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The Temporal Dynamics of Visual Attention

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Researchers have long debated how humans select relevant objects amid physically salient distractions. An increasingly popular view holds that the key to avoiding distractions lies in suppressing the attentional priority of a salient distractor. However, the precise mechanisms of distractor suppression remain elusive. Because the computation of attentional priority is a time-dependent process, distractor suppression must be understood within these temporal dynamics. In four experiments, we tracked the temporal dynamics of visual attention using a novel forced-response method, by which participants were required to express their latent attentional priority at varying processing times via saccades. We show that attention could be biased either toward or away from a salient distractor depending on the timing of observation, with these temporal dynamics varying substantially across experiments. These dynamics were explained by a computational model assuming the distractor and target priority signals arrive asynchronously in time and with different influences on saccadic behavior. The model suggests that distractor signal suppression can be achieved via a "slow" mechanism in which the distractor priority signal dictates saccadic behavior until a late-arriving priority signal overrides it, or a "fast" mechanism which directly suppresses the distractor priority signal's behavioral expression. The two mechanisms are temporally dissociable and can work collaboratively, resulting in time-dependent patterns of attentional allocation. The current work underscores the importance of considering the temporal dynamics of visual attention and provides a computational architecture for understanding the mechanisms of distractor suppression.

Public Significance Statement

We often need to search for certain objects (like a road sign) while avoiding being distracted by salient but irrelevant objects (like a billboard). How exactly do we do this? This seemingly simple question has been the subject of complex debates for decades. We argue that the answer lies in the time course of visual attention. It takes time for the attention system to process the search environment, and recognizing this fact is crucial for understanding how we overcome distraction. Using a novel approach, we identified two mechanisms of distractor suppression: a "slow" mechanism in which the distractor ceases to distract once the target is selected and a "fast" mechanism by which the distractor is quickly processed but then avoided. These results are important in understanding how visual attention works and may have implications for improving search efficiency in daily contexts.

Keywords: visual attention, attentional capture, visual search, eye movements, distraction

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Much of human cognitive life hinges on a struggle between habitual and goal-directed processes. The topic has attracted interest since the dawn of psychology, from William James' (1890) distinction between reflexive and voluntary attention to Kahneman's (2011) contrast between the fast and automatic System 1 and the slower but more deliberate System 2. Indeed, certain stimuli such as the bright, flashing light of an ambulance seem to automatically capture our attention. While attending to physically salient stimuli might serve important evolutionary functions, they are not necessarily the targets for which we are searching given our current goals.

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Then, what might be the mechanisms for the suppression of salient distractors?

The Role of Suppression in Visual Attention

A prominent paradigm used to study the interference by salient stimuli in visual search is the "additional-singleton" paradigm (Theeuwes, 1992). In a classic version of the task, participants search for a target item defined as a unique shape in a search array, such as a circle among diamonds. On a random half of the trials, one randomly chosen nontarget item appears in a unique color, thus becoming a color singleton. Although the color singleton is never the target, it substantially interferes with visual search: The presence of the color singleton prolongs the time to respond to the target (Theeuwes, 1992), attracts a sizeable proportion of the observer's first eye movements on each trial (Theeuwes et al., 2003), and elicits an event-related potential (N2pc) indicative of attentional selection of the color singleton's location (Hickey et al., 2010). These results have been taken as evidence that physically salient stimuli automatically capture visual attention even when they are in conflict with the observer's goals.

Yet, other studies have shown that attentional capture can be attenuated. Two well-known examples are when a salient distractor tends to appear at a regular spatial location (e.g., Wang et al., 2019; Wang & Theeuwes, 2018a, 2018b) or when the overall frequency of the distractor appearing is high (e.g., Geyer et al., 2008; Müller et al., 2009; Won et al., 2019). The largest attenuation of capture is typically observed in tasks where people are asked to search for a specific shape among heterogeneous shapes (e.g., Bacon & Egeth, 1994; Gaspelin et al., 2015, 2017). Participants search for a fixed target item (e.g., a green circle) among heterogeneous shapes such as squares, triangles, and hexagons. On a random half of the trials, one of the randomly chosen nontarget items appears in a unique color. In this condition, (a) response times are slightly faster when the distractor is present compared to absent, (b) initial eye movements to the distractor are below baseline levels, (c) the distractor elicits an event-related potential (Pd) which is indicative of attentional suppression of the distractor's location, and (d) recall for probe letters presented at the distractor's location is below baseline levels (for comprehensive reviews, see Gaspelin & Luck, 2018c; Gaspelin et al., 2023; Luck et al., 2021). In contrast to a pure salience-driven view, these results indicate that physically salient stimuli can be ignored if they are in conflict with the observer's goals.

In light of the mixed findings, the notion of suppression has been proposed to explain the malleability of attentional capture effects. In particular, the *signal suppression hypothesis* (Gaspelin & Luck, 2018c; Sawaki & Luck, 2010) asserts that a salient distractor automatically generates a priority signal, but this priority signal can be suppressed to avoid capture. Specifically, it is assumed that visual search is guided by a "priority map" that assigns attentional priority values to items in a display. The priority map is jointly influenced by the physical properties of the stimuli and the observer's attentional control settings. In the absence of appropriately configured attentional control settings, the priority map will be solely determined by the physical salience of the stimuli, thereby assigning the highest priority to a salient distractor. However, in the presence of certain attentional control settings, attentional priority to the salient distractor can be suppressed, preventing attentional capture by the distractor.

Despite emerging consensus on the existence of distractor suppression, the precise mechanism of suppression remains a topic of considerable debate (as reflected in Luck et al., 2021). Indeed, while attentional capture by a distractor can be prevented given certain "appropriately configured attentional control settings," just what these specific settings might be remains largely underspecified. This is the focus of the current work. Going beyond the conceptual framework of distractor suppression, we sought to provide (a) a novel application of a behavioral paradigm that allows us to track the temporal dynamics of visual attention and, based on data gathered from this paradigm, (b) a computational architecture for understanding how distractor suppression is implemented in visual search.

The Priority Map Evolves Over Time

Visual search is commonly assumed to be guided by a "priority map" that encodes both the physical salience and the goal relevance of items in a display (Awh et al., 2012; Bacon & Egeth, 1994; Luck et al., 2021; Sprague et al., 2018; Theeuwes, 2018; Wolfe, 2021). As mentioned, the concept of a priority map is also featured in theories of distractor suppression. Oftentimes, the priority map is implicitly assumed to be a static, time-invariant construct that is constructed instantaneously at the start of visual search. By this account, before participants deploy visual attention to select a specific item (e.g., by launching a saccade), the search display is completely analyzed, and attentional priority is fully computed and ready to guide attention. Then, participants either succeed or fail to suppress a salient distractor depending on this settled priority map.

Yet, in contrast to this simplistic view of the priority map, we know that the visual system needs time to analyze even very basic features such as color (e.g., Palmer et al., 2019). Beyond processing basic features, the computation of attentional priority may also involve higher order processes, such as memory retrieval and comparison to a search template. All these processes take time to complete. This suggests that the priority map is a time-dependent construct, with different sources of information influencing the map at different time points (for similar arguments, see Donk, 2021; Godijn & Theeuwes, 2002; Wolfe, 2021).

Supporting this idea, past studies have shown that an observer's attentional priority shifts depending on *when* the search is initiated. Specifically, saccades initiated rapidly following stimulus onset tend to be driven by physical salience, whereas slower saccades are much less affected by physical salience and more by goal relevance (N. C. Anderson et al., 2015; Godijn & Theeuwes, 2002; Hunt et al., 2007; Siebold et al., 2011; van Zoest & Donk, 2008; van Zoest et al., 2004). A similar pattern has also been observed with covert attention using the N2pc component as an index of attentional selection (e.g., Hickey et al., 2010). These results suggest that, depending on when visual attention is deployed, it is driven by a snapshot of the temporally evolving priority map. Attention can be biased toward a salient distractor if goal-driven processes have not yet been completed (Godijn & Theeuwes, 2002; see also Findlay, 1997).

In a similar vein, studies that controlled the viewing time of search stimuli have also found an early attentional bias toward salient stimuli (Donk & Soesman, 2010; Donk & van Zoest, 2008; Theeuwes et al., 2000). For example, Theeuwes et al. (2000) reported that in the additional-singleton task, the presence of a color-singleton distractor significantly increased response times when it was presented simultaneously with the target, but not when it was presented 150 ms before the target.

Another line of evidence comes from studies examining visually guided reaching behaviors, based on the assumption that attentional selection for action and perception share a common mechanism (e.g., Hunt et al., 2007; Kerzel & Schönhammer, 2013; Song & Nakayama, 2008; Wood et al., 2011). These studies show a similar time-dependent pattern in reaching behaviors. For example, Wood et al. (2011) showed that initial reach trajectories were biased toward more salient items in the display, even when salience did not predict the target's location. However, this salience bias was eliminated when participants were given a 500-ms preview of the display before initiating movement.

In sum, the bulk of evidence indicates that the priority map is a time-dependent construct. However, this temporal aspect has largely been overlooked in the study of distractor suppression (Donk, 2021). This neglect is, in part, due to the traditional reliance on aggregated indices of visual attention, such as mean response times and the overall proportion of saccade destinations. These measurements miss the time course of processing, leaving voids in our inspection of the underlying processes that unfold over time. That is, traditional behavioral methods provide just a snapshot at the end of processing when a response is emitted and do not directly reflect what happens during that processing along the way. To address this shortcoming, we present a behavioral paradigm, the forced-response method, that is capable of comprehensively tracking the temporal dynamics of visual attention.

The Forced-Response Method

The forced-response method involves fixing response latencies, manipulating stimulus onset time, and observing response expression (Ghez et al., 1997; Haith et al., 2016). Figure 1 shows a schematic illustration of the procedure. On each trial, participants received four equally spaced auditory signals. The last signal, played at $t = 3$ s, was at a higher pitch than the first three signals, serving as a "go" command. Participants were first trained on the procedure so that they could learn to make a saccade at the onset of the "go" command. Then, the search array was introduced in a subsequent set of trials, and participants were asked to make a saccade to the target item on the "go" command. Critically, the search array's onset time was systematically varied in relation to the "go" command, leading to variation in and control over the amount of processing time available before the initiation of a saccade. We used the direction of initial saccades as our primary measure because it provides an unambiguous indicator of overt visual attention at the time of saccade initiation. In essence, the forced-response method demands that participants express their current latent attentional priority through an overt saccade, enabling us to observe the temporal structure of the priority map.

The history of the forced-response method can be traced back to Schouten and Bekker (1967). In a simple choice task, they asked participants to respond at the last of three auditory beeps as a way to control speed–accuracy trade-offs. Interest in the method has since reemerged, in that some studies have used it to study the time course of motor planning (Ghez et al., 1997; Haith et al., 2016). More recently, the method has been extended to keyboard tasks involving response competition to dissociate habitual and goal-directed processes by our research group (e.g., Adkins & Lee, 2023, in a Simon task) and others (e.g., Hardwick et al., 2019, in a visuomotor learning task). It is a natural extension to apply this method to saccadic behavior to study the competition between a salient distractor and the target in the context of visual search.

The idea of applying the forced-response method to saccadic behavior is also founded on studies applying microstimulation to more directly evoke saccades in monkeys (Gold & Shadlen, 2000, 2003). In a motion discrimination task, Gold and Shadlen (2000) trained monkeys to make an upward or a downward saccade based on the net motion of a dynamic random-dot field. On some trials, electric currents were applied to the monkeys' frontal eye field, which resulted in a short-latency saccade due to the stimulation, followed by a voluntary saccade that indicated the monkey's chosen target. Critically, the electrically evoked saccade deviated in the direction of the chosen target, with the magnitude of deviation dependent on the amount of viewing time prior to stimulation. These findings suggest that the oculomotor system encodes dynamic states of visual processing and can be leveraged to track the temporal structure of the priority map.

