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# Proactive Enhancement and Suppression Elicited by Statistical Regularities in Visual Search

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The present study investigated how attentional selection is affected by simultaneous statistical learning of target and distractor regularities. Participants performed an additional singleton task in which the target singleton was presented more often in one location while the distractor singleton was presented more often in another location. On some trials, instead of the search task, participants performed a probe task, in which they had to detect the offset of a probe dot. This probe task made it possible to take a peek at the proactive selection priorities just at the moment the search display was presented. The results show that observers learn the regularities present in the search display such the location that is most likely to contain the target is enhanced while the location that is most likely to contain a distractor is suppressed. We show that these contingencies can be learned simultaneously resulting in optimal selection priorities. The probe task shows that both spatial enhancement and spatial suppression are present at the moment the actual search display is presented, indicating that the attentional priority settings are proactively modulated. We claim that through statistical learning the weights within the spatial priority map of selection are set in such a way that selection is optimally adapted to the implicitly learned regularities.

***Public Significance Statement***
Through statistical learning, we extract regularities present in the environment that allows us to optimize our search performance. An environment can be complex and have objects that are highly relevant and objects that need to be avoided. This study shows that we are able to extract these regularities and optimally adapt our search priorities even to such a complex environment. By means of an innovative task, the current study is able to provide a glimpse of the attentional priority settings at the moment the search display was presented.

*Keywords:* statistical learning, visual selection, proactive suppression, proactive enhancement, attention



To successfully navigate our environment, the selection and suppression of visual information is of central importance. The goal of visual selective attention is to focus processing resources on behaviorally relevant objects, and suppress objects that are irrelevant to us and can be distracting (Theeuwes, 2018, 2019). In daily live, we need to attend objects that are relevant for us while trying to ignore those objects that may distract us. For example, while driving through a busy street, we continuously look out for pedestrians that may want to cross the road while trying to ignore the flashing neon lights that are aimed to attract customers to the local stores. We basically search constantly, often for the same objects and often within the same (or similar) environments. People are very proficient in these types of search tasks because they have learned to expect particular objects to appear at particular locations within particular environments (Theeuwes, 2021). In addition to top–down and bottom–up control processes, recently it became clear that these learned expectations control attention much more than previously assumed (Awh et al., 2012; Failing & Theeuwes, 2018; Fiser & Aslin, 2002).

Recent studies have shown how regularities in the environment drive attentional selection. For example, it was shown that statistical regularities regarding the distractor location lead to faster target selection (Wang & Theeuwes, 2018a, 2018b, 2018c). Specifically, those studies used the additional singleton paradigm

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(Theeuwes, 1991, 1992) in which observers need to search for a unique shape singleton (i.e., the target) while ignoring a unique color singleton (i.e., the distractor). Critically, one of the eight locations was designed to contain the distractor more often than the other locations. The results showed that attentional capture by the distractor was diminished when the distractor was presented at the frequent distractor location (see also Ferrante et al., 2018; Goschy et al., 2014; Liesefeld & Müller, 2021; Reder et al., 2003; Sauter et al., 2018, 2019, 2021). Furthermore, target search was less efficient when the target was presented at this location (but see Goschy et al., 2014; Liesefeld & Müller, 2021; Sauter et al., 2018).

To explain these results, it was proposed that through statistical learning, the location that frequently contained the distractor became suppressed such that within the spatial priority map, the location competed less for attention than all other locations (Failing & Theeuwes, 2018; Ferrante et al., 2018; Theeuwes, 2018, 2019; Wang & Theeuwes, 2018a, 2018b, 2018c). Recent findings in the field of visual statistical learning have further suggested that the suppression of the frequent distractor location in the priority map is brought into force proactively, implying that it already occurs before display onset (Huang, Theeuwes, et al., 2021; Huang, Vilotijević, et al., 2021; Kong et al., 2020; Wang et al., 2019). For instance, using the additional singleton paradigm adapted for electroencephalogram (EEG) recording, Wang et al. (2019) found that the parieto-occipital alpha power contralateral to the frequent distractor location was persistently enhanced about 1,220 ms before the onset of the search display. Consistent with previous findings that have shown that the enhanced power in the alpha oscillation was closely related to the process of inhibition (Jensen & Mazaheri, 2010), these results imply that the suppression of the distractor location was applied proactively, before display onset (but see van Moorselaar et al., 2021).

Additional evidence for the proactive suppression was provided in a recent study conducted by Huang, Vilotijević, et al. (2021) who combined the classic additional singleton task with a probe task. In their study, observers were required to report the line orientation within a unique shape singleton in the presence of a color distractor singleton and six neutral singletons. To induce statistical learning, the distractor was presented more often in one of eight locations (the high-probability location) than in any of the other locations (the low-probability locations). Critically, on a subset of trials, the search display was replaced by a probe display where observers needed to detect the offset of a single dot. The probe dot offset occurred equally likely at each of eight locations that matched the spatial locations of the elements in the search display. Using a probe task in combination with the additional singleton task provided the opportunity to have a glimpse at the settings in the priority map at the moment of presentation of the search display. The results of the search task replicated the statistical learning effect, showing that search was more efficient when the distractor was presented at the high-probability location. Crucially, the results from the probe task showed that probe offset detection was significantly slower at the high-probability location compared with the low-probability locations, suggesting that the high-probability location was proactively suppressed within the priority map.

Note that the research questions with regard to distractor suppression and the underlying theoretical perspectives in these studies are quite distinct from an extant line of research where distractor suppression has been intensively studied (Chang & Egeth, 2019; Gaspelin et al., 2015; Gaspelin & Luck, 2018a, 2018b, 2018c; Kim & Cave, 1999; Sawaki & Luck, 2010; Stilwell & Gaspelin, 2021). For instance, a seminal work from that line of research (Gaspelin et al., 2015) used a letter-probe technique to show that the most salient element (i.e., distractor) in the search display was actively suppressed below baseline levels of processing. One substantial difference is that this type of distractor suppression is feature-based and could only be observed when the feature search mode is favored over the singleton detection mode (Bacon & Egeth, 1994). In contrast, distractor suppression induced by statistical learning is mostly space-based and is obtained not only in the feature search mode but also in the singleton detection mode (van Moorselaar et al., 2020, 2021; Wang & Theeuwes, 2018c). Furthermore, dissimilar to the line of work that aims to resolve the long-term debate between goal-driven and stimulus-driven theories, these studies were concerned with distractor suppression in the framework of selection history, which is recently suggested as the third mode of attentional control (Awh et al., 2012; Theeuwes, 2019).

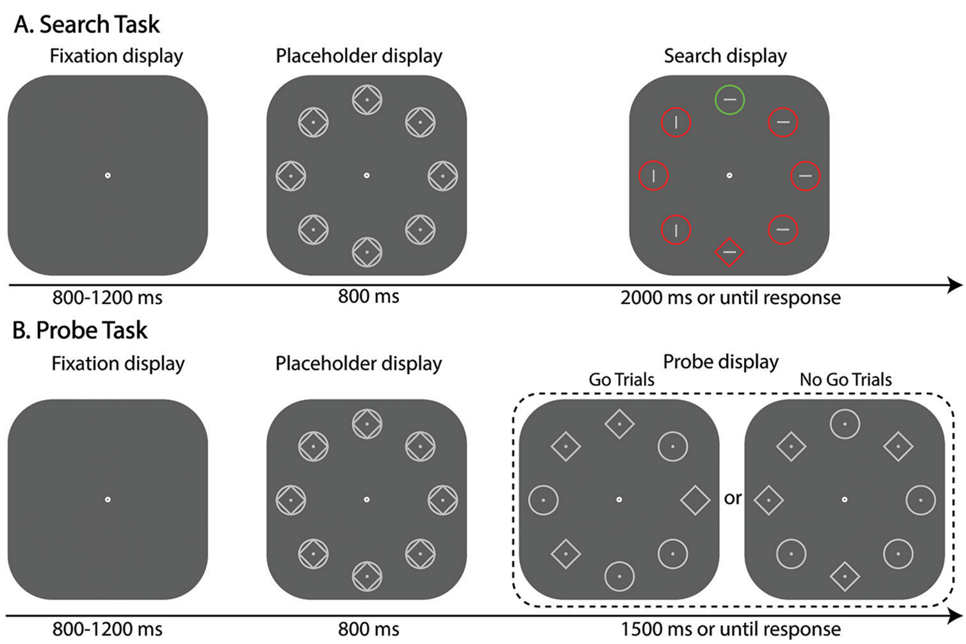
Statistical learning does not only occur in the presence of regularities regarding the distractor location but also in the presence of regularities regarding the target location. Contextual cuing is one of the well-known examples, which shows that visual search is more efficient by repeatedly presenting a target in the same context (Chun & Jiang, 1998, 1999). Specifically, this line of research has shown that search for a target is facilitated when it appears in a visual layout that was previously searched relative to visual layouts that were never seen before (Chun & Jiang, 1998, 1999). Other studies on target-related statistical learning revealed a substantial benefit for target detection when the target was presented at a high-probability compared with a low-probability location (Geng & Behrmann, 2002, 2005). Yet, the underlying mechanism of how regularities in the location of a target lead to statistical learning is less well understood.

