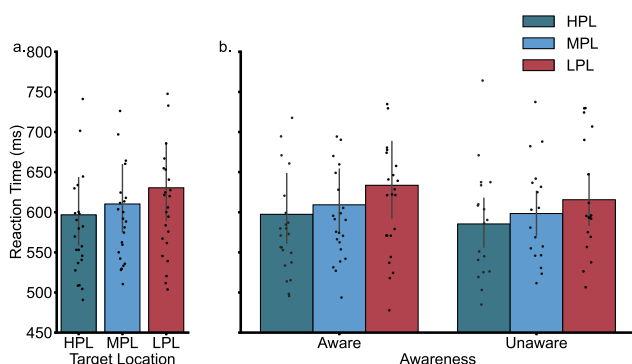
In line with the spatial priority literature (Chelazzi et al., 2014), we found RTs linearly decreased as the probability of encountering the target object at one location increased, which suggests that participants could create complex spatial priority maps including priorities of multiple locations based on goal-specific probability cueing. Consistent with previous statistical learning studies (Turk-Browne et al., 2005, 2009), we demonstrated the goal-specific probability cueing could be driven through implicit learning by showing a similar RT pattern with unaware objects only.

Experiment 5

While the previous studies are in line with the predictions of the goal-specific probability cueing hypothesis, it is also possible that our results could be driven by a simple associative learning process between the image cue and the high probability spatial location.¹ In this way, the cue item could be activating two separate cognitive processes simultaneously. First, it could be leading to the creation of a target template, utilizing attentional control. Second, it could be serving as a discriminative stimulus and activating an associated spatial priority map. Association between cues and spatial attention have been demonstrated previously in the auditory domain (Gabay et al., 2015; Zimmermann et al., 2017), and a similar process has been shown in scene-based contextual cuing (Brockmole et al., 2006; Wasserman et al., 2014). These two independent processes could be occurring, without any direct linkage between the target template and the spatial bias.

To address the possibility that the results of our prior experiments may be due to associative learning between the cue image and the spatial locations, in Experiment 5, we created a new testing block. In this testing block, participants were given a new search target, which they needed to find on each trial to make their response. The same item cues that had previously been associated with a HPL and LPL during the learning block were presented prior to each trial. If our results were driven by an association formed between the cued item and a spatial location, we would expect to

Figure 6
Sophisticated Representations of Target Likelihood Can Be Activated By Goal-Specific Probability Cueing



Note. Mean RTs at HPLs, MPLs and LPLs from Experiment 4 (a). Mean RTs at HPLs, MPLs, and LPLs for aware and unaware targets from Experiment 4 (b). Error bars indicate 95% confidence interval. HPL = high-probability location; LPL = low-probability location; MPL = medium probable location. See the online article for the color version of the figure.

¹ We would like to thank Dr. Doug Addelman and an anonymous reviewer for pointing out this possibility during the review process.

see a significant RT advantage for the PHPL compared to the PLPL in the testing block, as we saw in Experiment 2. However, if our effects are dependent on the search goal, and the activation of a target template, as proposed by the goal-specific probability cueing hypothesis, we would expect no difference in RTs between the PHPL and PLPL stimuli because the participants are utilizing a new target template.

Method

Participants

Another group of 24 undergraduates ($M_{\text{age}} = 19.40$, $SD = 1.14$, 11 females, 13 males) from Lehigh University participated in this experiment. All participants reported normal or corrected-to-normal vision and normal color perception.

Stimuli

The stimuli were the same as Experiment 2, with the exception of the testing block. In the testing block, participants were assigned a new target goal item that remained the same across the entire testing block. The trial sequence presentation was matched to the learning block, including one of the previously learned cues prior to the onset of the search array. In the search array, the test block target item was presented on each trial, along with three other randomly selected distractors. No items matching the cues appeared in the search arrays.

Procedure

The experimental procedure was similar to Experiment 2, except for the following changes. The practice and learning blocks were matched to Experiment 2, except all target items were associated with spatial bias during the learning block (e.g. there were no control target items). Prior to the testing block, participants received instructions on the screen indicating the task in the testing block was different than the prior trials. The instructions indicated that on each trial their new task was to find a novel target object, which was pictured below the written instructions. Participants needed to memorize this new target item for the upcoming search, as it was not presented again. Participants immediately began the testing block after receiving this information. In the testing block, image cues were still presented prior to search arrays, but those cue images became task-irrelevant. The new target item was equally likely to appear at the four locations during the testing block. That means, the target object could appear at the HPL or the LPL of the cued object, or other locations (control locations).

