Threat Stimuli Facilitate Learned Distractor Suppression Based on Location Probability

Authors: Nian Jingqing, Tan Jiang, Zhang Di, Zhang Yu, Luo Yu, Luo Yu

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Abstract

Threat stimuli possess strong priority in attentional processing, yet whether they facilitate or interfere with the formation of learned distractor inhibition remains unclear. This study examined the influence of threat stimuli on the formation of location-probability-based learned distractor inhibition through three experiments. The results across three experiments consistently revealed that when distractors appeared at high-probability distractor locations, individuals' responses to targets were significantly faster than when they appeared at low-probability distractor locations. Computational modeling results demonstrated that when distractors were presented at high-probability locations, individuals could establish learned distractor inhibition for color singletons after only a few trials, indicating that this learning process is stable and efficient. More importantly, when threat was presented in feature form during visual search tasks, it did not affect the formation of learned distractor inhibition, whereas when threat was presented as an object, it facilitated its acquisition. These findings indicate that the key to threat stimuli facilitating the formation of learned distractor inhibition lies in the threat object rather than isolated threat features. Threat stimuli may enhance the weight of selection history in attentional priority maps, thereby facilitating the inhibition of distractor stimuli at high-probability locations and improving target processing efficiency. This discovery extends the applicability of the salience-specific distractor inhibition theory from traditional visual salience to emotional salience, further highlighting the central role of emotional information in attentional inhibitory learning.

Full Text

Threatening Stimuli Facilitate Location-Probability-Based Learned Distractor Suppression

Nian Jingqing[1], Tan Jiang[1], Zhang Di[1,2], Zhang Yu[1,2], Luo Yu[1,2*]

[1]School of Psychology, Guizhou Normal University, Huaxi University Town, Guian District, Guiyang, Guizhou 550025, P.R. China
[2]Key Laboratory of Brain Function and Brain Disease Prevention and Treatment of Guizhou Province, Huaxi University Town, Guian District, Guiyang, Guizhou 550025, P.R. China

Abstract

Threatening stimuli possess hard-wired priority in attentional processing, yet it remains unclear whether they facilitate or interfere with the formation of learned distractor suppression. This study investigated how threatening stimuli influence the development of location-probability-based learned distractor suppression through three experiments.

Consistent across all three experiments, participants responded significantly faster to targets when distractors appeared at high-probability locations compared to low-probability locations. Computational modeling revealed that when distractors were presented at high-probability positions, individuals rapidly formed learned suppression of color singletons after only a few trials, demonstrating that this learning process is both stable and efficient.

Critically, when threat was presented as a feature in the visual search task, it did not affect the formation of learned distractor suppression; however, when threat was presented as an object, it facilitated the acquisition of suppression. These findings indicate that the key to threat stimuli promoting learned distractor suppression lies in threatening objects rather than isolated threat features. Threat stimuli may enhance the weight of selection history in the attentional priority map, thereby facilitating suppression of distractors at high-probability locations and improving target processing efficiency. This discovery extends the applicability of saliency-specific distractor suppression theory from traditional visual salience to emotional salience, further highlighting the central role of emotional information in attentional inhibitory learning.

Keywords: threatening stimuli, statistical learning, learned distractor suppression

Introduction

In complex and dynamic visual environments, the attentional system optimizes the allocation of limited cognitive resources through two functionally and neurally distinct yet cooperative processes: target enhancement and distractor suppression, enabling prioritized processing of task-relevant information while effectively inhibiting interference from irrelevant information (Hickey et al., 2009; Noonan et al., 2016). Traditional attention theories posit that attentional selection is primarily governed by top-down mechanisms guided by task goals or bottom-up mechanisms driven by stimulus physical salience (Theeuwes, 2010). However, recent research has increasingly recognized that selection history also plays a crucial role in attentional selection (Anderson et al., 2021; Awh et al., 2012; A. Kim & Anderson, 2022; Theeuwes, 2019, 2025). Selection history refers to attentional biases formed through past experiences in specific environments—previous attentional or response experiences with particular stimuli or locations automatically influence subsequent attentional allocation (Failing & Theeuwes, 2014, 2018). For instance, Failing and Theeuwes (2014) employed a color-reward association paradigm and found that even when a color no longer held relevance in the current task, it could still automatically capture attention and interfere with target detection if it had previously been associated with high reward, thereby prolonging response times. This result demonstrates that attentional allocation can be implicitly driven by past reward experiences.

Statistical learning, as a core component of selection history, has been widely acknowledged in numerous studies. Statistical learning refers to the ability to form attentional biases or inhibitory tendencies toward specific locations or features based on the spatial or feature-based presentation probabilities of stimuli, thereby flexibly adjusting attentional resource allocation (Fiser & Aslin, 2002; H. Kim et al., 2023; Sherman et al., 2020; Stilwell et al., 2019; Theeuwes et al., 2022; Turk-Browne et al., 2005; Wang & Theeuwes, 2018a, 2018b, 2018c; Bogaerts et al., 2022; Ferrante et al., 2023; Kerzel & Huynh Cong, 2021; Stilwell & Vecera, 2022; Zhang et al., 2021). For example, research has shown that in visual search tasks, when distractors appear more frequently at a specific spatial location, individuals can gradually develop location-specific inhibitory tendencies based on their occurrence probability, effectively reducing the attentional capture effect of distractors at that location (Wang & Theeuwes, 2018a, 2018b, 2018c). This selective attentional inhibitory mechanism, established through implicit learning of regularities in stimulus spatial distributions, is termed learned distractor suppression (Savelson et al., 2025; Vatterott & Vecera, 2012).