As mentioned, some studies have passively observed saccadic destinations as a function of saccadic latencies (e.g., van Zoest et al., 2004). However, obtaining a comprehensive temporal profile of the priority map can be challenging using just the standard free-response approach. Humans tend to have a preferred timing of saccade initiation and usually avoid saccadic latencies that are exceptionally short or long when responding in free-response tasks (Engbert et al., 2005; Sumner, 2011). However, saccades with longer and shorter-than-usual latencies are crucial for dissociating the underlying mechanisms of distractor suppression. Some studies attempted to change the speed–accuracy trade-offs in visual search via verbal instructions or response deadlines (e.g., Hunt et al., 2007). However, these methods do not impose tight control over response latencies on a trial-by-trial basis like the forced-response method does.

In sum, the forced-response method applied to saccadic behavior holds potential as an illuminating method for tracking the temporal dynamics of visual attention.

The Present Study

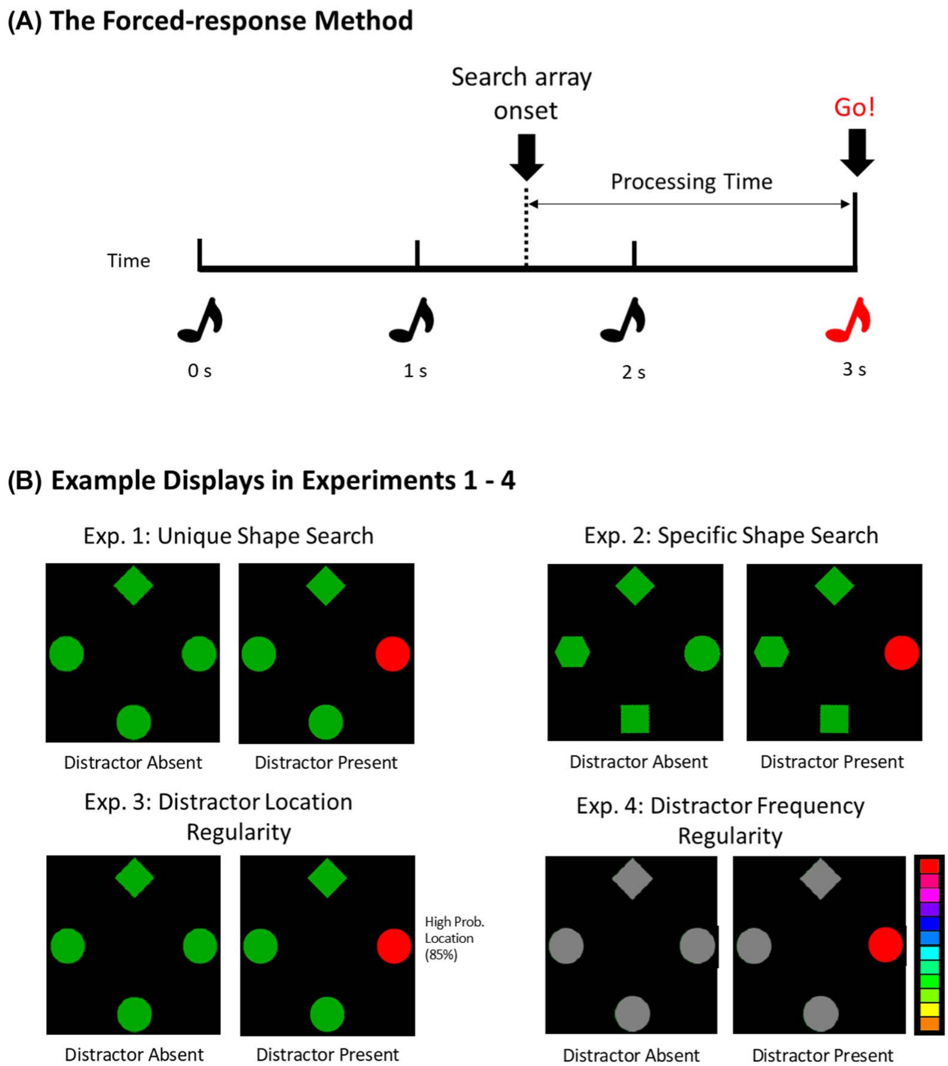
In four experiments, we applied the forced-response method in conjunction with a computational model to elucidate the mechanisms underlying the temporal evolution of visual attention. Experiment 1 adopted the classic additional-singleton task, in which participants searched for a unique shape while ignoring a color-singleton distractor. Experiments 2–4 each investigated a well-known condition that presumably involves distractor suppression. We show that these conditions were associated with very different time courses of visual attention. Despite so, these variations can be well accounted for by adjustments within the same small set of parameters in our computational model.

Details of the computational model will be introduced in a later section. Briefly speaking, the model specifies the latencies of when the distractor priority signal and the target priority signal arrive, as well as the probability that each priority signal will influence visual attention as measured by saccadic behavior. The fit to behavior will inform the specific mechanisms driving visual attention in each specific task.

Experiment 1: Unique Shape Search

In Experiment 1, participants (N = 28) completed a forced-response task adapted from the additional-singleton task, a classic

Figure 1
Schematic Illustrations of the Study's Experimental Approach



Note. Panel A: A schematic illustration of the forced-response method. Panel B: Example displays in Experiments 1–4 (not drawn to scale). See the online article for the color version of this figure.

paradigm assessing the interference of a salient color distractor on visual search (Theeuwes, 1992). In this task, participants searched for a unique shape (e.g., a diamond amidst circles) while a distractor item of a unique color appeared on half of the trials (see Figure 1B for an example). As mentioned, this task has consistently shown a strong overall capture effect, and a particularly convincing line of evidence is that the color singleton attracts a sizable portion of initial saccades (e.g., Gaspelin et al., 2017; Theeuwes et al., 2003). As such, it is often considered a classic example in which the distractor cannot be suppressed (Gaspelin & Luck, 2018c).

In the current task, participants were instructed to initiate a saccade at the time of the "go" command, with the temporal onset of the search array systematically varied in relation to this command. This experiment served to establish the utility of our method in tracking and modeling the temporal dynamics of visual attention.

Method

Transparency and Openness

For all experiments, we report how we determined our sample size, all data exclusions (if any), all manipulations, and all measures in the study. All data, analysis code, and experiment programs are available at https://osf.io/62pre/ (Zhang et al., 2024). This study's design and its analysis were not preregistered.

Participants

Due to the novelty of the research methodology, we were unable to find effect sizes from previous comparable studies to conduct a formal power analysis. Nevertheless, we conducted a pilot test using mouse tracking and determined that a sample size of 15 was sufficient to trace the entire temporal profile in this task (see the Supplemental Materials). We opted to double the sample size, with a target recruitment of 30 participants. In practice, we recruited a total of 32 participants from the University of Michigan Introductory Subject Pool to complete the study. Data from four participants were discarded due to experiment failures. The final sample size was 28 (M_{age}: 18.82, SD_{age}: .77, gender: 39.3% male, 57.1% female, 3.6% nonbinary).

The following applies to this and all subsequent experiments: All participants provided written informed consent, and all procedures were approved by the University of Michigan Institutional Review Board. All participants had normal or corrected-normal vision. Age was obtained via a free-response box, and gender information was obtained by giving participants options from which to choose. Participants received 1 hr of subject pool credit for completion.

Apparatus and Stimuli

The visual search task was presented on a 20.1-in. computer screen positioned approximately 90 cm from the participant. The task was implemented using Psychopy (Peirce, 2007) with eye movements recorded by an EyeLink 1000 System (SR Research Ltd.) at a sampling rate of 500 Hz using the desktop remote tracking mode. Saccades were detected at a velocity threshold of 40°/s and an acceleration threshold of 80,000°/s/s, per the Eyelink system's default for the remote tracking mode.

The search array comprised four filled shapes—top, left, bottom, and right—each positioned 4.86° from the screen center (Figure 2A). The items, either diamonds (with a 1.93° diagonal) or circles (with a 1.67° diameter), were drawn in red or green and presented on a black background. The auditory cues for the forced-response procedure were three 200-ms low-pitched tones (330 Hz) followed by a 500-ms high-pitched tone (660 Hz), played through a pair of speakers placed on each side of the screen.

Procedure

The task consisted of two practice phases and one experimental phase. In the first practice phase, participants practiced the imperative visual search task without forced-response timing. Each trial started with a fixation cross (1.3° × 1.3°) at the screen center. Participants were required to maintain their gaze on the fixation cross for 500 ms as a trigger for the search array to appear. The search array consisted of four shapes, with the target being a unique shape (e.g., a diamond among circles). The target's shape (a diamond or a circle), color (red or green), and location (top, bottom, left, or right) were all randomly decided on each trial. On a random half of trials, a nontarget item appeared in a unique color, serving as a salient distractor. The location of the distractor was randomly chosen from the three remaining locations excluding the target's location. Participants were asked to make a saccade toward the target item, with no manual response necessary. Saccades that began inside and ended outside the fixation cross were assigned to an item based on its quadrant (this was for providing online feedback only; we reclassified saccade destinations using offline data; see the "Data Preprocessing and Analysis" section for details). Once a valid saccade toward an item was detected, the search array was terminated, and depending on the saccade location, a feedback message ("Correct location!" or "Wrong location!") was displayed for 1,250 ms. The next trial began following a 750-ms blank interval. Participants completed 40 trials in this practice phase.

In the second practice phase, participants practiced the forced-response timing without the imperative search task. Each trial again started with a gaze-contingent fixation cross as in the previous practice. Then, participants heard four beeps at 1-s intervals. The last beep had a higher pitch than the first three beeps, signaling a "go" command. A single item appeared at a random time between 0 and 1,500 ms before the "go" command and remained on the screen until 500 ms after the "go" command. Participants were asked to make a saccade toward the item exactly at the "go" command. The fixation cross remained on the screen until the "go" command, serving as an anchor for the gaze. A saccade was considered on time if its initiation time did not deviate more than 200 ms from the "go" command. A feedback message was displayed for 1,250 ms based on saccade timing and location. If both location and timing were correct, "Good timing Correct location!" was displayed, accompanied by a high-pitched pleasant tone. If only the timing was correct, "Good timing Wrong location!" was displayed, accompanied by a low-pitched pleasant tone. If the timing was incorrect, regardless of whether the location was correct, "Too Slow!" or "Too Fast!" was displayed, accompanied by a warning sound. If there was no saccade with a starting position inside the fixation zone and an end position outside of the fixation zone, "No eye movement detected!" was displayed, accompanied by a warning sound. This was followed by a 750-ms blank interval before the next trial began. Participants completed a block of 40 trials during this practice and repeated the practice until they reached above 40% timing accuracy.

The experimental phase, as illustrated in Figure 1A, was a combination of the two practice phases. Participants were asked to make a saccade to the unique item exactly at the "go" command. Each trial included a gaze-contingent check and the forced-response signals, with the search array appearing randomly between 0 and 1,500 ms before the "go" command. Participants received the same feedback as in the second practice phase, followed by a 750-ms blank interval. This phase consisted of five blocks of 40 trials each.

The eye-tracker was calibrated at the beginning of the first and the second practice phases as well as at the beginning of each experimental block.