The question is whether the effects of target regularities can also be explained on the basis of proactive modulation of the priority map. It is probable that target facilitation might, like distractor inhibition, operate proactively by modulating the activity in the priority map at the moment of the display onset. Indeed, in a study conducted by Ferrante et al. (2018), it was found that the high-probability target location did not only increase search efficiency when a target was presented at this location but also induced stronger attentional capture when a distractor occurred at this location. Moreover, Ferrante et al. (2018) also found a correlation between performance in trials in which the target was presented at the high-probability target location and performance in trials in which the distractor was presented at this location, suggesting that the effect of target regularities rely on the same mechanism as the effect of distractor regularities. However, in this study there was no direct assessment of whether the variations in performance as a result of the target regularity were due to proactive changes in the priority map as performance at the moment of the display onset was not determined. Moreover, several studies argued that target facilitation might rely on entirely different processes (Kabata & Matsumoto, 2012; Walthew & Gilchrist, 2006; but see Goschy et al., 2014; Jones & Kaschak, 2012). For instance, it has been claimed that target facilitation induced by statistical learning can be explained in terms of lingering effects of intertrial location priming, as the statistical learning effect was no longer found once the repetitions of the target location between consecutive trials were controlled (Kabata & Matsumoto, 2012; Walthew & Gilchrist, 2006). Furthermore, many studies have shown dissociative electrophysiological correlates between target selection (indexed by the N2pc component) and distractor filtering (indexed by the Pd component), suggested that these two processes might indeed rely on entirely different mechanisms (Gaspelin & Luck, 2018c; Hickey et al., 2009; van Moorselaar et al., 2020; Wang et al., 2019).

The present study was designed to determine whether statistical regularities regarding the target would induce proactive changes in the priority map. In the current study, our dot-probe technique reveals how different spatial locations are prioritized or deprioritized for attentional resources at the moment of the presentation of the search display. Therefore, the term "proactive" refers to enhancement or suppression at the moment the search display is presented. The dot-probe technique is functionally similar to the letter-probe technique (Gaspelin et al., 2015; Gaspelin & Luck, 2018b, 2018a) with the same aim of uncovering the spatial distribution of attentional resources. However, it is important to realize that these probe techniques are quite different and suit different research questions. The letter-probe is typically superimposed on the actual search array consisting of a target, a distractor and several nontarget elements. This can reveal how attentional resources are allocated to the location and features of the target, of the distractor and of other nontarget elements. In the current experiment the dot-probe is presented independently of the search array (see Figure 1) to uncover how attentional resources are prioritized in space (i.e., spatial based). In fact, in probe trials, no search array is presented and as such feature-based activation or suppression does not come into play.

In the current study, we used a similar design as in our previous work (Huang, Vilotijević, et al., 2021). Participants searched for a unique shape singleton while ignoring a color distractor singleton. In Experiment 1, the target was more likely to appear at one specific location, the high-probability target location (HPTL), than at any other location. On a subset of trials, participants performed a probe detection task in which they needed to detect the offset of a single dot in a probe display. It is important to note that the probe display provides a snapshot of how attention is distributed at the moment the search display is presented. If, through statistical learning, the HPTL is enhanced within the priority map, at the moment of the presentation of the search display, attention should be proactively biased toward this location, leading to faster probe detection at the HPTL than at the other locations. In Experiments 2 and 3, we introduce spatial regularities regarding both the target and distractor. For simplicity, the location that contains the target and the location that contains a distractor more often we refer to as the HPTL and the high-probability distractor location (HPDL), respectively. The locations that are neither the HPTL nor the HPDL were referred to as the low-probability locations (LPL). We reasoned that if the underlying mechanism of target-related statistical learning is similar to that of distractor-related statistical

**Figure 1**
*Example of the Stimuli*




*Note.* (A) Example of consecutive displays presented in the search task. Participants were asked to search for the target shape singleton (either a diamond among circles or a circle among diamonds) in the presence of an irrelevant distractor color singleton (either a green shape among red shapes or a red shape among green shapes). (B) Example of consecutive displays presented in the probe task. Participants were asked to indicate the presence of a dot offset (Go trials) or refrain from responding (No-Go trials). See the online article for the color version of this figure.

learning, they should operate at the same priority map and provide attentional guidance simultaneously. That is, if within the same priority map, the HPTL is enhanced while the HPDL is suppressed, we expect to observe faster probe detection at the HPTL and slower detection performance at the HPDL, relative to the LPL.

## Experiment 1

In Experiment 1, we examined the effect of statistical learning regarding the target location. To this end, the target was presented more often in one location than in all other locations. We used a probe task to evaluate whether attention was proactively biased toward the HPTL.

### Method

#### *Participants*

A priori power analysis (using the *simr* package of Green & MacLeod, 2016) was done to determine the sample size. Based on the effect size ($\beta = 28.82$) reported in a previous experiment with similar measures (see Huang, Vilotijević, et al., 2021), we expected to find a mean RTs difference of 20 ms between the HPTL condition and the LPL condition. We took 20 ms as our effect size of interest and performed the power analysis using the data ($N = 60$) and the linear mixed model structure reported in Huang, Vilotijević, et al. (2021). This analysis indicated that a sample size of 60 participants would have a power of 79.7% (95% confidence interval, CI [77.07%, 82.15%] in 1,000 simulations) to detect a RT difference of 20 ms. Considering that Huang, Vilotijević, et al. (2021) were concerned with the effects of distractor location regularities while the current experiment investigates the effect of target location regularities, we chose to increase the sample size by 20%, yielding a desired sample size of 72 participants. Given that online studies are typically noisier than lab studies and yield some larger drop-outs, we recruited 88 students (71 females, $M_{\text{age}} = 20.5$, $SD_{\text{age}} = 4.1$) from the Vrije Universiteit Amsterdam via the SONA online platform. Participants either received course credits or got paid for their time. The experiment was approved by the Ethical Committee of the faculty of Behavioral and Movement Sciences of the Vrije Universiteit Amsterdam. Before the experiment, all participants gave informed consent in accordance with the Declaration of Helsinki.

#### *Stimuli and Task*

The experiment was created in OpenSesame (Mathôt et al., 2012) using OSweb, and run using JATOS (Lange et al., 2015). The experiment was run on PC devices. Item sizes and colors are reported in pixels (under the display resolution: 1024 × 768) and RGB values (red/green/blue). The experiment comprised a *search task* in two-thirds of the trials and a *probe task* in one-third of the trials. All stimuli were superimposed on a dark gray background (RGB: 94/94/94).

**Search Task.** The paradigm used was a version of the additional singleton task (Theeuwes, 1991, 1992). Each search trial began with a fixation dot display presented for an interval jittered between 800 and 1,200 ms, followed by a placeholder display for 800 ms. The fixation dot (18 × 18 px) remained on-screen throughout the search trial. The placeholder display consisted of eight equidistant elements (diamonds surrounded by circles) placed on an imaginary circle with a radius of 224 pixels around the central fixation dot. Each element was a light gray outline (92 × 92 px; RGB: 192/192/192) with a dot (10 × 10 px) in the center. Next, the search display was presented consisting of one shape singleton (the target), one color singleton (the distractor), and six other elements (see Figure 1A). Each element contained a gray line (36 × 4 px; RGB: 192/192/192) that was equally likely horizontally or vertically oriented. The target could either be a diamond (among circles) or a circle (among diamonds). The distractor was either colored red (among green elements) or green (among red elements). Note that the distractor was presented on each trial, which is different from the usual setting of the additional singleton task (Theeuwes, 1991, 1992; Wang & Theeuwes, 2018b). The shape of the target and the color of the distractor were randomly determined on each trial. One critical setting was that the target was more likely (61.5%) to be presented at one of the locations than at any of the remaining locations. The distractor was equally likely presented at each of the eight locations. The search display lasted for 2,000 ms or until a response was given. Participants were instructed to search for the target and indicate the line orientation within it as fast and accurately as possible by pressing either the “up” or “left” arrow key for vertical or horizontal orientations, respectively.