Building upon evidence for learned distractor suppression, researchers have begun investigating key factors influencing its formation and expression. Among these, stimulus salience has been identified as an important factor. Previous studies have found that stimuli with physically salient features (e.g., color, luminance, size) enhance the formation of learned distractor suppression (Failing & Theeuwes, 2020; Gong & Theeuwes, 2021). For instance, Gong and Theeuwes (2021) manipulated the presentation probability of distractors with varying salience across spatial locations using the additional singleton paradigm. Results showed that compared to low-salience distractors at high-probability locations, high-salience distractors at the same locations produced weaker interference effects, with participants responding faster to targets. This indicates that higher distractor salience leads to stronger learned distractor suppression effects at high-probability locations.

Beyond physical attributes, the emotional valence of stimuli has gradually attracted researchers' attention regarding its modulation of attentional processing. Studies have begun exploring whether reward influences the formation of learned distractor suppression (Le Pelley et al., 2022; Zhao et al., 2024). For example, Le Pelley et al. (2022) investigated how distractor reward value and location probability jointly influence learned distractor suppression. In this study, reward association and location probability learning occurred simultaneously within the same task phase—participants gradually accumulated statistical regularities about distractor locations while concurrently learning the reward value associated with distractors. Results showed that compared to distractors at low-probability locations, responses to targets were significantly faster when distractors appeared at high-probability locations, indicating the formation of learned distractor suppression at high-probability positions. Additionally, responses were significantly slower under high-value reward distractor conditions than low-value conditions, suggesting that high-value reward distractors still produced significant attentional capture effects. However, the interaction between reward value and location probability was not significant, indicating that reward value did not affect location-probability-based learned distractor suppression. In other words, despite reward stimuli having strong attentional capture effects, they did not interfere with the formation of learned distractor suppression, suggesting that the two factors independently influence attentional processing.

Compared to reward stimuli, threatening stimuli, due to their high evolutionary adaptiveness, often capture attentional resources more rapidly and automatically (Öhman et al., 2001; Vuilleumier, 2005). Therefore, whether threatening stimuli affect learned distractor suppression differently from reward stimuli remains to be investigated. Research has shown that threatening stimuli possess "hard-wired priority" in attentional processing—even as task-irrelevant distractors, they are difficult to effectively suppress by the attentional system (Anderson & Britton, 2020; Burra et al., 2019; Casalvera et al., 2023; Mulckhuyse & Dalmaijer, 2016; Pakai-Stecina et al., 2024; Schmidt et al., 2015a, 2015b; Zsidó et al., 2023). For instance, Schmidt et al. (2015b) employed a threat conditioning task where a neutral stimulus was paired with electric shock to create a threat stimulus, while another physically identical stimulus remained unpaired as a non-threat stimulus. Following conditioning, participants performed a visual search task where irrelevant threat or non-threat distractors were occasionally presented. Results showed that response times to targets were significantly longer in the threat distractor condition compared to the non-threat condition, indicating that previously threat-associated stimuli could still prioritize attention and interfere with target identification even when currently task-irrelevant.

Consequently, it is necessary to investigate whether threatening stimuli interfere with attentional inhibitory mechanisms, particularly the stability of learned distractor suppression. Recent studies have employed training-test two-phase paradigms to examine whether threatening stimuli disrupt learned distractor suppression established through neutral distractor location probabilities, thereby weakening the persistence of this inhibitory effect during the maintenance phase (H. Kim & Anderson, 2021; Theeuwes et al., 2025; Theeuwes & van Moorselaar, 2025). For example, Theeuwes et al. (2025) used a training-test paradigm and found that during the training phase, participants responded significantly faster to targets when distractors appeared at high-probability locations, indicating established learned distractor suppression. Subsequently, one color distractor was paired with electric shock to create a threat stimulus while another served as a non-threat stimulus, to examine whether this affected the existing inhibitory mechanism during the maintenance phase. During the test phase, threat stimuli enhanced attentional capture, but the suppression effect at high-probability locations remained significant, with no significant interaction between distractor type and location probability. This suggests that although threat information can attract attention, it does not weaken established learned inhibitory mechanisms, and the two factors are largely independent. Despite existing research focusing on the impact of threat stimuli on the maintenance phase of learned distractor suppression, overall, current evidence remains insufficient to answer a critical question: Do threatening stimuli affect the formation of learned distractor suppression?

In light of this, the present study employed a visual search task while simultaneously manipulating the threat level of distractor stimuli and their location probabilities to investigate how threatening stimuli influence the formation of location-probability-based learned distractor suppression. To precisely manipulate threat factors and control for interference from individual differences in emotional experience, we used a threat conditioning task to 赋予 threat meaning to neutral stimuli through pairing with electric shock, thereby generating threat and non-threat stimuli. Previous research has indicated that color salience facilitates learned distractor suppression (Failing & Theeuwes, 2020). Therefore, Experiment 1 examined whether color features associated with threat stimuli would modulate the formation of location-probability-based learned distractor suppression while controlling for color salience. Building upon Experiment 1, Experiment 2 further explored how color objects associated with threat influence the formation of location-probability-based learned distractor suppression. Notably, when distractors share high color similarity, threat generalization effects may occur (Dowd et al., 2016; Lissek et al., 2008; Struyf et al., 2017), making it difficult for individuals to accurately distinguish between threat and non-threat stimuli, thereby interfering with the formation of location-specific inhibitory mechanisms. To exclude this potential confound, Experiment 3 reduced color similarity based on Experiment 2 to effectively control threat generalization caused by color confusion, further validating how threatening stimuli influence the formation of location-probability-based learned distractor suppression. We expected that when distractors appeared at high-probability locations, participants' response times to targets would be shorter. If threatening stimuli could modulate location-probability-based learned distractor suppression, then at high-probability locations, response times in the threat distractor condition should be significantly faster than in the non-threat distractor condition.