Data Preprocessing and Analysis

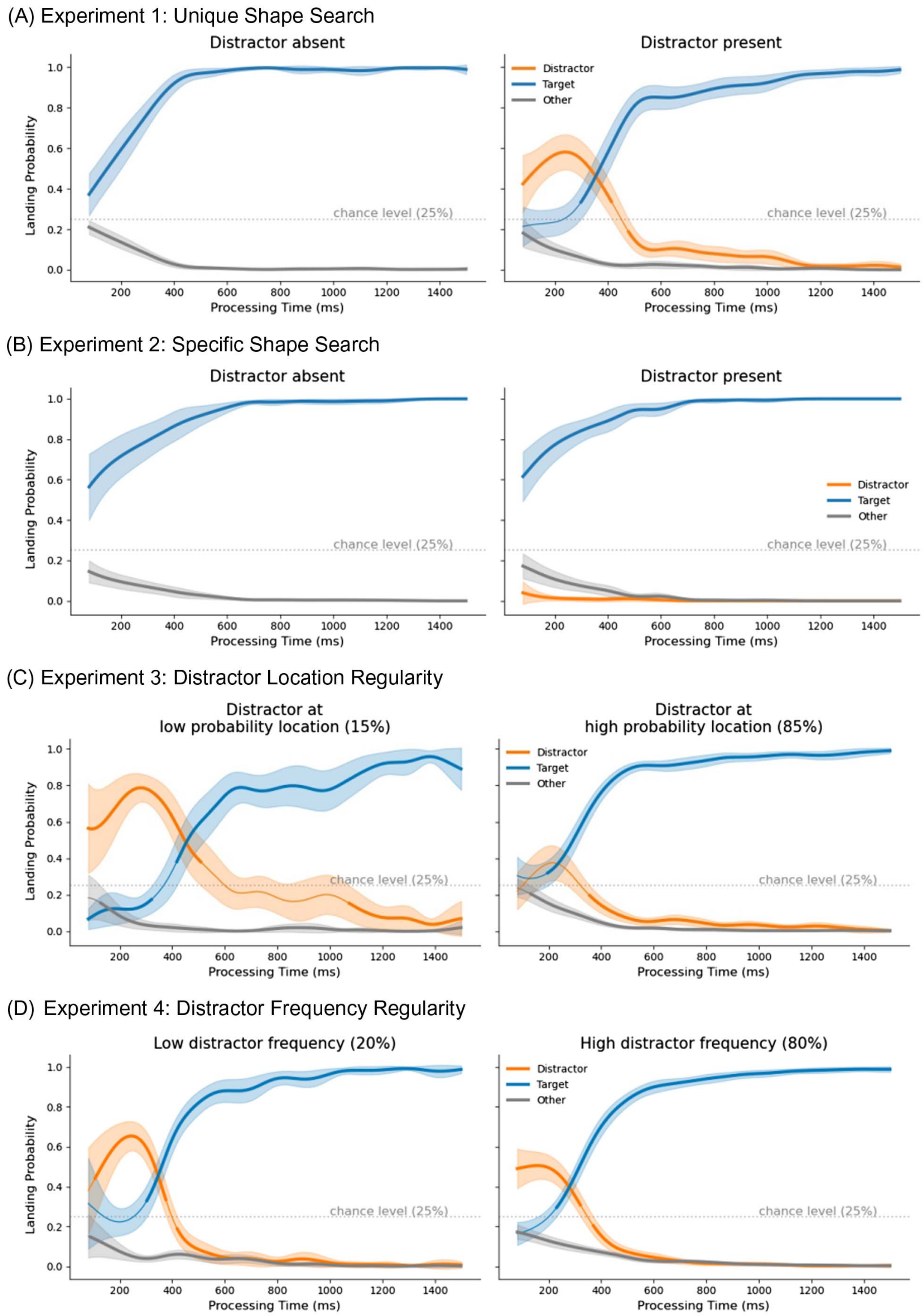
Data for each experiment underwent an identical set of preprocessing steps. A breakdown of the proportions of trials removed in each experiment at each processing step can be found in the Supplemental Materials.

First, trials were removed if they did not include a saccade with a starting position inside the fixation zone or an end position outside of the fixation zone, defined as the central screen area with a diameter of 1.3°.

Second, for each trial, we computed processing time as the duration from stimulus onset to the initiation of a saccade. For example, if the search array appeared at 2,500 ms, and a saccade was initiated at 3,050 ms, processing time was then calculated as 3,050 − 2,500 = 550 ms. This calculation method acknowledges that it is unrealistic for participants to respond exactly at the "go" command, and it accurately represents the actual time it took for participants to generate a response. The timing of saccade onset was determined in real-time by Eyelink's proprietary algorithm, as specified above.

Figure 2

The Smoothed Landing Probabilities as a Function of Processing Time in Experiments 1–4



Note. Intervals significantly deviating from the chance level, as indicated by the horizontal dotted line, are shown in thicker lines. The "Other" lines indicate the average landing probability of the remaining items in the search array (3 on distractor-absent trials and 2 on distractor-present trials). Error bands indicate a 95% confidence level. Panels C and D show data only of the distractor-present trials with high and low distractor regularity, in that this is the critical comparison in both experiments. Results for distractor-absent trials for these two experiments can be found in the Supplemental Materials. See the online article for the color version of this figure.

An analysis of the saccade latency distribution relative to the first auditory signal revealed that the bulk of the distribution was centered around the "go" command (see the Supplemental Materials), suggesting that participants effectively complied with the forced-response protocol. Trials with extreme processing times (<80 or >1,500 ms) were removed.

Third, landing positions of saccades were classified based on their angular distance to the nearest item. Specifically, for each saccade, we computed the angular distance between a straight line connecting the saccade's starting point and endpoint and a straight line connecting the screen center to each item's location. A saccade was assigned to an item if (a) its angular distance was the nearest to that item and (b) its angular distance to that item was smaller than 30°. Saccades that were not assigned to any item were removed from the analysis.

In addition, trials with curved saccadic trajectories were also removed. Two criteria were used to identify curved saccades. First, for each saccade, we computed the angular distance between a straight line connecting the starting point and the endpoint of a saccade and a straight line connecting the starting point and the midpoint of the same saccade (Godijn & Theeuwes, 2002). Second, for each saccade, we determined its landing position based on its midpoint using the same method as described above. A trial was categorized as "curved" either if the angular distance value based on the midpoint exceeded 30° from its endpoint or if the landing position calculated based on the midpoint differed from that calculated based on the endpoint.

To analyze landing probabilities as a function of processing time, we applied the SMART method to our data (van Leeuwen et al., 2019). The method involves first performing a Gaussian smoothing of the data along the processing time axis from each participant and then using a weighted average to construct a group-average time course. Cluster-based permutation testing was then performed to examine differences between time courses (akin to a paired-sample *t* test) or from a baseline (akin to a one-sample *t* test). Specifically, the data were analyzed to identify clusters of adjacent time points that show significant differences. Then, a cluster-level *t* value was computed by summing across *t* values within a cluster. This cluster-level statistic was then compared to a minimum threshold derived from random permutations of the original data. If the cluster-level *t* value was greater than the threshold value (i.e., 95th percentile of the permutated distribution), then the cluster was considered to be significant. For all experiments, we used a kernel standard deviation of 60 ms with a step size of 1 ms for smoothing. Cluster-based *t* tests were based on 1,000 permutations with an α level of .05. Additionally, for the other items (i.e., nontarget, nondistractor items), we applied the SMART procedure to calculate their average landing probability. Thus, the results indicate the landing probability for an averaged "other" item.

Results

Behavioral Data

Figure 2A shows the smoothed probability of initial saccades landing on each item, plotted against processing time, which represents the time from stimulus onset to the initiation of a saccade. As shown in the figure, when the distractor was present, there was a pronounced uptick in the probability of landing on the distractor, peaking at about 240 ms. This uptick is followed by a decrease that gradually reached toward the floor after processing time went past approximately 500 ms.

To formally characterize these temporal dynamics, we conducted cluster-based permutation *t* tests to identify periods during which landing probabilities significantly deviated from the chance level. We used what would be expected if participants initiated their saccades randomly (25%) to gauge whether visual attention was biased toward or away from a specific item. For all experiments, we report only the significant clusters within the time courses of the distractor and the target on distractor-present trials for the sake of brevity. Full results for each trial type can be found in the Supplemental Materials.

Using this procedure, we found that on distractor-present trials, the probability of landing on the distractor exceeded the chance level (25%) between 80 ms and 414 ms. This period can be interpreted as when visual attention was biased toward the distractor. However, from 478 ms onward, the probability of landing on the distractor fell significantly below chance, suggesting that visual attention was biased away from the distractor. For the target, landing probability exceeded the chance level (25%) starting at 299 ms and remained above chance thereafter. These results are visualized in Figure 2A.

Discussion

These results clearly demonstrate that visual attention differs depending on when attention is deployed. Consistent with previous findings, there was an early attentional bias toward the distractor. However, attention could also be biased away from the distractor if saccades were delayed. Such long-latency saccades, however, are rarely observed in typical free-response paradigms. For example, the mean saccade latencies in various versions of the additional-singleton task in Gaspelin et al. (2017) were about 200–250 ms, with a standard deviation in the range of 30–50 ms (see also Theeuwes et al., 2003). With the forced-response method, however, we could exert more control over response initiation and more comprehensively track the time course of visual attention.

Computational Model

What are the underlying mechanisms driving these dynamic shifts of attention? To answer this question, we employed a computational model that has been used to disentangle the preparation of competing responses (Adkins & Lee, 2023; Hardwick et al., 2019). A schematic illustration of the model is shown in Figure 3A. Below, we lay out the model's basic architecture and assumptions. See the Supplemental Materials for complete modeling details.

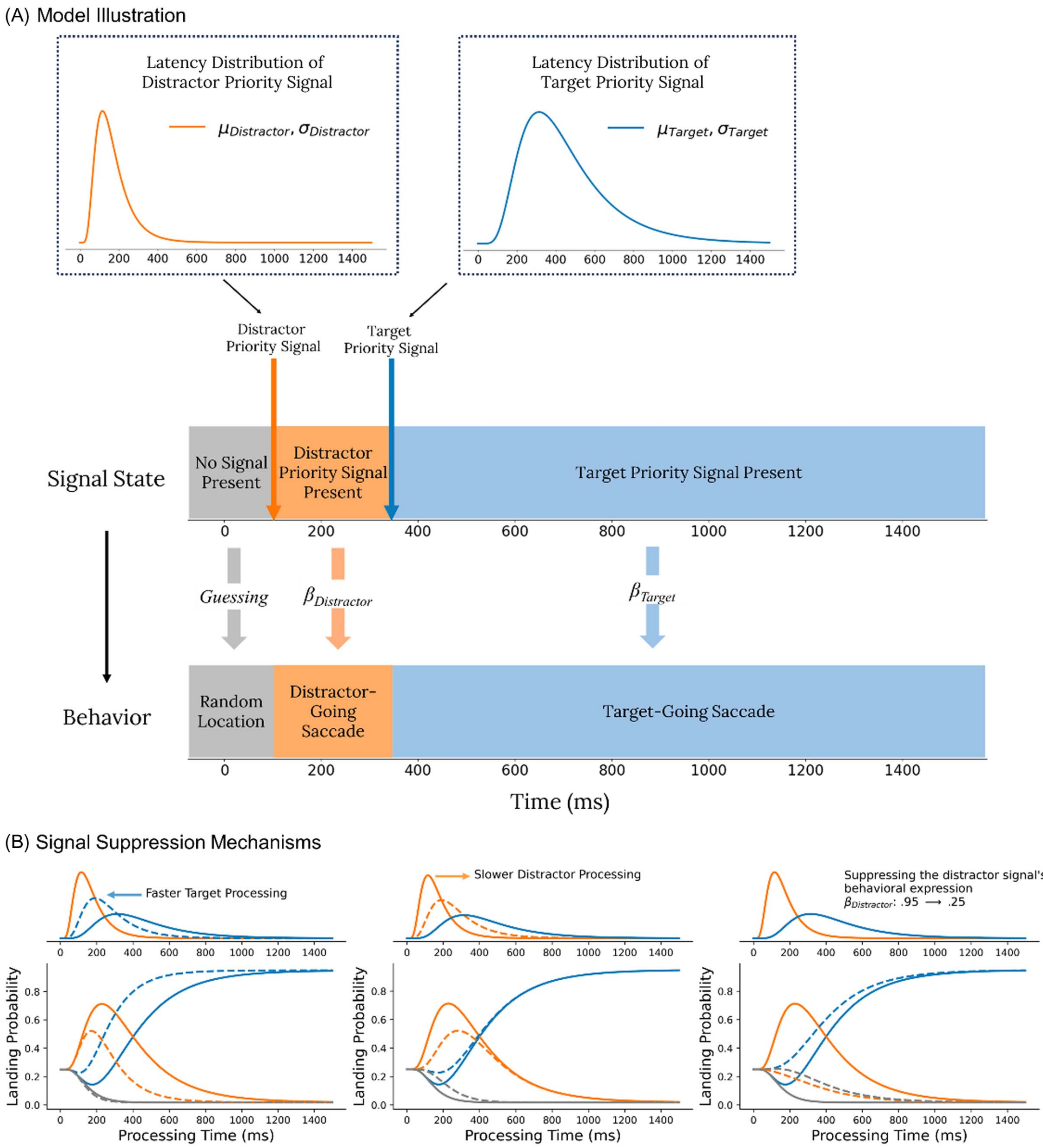
Basic Architecture

The model assumes that, in a search display with a salient distractor and a target, the salient distractor and the target invoke two separate processing streams, each producing a priority signal to the respective item. However, only one priority signal can ultimately be expressed as an overt saccade. Aligning with the task's goal, if the target priority signal is present, it overrides the distractor priority signal in behavioral expression.