**Probe Task.** The probe task was similar to the search task except that the placeholder display was followed by a probe display for 1,500 ms or until response. The probe display consisted of four circles and four diamonds randomly distributed within the visual array. On 20% of all probe-task trials (No-Go trials), each shape contained a light gray dot in the middle, similar to the placeholder display. On 80% of all probe-trials (Go Trials), one dot was missing in the probe display, creating a probe offset at that location relative to the placeholder display. The probe offset occurred equally likely at each of the eight locations. Participants were instructed to press the “A” key as fast as possible in trials with a probe offset (Go Trials) and withhold a response in trials without (No-Go trials). Both accuracy and speed were emphasized in this task.

#### *Design and Procedure*

The entire experiment consisted of a practice phase followed by an experimental phase. During the practice phase, participants received written and iconic instructions with regard to the search task followed by the first practice block consisting of 50 search trials that were randomly selected from the full pool of experimental search trials. Next, participants received written and iconic instructions about the probe task after which the second practice block was presented. This block also consisted of 50 trials but included both search and probe trials that were randomly selected from the full pool of experimental trials.

The experimental phase consisted of 400 search trials and 200 probe trials. Among the search trials, the high-probability target location (HPTL, 61.5%) remained constant for each participant but was counterbalanced across participants. Distractor color (red or green), target shape (circle or diamond), and line orientation within the target singleton (horizontal or vertical) were randomly determined on each search trial. The probe trials comprised 40

No-Go and 160 Go trials in which probe offsets occurred equally often at each of the eight locations. The search trials and the probe trials were randomly intermixed with the following constraints: (a) two probe trials could not be presented in sequence; (b) the first experimental block always started with a search trial; and (c) the probe trials in which the offset occurred at the HPTL could never be preceded by search trials in which the target was presented at that same location. This last constraint was introduced to prevent intertrial location priming as previous studies showed that the repetition of a target position on consecutive trials leads to faster RTs and higher accuracy compared with a nonrepetition (Maljkovic & Nakayama, 1996; Walthew & Gilchrist, 2006). Note that this last constraint only applies to the HPTL. That is to say, it is still possible for the probe to appear at the exact location of the target in the previous trial if that location is not the HPTL. Subsequently, these trials were separated into five blocks of 120 trials each. During the experiment, auditory and visual feedback was provided for incorrect responses for 800 ms. Participants either received a 2700 Hz tone (square waveform) and a red fixation dot for the search trials or a 1700 Hz tone (square waveform) and a red fixation cross for the probe trials. A blank screen lasting for an interval jittered between 800 and 1,000 ms was provided as a punishment for incorrect responses on the probe trials. In addition to trial-based feedback, participants received average RTs and the percent correct (calculated across trials regardless of trial types) at the end of each block. After the experiment, participants' awareness regarding the statistical regularities of the target location was assessed. Participants were asked if they were aware that one location contained the target more often than any of the other locations, and indicate which location they thought contained the target more often (they had to specify this location regardless of whether they had indicated that they noticed the regularity).

### *Data Analysis*

Participants whose mean accuracy was below 70% or exceeded 2.5 *SD* of the overall mean accuracy for either the search task ($N = 6$) or the probe task ($N = 5$) were excluded. Participants whose mean RT (collapsed across conditions) exceeded ±2.5 *SD* of the overall mean RT for either the search task ($N = 2$) or the probe task ($N = 3$) were excluded. In total, 16 participants were excluded based on these predetermined exclusion criteria, leaving 72 participants for analysis. To check how the results were affected by the exclusion criteria, we reran all the analyses without excluding any participant. These analyses yielded the same results as those obtained after participant exclusion. Incorrect responses were excluded from RTs analysis, as were RTs shorter than 200 ms or exceeding ±2.5 *SD* of the overall mean RT.

The accuracy data were analyzed with generalized linear mixed models (GLMMs) and RTs were analyzed with linear mixed models (LMMs) using the *lme4* package (Bates et al., 2015) in R (R Core Team, 2020). We chose (G)LMMs over repeated analysis of variance (ANOVA) for the reason that the current study is an unbalanced design and that (G)LMMs are opt for handling unbalanced dataset. Moreover, this approach is known for the merits of utilizing the dataset at an observation level (i.e., trial) that provided us more power to find the true effect (Brysbaert & Stevens, 2018). For example, it is possible to control factors that are irrelevant to the hypotheses without losing power. For the search task, the factors of interest were target location, which comprised the HPTL and the low-probability locations (LPL). The accuracy data and RTs were analyzed separately with target location (HPTL, LPL) as a fixed effect. The influence of the target features was controlled by including line orientation (horizontal, vertical), shape (circle, diamond), and color (green, red) as fixed effects. To control for the specific location on the screen, the physical locations of the target (0∼7) and the distractor (0∼7) were entered as fixed effects. We also included target location priming (yes, no), distractor location priming (yes, no), probe-target location priming (yes, no), and probe-distractor location priming (yes, no) as fixed effects to control for intertrial location priming. Finally, the fixed-effect structure also incorporated target awareness (yes, no) to control for the impact of the awareness state. The random-effect structure was determined by running the maximal effect structure justified by the design (Barr et al., 2013). The random-effect structure for the accuracy data and RTs included by-participants random intercepts and by-participants random slopes for target location. Additional analyses were conducted to examine the indirect effect of the distractor location (i.e., when the distractor appeared in the HPTL and in the LPL). We build the LMMs and GLMMs for the analysis of RTs and accuracy data, respectively, with the same fixed effect structure describe above except that target location (HPTL, LPL) was replaced by distractor location (HPTL, LPL) as the fixed effect of interest. The random-effect structure for both models included by-participants random intercepts and by-participants random slopes for distractor location.

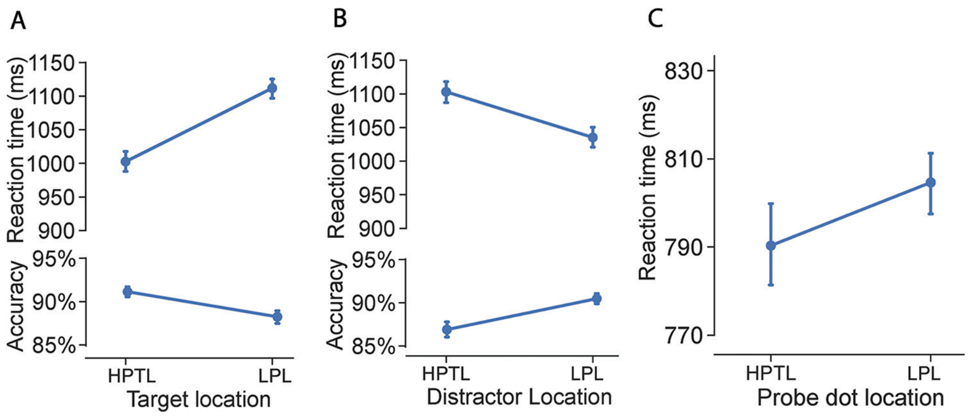
For the probe task, the factor of interest was the probe location that contained the HPTL, and the LPL. RTs were entered into the LMMs as a dependent variable with probe location (HPTL, LPL) as a fixed effect. The fixed-effect structure also included physical probe location (0∼7), target-probe location priming (yes, no), distractor-probe location priming (yes, no), and target awareness (yes, no). By-participants random intercepts and by-participants random slopes for probe location were included as random effects. All fixed effects were dummy coded. The degrees of freedom were estimated by Satterthwaite approximation and the *p*-values were obtained from the *lmerTest* package (Kuznetsova et al., 2017). The estimate (β) of each fixed effect of interest was provided as the measure of the effect size. One-tailed *p* values were calculated for the probe task as our hypotheses posited the specific direction of the effect.