Experiment 1

Experiment 1 aimed to examine whether threat features affect the formation of learned distractor suppression based on distractor location probability, using threatening and non-threatening color features with similar color properties but different emotional salience as distractors while controlling for color salience.

2.1.1 Participants

Sample size calculation using G*Power 3.1 indicated that at $= 0.05$, a minimum of 29 participants was required to detect a medium effect size of d = 0.54 in a within-subjects design with statistical power > 0.80 (H. Kim & Anderson, 2019). Considering potential invalid participants, 30 healthy adults (7 males, 23 females) were recruited through convenience sampling, aged 20-25 years. Female participants were required to have regular and stable menstrual cycles within the past three months. All participants passed safety screening using the Multi-Channel Electrical Stimulator Safety Checklist, scored as right-handed on the Edinburgh Handedness Inventory, had normal or corrected-to-normal vision, self-reported normal hearing, and showed no color blindness or weakness on the Color Blindness Test Chart (6th edition) and Color Vision Test Chart (4th edition). Participants signed informed consent before the experiment and received compensation afterward. The study was approved by the Human Subjects Protection Committee (IRB approval number: NO2022E[007]).

2.1.2 Experimental Design and Procedure

The study employed a 2 (distractor: absent/present) × 2 (distractor location probability: high/low) within-subjects design. The distractor-absent condition served as a baseline control to examine whether target processing would be affected by location probability in the absence of interfering stimuli. In the distractor-present condition, to investigate whether threat features would modulate attentional suppression effects based on distractor location probability, distractor stimulus type was further divided into threat and non-threat conditions.

Forty-eight hours before the experiment, researchers confirmed the specific experimental time with participants. Twenty-four hours prior to the experiment, participants were reminded to arrive at the designated location on time and informed of relevant precautions. Upon arrival, participants first verified their personal information and signed the informed consent form. They then completed the handedness test, color vision screening, and multi-channel electrical stimulator safety screening. Eligible participants proceeded to the electrical stimulation threshold calibration task. Following calibration, participants engaged in the threat conditioning task. After the acquisition phase, experimenters removed the electrodes and explicitly informed participants that no further shocks would be administered. Participants then completed the visual search task, followed by the implicit learning assessment questionnaire. The entire experiment lasted approximately 90 minutes.

2.1.3 Experimental Tasks

Before the experiment, screen brightness and color were measured and calibrated using PsyCalibrator and SpyderX, with calibrated parameters applied to subsequent stimulus presentation (Lin et al., 2023). Experimental tasks were programmed and presented using Matlab (2020b) and Psychtoolbox 3.0 on a Windows 10 computer (graphics card: AMD Radeon 520). Stimuli were displayed on a 21.5-inch LCD monitor (model: Lenovo LS2224) with a resolution of 1920×1080 pixels and a refresh rate of 60 Hz. Participants sat 72 cm from the monitor throughout the experiment and responded using a keyboard.

Threshold Calibration Task: Since subjective perception of identical electrical stimulation intensity may vary across individuals, each participant completed a standardized electrical stimulation intensity calibration procedure before the formal experiment. Each trial presented a white "" fixation point for 500 ms, followed by electrical stimulation of a specific intensity. Electrical stimulation was delivered via a multi-channel electrical stimulator (model: SXC-4A, Beijing Sanxia Technology Co., Ltd.) through two Ag/AgCl surface electrodes (skin contact area ~1 cm²) attached to the participant' s left forearm with a 6 cm inter-electrode distance. The stimulation signal consisted of constant-current square wave pulses (duration: 100 ms, frequency: 100 Hz, repetitions: 15, pulse width: 1000 s, inter-pulse interval: 10 ms). The initial current was 500 A, increasing in 200 A increments. After each shock, participants rated subjective discomfort on a visual analog scale from 0 to 10, where 0 indicated "completely comfortable" and 10 indicated "extremely uncomfortable" or "intolerable discomfort." A rating of 8 (extremely uncomfortable but tolerable) was used as the criterion for determining individual experimental stimulation intensity. Each participant repeated the calibration procedure three times, with the final intensity for each current level calculated as the average of the three values corresponding to a rating of 8, which remained constant throughout the threat conditioning task. Participants were explicitly informed that they could terminate the experiment at any time by pressing a designated key or informing the experimenter if they found the stimulation unbearable.

Threat Conditioning Task: As shown in Figure 1 [Figure 1: see original paper]A, this study employed a classic threat conditioning task comprising a habituation phase and an acquisition phase. Each trial randomly presented one of two colored objects: green (RGB: [0 73 0]) or cyan (RGB: [0 71 71]). One color object was paired with electric shock during the acquisition phase (threat condition), while the other was never paired with shock (non-threat condition), with color counterbalanced across participants.

The habituation phase consisted of 4 trials (2 threat trials and 2 non-threat trials without shock). Each trial presented a white "" fixation point for 500 ms, followed by an 8000 ms color object presentation. No shocks were administered, and participants made no responses, simply focusing on screen stimulus changes.

The acquisition phase comprised 16 trials (8 threat and 8 non-threat trials). Each trial presented a white " " fixation point for 500 ms, followed by an 8000 ms color object with an inter-trial interval randomly varying between 9000-15000 ms. Electric shock was delivered on 75% of threat trials at the intensity determined during calibration; the remaining 25% of threat trials and all non-threat trials involved no shock. Participants were informed that shock would be paired with only one of the two color objects but were not told which. No responses were required; participants simply attended to stimulus changes and remembered which color might be associated with shock. Following the task, a forced-choice test required participants to identify which colored circle had been paired with shock.