Critically, the production of the target and distractor priority signals each takes a different amount of time. The latencies with

Figure 3

A Schematic Illustration of the Computational Model



Note. Panel A: The model is based on the assumption that the salient distractor and the target invoke two separate processing streams, each producing a priority signal to the respective item. The latencies of the distractor and the target priority signals are drawn from separate lognormal distributions. Behavior will be guided by the target priority signal when the target signal is present, but behavior will be guided by the distractor priority signal when the distractor signal is present, and the target priority signal is not present. When neither signal is present, behavior is determined by a guessing parameter (set to .25). Furthermore, behavioral expression of the distractor priority signal and the target priority signal is controlled by $\beta_{Distractor}$ and β_{Target}, respectively. These response control parameters determine the probability (ranging from 0 to 1) that the priority signal is expressed as a saccade. Thus, the attentional priority at a given time point, in the form of a saccade, is a function of the probabilities that the distractor and the target priority signals are present at that time point and the probabilities that the signals are translated into behaviors. Panel B: Distractor signal suppression can occur by facilitating the "slow" mechanism, namely by reducing the time the distractor signal is present in the absence of the target signal. This can be achieved by having either a faster target signal (left panel) or a slower distractor signal (middle panel). Distractor signal suppression can also occur by facilitating the "fast" mechanism. That is, having a stronger suppression of the behavioral expression of the distractor signal when the target priority signal has not yet arrived (right panel). Each mechanism results in a distinct temporal profile of saccadic behavior. See the online article for the color version of this figure.

which each priority signal arrives are independently drawn from two lognormal distributions: Lognormal($\mu_{Distractor}$, $\sigma_{Distractor}$) and Lognormal(μ_{Target}, σ_{Target}). The ability to capture this temporal asynchrony is at the heart of the model. At each time point, there will be three possible signal states: No priority signal is present, only the distractor signal is present, or the target signal is present. Visual attention, as measured by saccadic behavior, will be guided by the target priority signal when it is present, but the target priority signal may not be present until a later time. Before that time, visual attention will be guided by the distractor priority signal when it is present, leading to a distractor-going saccade. When neither signal is present, visual attention will be determined by a guessing parameter, leading to a saccade in a random direction. This guessing parameter was set to .25 in all experiments, which corresponds to the chance level given four search items.

The model further includes two response expression parameters, $\beta_{Distractor}$ and β_{Target}, which control a priority signal's influence on behavior. That is, even if a priority signal is present, it will be subject to its corresponding β parameter that determines the probability (ranging from 0 to 1) that the priority signal is expressed.

Visual attention at a given time point, as measured by saccadic behavior, is a function of the probabilities that the distractor and the target priority signals are present at that time point (controlled by $\mu_{Distractor}$, $\sigma_{Distractor}$ and μ_{Target}, σ_{Target}) and the probabilities that a given priority signal is expressed as a saccadic response (controlled by $\beta_{Distractor}$ and β_{Target}).

Slow and Fast Distractor Suppression

Under the model's architecture, distractor suppression means preventing a distractor priority signal from manifesting as an actual distractor-going saccade. The model specifies two mechanisms to prevent this from happening (see Figure 3B). First, distractor suppression can be achieved via a "slow" mechanism, in which a later-arriving target priority signal overrides the distractor priority signal in guiding attention. This slow mechanism can be facilitated by delaying the distractor priority signal or accelerating the target priority signal. Second, distractor suppression can be achieved via a "fast" mechanism, in which the distractor priority signal, despite being rapidly produced, is suppressed from being translated into behavior. The two mechanisms are temporally dissociable: The slow mechanism depends on the arrival of the target priority signal. The distractor priority signal dictates saccadic behavior until the target priority signal arrives. In contrast, the fast mechanism depends on the arrival of the distractor priority signal. It directly suppresses the distractor priority signal's behavioral expression as soon as the signal arrives, even when the target priority signal has not yet arrived. This fast mechanism allows a salient distractor to be suppressed solely due to its status of being a distractor, without having a more appropriate item available for selection.

Signal Production Versus Expression

The model also includes an importantly assumed distinction between the production of a priority signal and its expression. Production does not necessarily imply expression. This reflects the current consensus that a salient distractor automatically produces a priority signal but will not necessarily result in a capture of attention (Luck et al., 2021), with the capture of attention defined as a distractor-going saccade in the present study. This specification allows the model to account for a decrease in distractor-going saccades even at the earliest processing times: A distractor priority signal can be produced rapidly, but its expression is controlled by another parameter ($\beta_{Distractor}$) that is independent from the timing of the signal.

This distinction is also featured in another recent model of visual attention, RAGNAROC, which differentiates between suppressing attention to a distractor and suppressing the distractor's representation (Wyble et al., 2020). In RAGNAROC, features of a salient distractor are processed within the Early Vision and Late Vision layers, but this information does not necessarily propagate to the final "Attention Map" that guides visual attention. More broadly, the distinction between signal production and expression aligns with findings from the motor planning literature, which shows that the readiness to perform an action does not necessarily result in the execution of that action (Haith et al., 2016; Hardwick et al., 2019).

Partial Suppression

A particularly novel feature of the model is that it allows for partial suppression of a distractor priority signal. This stems from the model's probabilistic nature. That is, the model estimates the probability of whether a priority signal is present at a given time point, and the probability that a priority signal, when present, is expressed. For example, a $\beta_{Distractor} = .5$ means that a distractor priority signal, even if present, will have a 50% chance of guiding saccadic behavior. Thus, the influence of a distractor priority signal on behavior varies on a continuous scale. This partial suppression feature gives the model the flexibility to account for data with dramatically different temporal patterns, as we shall demonstrate.

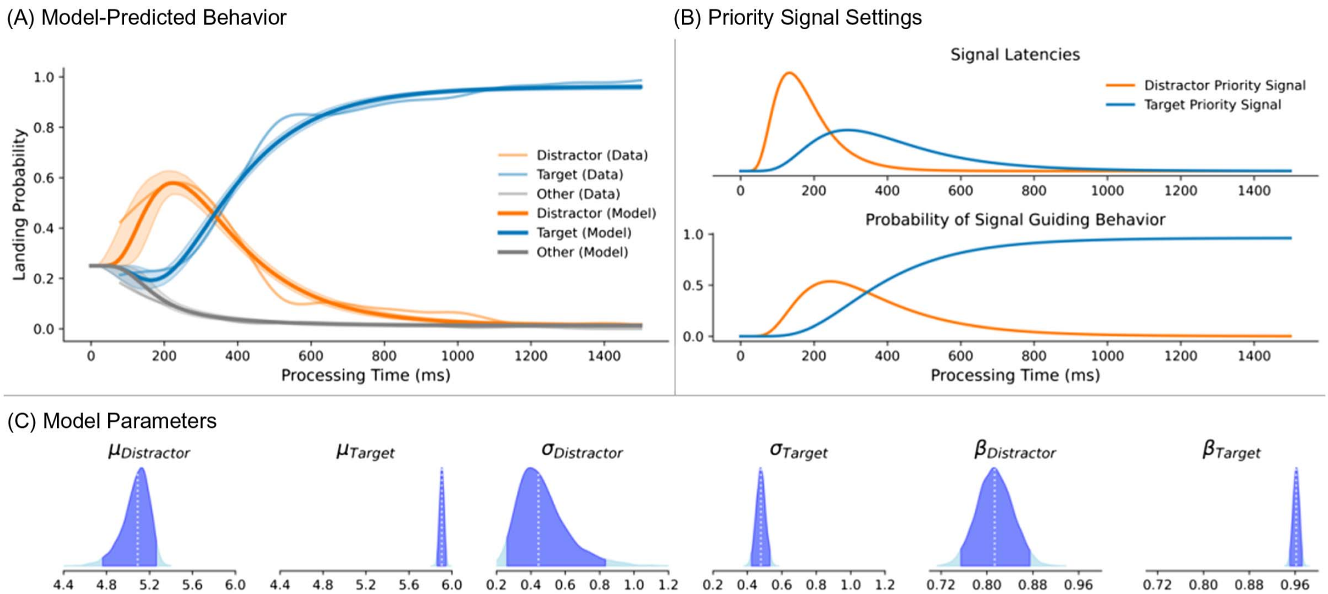
Partial suppression is also reflected in the slow mechanism, in which the target priority signal overrides the distractor priority signal. As shown in Figure 3A, the target priority signal is typically available at some point later than the distractor priority signal. This means that the probability of the target priority signal guiding behavior gradually increases over time. Distractor and target priority signals thus may both have substantial influence on visual attention at certain intermediate processing times, creating an "attentional limbo" period with equal probabilities of initiating saccades toward the target and the distractor (van Heusden et al., 2022). As processing time continues to increase, visual attention will be more likely to be guided by the target priority signal and less so by the distractor priority signal.

It is important to distinguish between model-estimated probabilities and actual events on a single trial. On each trial, there can be only one saccade destination. If a distractor priority signal is present at the time of response, it will be either expressed (resulting in a distractor-going saccade) or suppressed. This is a discrete event. However, these discrete events at the trial level are outcomes of underlying probabilities, and the model estimates these probabilities based on discrete-event data across all trials.

Fitting the Model to Data From Experiment 1

We applied the computational model to the data of Experiment 1, and posterior predictions are shown overlaid with the data in Figure 4A. The results show that the model provides a good fit to the data. In Figure 4B, we present the estimated latencies for the

Figure 4
Modeling Results of Experiment 1: Unique Shape Search



Note. Panel A: Posterior predictions of the model. The thicker lines indicate the model's predictions, with the bands indicating the 95% credible level. The thinner, more transparent lines indicate the observed data (as those in Figure 2A, without confidence bands). The model's predictions were based on 2,000 random draws from the model's posterior samples. The median values from these draws were used to generate the predictions. The 95% credible bands were generated using the values at 2.5% percentile and 97.5% percentile of these draws. Panel B: The estimated latency distributions of the distractor priority signal and the target priority signal (upper panel), and the probabilities that each signal was ultimately expressed as an overt saccade at each time point (lower panel). Panel C: Posterior distributions of the model parameters. The darker blue region represents the 95% credible intervals. The dotted vertical lines indicate the median values. Each μ and σ are on the lognormal scale. Thus, the exponential value of the median of μ represents the median latency of a priority signal, for example, $\exp(5.09) = 162$ ms for the distractor signal. Each β can range from 0 to 1. See the online article for the color version of this figure.

distractor and the target priority signals (upper panel), as well as the probability that each signal guides behavior (lower panel)—that is, the probability that a signal was ultimately expressed as an overt saccade. This graph shows that the probability that the distractor priority signal guides behavior did not reach zero (i.e., being fully suppressed) until about 1,000 ms.

Figure 4C displays the posterior distributions of model parameters. Note that μ and σ are parameters in a lognormal distribution. In all experiments, we used the value of μ, whose exponent represents the median latency of a priority signal, to evaluate whether one priority signal was overall produced faster than the other. Specifically, in Figure 4C, $\mu_{\text{Distractor}}$ was estimated at 5.09 (95% credible interval [4.76, 5.26]) and μ_{Target} was estimated at 5.91 (95% credible interval [5.86, 5.95]), which produces a difference of 0.82 (95% credible interval [0.63, 1.15]). These results correspond to a median latency of 162 ms for the distractor signal and 367 ms for the target signal, or a 205-ms difference between them. Thus, the distractor priority signal was overall generated faster than the target priority signal.

The values of $\beta_{\text{Distractor}}$ and β_{Target} theoretically range from 0 to 1. In Experiment 1, the value of $\beta_{\text{Distractor}}$ was estimated at 0.81 (95% credible interval [0.75, 0.88]), which indicates an 81% probability that the distractor priority signal was expressed in behavior when it was the only priority signal present. The value of β_{Target} was estimated at 0.96 (95% credible interval [0.95, 0.97]). This indicates that there was a very high probability (96%) that a target priority signal was expressed when present. β_{Target} essentially accounts for the performance ceiling in this task.

