The neural and behavioral basis of statistical learning of distractor suppression in visual search

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1 General Introduction

As we go about our daily lives, we are constantly bombarded by visual input. For instance, we are constantly searching for bus information on the platform display ride to work, or maybe even be drawn to a similar-colored bus on the road. Again, one might intentionally scan the crowd for a friend wearing a red hat, as you search, your attention is possible inadvertently to be drawn to the striking flowers lining the road. There is no doubt that visual attention is omnipresent and crucial on a daily basis. When interacting with a complex, constantly changing surrounding environment, our brain cannot handle overwhelming information. Many theories have emphasized that attentional selection is influenced not only by aspects of targets but distractions in the visual surroundings (Duncan & Humphreys, 1989; Geng & Witkowski, 2019; Jonides & Yantis, 1988; H. J. Müller et al., 1995; H. J. Müller & von Mühlenen, 2000; Töllner et al., 2015; Wolfe & Horowitz, 2004). Especially salient but task-irrelevant objects (distractors) often stand out in a visual scene and tend to capture our attention. It might be harmful, even potentially threatening your life (e.g., causing a car accident), if visual attention were drawn to any sudden novel stimuli while driving. In short, it is vital to study how to prioritize limited attentional resources on goal-related information and to deprioritize environmental pop-out distractions.

To date, the vast majority of studies provided critical insights that attentional selection is determined by an interaction of both top-down, i.e., goal-driven or voluntary mechanisms, and bottom-up, i.e., stimulus-driven or involuntary mechanisms (Egeth & Yantis, 1997; Folk et al., 1992; Orchard-Mills et al., 2013; Wolfe et al., 2003; Yantis & Egeth, 1999). Despite this well-established duality of attentional control, a new source of attentional bias called "selection history," which refers to the impact of previous selection experiences on the current selection, has recently been proposed (Anderson et al., 2021; Awh et al., 2012; M. Failing & Theeuwes, 2018; Kadel et al., 2017; Kristjánsson & Campana, 2010; H. J. Müller et al., 2010). For instance, visual search may be facilitated by statistical learning of spatial regularities of distractor location to reduce interference (Allenmark et al., 2019a; e.g., Goschy et al., 2014). Therefore, selection history neither belongs to the traditional top-down nor the bottom-up attention mechanism (Anderson et al., 2021; Theeuwes, 2019). Selection history effects mainly encompass statistical learning of target and distractor features and/or their spatial/contextual regularities (Chen et al., 2022; Fiser & Aslin, 2002; Gaspelin et al., 2019; Kerzel et al., 2022; Sauter et al., 2021; Turk-Browne et al., 2005; van Moorselaar & Slagter, 2019; B. Wang & Theeuwes, 2018a; Zellin et al., 2013), different characteristics of intertrial priming such as locations, colors, or auditory repetitions and so on (Allenmark, Gokce, et al., 2021; Geyer et al., 2007; Lamy et al., 2011; Lamy & Yashar, 2008; e.g., Maljkovic & Nakayama, 1994, 1996), and also due to motivational and emotional value of stimuli such as reward and threatening (Anderson, 2016, 2017; e.g., Bourgeois et al., 2016; M. Failing et al., 2015; M. Failing & Theeuwes, 2018; Kim & Porter, 2002; Nissens et al., 2017). Of note, the purpose of this thesis involves not only long-term statistical learning of distractor locations but short-term intertrial priming, even across-trial repetitions of distractor sequences, to facilitate selective attention.

It is well-known that attention can be facilitated by exploiting the spatial distribution of objects or context in the visual environment. Through this process, known as visual statistical learning, observers appear to prioritize attention selection to certain locations where relevant information is regularly encountered has been termed the ‘probability cueing effect’(Geng & Behrmann, 2002, 2005). For instance, if a cat got used to staying under the sofa, it would become easier to locate this cat since you frequently found her in this specific region and even avoid distracting salient shelter on the way of searching. Similarly, learning the spatial distribution of a salient but task-irrelevant distractor where it appears frequently and thereby improves search efficiency has been referred to as ‘distractor location probability cueing’ (Goschy et al., 2014; Sauter et al., 2018; Zhang et al., 2019). Additionally, intertrial priming effects have long been investigated to see how prior attentional selection experiences affect current selection (Maljkovic & Nakayama, 1994, 1996). According to a study by Goschy and colleagues (2014), the distractor-location probability cueing effect would be owing to both statistical learnings of the locations of the distractions and intertrial facilitation brought on by the repetition of the distractions on successive trials.

We have until now explained distractor suppression patterns solely by learning spatial regularities of distractor locations and short-term intertrial repetitions. In reality, real-world visual environments are much more complex and volatile, which is in line with the predictive-coding framework for perception (Friston, 2010; Friston & Kiebel, 2009), according to which the brain constantly makes predictions about the environmental causes of sensory inputs based on prior knowledge. On the basis of past research indicating that a highly volatile environment in which unexpected uncertainty resulting from changes in several variables will impact learning speed (Behrens et al., 2007; Ferrari et al., 2022; Jungerius et al., 2022). Very little is currently known about, however, whether we can exploit the volatile probability to adjust learning rates of distractor suppression. Moreover, research has not explicitly determined whether across-trial modulations of distractor locations also hold in volatility search environments based on history-driven attention control. Last but not least, we still lack a thorough understanding of the underlying neural mechanisms concerning to what degree the learned distractor suppression is implemented (namely, which stage the suppression work at) within the framework of search guidance to reduce interference. In the present thesis, we used the combination of oculomotor capture evidence and some neural markers, such as EEG components linked to visuospatial selection and, respectively, the processing of items in visual working memory (vWM), to address the above questions.

It begins with this introduction (1.1) which describes potential theoretical explanations of attentional selection, highlighting how attention is captured by distractors in a bottom-up manner, and how the potential interference from distractors can be minimized by a top-down attention control during visual attention. Next comes the second part of the introduction (1.2), which explains history-driven attentional selection as another source besides top-down and bottom-up attentional control since recent increasingly numerous studies demonstrate that observers can learn to minimize distraction over time from prior experience. Past knowledge of visual selection may guide attentional performance so that implicit or explicit experience shapes the current action of attentional selection. The third part of the introduction (1.3) mentions probability cueing effects, which are probed and replicated in the additional singleton paradigm and the typical visual search tasks (Goschy et al., 2014; Theeuwes, 1992) to examine the cognitive processing of history-driven selection and suppression strategies. The following subsection (1.4) describes in more detail the family phenomenons of history-based attentional selection, especially three critical components (i.e., spatial statistical learning, temporal across-trial regularities, and intertrial priming) as strongly related to this thesis to resolve distractor interference and facilitate our attention. Then, the fifth part of the introduction (1.5) outlines the neural dynamics underlying distractor-location learning inhibitory effects in visual attention. The last subsection of the introduction (1.6) lists the main aims of the doctoral thesis. Crucially, Chapter 2 contains the three individual studies, which constitute the main part of the cumulative doctoral dissertation. Finally, Chapter 3 concludes the thesis with a summarizing, comprehensive General Discussion. That is, Chapter 3 summarizes three studies—an EEG, an eye-tracking, and a behavioral study—to finish the doctoral thesis. A comprehensive conclusion and some suggestions for further research are given at the end of the General Discussion section.