Visual Search Task: Before the formal experiment, participants completed 20 practice trials and were required to achieve >85% accuracy to proceed. The formal task consisted of 16 blocks of 56 trials each, including 20 threat-distractor trials, 20 non-threat-distractor trials, and 16 no-distractor trials. As shown in Figure 1F, within each block' s threat and non-threat distractor trials, 13 trials presented the distractor at a fixed location among 8 possible positions (presentation probability ~65%), while the remaining 7 trials presented distractors once each at the other 7 positions (each with ~5% probability). Trial order and target locations were randomized within each block. After each block, participants received feedback on mean response time and accuracy.

As shown in Figure 1B, each trial began with a black (RGB: [5 5 5]) background displaying a 0.4° × 0.4° " " fixation point for 500 ms, followed by a visual search array presented for 1500 ms. The array consisted of 8 shapes equally spaced on a virtual circle (radius: 4.5°) centered on the screen, including 1 hollow diamond and 7 hollow circles (each 2.3° × 2.3°). Each shape contained a gray (RGB: [70, 70, 70]) line segment (1° × 1°) randomly oriented horizontally or vertically. Participants judged the line orientation within the diamond and responded via keypress as quickly as possible. The search array disappeared upon response. Incorrect responses or failures to respond within the time limit triggered a beep feedback. In no-distractor trials, all shape outlines were filled gray. In distractor-present trials, one circle' s outline was filled green or cyan, serving as threat or non-threat distractor attributes based on the color paired with shock during threat conditioning.

Implicit Learning Assessment: After the visual search task, participants completed a distractor color identification task to judge whether each color had been paired with shock. They then indicated whether distractors appeared equally often across the 8 locations; if not, they specified which locations had higher or lower frequencies. Finally, participants rated their confidence in each response on a 1 (least confident) to 7 (most confident) scale.

2.1.4 Data Analysis

During the visual search task, participants' response times and accuracy for target stimuli (line orientation within the diamond) were recorded. Behavioral data analysis was conducted in Rstudio (version 2024.09.0+375) using R (version 4.4.0). Response time data were preprocessed as follows: (1) removed the first two trials of each block; (2) excluded incorrect response trials; (3) removed trials with RT $<$ 200 ms; (4) excluded trials with RT exceeding $\pm$2.5 SD of the individual' s condition mean; (5) excluded participants with fewer than 75% valid trials remaining after screening. Following preprocessing, mixed linear model analysis of response times was performed using lme4 (version 1.1-35.5) and lmerTest (version 3.1-3) packages (Kuznetnetsova et al., 2017).

To investigate whether individuals formed learned distractor suppression at high-probability locations, separate mixed linear models were conducted for distractor-absent and distractor-present conditions. In the distractor-absent condition, distractor location probability (LocP) served as a fixed factor, target response time (RT) as the dependent variable, and subject (Subject) as a random factor to control for individual variability: RT LocP + (1 Subject). In the distractor-present condition, location probability and distractor stimulus type (CS) were fixed factors, target RT the dependent variable, and subject and target-distractor distance (TDD) random factors: RT CS $*$ LocP + (1 Subject) + (1 TDD). To examine significant differences between conditions/levels, post-hoc comparisons were performed using the emmeans package (1.10.6) with Tukey method for multiple comparison correction.

Additionally, in the distractor-present condition, to further explore how threatening stimuli influenced the temporal dynamics of location-probability-based learned distractor suppression, we adopted the smoothing method for analysis of response time-course (SMART) following van Leeuwen et al. (2019) to model trial-level RT data. SMART combines Gaussian kernel smoothing with weighted statistics to reconstruct high temporal resolution RT sequences and implements statistical significance testing through cluster permutation analysis (van Leeuwen et al., 2019).

2.2.1 Behavioral Results

Distractor-Absent Condition: As shown in Figure 2 [Figure 2: see original paper]A, the main effect of distractor location probability was significant (b = -26.30, SE = 2.83, t(6670) = -9.28, p $<$ 0.001, 95% CI = [-31.86, -20.75]; = -0.102, 95% CI = [-0.12, -0.08]). Further analysis revealed that responses were significantly faster when targets appeared at low-probability distractor locations (737.28 $\pm$ 13.50 ms) than at high-probability distractor locations (789.88 $\pm$ 14.36 ms) (b = -52.6, SE = 5.67, z = -9.28, p $<$ 0.001). These results indicate that individuals formed learned distractor suppression at frequently encountered interference locations, thereby inhibiting target processing at those positions.