## Results

### *Search Task*

Figure 2A and 2B show the mean RTs and mean accuracy as a function of target location (direct effect) and distractor location (indirect effect). The results of the mixed-effects models showed faster RTs ($\beta = 104.77$, $SE = 7.93$, $t(75) = 13.21$, $p < .001$) and a higher accuracy ($\beta = -.34$, $SE = .07$, $z = 4.76$, $p < .001$) when the target was presented at the HPTL compared with the LPLs (see Figure 2A), indicating that target search was facilitated when the target was presented at the HPTL. There was also an indirect effect of statistical learning: participants were slower ($\beta = -55.04$, $SE = 6.63$, $t(71.6) = 8.30$, $p < .001$) and less accurate ($\beta = .34$, $SE = .08$, $z = 4.20$, $p < .001$) when a distractor was presented at the

**Figure 2**
*Statistical Learning (SL) Effects in Experiments 1*




*Note*. (A) Mean RTs and accuracy in the search task when the target was presented at the high-probability target location (HPTL) or at a low probability location (LPL; direct effect of SL). (B) Mean RTs and accuracy in the search task when the distractor was presented at the HPTL or at a LPL (indirect effect of SL). (C) Mean RTs as a function of probe dot location (HPTL, LPL) in the probe task. Error bars denote $\pm 1$ $SE_{\text{mean}}$. See the online article for the color version of this figure.

HPTL than at the LPLs (see Figure 2B), suggesting a greater interference of the distractor when it was presented at the HPTL.

### *Probe Task*

The false alarm rate in the No-Go trials was 11.1% ($SD$ = .079), and the miss rates in the Go trials were 1.7% ($SD$ = .031) for the HPTL and 1.9% ($SD$ = .017) for the LPL. Figure 2C shows the mean reaction times in the probe task. Note that only the Go trials with correct responses were included in the RTs analysis. The LMMs analysis on RTs showed that the detection of probe offsets was faster at the HPTL than at the LPLs ($\beta$ = 12.67, $SE$ = 6.79, $t$(75) = 1.87, one-tailed $p$ = .033) suggesting that the HPTL was prioritized at the moment the search display came on.

### *Awareness Test*

Fifty-three out of 72 participants indicated that they were aware of the HPTL during the experiment. Fifty-one out of 53 participants who reported to be aware and 13 out of the 19 participants who reported to be unaware correctly indicated the HPTL. We then ran the model comparisons in the (G) LMMs by including or excluding the interaction between target awareness (yes, no) and target location (HPTL, LPL) in the search task (both for RTs and accuracy data) and the interaction between target awareness (yes, no) and probe location (HPTL, LPL) in the probe task. Participants were labeled as "yes" in the target awareness only if they claimed to be aware and correctly reported the HPTL. Planned-model comparisons in the RTs data showed that in the search task the interaction between awareness state and target location (HPTL, LPL) was significant ($\chi^2(1)$ = 4.15, $p$ = .042). Post hoc comparison showed that the effect of statistical learning (i.e., RTHPTL − $RT_{LPL}$) occurred in both the aware ($\beta$ = −114.8, $SE$ = 9.09, $t$(72.7) = 12.63, $p < .001$) and the unaware participants ($\beta$ = −80.1, $SE$ = 14.17, $t$(72.5) = 5.65, $p < .001$) but was stronger in the former group of participants ($\beta$ = 34.66, $SE$ = 16.73, $t$(71) = 2.07, $p$ = .042). Planned-model comparisons in the accuracy data in the search task and the RTs data in the probe task suggested that the model fit was not significantly improved by including awareness (all $p$s > .12).

## Discussion

Experiment 1 shows that during the search task, performance was better (i.e., faster RTs and higher accuracy rates) when the target was presented at the HPTL compared with when it was presented at any of the LPLs, suggesting that participants learned the spatial regularity regarding the target. In line with Ferrante et al. (2018), we also found an indirect effect of learning the target regularity as the distractor interfered more when it happened to be presented at the location that contained the target more often than at any of the other locations. The results of the probe task are consistent with these findings as probe detection performance was faster when the probe was presented at the HPTL than at the LPLs. This result indicates that the HPTL was enhanced, at the moment of the display onset, in a proactive fashion, providing evidence that the spatial priority map cannot only be proactively modulated through suppression, as shown by Huang, Vilotijević, et al. (2021) but also through enhancement. Yet, it remains unclear whether proactive enhancement as a result of a target location regularity and proactive suppression resulting from a distractor location regularity can operate simultaneously. To further investigate this question, we introduced an additional regularity regarding the distractor location in Experiment 2.

## Experiment 2

Experiment 2 investigated whether proactive suppression and proactive enhancement can operate simultaneously. To this end, we included spatial regularities regarding both the target and the distractor such that both the target and the distractor were more likely (61.6% probability) to appear in one of eight locations. If both regularities generate proactive guidance of attention simultaneously, we expect to find a faster detection of probes at the HPTL and a slower detection of probes at the HPDL relative to the LPLs.

## Method

### Participants

Ninety-four students (87 females, $M_{\text{age}} = 20.4$, $SD_{\text{age}} = 3.3$) were recruited from the Vrije Universiteit Amsterdam via the SONA online platform. Participants either received course credits or got paid for their time. The experiment was approved by the Ethical Committee of the faculty of Behavioral and Movement Sciences of the Vrije Universiteit Amsterdam. Before the experiment, all participants gave informed consent in accordance with the Declaration of Helsinki.

### Stimuli and Task

Stimuli and task were identical to those used in Experiments 1, except that both the distractor and the target were more likely (61.6% probability) to appear in one of eight locations with the constraint that both high-probability locations were at maximum distance from each other (i.e., opposite to each other). This resulted in two different statistical regularities: a spatial regularity regarding the target (HPTL = high-probability target location; LPL = low-probability location) and the distractor (HPDL = high-probability distractor location; LPL = low-probability location). The target and the distractor were equally likely to occur at each of the other positions including the other HP location. Note that the target was equally likely to be presented at any other location (including the HPDL) that is not the HPTL and the distractor was equally likely to be presented at any other location (including the HPTL) that is not the HPDL.

### Design and Procedure

The design and procedure were similar to those of Experiment 1 with the following exception: There were 401 trials in the search task that were randomly intermixed with 200 probe trials with the same constraints as in Experiment 1. These trials were then separated into four blocks of 120 trials each and one block of 121 trials. Among the search trials, the HPDL (61.6%) and the HPTL (61.6%) remained constant for each individual participant but were counterbalanced across participants. At the end of the experiment, the awareness of both the HPTL and the HPDL was assessed.

### Data Analysis

Participants whose mean accuracy was below 70% or exceeded 2.5 *SD* of the overall mean accuracy for either the search task ($N = 4$) or the probe task ($N = 17$) were excluded. Participants whose mean RT (collapsed across conditions) exceeded $\pm 2.5$ *SD* of the overall mean RT for either the search task ($N = 1$) or the probe task ($N = 0$) were excluded. In total, 22 participants were excluded based on these predetermined exclusion criteria, leaving 72 participants for analysis. We did all the analyses again without excluding any participants to check how the results were affected by the exclusion criteria. The rerun of all the analyses yielded similar results and all the findings remain unchanged. Different models were built to examine the direct effect and indirect effect in the search task. For the direct effect, the factors of interest were target location with HPTL = high-probability target location and LPL = low-probability location, and distractor location with HPDL = high-probability distractor location and LPL = low-probability location. Note that the LPL represents locations that were neither the HPTL nor the HPDL. These factors and their interaction were entered as the fixed effects for the analyses of the accuracy data and RTs. The random-effect structure for the accuracy data included by-participants random intercepts and by-participants random slopes for target location and distractor location. The random-effect structure for RTs included by-participants random intercepts and by-participants random slopes for target location, distractor location, and their interaction.

For the indirect effects, the factor of interest was either target location with HPDL and LPL, or distractor location with HPTL and LPL, which was entered as a fixed effect separately for the analyses of the accuracy data and RTs. The random-effect structure of the models for the accuracy data and RTs included by-participants random intercepts and by-participants random slopes for target location (for the model with target location as the fixed effect) or distractor location (for the model with distractor location as the fixed effect). In addition to the fixed effects mentioned above, all the models shared the same fixed-effect structure, including line orientation (horizontal, vertical), shape (circle, diamond), color (green, red), physical location of target (0∼7) and distractor (0∼7), target location priming (yes, no), distractor location priming (yes, no), probe-target location priming (yes, no), probe-distractor location priming (yes, no), target awareness (yes, no), and distractor awareness (yes, no). Participants were labeled as yes only if they claimed to be aware and reported the correct location of the HPTL (for target awareness) and the HPDL (for distractor awareness).