1.1 Top-down vs. bottom-up control of visual attention

Humans routinely perform visual attention in many situations, such as finding objects, navigating streets, browsing websites, operating vehicles, and engaging in sports. Visual attention allows us to selectively direct sensory processing toward information that is relevant to our goals and to prevent attentional perseveration on distractions that are unrelated to the tasks at hand (Chun & Marois, 2002; Egeth & Yantis, 1997; Folk et al., 1992; Geyer et al., 2006; Mazza et al., 2007; Treisman & Gelade, 1980; Wolfe & Horowitz, 2004). Therefore, the processing of attentional selection is dependent on the dual mechanisms of target selection and distractor suppression (Chun & Marois, 2002). Traditionally, attentional selection is believed to result from the interaction between two attentional control mechanisms, such as top-down (goal-driven) control and bottom-up (stimulus-driven) control (Egeth & Yantis, 1997; Folk et al., 1992; Orchard-Mills et al., 2013; Wolfe et al., 2003; Yantis & Egeth, 1999). This theory is widely held and has received widespread acceptance.

Top-down control implicit observers voluntarily shift attention to a specific goal (Buschman & Miller, 2007; Rosenholtz et al., 2012), such as searching our smartphone. It is commonly agreed that top-down control is goal-directed, volitional, and purposeful, and some form of conscious awareness may be a prerequisite for top-down selective attention (Itti & Koch, 2001; Wolfe & Gray, 2007). As a result, top-down guidance is also referred to as endogenous attention (Posner, 1980). The modulation of top-down attention is based on the memory representation of the target's critical features/locations (termed as “target template”) implicitly or explicitly: We can focus on a certain spatial location or feature, like a particular motion direction or color, to prioritize the processing of visual information in a scene (Chapman & Störmer, 2022; Duncan & Humphreys, 1989; H. J. Müller et al., 2009; Wolfe, 2021). For example, if participants were searching for a green diamond, the color-defined green and the shape-defined diamond would be used to navigate their visual attention. While, many studies have pointed out that visual selection is driven not only by the characteristics of targets but also by task-irrelevant salient stimuli (i.e., distractors) (Geng & Witkowski, 2019; Wolfe & Horowitz, 2004). In comparison to the top-down selection, this stimulus-driven selection is an involuntary process in which attention is automatically captured by a physically salient item and/or exogenous, physical saliences of the stimulus, referred to as bottom-up control or exogenous attention (Folk et al., 1992; H. J. Müller et al., 2010;

Theeuwes, 2010; Yantis & Egeth, 1999). Some studies suggested that it is entirely top-down control or bottom-up control, but rather that it is the result of a combination or interaction between these two factors (Wolfe & Gray, 2007; Yantis & Jonides, 1990). Over the past few decades, researchers have worked on studying whether and how top-down and bottom-up mechanisms are integrated to guide the attentional selection process.

A typical intermediate model called *search-mode account* by incorporating both top-down and bottom-up processing, which suggests that a known target can be detected in one of two strategies: *feature search mode* or *singleton detection mode (Bacon & Egeth, 1994)*. On the one hand, observers presumably monitor a retinotopic feature map, and direct attention to the location of the element that generates activation in that map, consistent with previous work (Treisman & Souther, 1985). Feature search mode is not susceptible to interference from variation in an irrelevant dimension so singleton presence costs can be eliminated by modifying the stimuli. That is, observers cannot find the target by looking for a singleton and must instead search for a specific feature value. On the other hand, observers may establish a *singleton detection mode* when they are searching for a singleton (target) defined in a particular dimension, a more salient singleton (distractor) defined in a task-irrelevant dimension would also capture attention. For instance, in a typical additional singleton paradigm (Theeuwes, 1992), participants were required to search for a shape-defined target (e.g., a green circle among seven green squares) in the presence of a salient but task-irrelevant singleton distractor (e.g., a red square). They found when the distractor was present, search performance was temporarily disrupted, measured by significantly longer response times (RTs) for distractor-present (vs. distractor-absent) trials (termed as *a singleton presence cost*), indicating that the salient but task-irrelevant distractor caused interference. However, this interference only appeared when the distractor singleton was more salient than the target singleton: searching for a shape-defined target but sometimes presenting with a color-defined singleton distractor would impair behavior performance, but not vice versa (Theeuwes, 1991, 1992, 1994; Theeuwes et al., 2000). Theeuwes (1994) also called this mode a *stimulus-driven attentional capture model* in which selection was entirely affected by the features of the items occurring in the visual field, even when participants knew they were task-irrelevant.

Nevertheless, Folk et al. (1992) introduced the *contingent attentional capture account*. In the spatial cueing paradigm, a cue display was present before the search display onset. In separate blocks of trials, the cue displays had no spatial cue, a spatial clue to the center (where the impending target never appeared), a 100% valid cue, or a 100% invalid cue. One group of participants searched for an abrupt-onset-defined target, and another group searched for a color-defined target. An evaluation of response time costs and benefits was conducted relative to a no-cue condition. As a result, valid cues improved search performance in the abrupt-onset detection group, whereas invalid cues impaired it. By contrast, observers in the color detection group only showed search benefits when valid cues were presented, but not search costs when invalid cues were presented. It suggested that invalid cues only produced significant response time costs when they shared the feature that defined the target, while valid cues produced significant response time benefits regardless of whether they shared the feature. According to this account, only irrelevant stimuli matching the features of the search task-relevant goal may capture attention (1992; Lien et al., 2008, 2010).

Taken all accounts together, although the stimulus-driven and goal-driven theories seem to offer contradictory predictions about when one should anticipate attention capture, it has been almost five decades since these rival theoretical approaches have thrived. However, one thing that has become abundantly evident to us is that while top-down objectives can have an effect on attentional acquisition, there are a great many scenarios in which irrelevant salient elements appear to catch attention. Interestingly, a growing body of research indicates that an acknowledged dichotomy of attentional control between top-down and bottom-up does not hold since there is another contributing source: prior experience with lingering attentional biases about past selection episodes (Anderson et al., 2021; i.e., selection history control; Awh et al., 2012; Kadel et al., 2017; H. J. Müller et al., 2010; Wolfe et al., 2003), which also affects the efficiency of current visual search.