Distractor-Present Condition: As shown in Figure 2B, the main effect of distractor location probability was significant (b = 16.82, SE = 1.28, t(16715) = 13.15, p < 0.001, 95% CI = [14.31, 19.32]; = 0.093, 95% CI = [0.08, 0.11]). Further analysis showed that responses were significantly faster when distractors appeared at high-probability locations (733.69 ± 13.67 ms) than at low-probability locations (767.32 ± 13.75 ms) (b = 33.6, SE = 2.56, z = 13.15, p < 0.001). The main effect of distractor stimulus type was not significant (b = -0.94, SE = 1.28, t(16715) = -0.73, p = 0.46, 95% CI = [-3.44, 1.57]; = -0.005, 95% CI = [-0.02, 0.01]). No significant difference in target RT was found between threat-feature (749.58 ± 13.71 ms) and non-threat-feature (751.44 ± 13.71 ms) distractor conditions (b = -1.87, SE = 2.55, z = -0.73, p = 0.46). The interaction between distractor stimulus type and location probability was significant (b = -4.40, SE = 1.28, t(16715) = -3.44, p < 0.001, 95% CI = [-6.90, -1.89]; = -0.026, 95% CI = [-0.04, -0.01]). Simple effects analysis revealed that for both threat-feature (low-probability: 761.98 ± 13.90 ms vs. high-probability: 737.15 ± 13.76 ms, b = 24.83, SE = 3.61, z = 6.87, p < 0.001) and non-threat-feature (low-probability: 772.65 ± 13.90 ms vs. high-probability: 730.22 ± 13.75 ms, b = 42.43, SE = 3.62, z = 11.73, p < 0.001) distractor conditions, target RTs were significantly slower at low-probability than high-probability locations. Meanwhile, at low-probability locations, target RTs were marginally faster in the threat-feature than non-threat-feature condition (b = -10.67, SE = 4.12, z = -2.59, p = 0.058). However, at high-probability locations, no significant difference existed between threat-feature and non-threat-feature conditions (b = 6.93, SE = 3.02, z = 2.30, p = 0.13).

Temporal Dynamics: SMART analysis revealed that when threat-feature distractors appeared at low-probability locations, target responses were significantly slower than at high-probability locations across five trial intervals (4-107, 132-246, 329-376, 409-556, 630-815). Similarly, when non-threat-feature distractors appeared at low-probability locations, responses were significantly slower than at high-probability locations across three intervals (1-349, 422-479, 498-896). Additionally, when distractors appeared at low-probability locations, threat-feature distractors produced marginally faster responses than non-threat-feature distractors across two intervals (608-630, 809-869). However, at high-probability locations, no significant differences existed between threat-feature and non-threat-feature conditions at the trial level.

2.2.2 Awareness Assessment Results

Among 30 participants, 8 reported not noticing that distractors appeared more or less frequently at specific locations, with mean confidence ratings of 5.13 ± 0.13 on the 7-point scale. The remaining 22 participants reported perceiving differential frequencies across locations, with mean confidence ratings of 3.91 ± 0.35. Importantly, the locations reported by these 22 participants did not correspond to the actual high/low-probability positions set in the experiment. These awareness assessment results suggest that participants did not explicitly recognize the statistical regularities of location probabilities, indicating that learned distractor suppression was primarily based on unconscious statistical learning processes.

2.3 Discussion of Experiment 1

Consistent with previous research (Wang & Theeuwes, 2018a, 2018b, 2018c), Experiment 1 demonstrated that individuals formed learned distractor suppression at high-probability locations. In the distractor-present condition, responses were significantly faster when distractors appeared at high-probability than low-probability locations. Conversely, in the distractor-absent condition, responses were significantly slower when targets appeared at high-probability distractor locations than at low-probability locations. SMART analysis further revealed that when distractors appeared at high-probability locations, individuals rapidly formed learned suppression of color singletons after minimal exposure, indicating a stable and efficient learning process (Savelson et al., 2025). After just 4 consecutive presentations of threat distractors and 1 presentation of non-threat distractors at high-probability locations, target responses were significantly faster than when the same distractors appeared at low-probability locations, with this effect remaining stable throughout the task. Interestingly, threat features did not interfere with learned distractor suppression formation. When threat stimuli appeared at high-probability locations, target responses were significantly faster than at low-probability locations, with no significant difference between threat and non-threat conditions at high-probability locations.

However, in Experiment 1' s visual search task, distractor stimuli only manipulated a single visual feature (color) of threat stimuli rather than threatening objects, potentially weakening their attentional capture effects (Pakai-Stecina et al., 2024). For example, Pakai-Stecina et al. (2024) found that compared to neutral objects similar to threat stimuli in visual features (e.g., worms), threatening objects (e.g., snakes) produced interference effects that were not modulated by spatial distance from the target, suggesting more automatic and difficult-to-suppress attentional capture. Eye-tracking results further showed that although participants fixated on threat distractors less frequently and for shorter durations than non-threat distractors, target fixation time decreased significantly when threat stimuli appeared. This indicates that threatening objects, compared to threat features, more readily elicit difficult-to-suppress attentional biases and hold higher attentional priority in allocation. Moreover, real-life threat stimuli typically exist not as isolated features but as integrated objects with multiple perceptual features and evolutionary significance. Therefore, Experiment 2 further investigated how color objects associated with threat influence the formation of location-probability-based learned distractor suppression.

Experiment 2

3.1.1 Participants

Sample size calculation and inclusion/exclusion criteria were identical to Experiment 1. Considering potential invalid participants, 31 healthy adults (8 males, 23 females) aged 20-25 were recruited through convenience sampling.

3.1.2 Experimental Design and Procedure

Identical to Experiment 1.

3.1.3 Experimental Tasks

Threshold Calibration Task: Identical to Experiment 1.

Threat Conditioning Task: Identical to Experiment 1.

Visual Search Task: The task setup was essentially identical to Experiment 1, with the only difference being shape fill configuration. As shown in Figure 1C, in no-distractor trials, all shapes were filled gray. In distractor-present trials, one circle was filled green or cyan while all other shapes remained gray. Green or cyan solid circles served as threat-object or non-threat-object distractor attributes, determined by the color paired with shock during threat conditioning.

Implicit Learning Assessment: Identical to Experiment 1.

3.1.4 Data Analysis

Identical to Experiment 1.