The empirical data show a notable early attentional bias toward the distractor, and the model accounts for this: The distractor priority signal had a 205-ms head start over the target priority signal, leaving a long period for the distractor priority signal to influence behavior. This head start was further coupled with a high probability (81%) of expressing the distractor priority signal, leading to an attentional bias to the distractor at early processing times.

Despite so, suppression eventually occurs. As shown in Figure 4B, lower panel, at around 350 ms, the distractor priority signal and the target priority signal had equal probabilities of guiding behavior. This intersection created an "attentional limbo" period during which there was no strong preference for either item, on average (van Heusden et al., 2022). After this point, the target priority signal gradually replaced the distractor priority signal in guiding behavior. The probability of the target priority signal guiding behavior reaches asymptote around 1,000 ms, after which point there was almost a 100% probability of target-going saccades. This type of suppression is rarely observed in free-response paradigms, as participants rarely make saccades with latencies this long to allow the suppression to be fully developed. But because the forced-response method exerts more control over response initiation, we could computationally dissociate the influences of the distractor priority signal and the target priority signal on the time course of visual attention.

These results demonstrate what the computational model adds beyond the empirical data: It provides a mechanistic understanding of the temporal dynamics of visual attention.

Experiment 2: Specific Shape Search

Having established the utility of our approach, we then investigated several experimental manipulations, the results of which have previously been interpreted as evidence for the existence of distractor suppression in visual search (e.g., Gaspelin et al., 2017; Geyer et al., 2008; Wang & Theeuwes, 2018a; Won et al., 2019). We had two goals: first, to characterize the potentially diverse evolution of visual attention in different contexts; second, to apply our computational model to understand the mechanisms facilitating distractor suppression in these different conditions.

One of the most well-documented examples of distractor suppression involves a variant of the task presented in Experiment 1, in which participants are required to search for a shape with predefined features (Bacon & Egeth, 1994; Gaspelin et al., 2017, 2019; Gaspelin & Luck, 2018b). In this modified display, the shape of each item in the display is unique, and participants search for a target with specific features (e.g., a green diamond) among heterogeneous items (see Figure 2B). On half of the trials, a uniquely colored nontarget item serves as the salient distractor. Past research indicates that such a display setting substantially decreases the overall capture effect of the distractor compared to the setup in Experiment 1 (Bacon & Egeth, 1994; Gaspelin et al., 2017, 2019; Gaspelin & Luck, 2018b).

Method

Participants

We decided to recruit a similar number of participants for Experiment 2. A total of 34 participants from the University of Michigan Introductory Subject Pool completed the study. Data from six participants were discarded due to experimental failures. The final sample size was 28 (M_{age}: 18.57, SD_{age}: .69, gender: 25% male, 71.4% female, 3.6% nonbinary).

Apparatus and Stimuli

All aspects were identical to Experiment 1, with one exception: In addition to a diamond and a circle, the search array now also included a triangle (1.61° × 1.61°) and a hexagon (1.77° × 1.77°).

Procedure

All aspects of the procedure were identical to Experiment 1, with a few exceptions detailed below. As shown in Figure 2B, the search array in this experiment consisted of four unique shapes: a circle, a diamond, a triangle, and a hexagon. Participants were asked to search for a fixed shape throughout the task. The shape and color of the target (diamond or circle, and red or green, respectively) were randomly chosen for each participant and remained constant throughout the experiment. Among distractor-present trials (50% of all trials), the color singleton appeared as one of the nontarget shapes with equal frequency but always in a color opposite to that of the target (e.g., green if the target color was red). The experimental phase consisted of five blocks, each containing 42 trials.

Results

Behavioral Results

As shown in Figure 2B, the time course of visual attention presents a striking contrast to those of Experiment 1. To detect biases in visual attention, we used the same cluster-based permutation, one-sample *t* test procedure to identify periods during which landing probabilities either exceeded or fell below the chance level. The results show that the probability of landing on the distractor consistently remained below chance across the entire range of examined processing times, from 80 ms to 1,500 ms. The probability of landing on the target consistently exceeded chance across the same range of processing times.

In similar search displays, Gaspelin et al. (2017; see also Stilwell et al., 2023) observed that the probability of initiating distractor-going saccades was not only below what would be expected if participants initiated their saccades randomly (25%) but also below a more conservative baseline defined by an average nontarget item (referred to as the “other” item in Figure 2B). To investigate whether we could replicate this effect, we conducted a cluster-based permutation paired-sample *t* test to directly compare the time course of saccades directed at the distractor and those directed at an average “other” item. Our results confirmed that the probability of initiating distractor-going saccades was indeed significantly lower than those going to an average “other” item from 80 ms to 455 ms. This difference ceased to become significant for longer processing times, as the probability of saccades going to other items also decreased.

Modeling Results

What caused the contrasting behavioral patterns between Experiment 2 and Experiment 1? We fit the model to the data of Experiment 2 to explore this difference. The posterior predictions of the model are displayed in Figure 5A, demonstrating a good fit to the data. Figure 5B presents, for both experiments, the latencies of the priority signals and their probabilities of guiding behavior (the probability that a signal is generated and overtly expressed). These results demonstrate an interesting pattern: Despite having an early onset, the distractor priority signal had a very low probability of being expressed as a distractor-going saccade.

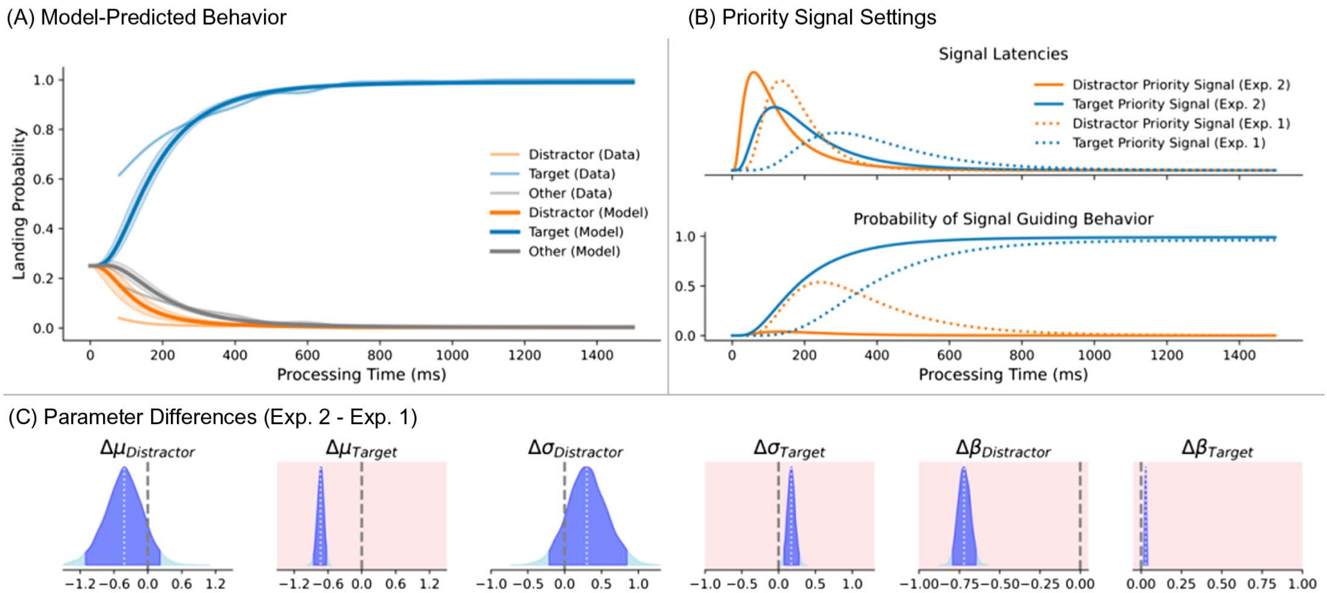
To assess how the model fit differed across the two experiments, we computed the differences in posterior samples for each parameter between the two (Experiment 2 vs. Experiment 1). Figure 5C presents the distribution of these resulting differences for each parameter. Comparisons with 95% credible intervals that do not include 0 are highlighted in pale red, indicating strong evidence for an effect on that parameter.

The results show that the target priority signal in Experiment 2 was overall produced faster compared to Experiment 1. The μ_{Target} difference was −0.73 (95% credible interval [−0.85, −0.63]). This corresponds to a 190-ms acceleration (177 vs. 367 ms) of the target priority signal compared to Experiment 1.

Though the 95% credible interval overlaps with 0, there was moderate evidence that the distractor priority signal was also produced faster; there was a difference of −0.42 in

Figure 5

Modeling Results of Experiment 2: Specific Shape Search



Note. Panel A: Posterior predictions of the model. The thicker lines indicate the model's predictions, with the bands indicating the 95% credible level. The thinner, more transparent lines indicate the observed data (as those in Figure 2B, without confidence bands). The model predictions were based on 2,000 random draws from the model's posterior samples. The median values from these draws were used to generate the predictions. The 95% credible bands were generated using the values at the 2.5% percentile and 97.5% percentile values of these draws. Panel B: The estimated latency distributions of the distractor priority signal and the target priority signal (upper panel), and the probabilities that each signal was ultimately expressed as an overt saccade at each time point (lower panel). Panel C: Posterior distributions of parameter differences (Experiment 2 − Experiment 1). The dotted vertical lines indicate the median values of the differences. The darker blue region represents the 95% credible intervals. Comparisons with 95% credible intervals that do not include 0 are highlighted in pale red. Exp. = experiment. See the online article for the color version of this figure.

$\mu_{\text{Distractor}}$ (95% credible interval [−1.10, 0.22]), which is equivalent to a 57-ms acceleration (105 vs. 162 ms) compared to Experiment 1. Furthermore, in Experiment 2, the distractor signal remained slightly faster than the target signal, with a −0.52 difference between $\mu_{\text{Distractor}}$ and μ_{Target} (95% credible interval [−1.19, 0.07]) that corresponds to a 72-ms difference. This difference was 205 ms in Experiment 1.

Critically, $\beta_{\text{Distractor}}$ substantially decreased from .81 in Experiment 1 to 0.09 in Experiment 2, resulting in a difference of −0.72 (95% credible interval [−0.79, −0.65]). That is, there was a 72% decrease in the probability of expressing the distractor signal when it was the only priority signal present. In contrast, β_{Target} slightly increased, from .96 in Experiment 1 to .99 in Experiment 2 (difference: 0.03, 95% credible interval [0.02, 0.04]). While a small effect size (3%), the larger β_{Target} indicates an increase in the probability of expressing the target priority signal when it was present.

Finally, σ_{Target} in Experiment 2 was larger compared to Experiment 1 (0.17, 95% credible interval [0.07, 0.28]), suggesting a more skewed latency distribution for the target priority signal (see Figure 5B, upper panel).

Discussion

The behavioral results show an early attentional bias away from the distractor from 80 ms to 455 ms compared to an average neutral item. These results are consistent with those in Gaspelin et al. (2017, Experiment 2), in which saccadic latencies were categorized into four groups, ranging from the fastest, with an average latency of 174 ms, to the slowest, with an average latency of 312 ms. They observed that the probability of initiating distractor-going saccades was lower relative to an average neutral item across all four latency categories. Even though our task differed from theirs in several aspects (e.g., display size, forced-response signal, etc.), our results replicated their findings.

Importantly, our computational model further explains the underlying mechanisms of distractor suppression. The model estimated (a) a lower $\beta_{\text{Distractor}}$, indicating a reduced probability of the behavioral expression of the distractor priority signal, and (b) a smaller μ_{Target}, indicating a faster arrival of the target priority signal. The shortened delay of the target priority signal means that it could start sooner to override the distractor priority signal in guiding behavior. In addition, even without the target priority signal, the distractor priority signal had a very low probability (9%) of being expressed. These two mechanisms worked together, resulting in a dramatic decrease in saccades to the distractor across all processing times.

Interestingly, despite strong suppression of its expression probability, the distractor priority signal was still produced rapidly, with a median latency of 105 ms. We shall return to this point in the General Discussion section.

Experiment 3: Distractor Location Regularity

Another well-documented manipulation that presumably involves distractor suppression pertains to the regularity of the distractor's location. It has been argued that through statistical learning of a distractor's likely location, the distractor's priority value on the priority map is suppressed relative to all other locations (e.g., Wang et al., 2019; Wang & Theeuwes, 2018a, 2018b). In Experiment 3, participants ($N = 45$) completed the same task as in Experiment 1, except that when the distractor was present, it was 17 times more likely to appear at one location (85%) than any other location (5% each).