1.2 History-based visual attention

History-based visual selection emphasizes how the current deployment of selective attention is influenced by prior knowledge of selection experience, referred to as *selection history* (Awh et al., 2012; M. Failing & Theeuwes, 2018; Kadel et al., 2017; H. J. Müller et al., 2010). Selection history encompasses many sources of attentional bias, such as statistical learning of features/locations (e.g., Fiser & Aslin, 2002; Gaspelin et al., 2019; Kerzel et al., 2022; Sauter et al., 2021; Turk-Browne et al., 2005; van Moorselaar & Slagter, 2019; B. Wang & Theeuwes, 2018a; Won et al., 2019; Zellin et al., 2013), intertrial priming effects on colors/locations/auditory repetitions (Addleman & Jiang, 2019; Allenmark et al., 2018; Allenmark, Gokce, et al., 2021; Feldmann-Wüstefeld & Schubö, 2016; Geyer et al., 2007; Lamy et al., 2011; Lamy & Yashar, 2008; e.g., Maljkovic & Nakayama, 1994, 1996), motivational and emotional value (e.g., reward, threat) of stimuli (Anderson, 2016, 2017; e.g., Bourgeois et al., 2016; Failing et al., 2015; Failing & Theeuwes, 2018; Kim & Porter, 2002; Nissens et al., 2017). The current thesis presents the history-based visual attention as a separate subsection. Because selection history neither belongs to the traditional top-down control which is driven by the observer's purpose, nor the bottom-up attention control which is driven by physically salient features (Anderson et al., 2021; Theeuwes, 2019). Here, supporting evidence from several studies will demonstrate this opinion.

First of all, recent work indicated attentional selection is biased by statistical regularities present in the environment. More and more studies have emerged that observers can learn from prior experience of spatial distribution to deprioritize locations where the salient but task-irrelevant singleton distractor frequently appears in the search display to (implicitly) minimize interference caused by such a distractor (Gao & Theeuwes, 2019; Goschy et al., 2014; Leber et al., 2016; Sauter et al., 2018; B. Wang & Theeuwes, 2018a). Eye-movement studies confirmed these findings: oculomotor capture was less likely when the singleton distractors occurred at frequent locations rather than rare locations (Allenmark, Shi, et al., 2021; Di Caro et al., 2019; Sauter et al., 2021; B. Wang, Samara, et al., 2019).

Secondly, even a short-term time scale of prior experience may also reduce distraction interference, referred to as intertrial priming effects (Kadel et al., 2017; Sauter et al., 2018; Theeuwes, 2018; Walthew & Gilchrist, 2006). For instance, a prior study (Geyer et al., 2010), using a paradigm similar to Maljkovic and Nakayama's (1996), found that facilitation priming when the target on a given Trial *n* presented at the target location on Trial *n-1*, produced RT facilitation. In contrast, inhibitory priming of distractor locations could even be evoked when the target on Trial *n* was presented at an empty but merely expected distractor location on the preceding Trial *n-1*, producing inhibition. Of note, the target and distractor colors switched across trials in this case. A similar position priming effect also can see in Krummenacher et al. (2009). Based on the frame called *dimension-weighting account* (Found & Müller, 1996; Muller et al., 2003; H. J. Müller et al., 1995, 2009; Zehetleitner et al., 2009), they suggested that different visual dimensions (e.g., motion, orientation, color, location) may be allocated to different attentional weights in an overall priority map, and what's more, observers would down-modulate the weight assigned to the irrelevant distractor dimension (or feature) after encountering a distractor defined in that dimension (or by that feature). That is, the visual system shielded against a distractor on a previous trial will carry over this shielding routine to the next trial. In contrast, the visual system facilitated search performance from the target on a previous trial and will carry over this facilitation routine to the next trial.

Lastly, previous studies have shown that reward-associated stimulus can capture attention even if the 'reward history' is associated with a non-salient and task-irrelevant stimulus (e.g., Anderson et al., 2011; Anderson & Halpern, 2017; Awh et al., 2012; Bourgeois et al., 2016; M. Failing & Theeuwes, 2018). Specifically, using the value-driven attentional capture paradigm (Anderson & Halpern, 2017), experimenters manipulated a training phase where the successful selection of the target is rewarded, resulting in a reward association for the specific visual feature of the target. Then, in the test phase, observers searched for a different target and no rewards are delivered. Typical findings in these studies demonstrated that previously rewarding stimuli might interfere with search performance even in situations where the reward item is a non-salient physical object (Della Libera & Chelazzi, 2009; M. F. Failing & Theeuwes, 2014; Hickey et al., 2010).

In short, three typical pieces of evidence discussed provided a novel framework for studying visual attention. History-driven selection helps us to gain further insight into understanding how past experiences influence attentional (de)prioritization, even when the visual stimulus is not salient (i.e., constitute no strong bottom-up signal) and even when they are completely irrelevant to the task at hand (i.e., constitute no top-down signal). Of note, the present thesis mainly focuses on statistical learning and intertrial priming effects of distractor locations. Therefore, in the next subsection, we will discuss how to establish the experiment context, as well as to what extent the manipulations of target/distractor locations need to be implemented for studying the mechanisms underlying statistically learned (de)prioritization.

1.3 Statistical learning as history effect: Probability cueing effect

It is ubiquitous to exploit the location information and deploy the spatial distributions in the real environment to guide our attention. For instance, we may be able to accomplish daily grocery shopping efficiently by developing relatively stable position information since the fruit area in a supermarket is always next to the vegetables. This phenomenon is known in cognitive experiments as the *contextual cueing effect*. In the experiment of Chun and Jiang's (1998), observers responded faster to the target when it occurred at the invariant search display (i.e., old spatial configurations) than at the variable display (i.e., new configurations). This finding is that observers learned the statistical contingencies that determine the target location, even though they couldn't state the spatial regularities driving their behavior. Similarly, numerous studies have found that probabilistic distributions in target locations would also help to facilitate visual search performance (Geng & Behrmann, 2002, 2005; Miller, 1988; e.g., Shaw & Shaw, 1977). In Geng and Behrmann's experiments (2002, 2005), observers responded faster to the target when it occurred at highly likely locations vs. unlikely locations, suggesting that observers can implicitly learn the spatial distributions of targets to their advantage during visual search - termed *location probability cueing effect.* An eye-tracking study confirmed that oculomotor capture was more probable to land on the target when it appeared at a frequent location as compared to other locations in the search display (Walthew & Gilchrist, 2006).

Building on the above work, increasing studies have well-established that observers can also take advantage of prior experience with uneven spatial distributions of the salient distractor singleton to minimize interference due to location probability learning (Leber et al., 2016; Sauter et al., 2018; B. Wang & Theeuwes, 2018a; Zhang et al., 2019). Commonly, researchers adopted either the additional singleton search paradigm (Allenmark et al., 2019b; B. Wang & Theeuwes, 2018a; Zhang et al., 2019) or the classical visual search paradigm with the probability manipulation to build up the uneven spatial distributions of distractors (Goschy et al., 2014; Liesefeld & Müller, 2020; Sauter et al., 2018, 2021). Collectively, in the additional singleton paradigm where participants should search for and respond to a unique shape-defined target (e.g., a circle among diamonds, or vice versa) while ignoring a salient color-defined distractor (e.g., a red or green singleton different in color from other, non-distractor items). Importantly, when present in the search display (with 24-item arrays in Allenmark et al., 2019a; e.g., with 4-item arrays in Ferrante et al., 2018; with 8-item arrays in

B. Wang & Theeuwes, 2018a), the salient distractor singleton appeared with high probability at one ‘frequent’ location and with low probability at one of the ‘rare’ locations (e.g., 65% on distractor-present trials, as compared to 5% for each of 7 the remaining, “rare” distractor locations in B. Wang & Theeuwes, 2018a), providing for statistical learning of the distractor-location distribution. Of note, the target was equally likely to appear at all locations on distractor-absent trials.