Results and Discussion

Trials with an incorrect response (5.5%) were excluded from RT analysis. Additionally, trials with an RT less than 200 ms or greater than 2.5 deviations above the individual mean (3.0% of trials) were excluded from all analyses.

Learning Block Accuracy

Significant higher mean accuracy was found when targets appeared at HPLs (95.0%) compared to LPLs (93.3%), $t(23) = 8.70$, $p < .001$, $d = 1.81$.

Learning Block RT

As shown in the Figure 7a, mean RT was faster when targets appeared at HPLs (593.96 ms, 95% CI [439.21–953.82 ms]) compared to LPLs (641.67 ms, 95% CI [488.39–967.00 ms]), $t(23) = 7.14$, $p < .001$, $d = 1.49$.

Testing Block Accuracy

Accuracy was 1% higher when targets appeared at PHPLs of cued images (93.2%) compared to PLPLs of cued images (92.2%), which was a significant difference, $t(23) = 6.99$, $p < .001$, $d = 1.46$. A repeated-measures ANOVA was conducted to compare accuracy among PHPLs, PLPLs, and control locations. A main effect was found, $F(2, 46) = 30.98$, $p < .001$, $\eta_p^2 = 0.57$. Accuracy at PHPLs of cued images was higher than control locations (92.9%), $t(23) = 2.68$, $p = .013$, $d = 0.56$. Accuracy at control locations were higher than PLPLs of cued images, $t(23) = 5.21$, $p < .001$, $d = 1.09$.

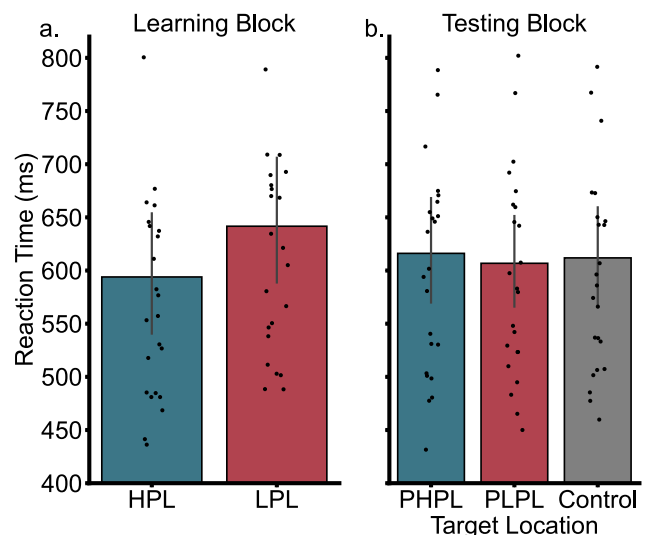
Testing Block RT

A repeated-measures ANOVA was conducted to compare RTs among PHPLs of cued images, PLPLs of cued images, and control locations (Figure 7b; PHPLs, 616.15 ms, 95% CI [457.98–877.85 ms]; control, 611.89 ms, 95% CI [469.95–872.95 ms]; PLPLs, 606.81 ms, 95% CI [458.77–834.65 ms]), no significant main effect was found, $F(2, 46) = 0.66$, $p = .520$, indicating there were no differences in RTs between target locations.

Our results are consistent with the goal-specific probability cueing effect. When the goal was changed in the testing block and cued

Figure 7

Assessing Learned Spatial Priorities Requires Activations of Attentional Templates



Note. Mean RTs at HPLs, LPLs in the learning block of Experiment 5 (a). Mean RTs at PHPLs, PLPLs of cued images, and two control conditions in the testing block of Experiment 5 (b). Error bars indicate 95% confidence interval. HPL = high-probability location; LPL = low-probability location; PHPL = previous high-probability location; PLPL = previous low-probability location. See the online article for the color version of the figure.

images became irrelevant to the task, the RTs were equivalent between the PHPL and PLPL locations of cued images. If the previous effects had been driven by a simple associative learning process between the cue item itself and the spatial location, we should have observed faster RTs at PHPLs, as the cues were still presented on each trial. We did find evidence of an associative learning effect in accuracy during the testing block, where accuracy was 1.0% higher at the PHPL than the PLPLs of cued images. While this difference was small, it was significant. The RT results demonstrate that the activation of the spatial priority maps depends on the activation of the search target, not merely the presentation of the cue item.