Method

Participants

A total of 60 participants from the University of Michigan Introductory Subject Pool completed the study. We decided to recruit a larger number of participants compared to Experiments 1 and 2 because the study involves a within-participant comparison regarding distractor location. Data from 15 participants were discarded due to experimental failures. The final sample size was 45 (M_{age}: 19.09, SD_{age}: 3.03, gender: 24.4% male, 75.6% female, 0% nonbinary).

Apparatus and Stimuli

All aspects were identical to Experiment 1.

Procedure

The procedure was identical to Experiment 1 except for the distractor's positioning. Specifically, on distractor-present trials, the distractor had an 85% probability of appearing in one location (top, left, bottom, or right, randomly chosen for each participant) and a 5% probability of appearing at each of the remaining locations, resulting a ratio of 17:1. The ratio was typically 13:1 in studies by Theeuwes and colleagues (e.g., Wang et al., 2019; Wang & Theeuwes, 2018a, 2018b). See Figure 2C for an illustration of example trials.

Results

Behavioral Results

Figure 2C illustrates the time courses of visual attention when the distractor appeared at a low- versus high-probability location. As in previous experiments, we used cluster-based permutation one-sample *t* tests to detect biases in visual attention. When the distractor appeared at a low-probability location, the probability of landing on the distractor was above the chance level from 80 ms to 509 ms and fell below the chance level after 1,074 ms. For the target, its landing probability started below chance from 80 ms to 321 ms and then went above chance level after 417 ms.

In contrast, when the distractor appeared at a high-probability location, there was no observed phase during which the probability of landing on the distractor exceeded the chance level; it simply fell below chance after 356 ms. For the target, its landing probability went above chance after 196 ms. A cluster-based permutation paired-sample *t* test shows that the probability of landing on the distractor was significantly lower from 80 ms to 1,170 ms in the high-probability condition compared to the low-probability condition.

Modeling Results

To examine the underlying mechanisms, we fit our computational model to these data. The model included two identical sets of parameters, with each set being separately fitted to one condition. Figure 6A shows the posterior predictions, indicating a good fit to the data in each condition. In Figure 6B, we present latency estimations for target and distractor priority signals (upper panel) as well as the probabilities of each signal guiding behavior (lower panel). To compare parameter differences between conditions, we computed differences in posterior samples and plotted them in Figure 6C. Comparisons with 95% credible intervals that do not include 0 are highlighted in pale red.

The results show several parameter differences between the high- and low-probability conditions. First, $\mu_{\text{Distractor}}$ in the high-probability condition was larger (0.54, 95% credible interval [0.02, 1.17]) compared to the low-probability condition. This means that the distractor priority signal was delayed for 96 ms in the high-probability condition (234 ms) compared to the low-probability condition (138 ms).

Second, μ_{Target} in the high-probability condition was smaller (−0.45, 95% credible interval [−0.53, −0.36]) compared to the low-probability condition. This means that the target priority signal arrived 176 ms earlier in the high-probability condition (312 ms) compared to the low-probability condition (488 ms).

Third, $\beta_{\text{Distractor}}$ in the high-probability condition (.67) was lower compared to the low-probability condition (.88), resulting in a 21% decrease in the probability of expressing the distractor priority signal when it was the only priority signal present (95% credible interval [−0.34, −0.07]).

Fourth, β_{Target} in the high-probability condition (.96) was higher compared to the low-probability condition (.93), resulting in a 3% increase in the probability of expressing the target priority signal when it was present (0.03, 95% credible interval [0.001, 0.06]).

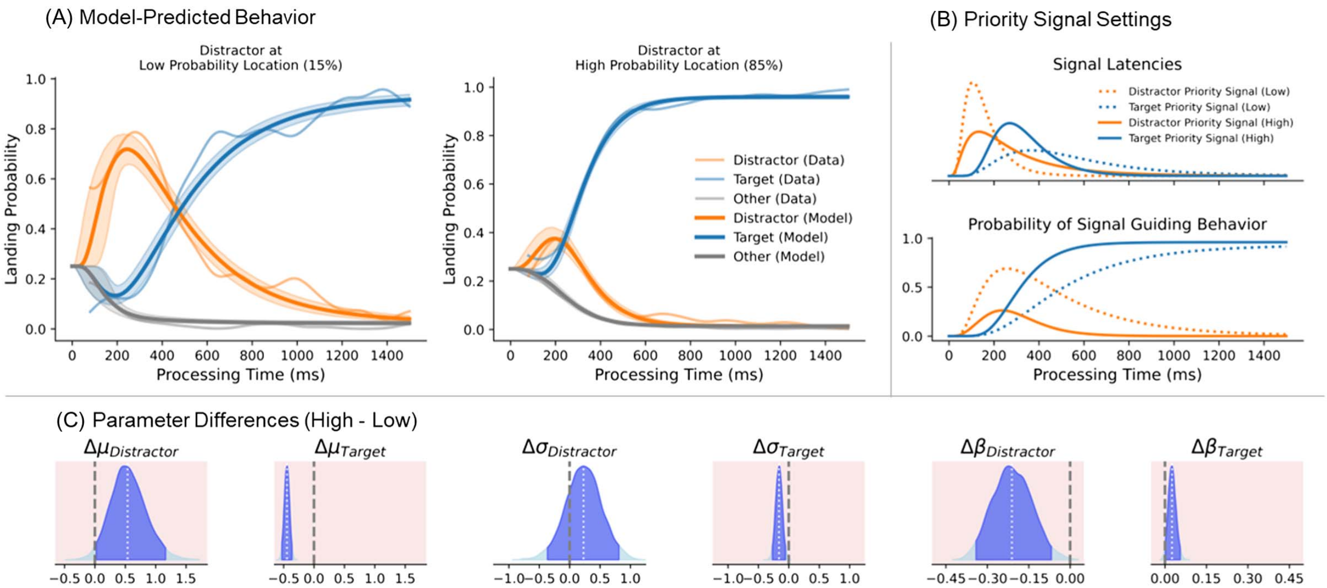
Finally, σ_{Target} in the high-probability condition was smaller compared to the low-probability condition (−0.16, 95% credible interval [−0.27, −0.05]), indicating a less skewed latency distribution for the target priority signal (see Figure 6B, upper panel).

Intertrial Repetitions

When the distractor appeared at the high-probability location, there was also an increased probability that the distractor appeared at the same location on the previous trial. To tease apart distractor suppression due to transient location repetition from that due to probabilistic learning, we performed the same analyses after removing trials in which the distractor successively appeared at the same location. Details of these analyses can be found in the Supplemental Materials. To briefly summarize, despite these exclusions, the behavioral and model results remained highly similar. The only notable difference is that the effect on $\mu_{\text{Distractor}}$ became smaller after the trial exclusion; the distractor priority signal was delayed for 47 ms in the high-probability condition

Figure 6

Modeling Results of Experiment 3: Distractor Location Regularity



Note. Panel A: Posterior predictions of the model. The thicker lines indicate the model's predictions, with the bands indicating the 95% credible level. The thinner, more transparent lines indicate the observed data (as those in Figure 2C, without confidence bands). The model predictions were based on 2,000 random draws from the model's posterior samples. The median values from these draws were used to generate the predictions. The 95% credible bands were generated using the values at the 2.5% percentile and 97.5% percentile values of these draws. Panel B: The estimated latency distributions of the distractor priority signal and the target priority signal (upper panel), and the probabilities that each signal was ultimately expressed as an overt saccade at each time point (lower panel). Panel C: Posterior distributions of parameter differences (High − Low). The dotted vertical lines indicate the median values. The darker blue region represents the 95% credible intervals. Comparisons with 95% credible intervals that do not include 0 are highlighted in pale red. See the online article for the color version of this figure.

compared to the low-probability condition, whereas the difference was 96 ms without the trial exclusion.

Discussion

The behavioral results are consistent with previous findings showing an attenuation of the capture effect induced by distractor location regularity. However, visual attention to the distractor fell below the chance level (25%) after 356 ms. In contrast, in Experiment 2, visual attention to the distractor was not only below the 25% chance level but also below a more conservative baseline defined by an average neutral item, even for the fastest saccades. Indeed, previous studies reported that distractor location regularity reduced but did not eliminate attentional capture (e.g., Wang et al., 2019; Wang & Theeuwes, 2018a, 2018b). For example, despite a reduction in distractor-going saccades in the high-probability condition, there was still about 14% of initial saccades that landed on the distractor (Wang et al., 2019).

These behavioral results were mostly driven by three model parameters: (a) a larger $\mu_{\text{Distractor}}$, signifying a slower arrival of the distractor priority signal; (b) a smaller μ_{Target}, signifying a faster arrival of the target priority signal; and (c) a smaller $\beta_{\text{Distractor}}$, signifying stronger suppression of the distractor priority signal's behavioral expression.

The first two effects collectively resulted in a narrower time window for the distractor priority signal to influence behavior. In the low-probability condition, the distractor priority signal had a 350-ms head start over the target priority signal. However, in the high-probability condition, this advantage was reduced to just 78 ms. This 78-ms gap in the high-probability condition is similar to the 72-ms gap observed in Experiment 2. However, in the current experiment, the probability of the distractor priority signal being expressed was 67%, which is much higher compared to the 9% in Experiment 2. As such, even in the high-probability condition, the distractor priority signal still had a substantial influence on early saccades (see Figure 6B, lower panel). These results highlight that distractor suppression operates on a continuum; the extent of distractor suppression varies across different experimental conditions.

The slower arrival of the distractor priority signal differed from Experiment 2 (and, to foreshadow, from Experiment 4 as well). This effect was reduced after removing successive trials with repeated distractor locations (see the Supplemental Materials). These results are consistent with the notion that local habituation contributes to distractor suppression induced by distractor location regularity (Allenmark et al., 2022). That is, the visual system habituates to the salient distractor when it appears again at the exact same location, resulting in a reduced "orienting reflex" as if the salient distractor becomes less salient. The contribution of distractor suppression due to local habituation to the salient distractor appears to be reflected as a slower arrival of the distractor priority signal in our model. On the other hand, the effects on μ_{Target} and $\beta_{\text{Distractor}}$ persisted after removing those trials, suggesting these effects reflect probabilistic learning of the distractor's likely location rather than habituation to the distractor's salience.

Experiment 4: Regularity in Distractor Frequency

In Experiment 4, we examined another classic manipulation that presumably involves distractor suppression: the distractor frequency effect. The idea is that capture can be reduced by simply increasing the frequency of the distractor (e.g., Geyer et al., 2008; Müller et al., 2009; Won et al., 2019). In particular, a recent study by Won et al. (2019) shows that the distractor frequency effect exists even with a random distractor color. These results, according to the authors, suggest a second-order distractor suppression effect (i.e., suppressing a color singleton of any color) based on probabilistic expectations.

We recruited participants ($N = 70$) to complete a forced-response visual search task in which we manipulated distractor frequency. In low-frequency blocks, the distractor was present on 20% of the trials, whereas in high-frequency blocks, it appeared on 80% of the trials. To control for potential carryover effects, the order of blocks was counterbalanced. On all distractor-present trials, the location of the distractor was chosen randomly. Furthermore, following Won et al. (2019), the color of the distractor was randomly chosen from a pool of 12 colors (evenly distributed on the color wheel), with the constraint that a particular distractor color never repeated. The variability in both location and color ensured that any observed effect can be attributed to the mere frequency of the distractor (i.e., second-order suppression), rather than an increased likelihood of the distractor appearing with specific features.

Method

Participants

A total of 85 participants from the University of Michigan Introductory Subject Pool completed the study. We decided to recruit a larger sample size compared to Experiments 1 and 2 because participants completed two types of blocks (details below). Data from 14 participants were discarded due to experimental failures. The final sample size was 70 (M_{age}: 18.93, SD_{age}: 1.32, gender: 36.6% male, 60.6% female, 2.8% nonbinary).