The robust result of such manipulation was distractor interference was significantly reduced on distractor-present trials when the distractor occurred in the frequent- as opposed to the rare distractor location - so-called *distractor location effect*. On top of that, there is the *target location effect* on distractor-absent trials where responding to the target was slower when it presented at the frequent distractor location as opposed to a rare one. In fact that the target location effect tends to be less evident than the distractor location effect because some previous studies reported both effects (e.g., B. Wang & Theeuwes, 2018a, 2018b), while others failed to find the target location effect (e.g., Ferrante et al., 2018; Valsecchi & Turatto, 2021). Recent evidence has found that when the distractor's color is unique and fixed as compared to non-distractor items, attentional capture is modulated by the probability cueing of distractor locations, whereas the target-location effect disappears, indicative of feature-based inhibition (Allenmark et al., 2019a; Zhang et al., 2019).

Again, a more dense search display is performed using the typical visual search paradigm, in which a ‘frequent’ region contains multiple possible locations such as half of the entire display, usually in a very dense arrangement (e.g., 36-item within three concentric rings in Goschy et al., 2014; e.g., 60-item within four concentric rings in Liesefeld & Müller, 2020). The evaluation of the statistical distribution of salient distractors showed that observers can exploit spatial regularities of salient distractors to reduce interference (less RTs) when distractors occurred at the frequent region as compared to rare locations, referred to as *distractor-location probability cueing effect* in Goschy et al.(2014). In addition, Goschy provided powerful evidence in this study to show that statistical learning and intertrial facilitation as underlying mechanisms of the probability cueing effect are not necessarily mutually exclusive: the distractor-location probability cueing effect would be owing to both statistical learnings of distractor locations and intertrial facilitation brought on by the repetition of the distractions on successive trials. However, how does the distractor get learned and suppressed over time? The current dissertation focuses on to what degree the visual system learned to minimize interference induced by the salient distractor depending on the long-term probability cueing and the short-term inter-trial facilitation. Also, how is this implemented in its cognitive architecture of search guidance and its neural marker of visual attention?

1.4 Across-trial statistical learning bias distractor suppression

So far, extensive research has been carried out on the probability cueing effects but mostly restricted to stationary spatial regularities (e.g., high- vs. low probability locations), but the regularities are sequential in nature. That is, in every single day, regularities are mostly relied on what happened before, a particular event A is followed by events B and C on the temporal sequences (for a review, Theeuwes et al., 2022). However, we have as yet a scant understanding of the underlying mechanisms of how statistical learning by taking the form of across-trial sequences to attenuate the influence of distractors. This issue is a well noteworthy aspect of the experience-driven attention topic so that the current dissertation will address it.

It is well-established that observers can take advantage of prior experience with uneven spatial distributions of the distractor to reduce attentional capture due to statistical learning of distractor locations (Gao & Theeuwes, 2019; Goschy et al., 2014; Leber et al., 2016; Sauter et al., 2018; B. Wang & Theeuwes, 2018a). These studies inspire us to concern to what extent our visual system learned to bias attention across trials, indicative of the statistical learning of temporal sequences (e.g., trial-to-trial transitions of distractor locations where the location of a distractor on Trial n-1 predicts its subsequent location on Trial n, mentioned in a review of Theeuwes et al. 2022). In the experiment of Li & Theeuwes (2020), for instance, demonstrated that participants may extract trial-to-trial statistical learning of target locations. In this visual search task, observers should respond to a shape-defined singleton target among seven other items. Here, experimenters manipulated two regularity conditions regarding the location of targets across trials: a target at rightmost on the preceding trial (Trial *n–1*) and a target at leftmost on the current trial (Trial *n*) for the regular condition, and trials whose target locations not matched with Trial *n–1* for the nonregular condition. The finding is RTs were faster in the regularity condition rather than the nonregularity condition, not only on distractor-absent but also distractor-present trials - suggesting that attentional selection was affected by across-trial regularities. Importantly, another behavioral and electroencephalogram (EEG) study revealed the repetition benefits of distractor location learning in across-trial sequences helped the brain resolve attentional capture when the distractor was repeated at the same location in subsequences over 1 to 12 trials, as reflected by the reduced RTs and the repetition-related reduction in the Pd component (van Moorselaar & Slagter, 2019).

Considering the repetition priming effects, some studies have indicated that repeating the target/distractor properties (i.e., location or features) on consecutive trials may improve visual search performance compared to those whose properties are unchanged (e.g., Allenmark, Gokce, et al., 2021; Geyer et al., 2006; Kabata & Matsumoto, 2012; Maljkovic & Nakayama, 1994, 1996; Won et al., 2019). In distractor suppression investigations, Goschy and colleagues (2014) proposed that the distractor-location probability cueing effect may benefit from statistical learning of distractor locations and intertrial facilitation. Notably, intertrial repetition effects are another account of selection history theories (Kadel et al., 2017; Sauter et al., 2018; Theeuwes, 2018). Regarding the across-trial statistical learning mechanism, we supposed that visual search might also be facilitated by the statistical learning of stimulus and the intertrial repetition priming of stimulus properties in the environments.

Supporting evidence comes from a series of studies (Ferrante et al., 2018; Liesefeld & Müller, 2019; Turatto & Valsecchi, 2022; Valsecchi & Turatto, 2021; van Moorselaar & Slagter, 2019; e.g., B. Wang & Theeuwes, 2018a; Zhang et al., 2019): distractor-location probability cueing reflects the modulation of spatial priority maps. The reduced interference regarding the most probable location of a distractor would attenuate the weight of saliency signals at this specific location in attentional-priority computations and thus reducing attentional capture, termed *proactive suppression* (Geng, 2014; Luck et al., 2021; Sauter et al., 2021; Theeuwes et al., 2022). Alternatively, there is also a mechanism of *reactive suppression* imply that if a distractor captures attention, its location needs to be suppressed ‘reactively’ on consecutive trials so as to disengage attention from the distractor and reallocate it to the target location, and this carry-over suppression was gradually adjusted on a trial-by-trial basis and eventually affect priority maps so that it gave rise to lower costs in search performance (Allenmark, Shi, et al., 2021; Geng, 2014; Theeuwes & Failing, 2020; Won et al., 2019). Consequently, the attentional weight (i.e., the level of neural activity determining the processing efficiency within the corresponding input module) was allocated. Moreover, the higher weights for task-relevant features and lower weights for task-irrelevant features do carry over to subsequent trials in an automatic manner (Feldmann-Wüstefeld &

Schubö, 2016; H. Müller et al., 2004). Several studies have established that the visual field is represented by cortical and subcortical networks with priority maps of space (frontal eye field, lateral intraparietal area, inferotemporal cortex, superior colliculus) and indirectly (via the aforementioned nodes) by lower-order areas that have a retinotopic organization (Hikosaka et al., 2000; Theeuwes et al., 2022; Zhang et al., 2022).