General Discussion

In this study, we aimed to test the *goal-specific probability cueing* hypothesis, which proposes that specific explicit top-down search goals can unlock distinct implicitly learned spatial biases learned through probability cueing. Experiment 1 provided preliminary evidence for the hypothesis by showing that participants were faster to respond to a target presented at a HPL specific to that target. Experiment 2 ruled out an intertrial priming alternative explanation, instead supporting the idea that goal-specific probability cueing relied on a statistical learning mechanism. Experiment 3 ensured the results were driven by attentional benefits at the HPL, not benefits due to faster object identification at HPLs. Finally, Experiment 4 demonstrated participants could create complex target-specific spatial priority maps including priorities of multiple locations for each of the targets. In addition, Experiment 4 revealed the goal-specific probability cueing was implicit. Finally, Experiment 5 demonstrated that when the goal to search for the cued item was removed in the testing block, the learned spatial biases effects on RT were also removed. This demonstrates that the spatial biases are linked directly to the attentional template. Together, our research shows our explicit search goals can unlock implicitly learned spatial biases on a trial-by-trial basis, demonstrating a previously unrecognized flexibility in location probability cueing.

Our findings have significant implications for spatial statistical learning. Probability cueing literature provides a clear demonstration of how spatial biases develop quickly through statistical learning within an experimental session (Y. V. Jiang, 2018; Y. V. Jiang et al., 2013, 2014). In prior experiments, participants had a consistent search goal, and an emphasis has been placed on the stability and persistence of the spatial biases, connecting the bias to a habit formed over time (Y. V. Jiang, 2018). However, in real-life search, goals change frequently as we move through our day. The stable, persistent spatial bias emphasized by prior work on probability cueing would only benefit searches for one goal, whereas it could interfere with performance when search goals change. In contrast, the goal-specific probability cueing effect demonstrated in this study addresses this issue by allowing different goals to activate separate spatial priority maps. This leverages the benefits of statistical learning as well as the flexibility of goal-directed behavior. In sum, the goal-specific probability cueing effect provided evidence for a flexible spatial statistical learning mechanism that would be more likely to benefit search in complex and rapidly changing visual environments encountered in daily life.

The mechanism of goal-specific probability cueing is related to the concept of *conditional automaticity* (Bargh, 1989). While selection history effects like probability cueing are generally considered

to be implicit and automatic, not dependent on top-down control (Y. V. Jiang & Sisk, 2019), this leads to a limitation in the effects are also inflexible. However, conditional automaticity, in this case a goal-dependent automaticity, allows for more flexibility. Here, the automatic process occurs, but only under a specific set of conditions, in our case, when a specific goal is activated. Thus, the process of spatial probability cueing may continue to be habit-like (Y. V. Jiang & Sisk, 2019), but the habit is conditional on the specific search target. This type of trial-by-trial spatial cueing implicitly learned location can also be seen in the phenomenon of contextual cueing. In contextual cueing, the spatial arrangement of distractor items serves as the contextual information used to retrieve spatial priorities which influence attention (Chun, 2000; Chun & Jiang, 1998; Chun & Nakayama, 2000). However, note that in contextual cueing it is the search array itself, which activates a particular spatial bias, whereas in goal-specific probability cueing the activation of the target template leads to the generation of spatial biases prior to the onset of the search array as indicated by the attentional probes in Experiment 3. Effects of context have also been identified in some studies on probability cueing, which seems to depend on the task relevance of contextual information (Hong et al., 2020; Y. Jiang & Leung, 2005; but see Vadillo et al., 2020). Responses to targets at the learned location are speeded after learning these spatial priorities. Our studies demonstrated that search goals could function similarly as contextual information.

Effects of goal-specific probability cueing are likely implemented through dynamic shifts in spatial priority maps. Spatial priority maps are neural representations of the relative salience of locations in the visual field that determine the spatial allocation of attentional resources (Ferrante et al., 2018; Y. V. Jiang 2018; Theeuwes, 2019; Todd & Manaligod, 2018). Consistent with previous research, our studies have shown that spatial priority maps can be altered through learning (Chelazzi et al., 2014; De Groot et al., 2016; Ferrante et al., 2018). Additionally, our studies examined the dynamic nature of spatial priority maps by showing learned spatial priority maps can be selectively prioritized based on search goals. This dynamic characteristic of spatial priority maps is consistent with the priority state space framework, which proposed that spatial priority maps should be quickly updated to the current goal (Todd & Manaligod, 2018). Relating our findings to the priority state space framework, we proposed a goal-specific spatial priority framework. We argued that when certain goal information is prioritized in the attention system, its associated spatial priorities maps would be retrieved and fed into the spatial priority framework (see Figure 1).