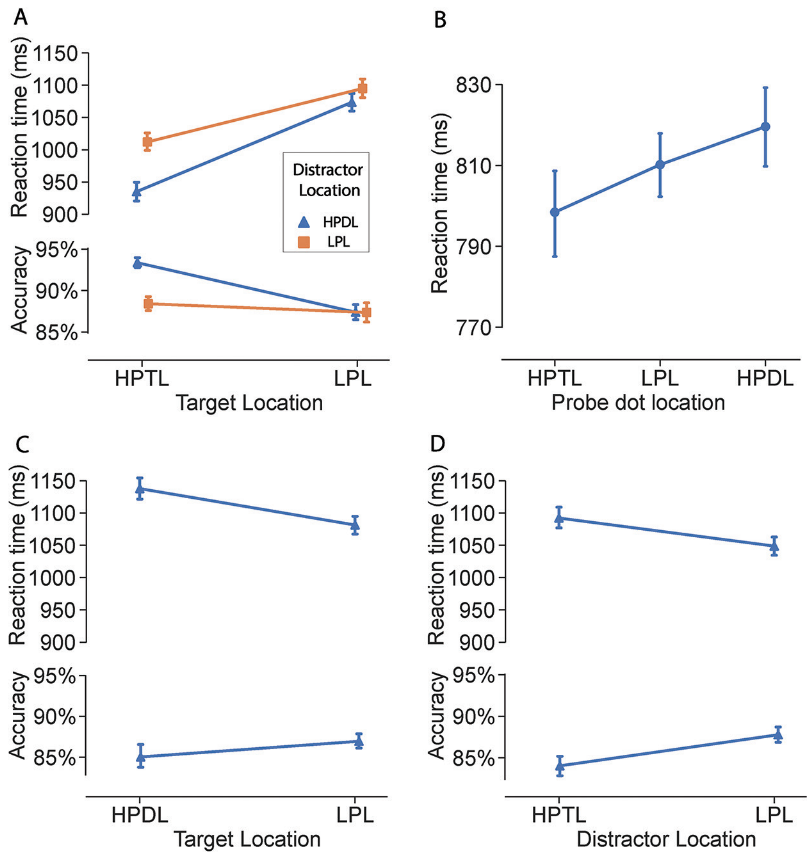
For the probe task, the factor of interest was the probe location that contained the HPTL, the HPDL, and the LPL. RTs were entered into the LMMs as a dependent variable with probe location (HPTL, HPDL, and LPL) as a fixed effect. The fixed-effect structure also included physical probe location (0∼7), target-probe location priming (yes, no), distractor-probe location priming (yes, no), target awareness (yes, no), and distractor awareness (yes, no). By-participants random intercepts and by-participants random slopes for probe location were included as random effects. All fixed effects were dummy coded. The Bonferroni correction was applied to control for Type I error rate in multiple comparisons.

## Results

### Search Task

Mean reaction times and mean accuracy as a function of target location (HPTL, LPL) and distractor location (HPDL, LPL) are shown in Figure 3A. The LMMs analysis on the RTs showed significant main effects of target location ($\beta = 136.54$, $SE = 8.10$, $t(77) = 16.86$, $p < .001$) and distractor location ($\beta = 75.89$, $SE = 5.78$, $t(73) = 13.12$, $p < .001$). There was also a significant interaction between these two factors ($\beta = -56.80$, $SE = 9.14$, $t(71) = 6.22$, $p < .001$). Overall, participants were 119 ms faster to detect the target when it was presented at the HPTL than when presented at a LPL, providing clear evidence that the spatial regularity

**Figure 3**
*Statistical Learning (SL) Effects in Experiments 2*




*Note*. (A) Mean RTs and accuracy in the search task when the target was presented at the high-probability target location (HPTL) or at a low probability location (LPL) while the distractor was presented at the high-probability distractor location (HPDL) or at a LPL (direct effect of SL). (B) Mean RTs as a function of probe dot location (HPTL, LPL, and HPDL) in the probe task. (C) Mean RTs and accuracy in the search task when the target was presented at the HPDL or at a LPL (indirect effect of SL). (D) Mean RTs and accuracy in the search task when the distractor was presented at the HPTL or at a LPL (indirect effect of SL). Error bars denote $\pm 1$ $SE_{\text{mean}}$. See the online article for the color version of this figure.



regarding the target had a large effect on search. Moreover, participants were 54 ms faster to respond to the target when the distractor was presented at the HPDL than when presented at a LPL, providing evidence for suppression of the high-probability distractor location (see Wang & Theeuwes, 2018a, 2018b, 2018c). This latter effect was particularly strong when the target was also presented at the HPTL ($\beta = -75.90$, $SE = 5.78$, $t(73) = 13.12$, $p <$ .001). The GLMMs analysis on the accuracy data revealed a significant main effect of target location ($\beta = -.714$, $SE = .074$, $z =$ 9.63, $p < .001$), distractor location ($\beta = -.633$, $SE = .068$, $z =$ 9.28, $p < .001$), and a significant interaction between these factors ($\beta = .647$, $SE = .097$, $z = 6.69$, $p < .001$). In particular, when the target was presented at the HPTL, participants were more accurate on trials where the distractor occurred at the HPDL than at a LPL ($\beta = .633$, $SE = .068$, $z = 9.28$, $p < .001$). No such difference was found when the target was presented at a LPL ($\beta = -.014$, $SE =$ .087, $z = .16$, $p = .876$).

Figure 3C and 3D show the indirect effects of distractor location and target location, respectively. The results of the indirect effect of distractor location indicated that participants produced slower responses ($\beta = -51.76$, $SE = 7.75$, $t(2,410) = 6.68$, $p < .001$) when the target occurred at the HPDL than at the LPLs (see Figure 3C). The same comparison in the accuracy data showed no significant difference ($\beta = .09$, $SE = .10$, $z = .99$, $p = .32$). The results of the indirect effect of target location showed longer RTs ($\beta =$ -35.13, $SE = 9.76$, $t(74) = 3.60$, $p < .001$) and a lower accuracy ($\beta$ = .39, $SE = .09$, $z = 4.14$, $p < .001$) when the distractor was presented at the HPTL compared with the LPLs (see Figure 3D).

### *Probe Task*

The false alarm rate in the No-Go trials was 9.0% ($SD = .075$) and the miss rates in the Go trials were 1.9% ($SD = .041$), 1.7% ($SD = .018$), and 1.4% ($SD = .025$) for the HPDL, the LPL, and the HPTL, respectively. Figure 3B shows the mean reaction times in the probe task. The LMMs analysis on the RTs showed that the detection of probe offset was significantly slower at the HPDL than at the HPTL ($\beta = 26.05$, $SE = 10.19$, $t(81) = 2.56$, one-tailed

$p$ = .019), and (marginally so) at the HPDL than at a LPL ($\beta$ = 13.06, $SE$ = 6.73, $t(114)$ = 1.94, one-tailed $p$ = .082). However, no RTs difference was found between the HPTL and the LPL ($\beta$ = −12.99, $SE$ = 7.40, $t(72)$ = 1.76, one-tailed $p$ = .125).

### Awareness Test

Fifty out of 72 participants indicated that they were aware of the HPTL during the experiment. Forty-eight out of 50 participants who reported to be aware and 16 out of the 22 participants who reported to be unaware correctly indicated the HPTL. Twenty-four out of 72 participants indicated that they were aware of the HPDL during the experiment. Thirteen out of 24 participants who reported to be aware and 27 out of the 48 participants who reported to be unaware correctly indicated the HPDL. We then compared the models with or without the interaction between target awareness (yes, no), distractor awareness (yes, no), target location (HPTL, LPL), and distractor location (HPDL, LPL) for the search task (both for RTs and accuracy data), and the interaction between target awareness (yes, no), distractor awareness (yes, no) and probe location (HPTL, LPL) for the probe task. Participants were labeled as "yes" in target awareness or distractor awareness only if they claimed to be aware and also correctly reported the HPTL or claimed to be aware and also correctly reported the HPDL. Planned-model comparisons revealed a significant interaction between target awareness, distractor awareness, target location, and distractor location on accuracy ($\chi^2(1)$ = 4.50, $p$ = .034). Post hoc comparisons showed that the regularity in both the target and the distractor location (i.e., $Acc_{(HPTL,HPDL)} - Acc_{(HPTL,LPL)}$ as shown in Figure 3A) induced statistical learning in aware as well as unaware participants (all $p$s $<$ .028). Planned-model comparisons in the RTs data in the search task and the probe task suggested that the model fits were not significantly improved when including the specified interaction (all $p$s $>$ .078).