In fact, real visual environments are much more dynamic and volatile, as is the account of the Predictive-coding framework of perception (Friston, 2010; Friston & Kiebel, 2009): the brain continually makes predictions, based on prior knowledge, about the environmental causes of the sensory inputs it receives. If a discrepancy between the top-down prediction and the actual sensory input (i.e., a prediction error) occurs, the brain attempts to reduce this mismatch by integrating the top-down prior information and the sensory input and adjusting its internal generative model accordingly. Additionally, some studies supposed that the priority map could be tuned so flexibly across trials by continuously adjusting weights, which at any moment in time dynamically controls the deployment of covert attention and gaze (Theeuwes et al., 2022; L. Wang et al., 2021). For instance, Wang and colleagues (2021) compared distractor suppression effects driven by across-trial learning of distractor locations in the learning group (i.e., the distractor location occurred in either a clockwise or anticlockwise subsequent of every eight trials) with the baseline group (i.e., the distractor location occurred randomly across trials), and they found observers have implicitly learned the trial-to-trial transitions of distractor locations to reduce attentional capture, and in anticipation of the presentation of the salient distract, suppression is proactively applied. However, while such across-trial statistical learning for sequence pairs suggested a flexible priority map of attentional selection about up-weighting or down-weighting of the predicted location on the next trial base on the past experience of the preceding trial, far too little attention has been paid to how the volatility of an overall search environment can influence the speed of learning of distractor inhibition. In the current study, we specifically set out to examine the influence of environment volatility on the statistical learning of distractor locations to minimize the attentional capture by salient distractor singleton.

1.5 Neural mechanism of history-based visual attention

We are confronted with a large amount of visual information every day. However, the information processing capacity of the human brain is limited (Marois & Ivanoff, 2005; Slagter et al., 2007). Substantial evidence now indicates that the brain maintains a priority map in which attentional selection is responsible for the allocation of limited processing resources: to prioritize task-relevant information while deprioritizing task-irrelevant distracting information (e.g., Carrasco, 2011; Gaspelin & Luck, 2018a; Slagter & van Moorselaar, 2021; Wolfe, 2021). To be more specific, the spatial priority map encodes a topographic geographic representation of individual location priorities based on signals from sensory input (bottom-up), the current target state (top-down or behavioral correlation), and statistical learning (history-driven) (for a review, Theeuwes et al., 2022). The priority map of attentional selection is associated with a distributed neural network including frontal, partial, and temporal areas (for a review, Theeuwes & Failing, 2020). As a rule, frontal brain regions (including the anterior cingulate) were associated with construing the top-down attention processing; whereas early visual areas and structures like the superior colliculus participated in the bottom-up attention control (for a review, Itti & Koch, 2001); medial temporal lobe (including the hippocampus) was associated with selection history (e.g., visual statistical learning), and these brain regions feed into the priority map to guide visual selection (Theeuwes et al., 2022; K. G. Thompson & Bichot, 2005).

Despite the fact that there is little known about the neural substrates driving learned statistical learning of target/distractor locations, numerous studies provide strong evidence that a common neurophysiological marker N2pc may reflect the deployment of visuospatial attention in a multi-stimulus display (Eimer, 1996; Kiss et al., 2008; Luck & Hillyard, 1994a, 1994b; Sawaki & Luck, 2013; Töllner et al., 2012; Woodman & Luck, 1999). The N2pc component is elicited at approximately 200–350 ms latencies poststimulus at posterior electrodes (i.e., PO7/PO8) contralateral to the target location in spatial attention tasks(Gaspar et al., 2016; Kiss et al., 2008). Following the N2pc component, the distractor positivity (Pd) component is a positive increase in activity contralateral to the distractor over the posterior electrode sites, which is taken to reflect an active suppression mechanism when the visual system spatially identified the target item but and suppressed the nearby task-irrelevant distractors (Gaspar & McDonald, 2014; Gaspelin & Luck, 2018b; Hickey et al., 2009; Sawaki et al., 2012; Sawaki & Luck, 2013). For example, Wang et al.(2019) recently reported the N2pc to be delayed and reduced in amplitude when the target occurred at the (single) frequent relative to one of the rare distractor locations, potentially reflecting a lingering suppression component (i.e., Pd) at the frequent location. In contrast, van Moorselaar et al.(2021) failed to find any difference in the N2pc elicited by targets occurring at the frequent vs. a rare distractor location, even though they found that the N2pc elicited by lateralized targets is reliable in a context processing across spatial bias learning and feature level conditions. Moreover, in an earlier study by Sauter et al. (2017), the distractor-elicited N2pc amplitude was actually larger for distractors appearing at locations in the frequent vs. the rare (distractor) region in the midline-target/lateral-distractor condition; on the other hand, the target-elicited N2pc was delayed for targets appearing in the frequent vs. the rare region, which Sauter et al.(2017) took to be indicative of a larger amount of attentional resources being required to detect a target stimulus in a region that is pro-actively suppressed as a result of distractor-location learning. In any case, the relevant literature provides no coherent picture of the N2pc effects, and new evidence is needed to resolve the inconsistencies.These findings embody the probability cueing effect based on distractor suppression is flexible, which relies on the different hierarchical dimensions combined with the statistical learning of distractor locations (Allenmark et al., 2019; Heinrich R. Liesefeld & Müller, 2020; van Moorselaar et al., 2020; Zhang et al., 2019). Indeed, the neural evidence of it is still poorly understood and controversial. More neuroscience researchers are waiting to fill the gaps in the neural mechanisms of statistical learning based on distractor suppression.

The sustained posterior contralateral negativity (SPCN) is a relatively late component (> 300 ms; e.g., 500 to 1000 ms post-stimulus), which is regarded as an attentional selection of cued memory items or stored visual working memory representations (Eimer & Kiss, 2010). For example, the SPCN has been observed in visual discrimination tasks requiring detailed analysis of selected target items (Mazza et al., 2007, 2009), as well as complex choice or visuo-spatial configuration judgment tasks that require a great involvement of attention and visual working memory (Jolicoeur et al., 2008; Maheux & Jolicœur, 2017). Given this, in Chapter 2.1, we considered the SPCN to potentially provide a useful indicator of the processing demands posed by the analysis of a critical item, such as a target appearing at a previous distractor location that participants first look at but initially fail to recognize.

Finally, we are also concerned about whether any anticipatory suppression effects of spatial bias distractor locations will happen beforehand is a fundamental metric to study when discussing the neural mechanisms of statistical learning of distractor locations across trials.