In addition to the importance of goal-specific probability cueing for our understanding of selection history, this finding also has interesting implications for our understanding of the concept of attentional templates utilized in top-down control. Many theories of attentional control suggest attentional templates are held in WM (Bundesen, 1990; Desimone & Duncan, 1995). Attentional theories like guided search (Wolfe, 2021) suggest our search for a target depends on increasing the weight of target-defining features in specific priority maps. However, goal-specific probability cueing highlights that attention is guided not just by the currently activated information in WM, but also associated information held in long-term memory. This suggests a broader vision of what constitutes an attentional template may be necessary (Moore et al., 2003; Olivers, 2011). The connection between object identity and location may be a particularly powerful type of association, as previous

findings indicate object feature and location information were typically bound during encoding (De Groot et al., 2016; Kaiser & Cichy, 2018a). For example, in visual prime paradigms, the prime effect was reduced when the positions of prime components slightly changed, indicating object representation involved in the prime effect may be positional dependent (Bar & Biederman, 1998; Newell et al., 2005). Previous findings also support the idea that object identity information cues lead to retrieval of the location information of the object (Ferreira et al., 2008; Richardson et al., 2009). People frequently made eye movements to locations where the target objects previously appeared, even when target location information was irrelevant, suggesting a strong binding between objects and spatial information in the memory system, which can influence attention (Altmann, 2004; Richardson & Kirkham, 2004). In addition, behavioral and eye tracking studies demonstrated that objects appearing at their typical locations (shoes on the floor) in scenes can be located faster compared with objects appear at atypical locations (Henderson et al., 1999, 2009; Malcolm & Henderson, 2010; Spotorno et al., 2014), suggesting a coordination between object identity and location information in guiding attention. Taking these findings into account, the goal-specific probability cueing likely relies on close interactions between object feature information and location information during both memory encoding and retrieval (Kaiser et al., 2019; Kravitz et al., 2008). Our work suggests a more accurate view of attentional templates should include not only on currently activated information in WM (Carlisle et al., 2011; Desimone & Duncan, 1995), but also on the activation of associated information in long-term memory (Moores et al., 2003; Olivers, 2011).

The associations utilized during goal-specific probability cueing show a sophisticated coordination of attentional processes that are considered distinct. First, the effect depends on a tight coordination of top-down attention and selection history, which are typically described as independent drivers of attention (Awh et al., 2012; Y. V. Jiang, 2018; Theeuwes, 2019), although growing work has begun to explore potential interactions among them (Awh et al., 2012; Y. V. Jiang 2018; Theeuwes, 2019; Todd & Manaligod, 2018). Second, our results highlight a close coordination between feature-based attention and spatial attention. Feature-based attention and spatial attention differ in terms of efficacy (Baldassi & Verghese, 2005; Liu et al., 2007; Shih & Sperling, 1996), time course (Andersen et al., 2011; Hayden & Gallant, 2005; Liu et al., 2007), and brain mechanisms (Cohen & Maunsell, 2011; Giesbrecht et al., 2003; Patzwahl & Treue, 2009). In feature attention research, participants were typically cued with target features to find a predefined target (Cave & Wolfe, 1990; Treisman, 1985; Treisman & Gelade, 1980; Wolfe, 1994, 2007; Wolfe et al., 1989), whereas in spatial attention literature, participants usually have the target location information only and use that information to find the target (Y. V. Jiang et al., 2013, 2014; Posner, 1980; Posner et al., 1980). Our results imply a tight coordination between feature attention and spatial attention, which is driven by learned associations (see also Altmann, 2004; De Groot et al., 2016; Ferreira et al., 2008; Kaiser & Cichy, 2018a; Richardson et al., 2009; Richardson & Kirkham, 2004).

While the research presented in this study establishes the goal-specific probability cueing effect, there are many questions that remain unanswered. Future work should explore the circumstances necessary for goal-specific probability cueing to be learned, the

generalization of the learned spatial biases across categories, as well as the specific mechanisms underlying the activation of spatial biases from specific target goals.

Conclusions

Our work provides the first evidence of a goal-specific probability cueing effect, showing that explicit search goals can unlock implicit probability cueing. We feel that the findings of the current paper advance our understanding of visual search in two compelling ways: First, the idea that the target template is not just a currently activated representation in WM (as proposed by multiple major theories of attention), but also activates associated spatial information gained through implicit statistical learning provides an important advance in our understanding of what constitutes the attentional template. Second, this work is important to the probability cueing literature, as it shows that although implicitly learned biases may be persistent and inflexible in certain contexts, our goals can flexibly activate these biases and may be a critical determinant of *when* implicitly learned information is utilized in task performance. This goal-specific probability cueing effect demonstrates attentional control can rely on a close coordination between aspects of cognition that are typically described as distinct: top-down control and selection history, feature-based attention and spatial attention, WM and long-term memory, and explicit and implicit memory. Our results suggest attentional templates are complex and driven by many cognitive systems.

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