## Discussion

Experiment 2 shows that during search, performance was best when both the distractor and the target appeared at their corresponding high-probability locations, suggesting that the spatial regularities of both the target and the distractor are learned and jointly used to optimize attentional selection. Both manipulations concurrently contributed to visual search performance. Moreover, our findings also show indirect effects induced by the spatial regularities of both the target and the distractor: participants were slower to respond when the target was presented at the frequent distractor location or when the distractor was presented at the frequent target location. In terms of proactive guidance elicited by the regularities regarding the target location and the distractor location, the results of the probe task did not provide a clear picture. Responses were slower when the HPDL was probed compared with when the HPTL was probed, suggesting that either the HPDL was proactively suppressed, the HPTL was proactively facilitated, or both occurred simultaneously. However, the further comparison of probe RTs between the HPDL and the LPLs only revealed a marginal difference whereas no difference was found between HPTL and the LPLs.

Nevertheless, visual inspection of Figure 3B shows a data pattern suggesting that probe RTs gradually decreased from HPDL, LPL, to HPTL. It is possible that the effect of proactive enhancement of the frequent target location was present but was attenuated by the presence of a stronger effect of proactive suppression as induced by the regularity in the distractor location. Moreover, as also evident from the results obtained in Experiment 1, the true effect size of the regularity in the target location might have been smaller than the estimated smallest effect size (20 ms, see Method section of Experiment 1) that we had determined on the basis of a regularity in the distractor location. Possibly, our sample size was just not large enough to detect the presence of a similar effect of target regularity. We resolved these concerns in Experiment 3 by (a) lowering the spatial regularity of the distractor while keeping the spatial regularity of the target the same, and (b) increasing the sample size to ensure sufficient power.

# Experiment 3

In Experiment 3, we rerun Experiment 2 with two modifications: (a) the distractor was presented at the HPDL in 41.7% instead of in 61.6% of all trials, and (b) the sample size was increased. If the spatial regularity of the target and the distractor would provide proactive guidance of attention simultaneously, we expect to find RT differences in the probe task between the HPTL and the LPL, and between the HPDL and the LPL. In contrast, if proactive guidance due to the spatial regularities of the target and the distractor cannot function simultaneously, we expect to find a RT difference either between HPTL and LPL, or between HPDL and LPL.

## Method

### Participants

An a priori power analysis was run to determine the sample size for Experiment 3. The power analysis was based on the results in Experiment 2 with the aim of detecting a 13 ms RT difference between the HPTL and the LPL. Using the data ($N$ = 72) and the liner mixed model structure of the probe task in Experiment 2, the power simulation suggested that a sample size of 180 participants would have a power of 80.3% (95% CI [77.7%, 82.72%] in 1,000 simulations) to detect a probe RT difference of 13 ms. As a number of participants might be excluded based on the predetermined exclusion criteria, we recruited 212 participants (75 females, $M_{age}$ = 24.5, $SD_{age}$ = 4.6) via the Prolific platform. All participants received a monetary reward (£5.63) in exchange for 45 min of participation. Before the experiment, all participants provided written informed consent. The experiment was approved by the Ethical Review Committee of the Faculty of Behavioral and Movement Sciences of Vrije Universiteit Amsterdam and was conducted in accordance with the guidelines of the Helsinki Declaration.

### Stimuli and Task

The stimuli and task were the same as in Experiment 2.

### Design and Procedure

The design and procedure were equal to those of Experiment 2 with the following exception: 396 trials were used in the search task that were randomly intermixed with 200 probe trials with the same constraints as in Experiment 2. These trials were then separated into four blocks of 120 trials each and one block of 116 trials. Among the search trials, the distractor was 41.6% more likely to appear at one of eight locations than the other locations and the target was 61.1% more likely to appear at one of eight locations than the other locations. The target probability was equal across all LPLs and the HPDL (=.056) and the distractor probability was equal across all LPLs and the HPTL (=.083).

### Data Analysis

The exclusion criteria and the mixed-effects models for both tasks were the same as in Experiment 2. Participants whose mean accuracy was below 70% or exceeded 2.5 *SD* of the overall mean accuracy for either the search task ($N = 12$) or the probe task ($N = 17$) were excluded. Participants whose mean RT (collapsed across conditions) exceeded ±2.5 *SD* of the overall mean RT for either the search task ($N = 2$) or the probe task ($N = 1$) were excluded. In total, 32 participants were excluded based on the predetermined exclusion criteria, leaving 180 participants for analysis. We did all the analyses again without excluding any participants to check how the results were affected by the exclusion criteria. The rerun of all the analyses yielded similar results and the findings remained the same.

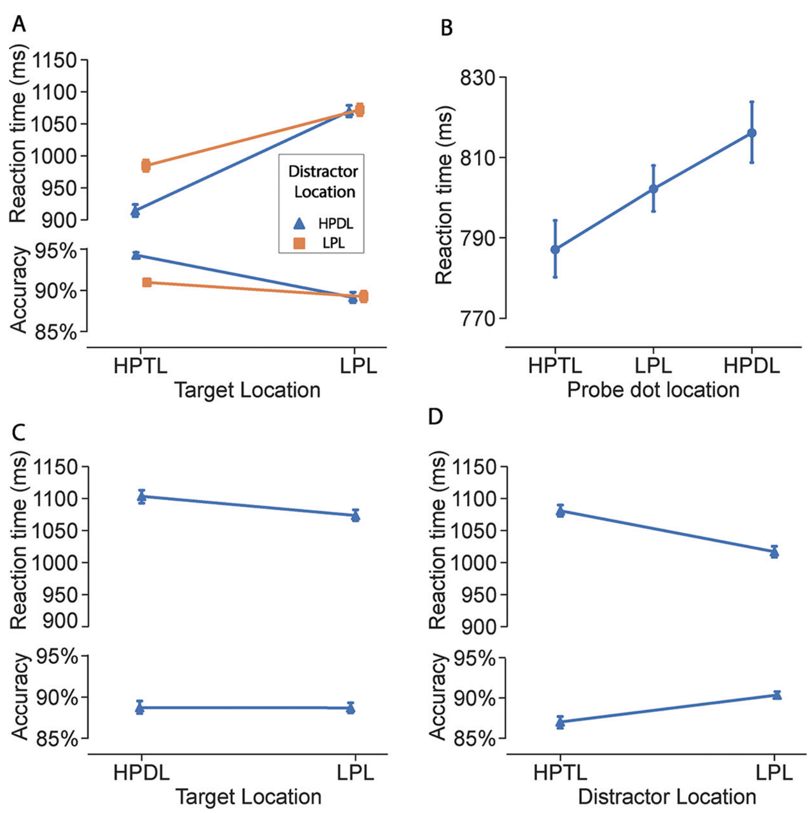
## Results

### Search Task

Mean accuracy and mean reaction times as a function of target location (HPTL, LPL) and distractor location (HPDL, LPL) are shown in Figure 4A. The LMMs analysis on the RTs showed significant main effects of target location ($\beta = 154.51$, $SE = 5.37$, $t(188) = 28.80$, $p < .001$) and distractor location ($\beta = 69.05$, $SE = 3.34$, $t(187) = 20.66$, $p < .001$). There was also a significant interaction between these two factors ($\beta = -68.57$, $SE = 5.10$, $t(179) = 13.45$, $p < .001$). In particular, when the target was presented in the HPTL, responses were 70 ms faster on trials where the distractor was presented in the HPDL than in a LPL ($\beta = -69.05$, $SE = 3.34$, $t(187) = 20.66$, $p < .001$). In contrast, no difference was found on the same comparison when the target was presented in a LPL ($\beta = -.48$, $SE = 3.87$, $t(188) = .13$, $p = .90$). The GLMMs