3.2.1 Behavioral Results

Distractor-Absent Condition: As shown in Figure 4 [Figure 4: see original paper]A, the main effect of distractor location probability was significant (b = -23.48, SE = 2.92, t(6854) = -8.03, $p < 0.001$, 95% CI = [-29.21, -17.75]; = -0.09, 95% CI = [-0.11, -0.06]). Further analysis revealed that responses were significantly slower when targets appeared at high-probability distractor locations (803.47 ± 16.70 ms) than at low-probability locations (756.51 ± 15.91 ms) (b = -47, SE = 5.85, z = -8.03, $p < 0.001$). These results replicated Experiment 1, demonstrating learned distractor suppression at high-probability locations that inhibited target processing at those positions.

Distractor-Present Condition: As shown in Figure 4B, the main effect of distractor location probability was significant (b = 20.21, SE = 1.34, t(17196) = 15.06, $p < 0.001$, 95% CI = [17.58, 22.84]; = 0.10, 95% CI = [0.09, 0.11]). Further analysis showed that responses were significantly faster when distractors appeared at high-probability locations (762.10 ± 18.28 ms) than at low-probability locations (802.52 ± 18.34 ms) (b = 40.4, SE = 2.68, z = 15.06, $p < 0.001$). The main effect of distractor stimulus type was significant (b = -3.76, SE

= 1.34, t(17196) = -2.80, p = 0.005, 95% CI = [-6.39, -1.13]; = -0.02, 95% CI = [-0.033, -0.006]). Further analysis revealed that responses were significantly faster in the threat-object distractor condition (778.55 ± 18.31 ms) than in the non-threat-object condition (786.07 ± 18.31 ms) (b = -7.52, SE = 2.68, z = -2.80, p = 0.005). The interaction between distractor stimulus type and location probability was marginally significant (b = 2.45, SE = 1.34, t(17196) = 1.83, p = 0.067, 95% CI = [-0.17, 5.08]; = 0.013, 95% CI = [-0.001, 0.026]). Simple effects analysis showed that for both threat-object (low-probability: 801.21 ± 18.47 ms vs. high-probability: 755.89 ± 18.35 ms, b = 45.33, SE = 3.80, z = 11.93, p < 0.001) and non-threat-object (low-probability: 803.82 ± 18.47 ms vs. high-probability: 768.31 ± 18.35 ms, b = 35.51, SE = 3.79, z = 9.38, p < 0.001) conditions, target RTs were significantly slower at low-probability than high-probability locations. Additionally, at high-probability locations, target RTs were significantly faster in the threat-object than non-threat-object condition (b = -12.42, SE = 3.17, z = -3.92, p < 0.001). However, at low-probability locations, no significant difference existed between threat-object and non-threat-object conditions (b = -2.61, SE = 4.32, z = -0.603, p = 1.00).

Temporal Dynamics: SMART analysis revealed that when threat-object distractors appeared at low-probability locations, target responses were significantly slower than at high-probability locations across three trial intervals (1-503, 517-694, 738-896). Similarly, when non-threat-object distractors appeared at low-probability locations, responses were significantly slower than at high-probability locations across two intervals (12-158, 243-896). Additionally, when distractors appeared at low-probability locations, no significant differences existed between threat-object and non-threat-object conditions at the trial level. However, at high-probability locations, threat-object distractors produced significantly faster responses than non-threat-object distractors across three intervals (37-64, 193-235, 372-491).

3.2.2 Awareness Assessment Results

Among 31 participants, 6 reported not noticing differential frequencies across locations, with mean confidence ratings of 4.33 ± 0.42. The remaining 25 participants reported perceiving differential frequencies, with mean confidence ratings of 4.08 ± 0.29. Importantly, the locations reported by these 25 participants did not correspond to the actual high/low-probability positions. These results suggest that participants did not explicitly recognize location probability regularities, indicating that learned distractor suppression was primarily based on unconscious statistical learning.

3.3 Discussion of Experiment 2

Consistent with Experiment 1, Experiment 2 demonstrated that individuals formed stable and efficient learned distractor suppression at high-probability locations. Unlike Experiment 1, we found that threatening objects facilitated learned distractor suppression at high-probability locations. Specifically, when threatening objects appeared at high-probability locations, target responses were significantly faster than when non-threatening objects appeared at those locations. This result suggests that learned suppression is adaptive and consistent with theoretical predictions that more salient stimuli produce stronger suppression (Failing & Theeuwes, 2020; Gong & Theeuwes, 2021). However, Experiment 2 found no significant difference in target RTs between threatening and non-threatening objects at low-probability locations. One possible explanation is that high color similarity between the two object types induced threat generalization effects (Dowd et al., 2016; Lissek et al., 2008; Struyf et al., 2017). Research indicates that when threat and neutral stimuli share highly similar perceptual features, individuals may misidentify neutral stimuli as threats, leading to emotional response generalization. This generalization effect may have prevented participants from accurately distinguishing between threatening and non-threatening objects at low-probability locations, thereby affecting attentional capture. To exclude this potential confound, Experiment 3 reduced color similarity between the two object types to effectively control threat generalization caused by color confusion, further validating how threatening objects influence the formation of location-probability-based learned distractor suppression.

Experiment 3

4.1.1 Participants

Sample size calculation and inclusion/exclusion criteria were identical to Experiment 1. Considering potential invalid participants, 31 healthy adults (9 males, 22 females) aged 20-25 were recruited through convenience sampling.

4.1.2 Experimental Design and Procedure

Identical to Experiment 1.

4.1.3 Experimental Tasks

Threshold Calibration Task: Identical to Experiment 1.