Apparatus and Stimuli

The visual search task was adapted from Won et al. (2019). All aspects were identical to Experiment 1 except for a key difference in color selection. The distractor could appear in one of 12 distinct colors. These colors were selected from the hue, saturation, and value/brightness color space, each with a hue differing by 30°, while keeping saturation and brightness fixed at 100%, that is, from (30°, 1, 1) to (360°, 1, 1). The target item was consistently displayed in gray to mimic the original design. See Figure 2D for an illustration of example trials.

Procedure

The procedure was identical to Experiment 1 except for the following. First, participants completed two blocks with high distractor frequency and two blocks with low distractor frequency with reverse counterbalancing. In the high-frequency blocks, the distractor appeared on 80% of the trials (i.e., 32 out of 40 per block), while in the low-frequency blocks, the distractor appeared on 20% of the trials (i.e., eight out of 40 per block). These distractor frequencies were the same as in Won et al. (2019). The color of the distractor was randomly chosen from a pool of 12 colors, with the constraint that it never replicated the previous distractor color. Second, several adjustments were also made to the timing practice for a more friendly introduction to the timing regime. Instead of practicing with a single item, participants were given distractor-present trials, wherein all four items were displayed, and they were asked to make a saccade toward the unique shape on the "go" command. Moreover, the timing practice was divided into stages. Participants initially practiced with trials in which the search array appeared early (1,300–1,500 ms before the "go" command). Next, they practiced with trials in which the search array appeared late (0–200 ms before the "go" command). Finally, participants practiced with trials that had random timing, mirroring the experimental blocks (0–1,500 ms before the "go" command). Participants were required to achieve over 60% accuracy with at least 10 trials for each stage before advancing to the next practice stage.

Results

Behavioral Results

Figure 2D shows the time course of visual attention in the high- and low-distractor frequency conditions. As in previous studies, to detect biases in visual attention, we conducted cluster-based permutation t tests to identify intervals that significantly deviated from chance levels. In the low-frequency condition, the probability of landing on the distractor was above chance from 106 ms to 376 ms, before falling below chance after 419 ms. For the target, its landing probability rose above chance after 303 ms.

In the high-frequency condition, the probability of landing on the distractor was above chance from 80 ms to 321 ms and it fell below chance after 370 ms. For the target, its landing probability in the high distractor frequency condition went above chance after 230 ms. A cluster-based permutation paired-sample t test shows that the probability of landing on the distractor was significantly lower in the high-frequency condition compared to the low-frequency condition in a period from 177 ms to 423 ms.

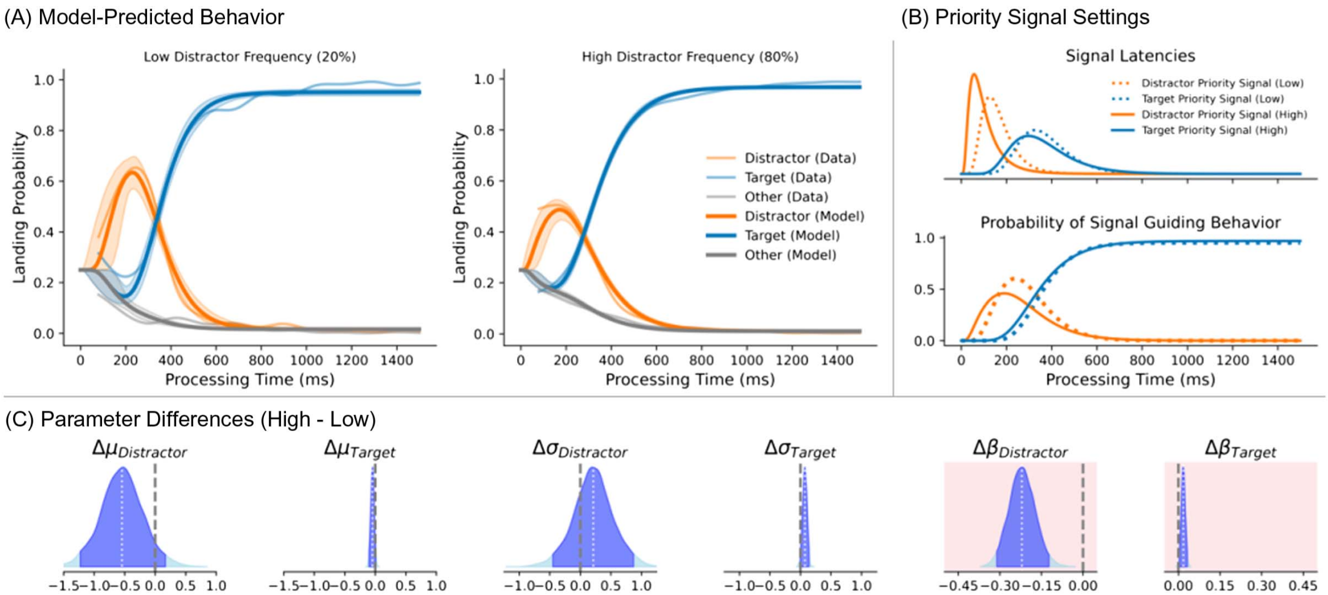
Modeling Results

To pinpoint the underlying mechanisms driving these behavioral effects, we fit our model to the data of Experiment 4. Figure 7A displays the posterior predictions of the model for both conditions, again showing a good fit to the data. Figure 7B presents the latency estimations for target and distractor priority signals (upper panel) as well as the probabilities of each signal guiding behavior (lower panel). To compare parameter differences, we computed the differences in posterior samples between the high-frequency and low-frequency conditions for each parameter. In Figure 7C, we highlight comparisons with 95% credible intervals that do not include 0 in pale red.

The model reveals a lower $\beta_{\text{Distractor}}$ in the high-frequency condition (.55) compared to the low-frequency condition (.77),

Figure 7

Modeling Results of Experiment 4: Distractor Frequency Regularity



Note. Panel A: Posterior predictions of the model. The thicker lines indicate the model's predictions, with the bands indicating 95% credible level. The thinner, more transparent lines indicate the observed data (as those in Figure 2D, without confidence bands). The model predictions were based on 2,000 random draws from the model's posterior samples. The median values from these draws were used to generate the predictions. The 95% credible bands were generated using the values at 2.5% percentile and 97.5% percentiles of these draws. Panel B: The estimated latency distributions of the distractor priority signal and the target priority signal (upper panel), and the probabilities that each signal was ultimately expressed as an overt saccade at each time point (lower panel). Panel C: Posterior distributions of parameter differences (High frequency − Low frequency). The dotted vertical lines indicate the median values. The darker blue region represents the 95% credible intervals. Comparisons with 95% credible intervals that do not include 0 are highlighted in pale red. See the online article for the color version of this figure.

resulting in a 22% reduction in the probability of expressing the distractor priority signal when it was the only priority signal present (95% credible interval [−0.31, −0.12]).

Though the 95% credible interval overlaps with 0, there was some moderate evidence that $\mu_{Distractor}$ in the high-frequency condition was smaller (−0.05, 95% credible interval [−0.10, 0.008]). This corresponds to a 65-ms acceleration of the distractor priority signal in the high-frequency condition (86 ms) compared to the low-frequency condition (151 ms).

There was little difference in the latency of the target priority signal between the high- and low-frequency conditions, as the difference in $\mu_{Distractor}$ was −0.05 (95% credible interval [−0.10, 0.08]). This corresponds to a mere 17-ms acceleration of the target priority signal in the high-frequency condition (341 ms) compared to the low-frequency condition (358 ms).

In addition, there was also an increase in β_{Target} in the high-frequency condition (.97) compared to the low-frequency condition (.95), resulting in a small increase (2%) in the probability of expressing the target priority signal when it was present (95% credible interval [0.003, 0.03]).

Intertrial Repetitions

A high distractor frequency leads to intertrial repetitions at both the first level (exact repetition of a distractor's color and location) and the second level (repetition of the mere presence of a distractor). We analyzed two subsets of trials to investigate their contributions to the current findings. First, we removed trials in which the distractor appeared at the exact location as in the previous trial (there was no color repetition due to the large color set we used). This procedure removed all first-level repetitions but preserved second-level repetitions. Second, we removed trials in which the distractor appeared successively, thereby removing all second-level repetitions. Details of these analyses can be found in the Supplemental Materials. To briefly summarize, after excluding first-level repetitions, the behavioral and the model results were highly similar to those based on full trials. However, after excluding second-level repetitions, there was little difference between high-frequency and low-frequency conditions, both at the behavioral and modeling levels.

Discussion

The effect of distractor frequency produced yet another distinct set of results. First, high distractor frequency reduced but did not eliminate an early attentional bias toward the distractor. This result is consistent with those in Won et al. (2019), which showed that there was still about 30%–40% of first saccades going to the distractor even in the high-frequency condition (also see Geyer et al., 2008). These results again present a sharp contrast to those in Experiment 2.

Results of the computational model show that the effect of high distractor frequency mostly came from a reduced behavioral expression of the distractor priority signal (i.e., a lower $\beta_{\text{Distractor}}$). Note again that the magnitude of this suppression (55%) was still substantially weaker compared to Experiment 2 (9%), and thus an early attentional bias toward the distractor was reduced but not eliminated. Different from Experiments 2 and 3, there was no substantial evidence of changes in the latency of the target priority signal. The distractor priority signal was produced slightly faster in the high-frequency condition compared to the low-frequency condition, resembling findings from Experiment 2 (specific shape search), yet contrasting with those observed in Experiment 3 (distractor location regularity).

The intertrial repetition results are highly consistent with those of Won et al. (2019), which found no repetition effect of distractor location but a significant repetition effect of distractor presence. Together, these results suggest that in the current experiment, the effect of high distractor frequency was primarily driven by the carryover of attentional control settings from the previous trial rather than probabilistic learning of the distractor's global frequency. Importantly, though, this carryover effect operated on the second level, enabling the suppression of a salient distractor with random colors and locations. As such, the effect on $\beta_{\text{Distractor}}$ cannot be attributed to feature-specific habituation or priming effects.

General Discussion

In four experiments, we employed a novel forced-response method along with a computational model to understand the temporal dynamics of visual attention. We show that the deployment of visual attention could be biased either toward or away from a salient distractor depending on the timing of the observation, with these temporal dynamics varying substantially across experiments. These different temporal patterns were well explained by a single computational model assuming the distractor and target priority signals arrive asynchronously in time with different influences on saccadic behavior.

Summary of Behavioral Results

Experiment 1 was adapted from the classic additional-singleton task, which is known to produce a strong overall attentional capture effect. While there was indeed an early attentional bias toward the salient distractor, attention could also be biased away from the distractor if saccades were delayed. As argued, this late bias is hard to observe in free-response tasks, as participants rarely make a saccade this late if allowed to respond freely.

In contrast, in Experiment 2, saccades initiated as early as 80 ms were already biased away from the distractor. Intense debates have revolved around how people can so effectively ignore the distractor in this task, with the rapid disengagement account positing that attention is first captured by the distractor and then quickly shifts away from it (e.g., Theeuwes et al., 2000). However, our results, along with evidence from other studies (Gaspelin & Luck, 2018c), challenge this account as there were no signs of an early shift of attention to the distractor. Instead, the results appear to be consistent with a proactive suppression account, which posits that the distractor is suppressed before the first shift of overt attention.

The behavioral results in Experiment 3 (distractor location regularity) and Experiment 4 (distractor frequency regularity) differed significantly from one another and from those in Experiment 2. The bias in visual attention away from the distractor occurred at a much later time point. Notably, in Experiment 4, there was an early attentional bias toward the distractor in the high-frequency condition.

In sum, data obtained from the forced-response method show the temporal structure of the priority map for each experiment. We believe this represents a step toward more accurately characterizing the dynamic and distributed nature of attentional priority, moving beyond making binary judgments of capture versus no capture (B. A. Anderson, 2021).

Summary of Modeling Results

The temporal variations in visual attention were well explained by a model that specifies distractor suppression in terms of the temporal delay of the target priority signal relative to the distractor priority signal (the slow mechanism) and the probability of a distractor priority signal being expressed before the target priority signal arrives (the fast mechanism). The model results are summarized in Table 1.