Lateralization alpha-band (8-12 Hz) oscillations have been instrumental in understanding anticipatory suppression effects(Jensen & Mazaheri, 2010; Kelly et al., 2006; Worden et al., 2000). To date, some EEG research has been carried out on this question addressed with pre-stimulus alpha-band oscillations in the parieto-occipital visual region representing the spatial modulation of likely distractor locations on previous trials. Such that conducted by Wang(B. Wang, van Driel, et al., 2019) found evidence to interpret anticipatory suppression of the high probability location, that is, enhanced alpha power contralateral to the high prob.distractor location is observed prior to display onset. On the contrary, several similar EEG studies find no evidence to interpret probability-bias distractor locations will induce any neural changes of pre-stimulus alpha-band activity beforehand in visual regions(Noonan et al., 2016; van Moorselaar et al., 2020, 2021; van Moorselaar & Slagter, 2019).

Given that the evidence is somewhat mixed, the current dissertation aims to explore the underlying neural mechanism of distractor position suppression by long-term statistical learning and short-term inter-trial distractor target position dynamics.

1.6 Aims of the thesis

The goal of the current dissertation is to advance our understanding of the cognitive and the neural dynamics underlying statistical distractor-location learning and inhibitory intertrial effects in visual attention, and further to establish how to make use of across-trial regularities of distractor locations to reduce attentional capture in volatile environments. To tackle these issues, classical behavioral experiments, eye-tracking and EEG techniques are employed.

To begin with, in Chapter 2.1, to conclude the locus of the learned distractor location suppression within the functional architecture of search guidance to reduce interference in the frequent locations, the dissertation adopted the additional singleton search paradigm of Wang and Theeuwes (2018a): in which participants look for and respond to a unique shape-defined target (e.g., a circle among diamonds, or vice versa) while ignoring a salient color-defined distractor (e.g., a red or green singleton different in color from other, non-distractor items). Importantly, when present in the search display, the salient distractor singleton appeared with high probability at one ‘frequent’ location and with low probability at one of the ‘rare’ locations, providing for statistical learning of the distractor-location distribution. Combining the EEG approach in the additional singleton paradigm, the dissertation first explores (1) how the long-term probability of distractor location and the short-term inter-trial coincidence of the distractor and target locations modulate attentional selection across trials at the neural level, by examining the N1pc, N2pc and SPCN components when the target (Trial *n*) occurs at the previous distractor (Trial *n–1*) location; and (2) whether any anticipatory suppression occurs prior to search display onset, by examining the pre-stimulus alpha activity.

Subsequently, in Chapter 2.2, to investigate whether observers can adaptively adjust learning rates of distractor suppression based on environmental volatility. To do this, we used the Markov-chain function (Hamilton, 1990) and the classical visual search paradigm (Goschy et al., 2014) to create a high and a low volatility environment, which differed in terms of the frequency of alternation between distractor-present and distractor-absent trials in the search display. This resulted in consecutive distractor-present trials with different lengths of subsequent repetitions (i.e., 0, 1, 2, 3, 4, and above times) of distractor location. We manipulated the probability of repeating the same distractor state ("present" or "absent") from one trial to the next, with a 30% probability in the high- and 70% probability in the low-volatility session. In addition, we examined oculomotor capture and disengagement during the visual search task as the attentional and oculomotor systems are known to be associated (Deubel & Schneider, 1996; McPeek et al., 1999; B. Wang, Samara, et al., 2019). Given this, this experiment was designed to examine (1) whether salient distractors capture attention and whether volatile environments affect the learning speed of distractor suppression; (2) Crucially, whether observers can also make use of local trial-to-trial regularities of distractor locations to reduce attentional capture. If so, the longer subsequence of distractor location repetitions increasingly speeded up RTs, with more first saccades towards the target and/or shorter dwell times to the distractor due to decreasing the interference of the distractor at this location. Also, if this were the case, distractors in the global low-volatility environment should cause less interference compared to distractors in the global high-volatility environment; (3) Since the volatile environment caused by contextual contingencies when the distractor states changed, it would generate switching costs at the beginning of a new context period (Ferrari et al., 2022; Koch, 2008; Lien & Ruthruff, 2008). It was hypothesized that search performance would be better when the distractor did not switch conditions from Trial *n-1* to Trial *n* (i.e., AA, PP), as there is an advantage to repeating the same state across trials. In contrast, it was expected that search performance would be slowed when the distractor switched conditions from Trial *n-1* to Trial *n* (i.e., AP, PA), as the transitional states across trials may impair target selection processing.

Finally, Chapter 2.3 set out to examine (1) whether salient distractors capture attention, and if so, whether a distractor probability cueing effect could be firmly established. We hypothesized that if participants are able to extract and learn these spatial-based regularities, distractors at frequent locations cause less interference (i.e., faster RTs) than distractors at rare locations. (2) how to make use of across-trial regularities of distractor locations to reduce attentional capture in volatile environments; (3) crucially, whether volatile environments affect the learning speed of distractor suppression. According to the above two questions, the longer subsequence of distractor location repetitions increasingly speeded up RTs due to decreasing the interference of the distractor at this location. Also, if this were the case, distractors in the global low-volatility environment should cause less interference compared to distractors in the global high-volatility environment. (4) to investigate whether distractor suppression effects can be implemented through inter-trial transitions of distractor states. The hypothesis was that search performance would be better when the distractor did not switch conditions from Trial *n-1* to Trial *n* (i.e., AA, PP), as there is an advantage to repeating the same state across trials. In contrast, it was expected that search performance would be slowed when the distractor switched conditions from Trial *n-1* to Trial *n* (i.e., AP, PA), as the transitional states across trials may impair target selection processing. To do this, we resorted to the Markov-chain function to create a high and a low volatility environment, which differed in terms of the frequency of alternation between distractor-present and distractor-absent trials in the search display. This resulted in consecutive distractor-present trials with different lengths of subsequent repetitions (i.e., 0, 1, 2, 3, 4, and above times) of distractor location. We manipulated the probability of repeating the same distractor state ("present" or "absent") from one trial to the next, with a 30% probability in the high- and 70% probability in the low-volatility session. Additionally, we implemented the probability cueing of distractor locations in the classical visual search paradigm (Goschy et al., 2014), where participants had to search for a target item among numbers of several non-targets.

2 Cumulative Thesis

Cumulative thesis includes three quantitative-empirical studies (2.1 - 2.3).

2.1 Long-term (statistically learnt) and short-term (inter-trial) distractor-location effects arise at different pre- and post-selective processing stages

CONTRIBUTIONS

Nan Qiu: Conceptualization, Formal analysis, Data collection & curation, Methodology, Project administration, Visualization, Writing – original draft, Review, and Editing. Bei Zhang: Conceptualization, Data collection & curation, Methodology, Analysis, Validation. Fredrik Allenmark: Conceptualization, Methodology, Analysis, Resources, Validation, Review, and Editing. Jan Nasemann: Analysis, Methodology, Validation, Review, and Editing. Shao-Yang Tsai: Analysis, Methodology, Validation, Review, and Editing. Hermann J. Müller: Funding acquisition, Methodology, Resources, Supervision, Validation, Writing, Resources, Review, and Editing. Zhuanghua Shi: Conceptualization, Funding acquisition, Analysis, Methodology, Supervision, Validation, Writing, Project administration, Resources, Review, and Editing.