Threat Conditioning Task: As shown in Figure 1D, the task procedure was essentially identical to Experiment 1, with the only difference being color stimuli: Experiment 3 used more discriminable orange (RGB: [255, 69, 0]) and blue (RGB: [0, 128, 255]) colors, counterbalanced across participants.

Visual Search Task: As shown in Figure 1E, the task setup was essentially identical to Experiment 2, with the only difference being distractor colors: in distractor-present trials, one circle was filled orange or blue while all other shapes remained gray. Orange or blue served as threat or non-threat distractor attributes based on the color paired with shock during threat conditioning.

Implicit Learning Assessment: Identical to Experiment 1.

4.1.4 Data Analysis

Identical to Experiment 1.

4.2.1 Behavioral Results

Distractor-Absent Condition: As shown in Figure 6 [Figure 6: see original paper]A, the main effect of distractor location probability was significant (b = -38.11, SE = 2.84, $t(6956) = -13.42$, $p < 0.001$, 95% CI = [-43.68, -32.54]; = -0.14, 95% CI = [-0.16, -0.12]). Further analysis revealed that responses were significantly slower when targets appeared at high-probability distractor locations (819.87 ± 15.74 ms) than at low-probability locations (743.64 ± 14.95 ms) (b = -76.2, SE = 5.68, z = -13.42, $p < 0.001$). Consistent with the previous experiments, these results indicate that individuals formed learned distractor suppression at high-probability locations, inhibiting target processing at those positions.

Distractor-Present Condition: As shown in Figure 6B, the main effect of distractor location probability was significant (b = 21.82, SE = 1.28, $t(17471)$ = 17.08, $p < 0.001$, 95% CI = [19.32, 24.32]; = 0.12, 95% CI = [0.10, 0.13]). Further analysis showed that responses were significantly faster when distractors appeared at high-probability locations (744.24 ± 15.72 ms) than at low-probability locations (787.87 ± 15.79 ms) (b = 43.6, SE = 2.56, z = 17.08, $p <$ 0.001). The main effect of distractor stimulus type was not significant (b = 0.56, SE = 1.28, $t(17471)$ = 0.44, p = 0.66, 95% CI = [-1.95, 3.06]; = 0.003, 95% CI = [-0.01, 0.02]). No significant difference in target RT was found between threat-object (766.61 ± 15.75 ms) and non-threat-object (765.50 ± 15.76 ms) distractor conditions (b = 1.11, SE = 2.55, z = 0.44, p = 0.66). The interaction between distractor stimulus type and location probability was significant (b = 4.48, SE = 1.28, $t(17471)$ = 3.51, $p < 0.001$, 95% CI = [1.98, 6.99]; = 0.03, 95% CI = [0.01, 0.04]). Simple effects analysis showed that for both threat-object (low-probability: 792.91 ± 15.92 ms vs. high-probability: 740.31 ± 15.79 ms, b = 52.60, SE = 3.61, z = 14.58, $p < 0.001$) and non-threat-object (low-probability: 782.84 ± 15.92 ms vs. high-probability: 748.16 ± 15.80 ms, b = 34.68, SE = 3.62, z = 9.58, $p < 0.001$) conditions, target RTs were significantly slower at low-probability than high-probability locations. Additionally, at low-probability locations, target RTs were marginally slower in the threat-object than non-threat-object condition (b = 10.07, SE = 4.12, z = 2.44, p = 0.087). At high-probability locations, target RTs were marginally faster in the threat-object than non-threat-object condition (b = -7.85, SE = 3.02, z = -2.60, p = 0.056).

Temporal Dynamics: SMART analysis revealed that when threat-object distractors appeared at low-probability locations, target responses were significantly slower than at high-probability locations across the trial interval (1-896). Similarly, when non-threat-object distractors appeared at low-probability locations, responses were significantly slower than at high-probability locations across four intervals (1-352, 446-587, 660-740, 793-889). Additionally, when distractors appeared at low-probability locations, threat-object distractors produced significantly slower responses than non-threat-object distractors across interval (378-483). When distractors appeared at high-probability locations, threat-object distractors produced significantly faster responses than non-threat-object distractors across three intervals (195-231, 348-385, 574-657).

4.2.3 Awareness Assessment Results

Among 31 participants, 11 reported not noticing differential frequencies across locations, with mean confidence ratings of 3.36 ± 0.58. The remaining 20 participants reported perceiving differential frequencies, with mean confidence ratings of 4.10 ± 0.28. Importantly, the locations reported by these 20 participants did not correspond to the actual high/low-probability positions. These results suggest that participants did not explicitly recognize location probability regularities, indicating that learned distractor suppression was primarily based on unconscious statistical learning.

4.3 Discussion of Experiment 3

Consistent with Experiment 2, Experiment 3 further demonstrated that individuals formed stable and efficient learned distractor suppression at high-probability locations, and that threatening stimuli facilitated this formation. Specifically, when threatening stimuli appeared at low-probability locations, target responses were significantly slower than when non-threatening stimuli appeared at low-probability locations. Conversely, when threatening stimuli appeared at high-probability locations, target responses were significantly faster than when non-threatening stimuli appeared at high-probability locations. This indicates that learned suppression is adaptive and consistent with theoretical predictions that more salient stimuli produce stronger suppression (Failing & Theeuwes, 2020; Gong & Theeuwes, 2021).