**Figure 4**

*Statistical Learning (SL) Effects in Experiments 3*




*Note.* (A) Mean RT and accuracy in the search task when the target was presented at the high-probability target location (HPTL) or at a low probability location (LPL) while the distractor was presented at the high-probability distractor location (HPDL) or at a LPL (direct effect of SL). (B) Mean RT as a function of probe dot location (HPTL, LPL, and HPDL) in the probe task. (C) Mean RT and accuracy in the search task when the target was presented at the HPDL or at a LPL (indirect effect of SL). (D) Mean RT and accuracy in the search task when the distractor was presented at the HPTL or at a LPL (indirect effect of SL). Error bars denote ±1 $SE_{mean}$. See the online article for the color version of this figure.

analysis on the accuracy data revealed a significant main effect of target location ($\beta = -.780$, $SE = .066$, $z = 11.79$, $p < .001$), distractor location ($\beta = -.612$, $SE = .050$, $z = 12.25$, $p < .001$), and a significant interaction between these factors ($\beta = .640$, $SE = .075$, $z = 8.53$, $p < .001$). Post hoc comparisons showed that when the target was presented in the HPTL, participants were more accurate on trials where the distractor was presented in the HPDL than in a LPL ($\beta = .612$, $SE = .050$, $z = 12.25$, $p < .001$). Such a difference was not found when the target was presented in the LPL ($\beta = -.028$, $SE = .058$, $z = .49$, $p = .63$).

Figure 4C and 4D show the indirect effects of target location and distractor location. The results of the indirect effect of distractor location indicated that participants produced slower responses ($\beta = -27.09$, $SE = 5.07$, $t(179) = 5.34$, $p < .001$) when the target was presented at the HPDL compared with the LPL (see Figure 4C). The same comparison in the accuracy data showed no significant difference ($\beta = -.06$, $SE = .07$, $z = .84$, $p = .40$). The results of the indirect effect of target location showed longer RTs ($\beta = -55.26$, $SE = 4.45$, $t(184) = 12.43$, $p < .001$) and a lower accuracy ($\beta = .31$, $SE = .06$, $z = 5.35$, $p < .001$) when the distractor was presented at the HPTL compared with the LPL (see Figure 4D).

### *Probe Task*

The false alarm rate in the No-Go trials was 9.2% ($SD = .073$) and the miss rates in the Go trials were 2.2% ($SD = .039$), 2.1% ($SD = .029$), and 2.3% ($SD = .041$) for the HPDL, the LPL, and the HPTL, respectively. Figure 4B (solid line) shows the mean RTs in the probe task. The LMMs analysis on the RTs showed that the detection of probe offset was significantly slower at the HPDL than at the HPTL ($\beta = 38.18$, $SE = 6.05$, $t(184) = 6.31$, one-tailed $p < .001$), and at the HPDL than at a LPL ($\beta = 18.87$, $SE = 4.20$, $t(204) = 4.49$, one-tailed $p < .001$). Moreover, RTs were significantly faster when probe offset occurred at the HPTL than at a LPL ($\beta = -19.31$, $SE = 4.22$, $t(184) = 4.58$, one-tailed $p < .001$).

### *Awareness Test*

One hundred twenty-eight out of 180 participants indicated that they were aware of the HPTL during the experiment. One hundred seventeen out of 128 participants who reported to be aware and 32 out of the 52 participants who reported to be unaware correctly indicated the HPTL. Fifty-five out of 180 participants indicated that they were aware of the HPDL during the experiment. Twenty-three out of 55 participants who reported to be aware and 93 out of the 125 participants who reported to be unaware correctly indicated the HPDL. We then ran the model comparisons same as Experiment 2. Planned-model comparisons in the RTs data showed that in the search task the interaction between target awareness and target location was significant ($\chi^2(1) = 8.61$, $p = .003$). Post hoc comparison showed that the effect of statistical learning (i.e., RTHPTL – $RT_{LPL}$) was present in both aware ($\beta = -126.8$, $SE = 5.50$, $t(189) = 23.05$, $p < .001$) and unaware participants ($\beta = -99.4$, $SE = 7.45$, $t(186) = 13.34$, $p < .001$) but was stronger in the group of aware participants ($\beta = 27.4$, $SE = 9.17$, $t(180) = 2.99$, $p = .003$). Planned-model comparisons in the accuracy data of the search task showed a significant three-way interaction between target awareness, target location and distractor location ($\chi^2(1) = 5.37$, $p = .021$). Post hoc comparison showed that the statistical learning effect of both the target location and the distractor location (i.e., $Acc_{(HPTL,HPDL)} - Acc_{(HPTL,LPL)}$ as shown in Figure 4A) occurred in both aware ($\beta = .59$, $SE = .05$, $z = 11.76$, $p < .001$) and unaware participants ($\beta = .37$, $SE = .06$, $z = 5.94$, $p < .001$). Planned-model comparisons in the RTs data of the probe task suggested that the model fits did not significantly improve when the specified interactions were included (all $p$s $> .25$).

## Discussion

The results of Experiment 3 show that search performance is best when both the target and the distractor are presented in their respective high-probability locations. This indicates that both the regularity regarding the target and that of the distractor are learned and simultaneously bias attentional selection. Moreover, the observed indirect effects are in line with this notion: participants took more time to find the target when it was presented in the HPDL and when the distractor was presented in the HPTL. The results in the probe task indicate that compared with a probe at a LPL, participants were faster to detect a probe that occurred at the HPTL while they were slower to detect a probe at the HPDL. These findings provide strong support for the notion that both the frequent target location and the frequent distractor location were proactively and simultaneously modulated in the priority map.

# General Discussion

The present study provides evidence supporting the view that statistical regularities regarding target and distractor can bias the allocation of attention by inducing spatial enhancement of the frequent target location and spatial suppression of the frequent distractor location. Critically, the probe results reveal that spatial enhancement and suppression are applied proactively and simultaneously. In other words, participants can simultaneously learn about the probabilities of the target and distractor, and optimize selection accordingly. It implies that learning about the likely target location and the likely distractor location modulates the weights within the spatial priority map in a similar way by either increasing (enhancement) or decreasing (suppression) the weights. These weights alter the biased competition within the spatial priority map.

The results provide compelling insights in the way proactive facilitation and inhibition shape attentional selection. In Experiment 2 and 3 participants were much faster (>100 ms) when the target was presented at the high probability target location than at a low probability location. This implies a strong enhancement of the target location. However, participants were also faster when the distractor was presented at a high probability distractor location than a low probability location which suggests that the location that was likely to contain a distractor was suppressed relative to the low probability location. The critical finding is that these two factors also interact. This implies that even when there is a very strong bias prioritizing the location of the target, selection is further improved when the distractor is located in a HPDL. In other words, even when there is a strong bias to prioritize the target location, selection becomes even more efficient when the distractor is presented at a location that is suppressed. It demonstrates how the weights within the spatial priority map increase or decrease the attentional biases consistent with the basic notion underlying biased competition (Desimone & Duncan, 1995). The indirect effects on selection elegantly fit this pattern of results: if the target happens to be presented at a location that usually contains a distractor (HPDL), participants are slower to respond because the target is presented at a location that is suppressed relative to all other locations (Figures 3C and 4). It should be noted that it is feasible that these indirect effects of suppressing the target when it happens to be presented at a location that usually contains a distractor, are only reported in experiments in which the features of the target and distractor randomly swap across trials (Allenmark et al., 2019; Goschy et al., 2014; Liesefeld & Müller, 2021; Sauter et al., 2018; Zhang et al., 2019). Similarly, if a distractor happens to be presented at the prioritized (enhanced) HPTL location, there is a large price to pay as interference caused by the distractor is much higher (Figures 3D and 4). It shows that due to statistical learning the weights within the spatial priority map are altered such that some locations are prioritized while others are suppressed.