The specific shape search condition in Experiment 2 has been interpreted as suppression of a specific feature (Gaspelin & Luck, 2018b), while the effect of distractor location regularity implies

Table 1
Summary of Key Model Results Across Experiments

Condition	Distractor signal latency (ms)	Target signal latency (ms)	Target signal delay (ms)	Distractor signal expression
Unique shape search	162	367	205	81%
Specific shape search	105	177	72	9%
Distractor location				
High probability	234	312	78	67%
Low probability	138	488	350	88%
Distractor frequency				
High frequency	86	341	255	55%
Low frequency	151	358	207	77%

Note. Signal latencies were calculated from the exponential value of $\mu_{\text{Distractor}}$ and μ_{Target}, which represents the median of their respective latency distributions. Distractor signal expression is the value of $\beta_{\text{Distractor}}$, which indicates the probability that a distractor priority signal will be expressed in the absence of the target priority signal.

suppression of a spatial location (Wang & Theeuwes, 2018b), and the effect of distractor frequency suggests suppression of any color singletons (Won et al., 2019). In contrast, the search task in Experiment 1 is commonly taken as an example of the absence of suppression. The fact that a single model accounts for data across various search conditions may also be regarded as a step forward, potentially unifying our conceptualization of suppression mechanisms.

The model's ability to account for different data patterns comes from its partial suppression feature, which allows for the model to fine-tune the influence of a distractor priority signal on a continuum. Thus, a potential implication of the model is that processes that are often presumed to be categorically distinct based on behavioral data may in fact operate on the same continuum. For example, saccadic behavior in Experiment 4 shows an early attentional bias that is not present in Experiment 2. At face value, these data might suggest fundamentally different mechanisms. The former aligns with the notion of proactive suppression, whereas the latter could be interpreted as reactive rejection following initial capture. However, dichotomies commonly made from behavioral data—such as capture versus no capture and, by extension, reactive versus proactive—are in fact governed by the same mechanisms in our computational model, differing only in their parameter values. As shown in the right panel of Figure 3B, the degree of an early distractor bias largely comes down to the value $\beta_{\text{Distractor}}$, which modulates the influence of a distractor priority signal on saccadic behavior before the target priority signal arrives.

The model may also help to separate the role of distractor feature suppression from target feature enhancement in guiding attention. This topic is highly debated, as it has been argued that certain behavioral suppression effects, such as an initial bias away from the distractor in saccade direction, might stem from both the suppression of distractor features and the enhancement of target features (e.g., Chang & Egeth, 2019; Oxner et al., 2023). In the current model, target enhancement is indicated by an accelerated arrival of the target priority signal (as evidenced by the differences in target signal latency between Experiments 2 and 1) and, to a smaller degree, by an increased probability of the target priority signal's behavioral expression (a higher β_{Target}). Importantly, the model considers enhanced target processing as a mechanism for distractor signal suppression. An accelerated target priority signal will replace the distractor priority signal in guiding attention. At the behavioral level, this will direct saccades away from the distractor and toward the target at an earlier time point (see Figure 3B, left panel). A more isolated form of distractor suppression—one that does not depend on enhanced target processing—would involve directly delaying the arrival of the distractor priority signal or reducing its influence on behavior (see Figure 3B, middle and right panels). Because distractor and target processing were modeled separately, the model could be useful for quantifying the role of each in guiding attention.

Finally, the effects of specific shape search (Experiment 2 vs. Experiment 1) and distractor frequency (high vs. low frequency) both involved a slightly faster arrival of the distractor priority signal but a lower probability of expressing that signal. In Experiment 2, the distractor consistently appeared in a particular color, as is common in this task setting (Bacon & Egeth, 1994; Gaspelin et al., 2017, 2019; Gaspelin & Luck, 2018b). In Experiment 4, the distractor appeared repeatedly across trials. We speculate that the reason for this slightly faster distractor priority signal lies in the fact that the distractor's location was unpredictable. Because participants could not anticipate where the distractor would appear, it seems plausible that a distractor had to be rapidly processed, resulting in the production of a distractor priority signal, which was then suppressed from behavioral expression (Geng, 2014). In fact, the faster the distractor can be processed, the earlier it is suppressed from behavioral expression. Note that this suppression mechanism operated at the level of priority signals and led to fewer distractor-going saccades at the behavioral level, rather than more distractor-going saccades as suggested by "rapid disengagement" (Theeuwes et al., 2000) and "search-and-destroy" accounts (Moher & Egeth, 2012). These results contrast with those in Experiment 3, in which the distractor's location *was* predictable. In this case, there was a slightly slower distractor priority signal, even after removing intertrial repetitions.

Caveats in Model Interpretation

Like all computational models, our model was built on certain assumptions. Specifically, our model is based on the signal suppression hypothesis (Gaspelin & Luck, 2018c), assuming that there is always a distractor priority signal produced at a certain latency, but it is not necessarily expressed. While we found this design choice reasonable and the inferences drawn from this model compelling, we cannot completely rule out alternative models. For example, one might argue that the specific shape condition in Experiment 2 did not produce a distractor priority signal to begin with, presumably because the distractor was not salient enough (Wang & Theeuwes, 2020) or because the observer adopted a small attentional window that excluded the distractor's location (Theeuwes, 2023). It is worth noting that both accounts have been refuted (Lien & Ruthruff, 2023; Stilwell et al., 2023; Stilwell & Gaspelin, 2021). Despite so, other mechanisms not formalized in our model could be contributing to the pattern of results seen here. Nevertheless, we show here that a model based on the signal suppression hypothesis is computationally tractable and widely applicable to various search conditions.

Another important model assumption is the independence of distractor and target processing. This is a simplification and likely not entirely accurate, given that in our tasks both types of stimuli appeared simultaneously in the same display and were processed by the same brain. One could imagine a trade-off between distractor and target processing due to the limited pool of cognitive resources. For example, in Experiment 3, the regularity of the distractor's location could have allowed more cognitive resources to be allocated to other locations, potentially expediting the production of the target priority signal (Kong et al., 2020). Importantly, this does not necessarily invalidate our model, as it still effectively captures these signal latencies; the model simply does not incorporate the potential nonindependence explicitly.

Finally, we have refrained from proposing a direct correspondence between model parameters and specific cognitive processes. For example, although the present results strongly indicate that selection history influences distractor suppression through the fast mechanism, it remains an open question whether other factors, such as explicit goals, might lead to a similar effect. Similarly, the early advantage of the distractor priority signal should not be attributed solely to physical salience. Value-driven attention (B. A. Anderson et al., 2011) and other processes might also speed up its arrival. Nevertheless, our model may serve as a valuable tool for investigating how different processes contribute to the temporal dynamics of visual attention.

Future Directions

Isolating the Effect of a Single Variable

The current results elucidate the signal suppression mechanisms in three well-known conditions. We have chosen these conditions to demonstrate the generality of our approach. A downside, however, is that the differing aspects of the tasks prevented a systematic examination of the effects of a single variable, such as physical salience, in a focused manner. A fruitful future direction might be to parametrically manipulate a certain variable, such as physical salience, and observe its effect on the behavioral results as well as on the model parameters. For example, in a task like Experiment 1 in which suppression largely depends on the slow mechanism, the model would predict that having a less physically salient target item would further delay the arrival of the target priority signal, and therefore lead to even more sustained bias to the distractor. Conversely, decreasing the distractor's physical salience might slow down distractor processing, reducing the temporal delay before the target priority signal takes over and guides behavior.

As another example, some recent studies show that distractor interference can also be mitigated by the regularity of the distractor's color (e.g., Stilwell et al., 2019). Then, one could design a forced-response experiment in which the regularity of the distractor's color is parametrically varied. While it is not feasible to address every condition that demonstrates a reduction in attentional capture within a single article, we are confident that our approach offers a generalizable framework. This framework enables researchers to systematically vary specific variables and gain insights into attentional processes as reflected by model parameters.

Electrophysiological Basis of Model Parameters

Another intriguing question is the relationship between our model parameters and electroencephalogram (EEG) indices of attentional processing. EEG components measure covert attention whereas our model estimates are based on saccadic behavior (Weaver et al., 2017). Nevertheless, there is evidence suggesting that our model estimates are consistent with the timing of EEG components. For example, in a display similar to Experiment 2, Gaspelin and Luck (2018a) found that the distractor-elicited Pd component (indicating distractor suppression) emerged approximately 100 ms poststimulus, while the target-elicited N2pc component (indicating attentional selection) appeared around 200 ms poststimulus. These timings generally align with our model's estimated median latencies for distractor and target priority signals in Experiment 2 (105 and 177 ms, respectively). In this task, the Pd component may reflect the role of $\beta_{\text{Distractor}}$, which suppresses the behavioral expression of the distractor priority signal as soon as it emerges. Furthermore, in a unique shape search task, Hickey et al. (2010) demonstrated that trials with a faster target-elicited N2pc component and a slower distractor-elicited N2pc component were associated with quicker search reaction times, suggesting less capture. These results are consistent with our model's predictions regarding how changes in target and distractor signal latencies affect saccade landing probabilities. The relationship between our model parameters and EEG components remains a promising venue for future research.

Integration With Other Models

Our model offers a high-level summary of the time course of visual attention, abstracting away from specific details such as how specific stimulus features are integrated or how task-relevant information is retrieved from memory. Such details can be found in some other existing models (Harel et al., 2007; Itti & Koch, 2000; Wolfe, 2021; Wyble et al., 2020). One advantage of this abstraction is that it maintains parsimony and allows us to focus exclusively on modeling the time course of visual attention. Although this model is agnostic as to the lower level computational processing that gives rise to priority signals, such detail could be added by replacing or adding additional parameters to the model.

For example, our model may be integrated with the RAGNAROC model (Wyble et al., 2020), which also implements two mechanisms for distractor suppression. Simply put, RAGNAROC assumes an architecture in which visual input travels through a hierarchy of maps. Specifically, physical salience is processed at lower hierarchies, then weighted by task relevance, and finally propagated to a common priority map ("Attention Map") that guides visual attention. The model further includes an inhibitory circuitry that allows activation of the Attention Map at one location to inhibit nearby activations with lower priority values. In this architecture, a salient distractor's attentional priority on the Attention Map can be proactively suppressed by reducing the task-relevance weight associated with the distractor's features, or reactively and indirectly suppressed by the presence of target activation on the Attention Map (Tam et al., 2022). Similar to our model, the "proactive" mechanism acts on distractor-specific features and thus mimics the function of $\beta_{\text{Distractor}}$ in our model. Conversely, the "reactive" mechanism depends on the presence of target activation on the Attention Map, mimicking the override by the target priority signal in our model.[1] Notably, our model assumes that the distractor and target priority signals may arrive asynchronously. If only the distractor priority signal is present, then attentional deployment will be at the mercy of the $\beta_{\text{Distractor}}$, which determines the probability that the distractor priority signal will be expressed. Overall, our model and RAGNAROC appear to complement each other, and integrating these models may provide us with more comprehensive insights into visual attention.

Concluding Remarks

In conclusion, the current work demonstrates the diversity in the temporal dynamics of attentional priority and highlights a computational framework for understanding the processes of distractor suppression. The versatility of the computational model

[1] Not labeling the fast and slow mechanisms as "proactive" and "reactive" was a deliberate choice. Researchers debate what exactly "proactive" and "reactive" mechanisms entail (Liesefeld et al., 2024). For example, "proactive" could refer to processes that take place before the onset of the display or to those occurring after the onset but prior to the initial shift of attention. Yet, this latter period has been labeled "reactive" by some, as it follows the display onset. Depending on one's perspective, the interpretation of proactive and reactive processes may vary significantly. Our model is agnostic to whether $\beta_{\text{Distractor}}$ exists before or after stimulus onset; it is simply ready to modulate the distractor priority signal when the signal is present.

used here can potentially extend to a wide array of tasks that involve a conflict between habitual and goal-directed processes. While its utility has been demonstrated in visual search, there are a multitude of other behavioral paradigms that feature the influence of distraction, such as the flanker task, the Stroop task, go/no-go tasks, and others, that could benefit from similar analytic techniques. A compelling question for future research is whether conflict-resolution mechanisms are universally applicable across these diverse tasks.

Constraints on Generality

Our study involved college students from an elite university, who completed contrived psychological tasks in highly controlled experimental settings. These aspects may limit generalization to broader age groups and diverse populations. In addition, given that the tasks we used involved simple item searches, our findings may not extend directly to different cultural or environmental contexts, where visual search is often more complex.

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