General Discussion

This study employed a threat conditioning task to generate threat and non-threat stimuli, then manipulated the spatial presentation probabilities of distractor stimuli in a visual search task across three experiments to investigate how threatening stimuli influence the formation of learned distractor suppression. Consistent across all three experiments, in the distractor-present condition, participants responded significantly faster to targets when distractors appeared at high-probability locations than at low-probability locations; conversely, in the distractor-absent condition, responses were significantly slower when targets appeared at high-probability distractor locations than at low-probability locations. Computational modeling further revealed that when distractors appeared at high-probability locations, individuals rapidly formed learned suppression of color singletons after minimal exposure, demonstrating that this learning process is stable and efficient. Critically, when threat was presented as a feature in the visual search task, it did not affect learned distractor suppression formation; however, when threat was presented as an object, it facilitated acquisition. This aligns with previous findings that more salient stimuli produce stronger suppression effects and extends this salience characteristic beyond visual to emotional salience.

First, individuals formed stable and efficient learned distractor suppression at high-probability distractor locations. Consistent with previous research (Wang & Theeuwes, 2018a, 2018b, 2018c), even threatening distractors at high-probability locations elicited significantly faster target responses than at low-probability locations. These results indicate that despite threat stimuli possessing hard-wired priority in attentional processing, when they frequently appear at specific spatial locations, the visual system can flexibly integrate environmental statistical regularities to reduce their attentional capture. Furthermore, SMART computational modeling showed that individuals required only minimal exposure to form learned distractor suppression, consistent with prior findings (Gaspelin & Luck, 2018; Savelson et al., 2025). Savelson et al. (2025) found through moving RT analysis that learned distractor suppression could be established after only 2-3 encounters with distractors. These results demonstrate that learned distractor suppression formation is both efficient and stable.

Second, threat features did not interfere with learned distractor suppression formation, whereas threatening objects facilitated this mechanism. In Experiment 1, threat features did not affect learned distractor suppression formation—no significant difference in target RTs existed between threat-feature and non-threat-feature distractors at high-probability locations. This aligns with previous findings that reward-feature distractors do not interfere with learned distractor suppression formation (Le Pelley et al., 2022; Zhao et al., 2024). However, unlike Experiment 1, Experiments 2 and 3 showed that threatening objects facilitated learned distractor suppression formation. The discrepancy between threat features and threatening objects may stem from differences in their salience. Experiments 1 and 3 revealed differential performance between the two stimulus types at low-probability locations: in Experiment 1, target responses were faster when threat-feature distractors appeared at low-probability locations than non-threat-feature distractors; in Experiment 3, responses were slower when threat-object distractors appeared at low-probability locations than non-threat-object distractors. This suggests that attentional capture may be a prerequisite for learned distractor suppression formation (Gaspelin et al., 2025). Furthermore, threatening objects are more visually salient than single threat features and are therefore more readily tagged as "to-be-ignored" at high-probability locations, facilitating learned distractor suppression formation. This provides new evidence for the saliency-specific mechanism of distractor suppression, which posits that higher stimulus salience induces stronger learned distractor suppression effects at high-probability locations (Failing & Theeuwes, 2020; Gong & Theeuwes, 2021). For instance, Failing and Theeuwes (2020) found that when high-salience distractors (in color or luminance) appeared at their high-probability locations, target responses were significantly faster than at low-probability locations. Moreover, regardless of distractor salience level, interference effects were significantly reduced when appearing at high-probability locations of high-salience distractors. These results align with our findings that threatening objects at high-probability locations elicited significantly faster target responses than non-threatening objects, demonstrating that salience effects extend to emotional processing domains. In summary, the current study expands the applicability of the saliency-specific distractor suppression mechanism, showing that not only traditional visual salience but also emotional salience can modulate learned distractor suppression formation.

Finally, this study provides new evidence for the interaction between emotional valence and statistical learning. We found a significant interaction between threatening objects and location probability. However, Theeuwes et al. (2025) did not observe such an interaction. This discrepancy may be attributed to their experimental design, which included a pre-conditioning phase where participants formed learned suppression of high-probability locations before stimuli acquired threat properties. Consequently, even when a distractor was subsequently 赋予 threat meaning, since it remained a distractor in the task, participants could continue effectively suppressing it without additional attentional resources. Despite differences in result patterns between the two studies, both indicate that threat stimuli can influence attentional selection processes through unique mechanisms under specific conditions, whether or not this manifests as an interaction with location probability. From the perspective of the Tripartite Model of Attentional Control, attentional selection is jointly influenced by bottom-up drive, top-down control, and selection history. These three factors compete in the attentional priority map through a "winner-take-all" mechanism to determine final attentional resource allocation (Anderson et al., 2021; Awh et al., 2012; Theeuwes, 2025). The inconsistent findings precisely reflect that the role of threat stimuli in the attentional system is not fixed but depends on its integration and competition with other attentional drive factors in the current context: in some situations, threat stimuli may dominate attentional capture through strong bottom-up signals; in others, they may be integrated into biases established by selection history, thereby influencing spatial attention allocation. Therefore, regardless of whether a significant interaction exists, both studies support the dynamic competitive nature of attentional resource allocation emphasized by the tripartite model. In summary, the present study further suggests that threat stimuli may enhance the weight of selection history in the attentional priority map, facilitating suppression of distractors at high-probability locations and thereby improving target processing efficiency.

This study has certain limitations. Although using color-shock conditioned stimuli as threat induction offers high experimental controllability, such threat stimuli lack ecological validity compared to real-life threats (e.g., snakes, spiders). Future research could incorporate higher ecological validity threat stimuli to further validate the generalizability and external validity of our findings.

In conclusion, individuals can stably and efficiently form learned distractor suppression through statistical learning of distractor location probabilities. Critically, threat stimuli may enhance this mechanism by increasing the weight of selection history in the attentional priority map, thereby strengthening the distractor suppression mechanism established by the visual system based on statistical regularities.

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