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Long-term (statistically learnt) and short-term (inter-trial) distractor-location effects arise at different pre- and post-selective processing stages

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Abstract

A salient distractor interferes less with visual search if it appears at a location where it is likely to occur, referred to as distractor-location probability cueing. Conversely, if the current target appears at the same location as a distractor on the preceding trial, search is impeded. While these two location-specific ‘suppression’ effects reflect long-term, statistically-learnt and short-term, inter-trial adaptations of the system to distractors, it is unclear at what stage(s) of processing they arise. Here, we adopted the additional-singleton paradigm and examined lateralized event-related potentials (L-ERPs) and lateralized alpha (8–12 Hz) power to track the temporal dynamics of these effects. Behaviorally, we confirmed both effects: reaction times (RTs) interference was reduced for distractors at frequent vs. rare (distractor) locations, and RTs were delayed for targets that appeared at previous distractor vs. non-distractor locations. Electrophysiologically, the statistical-learning effect was not associated with lateralized alpha power during the pre-stimulus period. Rather, it was seen in an early N1pc referenced to the frequent distractor location (whether or not a distractor or a target occurred there), indicative of a learnt top-down prioritization of this location. This early top-down influence was systematically modulated by (competing) target- and distractor-generated bottom-up saliency signals in the display. In contrast, the inter-trial effect was reflected in an enhanced SPCN when the target was preceded by a distractor at its location. This suggests that establishing that an attentionally selected item is a task-relevant target, rather than an irrelevant distractor, is more demanding at a previously ‘rejected’ distractor location.

Keywords: distractor-location suppression, EEG, N1pc, N2pc, probability cueing, SPCN

1 Introduction

Imagine you are in a central railway station. While you are searching for updated information on the information board, your attention is captured by an announcement broadcast via loudspeakers. But then you realize the announcement is not related to your schedule, and you return to your search task. This is a typical scenario depicting how our attention may be oriented to and captured by goal-relevant and irrelevant but salient stimuli, respectively. It is commonly agreed that attentional selection is determined interactively by top-down, i.e., goal-driven or voluntary, and bottom-up, i.e., stimulus-driven or involuntary, mechanisms (Awh et al., 2012; Egeth & Yantis, 1997; Orchard-Mills et al., 2013; Soto-Faraco et al., 2004; Wolfe et al., 1989).

Apart from explicit goal-driven guidance, top-down guidance can also be learned based on past experiences, such as the statistical spatial distribution of task-relevant targets or task-irrelevant salient distractors in the search scene (Geng & Behrmann, 2005; Goschy et al., 2014; Shaw & Shaw, 1977; Zhang et al., 2019). Attentional guidance based on statistical learning of the spatial distribution of target or salient distractor items has been referred to as *target-* or, respectively, *distractor-location probability cueing* (Geng & Behrmann, 2002; Miller, 1988; Müller & Findlay, 1987). Having learned the respective spatial distribution, observers can prioritize locations for attentional selection at which the searched-for target is encountered regularly (Geng & Behrmann, 2005; Shaw & Shaw, 1977), or deprioritize locations at which salient but irrelevant distractors frequently appear (Leber et al., 2016; Sauter et al., 2018; Wang & Theeuwes, 2018). In the latter case, which is the focus of the present study, distractors occurring at frequent (distractor) locations cause less interference than distractors occurring at rare locations.

This reduction of interference by distractors occurring at likely locations is partly attributable to (in Geng, 2014, terms) *proactive* distractor-location suppression, reducing the weight of signals at these locations in attentional-priority computations and thus reducing attentional capture; and partly to *reactive* suppression after attentional capture, placing inhibition on the distractor location so as to disengage attention from the distractor and reorient it to another (likely the target) location. Consistent with this, in oculomotor-capture studies, the power of distractors to attract the eye is reduced in frequent vs. rare distractor regions (evidencing proactive suppression), and disengagement of the eye is expedited from distractors at frequent vs. rare locations, consistent within the idea that less reactive suppression is necessary to re-orient attention to another, likely the target, location (e.g., Sauter et al., 2021). Also, one proposal has been that proactive suppression (to avoid capture) is the cumulative result of reactive, post-capture suppression: When a distractor repeatedly appears at a particular location, it initially captures attention more frequently, and requires more effort to ‘reject’, i.e., reactively inhibit to redeploy attention; these reactive inhibitions act as training signals, making the priority computation system to learn over time and long-term reduce the selection weight allocated to distractor locations (Sauter et al., 2021; Zhang et al., 2022).

The effects of distractor-location reactive suppression manifest in short-term inter-trial effects (Goschy et al., 2014; Sauter et al., 2018; Wang & Theeuwes, 2018): search RTs are reduced when a distractor (on the current Trial *n*) occurs at the same location as a distractor on the preceding trial (*n–1*), as compared to a different location; while this *distractor-distractor* inter-trial effect is performance-enhancing, the downside is that a target appearing at the previous distractor location is responded to slower compared to a target at a different location (*distractor-target* inter-trial effect; for a detailed analysis of this effect pattern, including target-distractor and target-target effects, see the Supplementary in Sauter et al., 2018). A common interpretation of this distractor-distractor (and distractor-target) effect is that when a distractor at a particular location is rejected on the previous trial (on Trial *n–1*), this reactive rejection temporarily down-modulates the attention-capturing potential of a distractor (or, respectively, target) appearing subsequently at that location (on Trial *n*). This happens during the pre-attentive phase of attentional-priority computation. However, it is also possible that, rather than reflecting a short-term ‘inhibition-of-return’ tag placed on the rejected distractor location, the rejection may change the criteria for the post-selective decision about whether an item encountered at that location is a target or a distractor: if the rejection biases towards a ‘distractor’ decision (in a Ratcliff-type, (1979), two-boundary, distractor/target evidence-accumulation/diffusion process), it would have multiple consequences: (i) it would speed up the identification of another distractor at that location as a ‘distractor’, which would allow faster distractor rejection and reorientation of attention to the target at another location, leading to a faster search RT; and (ii) it would prolong the identification of a target appearing at the rejected distractor location, thus slowing search RTs on such trials (see similar conclusions in Allenmark et al., 2018). This alternative account could also fully explain the inter-trial distractor-distractor and distractor-target effects reported in the literature. In addition, due to the stochastic nature of the diffusion process, it would potentially have a third consequence: (iii) it might increase the rate of false ‘distractor’ decisions at the post-selective (item-identification) stage when a target appears at the previous distractor location (i.e., the target will be missed). Indirect evidence of such increased miss rates was recently provided by an eye-movement study of Allenmark et al. (2021): when the singleton target on (distractor-absent) trial *n* appeared at the rejected distractor location, observers (in particular, individuals with Asperger Spectrum Disorder, ASD) still directed their first saccade to the target, but then, instead of responding, went on to scan other locations before eventually making a return saccade to the target location and issuing the response. The effect was particularly striking (in individuals with ASD) when a distractor occurred at an unlikely location. In other words, the salient target still attracted (overt) attention to its location, but post-selective processing of the (target) item in the focus of attention failed, as a result of which the search proceeded to other (candidate) locations. A similar pattern had previously been described by Zhaoping and Guyader (2007) in a low-level feature-pop-out search task. Allenmark et al. (2021) interpreted their eye-movement pattern in terms of a predictive-coding framework (Auksztulewicz & Friston, 2016): rather than being attributable to inhibition of the distractor location itself that is carried over into the next trial (reducing the attentional priority of this location and, thus, oculomotor capture on that trial), it reflects a predictive bias as to the identity of the stimulus that is encountered at this location, that is: a post-selective bias towards a ‘distractor’ decision. It should be noted that these alternative accounts are not necessarily mutually exclusive and may in fact coexist.