It is important to note that in the current task (that is a version of the additional singleton task of Theeuwes, 1991) the target shape and the distractor color switched randomly from trial to trial inducing what has been labeled as the "singleton detection mode" (Bacon & Egeth, 1994). It is known that no top–down control can be applied when this version of the task is used as participants never know which target feature they are looking for. Critically, however, the present study shows that even under these circumstances in which top–down control is not possible, participants can learn to suppress and enhance particular locations in space. Note that previous studies have shown that even if Bacon and Egeth's (1994) "feature search mode" is induced, participants still learn to suppress the location of the frequent salient singleton, even though the salient distractor should no longer interfere with the search for the target when using feature search mode (van Moorselaar et al., 2020, 2021; Wang & Theeuwes, 2018c). These findings suggest that statistical learning takes place independently of the search mode used (Wang & Theeuwes, 2018c).

The results of the probe task indicate that enhancement and suppression of the specific locations are already in place at the moment the participants saw the search display. Indeed, probe detection took place in those trials in which the search display was not yet presented. The only link between the probe task and the search task is that the probe array and the search array are presented at the same physical location and at the same (expected) time. This is different from the capture-probe paradigm (Gaspelin et al., 2015; Gaspelin & Luck, 2018b, 2018a) where the letter-probe is superimposed on the search array. Accordingly, the probe results in their task would reflect the allocation of attentional resources based on the features of the target or the distractor. While in the current probe trials, when enhancement and suppression are applied, participants cannot know at which location the target and distractor singleton will be presented. Therefore, this design rules out an enhancement or suppression that is based on target and distractor features as shown for example, by Gaspelin et al. (2015, 2017, 2019). Note that in the current study, the probe dot we used to retrieve the attentional priority setting in space is not salient at all, hence it remains unclear whether the spatial suppression on the frequent distractor location would be powerful enough to prevent attentional capture once a salient item is presenting at this location. Additionally, the results of the probe task also explain the current indirect effect on selection: because one location is enhanced and another location is suppressed, regardless of which display element is presented at that location, there is a large price to pay. When a distractor is presented at an enhanced location, interference by the distractor is much higher relative to other locations and when a target is presented at the suppressed location, selection of the target is slower than at other locations. The latter finding that there is strong suppression even when a target is presented at the high probability location is consistent with the notion that suppression induced by statistical learning is spatial-based, feature blind (e.g., Wang & Theeuwes, 2018c) and proactive (Huang, Vilotijević, et al., 2021; Wang et al., 2019).

As outlined, we argue that through statistical learning, the weights within the spatial priority map are adjusted resulting in location-based enhancement and suppression. We suggest that this enhancement and suppression is implicit even though in the current experiments, most participants were aware of at least the high probability target location (not of the high probability distractor location). As such one can question our claim that learning is truly implicit. Still there are several reasons that seem to hint in the direction that learning is implicit. First, even though the majority of participants showed awareness of the target location, awareness could not account for the observed statistical learning effects. In fact, our results show that the regularity in the target location affected both aware and unaware participants. We additionally ran the (G)LMMs models on the participants who were unaware of the target regularity ($N = 108$, collapsed across three experiments). The results showed faster ($\beta = 106.24$, $p < .001$) and more accurate ($\beta = -.35$, $p < .001$) responses when the target was presented at the HPTL than at the LPL. This suggests that statistical learning occurred even for participants who were not explicitly aware of the regularities. As such awareness is not critical for obtaining the current results. Second, recently Gao and Theeuwes(2020a) investigated whether explicit knowledge and awareness regarding the regularities present in the display affected statistical learning. They created conditions in which one group of participants was fully aware of the regularities in the display while another group of participants was fully unaware. The results showed equally effective suppression of the high probability location suggesting that explicit knowledge and awareness do not contribute to statistical learning. Third, in another study Gao and Theeuwes (2020b) showed that implicit biases due to statistical learning and explicit top–down attention each contribute independently to attentional selection. As such top–down spatial attention seems to represent a different process than implicit biases induced by statistical learning. Fourth, another study Gao and Theeuwes (in press) showed that statistical learning is an implicit and automatic process that does not rely on any top–down processes such as working memory or executive control resources.

The notion that both attentional enhancement and suppression rely on the same neuronal machinery is consistent with the findings of Ferrante et al. (2018) who showed a cross-talk between statistical learning of target selection and distractor filtering. Note that even though the general claims are the same, the Ferrante et al. (2018) study was different from the current study in many ways. First, in the Ferrante et al. (2018) study there were only four display elements that render both the target and the distractor singleton nonsalient. In a recent study Wang and Theeuwes (2020) showed that when only a few elements are present in the display (e.g., when there are only four display elements as in Ferrante et al., 2018), none of the elements are salient enough to capture attention (but see Stilwell & Gaspelin, 2021). Suppression and enhancement of nonsalient items are likely to be quite different from suppression and enhancement of elements that are salient and stand out from the background as in the current study (see Luck et al., 2021, for discussion). Consistent with the claims of Wang and Theeuwes (2020), recently Liesefeld and Müller (2020) argued that in sparse displays, the target and distractor may be so "nonsalient" that participants have to rely on serial clump-wise search to find the target. In such a scenario, the priority map is unemployed as it has no benefit for guiding visual search (Liesefeld et al., 2021). As argued before, in those circumstances, salient singletons do not longer capture attention (see Theeuwes, 1994, 2004).

Second, in the study of Ferrante et al. (2018), no indirect effect of statistical learning of distractor location was reported. They demonstrated a common learning mechanism by showing that there was a correlation between target- and distractor-related statistical learning. Instead of just a correlation, here we show that target selection is hampered when the target is presented at the HPDL and distractor interference is increased when the distractor is presented at the HPTL. This strongly suggests a common mechanism. Finally, and most critically, with our probe task, we were able to take a peek at the priority map at the time of the presentation of the display and show that there is simultaneously proactive enhancement and suppression of the two critical locations.

It is important to note that the proactive guidance of attention as corroborated by the results of the probe task has no bearing on the effect of intertrial location priming. To prevent any benefit driven by location repetition, we intentionally manipulated the trial sequence such that the frequent target location would never be probed if a target was presented at this location in the preceding search trial. Thus, the speeded detection of a probe at the frequent target location could not be accounted for by target priming. The results in the search task also could not be interpreted as the effect of target priming as priming was controlled through the used linear mixed models (see Method). However, other studies investigating the relationship between priming and statistical learning suggested differently. For instance, in a completely different task than the current one, Kabata and Matsumoto (2012) instructed participants to look for a target 'T' among three distractors 'L' in four locations, one of which was more likely to contain the target. In this study, intertrial location priming was constrained such that the target could not be presented in the same location in consecutive trials. The result was that statistical learning did not occur under these conditions, suggesting that statistical learning is contingent upon intertrial priming (see also Walthew & Gilchrist, 2006; but see Goschy et al., 2014; Jones & Kaschak, 2012). Our results suggest differently indicating that further work is required to develop a full picture of the relationship between priming and statistical learning.

We claim that the weights within the spatial priority map are in place at the moment the display comes on. It is feasible that the enhancement and suppression that we report here is specifically tuned to the moment in time when the search display is expected to appear. Indeed, recent work using a version of the additional singleton paradigm has shown that attentional enhancement and suppression can be tuned to particular moments in time (Xu et al., 2021). Instead of just one HPDL, in the Xu et al., study, there were two locations that were more likely to contain a distractor. The critical manipulation was that one (high probability) location was more likely to contain a distractor early in time (after a short interval of 500 ms following the fixation point) while the other location was more likely to contain a distractor late in time (after a long interval of 1,500 ms). The results showed better performance for detecting targets when the distractor appeared at a high probability location after its associated time interval than when it appeared at that location after the nonassociated interval. These findings indicate that suppression was tuned to the moment in time the location was most likely to contain a distractor suggesting that the weights within the spatial priority map can be tuned to specific moments in time (see also Xu et al., 2021). It is also possible that in the current study the weights of the priority maps were not tuned to the moment in time the display came on but instead that the priority map was adjusted as soon as the placeholder display was presented. It is feasible that the presentation of the placeholder display served as a cue to activate the settings in the priority map. In that case, the weights would be in place about 800 ms before the display would be presented. Future research can reveal the temporal dynamics of the priority map settings.

In summary, the present study shows that observers learn the regularities present in the display in terms of the location that is most likely to contain the target being enhanced while the location that is most likely to contain a distractor is suppressed. We assume that within the spatial priority map of selection, weights are increased for the likely target location and decreased for the likely distractor location. We show that these contingencies can be learned simultaneously and biased the deployment of attentional resources in a proactive way.

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