However, to what degree such looking-but-not-seeing depends on the long-term probability of the distractor and short-term inter-trial distractor-target coincidence remains elusive. Also, we have as yet a scant understanding of the underlying neural mechanisms, even though certain ‘brain’ measures permit us to more directly distinguish between pre-attentive and post-selective processes compared to behavioral measures, in particular: EEG components associated with visuo-spatial item selection and, respectively, the processing of items in visual working memory (vWM). Accordingly, in the present study, we focused on lateralized event-related potentials (L-ERPs) related to visuo-spatial attention and working memory functions, in particular: the early posterior-contralateral negativity (N1pc), the posterior-contralateral positivity (Ppc or early Pd), the posterior-contralateral N2 (N2pc), and the (late) sustained posterior contralateral negativity (SPCN) component.

The early posterior-contralateral negativity (N1pc), emerging 120 to 180 ms after stimulus onset, has been considered to reflect early sensory registration of and/or orienting to a salient object or (non-reportable) exogenous cue (Dodwell et al., 2021; Itthipuripat et al., 2014; Johannes et al., 1995; Schettino et al., 2016). However, in the same time window, a posterior-contralateral positivity (Ppc) may arise, for instance, when a salient stimulus (e.g., a square) that moves around a circle unexpectedly changes its shape (to a diamond) at the final, lateralized location, violating an 'object-continuity' expectation[1] (Baker et al., 2022); or when, in the additional-singleton paradigm, a salient but task-irrelevant (and so to-be-ignored or 'suppressed') distractor appears lateralized (in the presence of a non-lateralized target), in which case the positivity is referred to as P_D (Kerzel & Burra, 2020; Sawaki & Luck, 2010). Of note: while both the Ppc/Pd (positivity) and the negativity N1pc (negativity) reflect a lateralized bias in some early attention-related process, whether an L-ERP difference is considered a positivity or a negativity depends on how the difference wave is referenced. Interestingly in this regard, Kerzel and Burra (2020) observed a (distractor-referenced) P_D which preceded a distractor-referenced negativity, indicative of the distractor being selected rather than suppressed; and this P_D was just the mirror image of the target-referenced negativity when the target appeared lateralized (with or without a distractor on the vertical midline). Given this, Kerzel and Burra (2020) reasoned that "*the initial 'P_D' is not a positivity to the distractor* [i.e., a positivity indicative of distractor suppression] *but rather a negativity ... to the contralateral context element*" (p. 1170); in other words, the P_D is actually an early negativity referenced to the contralateral element (which, given the target occupied a location on the vertical midline, was a non-target item) – indicating that this item was selected first in the search process. Interestingly, in a study of 'contextual cueing' of visual search (Chun & Jiang, 1998), Zinchenko et al. (2020) observed an N1pc/Ppc polarity shift with respect to statistically learnt target locations within repeated arrangements (or 'contexts') of non-target items. Following an initial training phase in which participants acquired the search-guiding context cues, the target locations were switched to positions on the opposite side of the repeated non-target arrays in a test phase, abolishing the cueing effect. Electrophysiologically, Zinchenko et al. found an N1pc referenced to the initial target locations in the training phase, which was followed by a Ppc referenced to the re-located

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[1] The movement of the object and its potential shape change was task-irrelevant (participants had to perform a central monitoring task), so the Ppc response to the changed shape would be an implicit effect. Of note, though, the shape change also involved the change of the shape of the placeholder at the final location, potentially creating an additional (salient) local change signal (over and above that produced by the object's movement) – which may have contributed to the elicitation of the Ppc (in addition to the violation of the continuity expectation).

target positions in the test phase. Zinchenko et al. (2020) took this Ppc to be indicative of a persistent 'mis-guidance' of attention (i.e., essentially a persistent N1pc referenced) to the initial, statistically learnt target location.

The N2pc component is commonly observed in salient pop-out search tasks, regarded as a signature of the allocation of focal attention to a target item in visual search (Eimer, 1996; Kiss et al., 2008; Luck & Hillyard, 1994; Sawaki & Luck, 2013; Töllner et al., 2012; Woodman & Luck, 1999). Its amplitude and latency are modulated by the target's feature contrast (or 'saliency') relative to the non-target items (Luck et al., 1997), as well as by target repetition (van Moorselaar & Slagter, 2019). For example, when the target location repeats on consecutive trials, the amplitude of N2pc is reduced – reflecting more efficient guidance of attention to the target through positional intertrial priming (van Moorselaar & Slagter, 2019). However, with regard to distractor (location) inhibition in the context of distractor-location probability manipulations, the pattern of N2pc amplitude and latency effects is less clear. Wang et al. (2019) recently reported the N2pc to be delayed and reduced in amplitude when the target occurred at the (single) frequent relative to one of the rare distractor locations, potentially reflecting a lingering suppression component (such as the distractor positivity, Pd) at the frequent location. In contrast, van Moorselaar et al. (2021) failed to find any difference in the N2pc elicited by targets occurring at the frequent vs. a rare distractor location. In an earlier study by Sauter et al. (2017), the distractor-elicited N2pc amplitude was actually larger for distractors appearing at locations in the frequent vs. the rare (distractor) region in the midline-target/lateral-distractor condition; on the other hand, the target-elicited N2pc was delayed for targets appearing in the frequent vs. the rare region, which Sauter et al. (2017) took to be indicative of a larger amount of attentional resources being required to detect a target stimulus in a region that is pro-actively suppressed as a result of distractor-location learning. In any case, the relevant literature provides no coherent picture of the N2pc effects, and new evidence is needed to resolve the inconsistencies.

The sustained posterior contralateral negativity (SPCN) is a relatively late component (> 300 ms; e.g., 500 to 1000 ms post-stimulus), which is regarded as attentional selection of cued memory items or stored visual working memory representations (Eimer & Kiss, 2010). For example, the SPCN has been observed in visual discrimination tasks requiring detailed analysis of selected target items (Mazza et al., 2007, 2009), as well as complex choice or visuo-spatial configuration judgment tasks that require a great involvement of attention and visual working memory (Jolicoeur et al., 2008; Maheux & Jolicœur, 2017). Given this, we considered the SPCN to potentially provide a useful indicator of the processing demands posed by the analysis of a critical item, such as a target appearing at a previous distractor location that participants first look at but initially fail to recognize.

In addition to examining the above L-ERP components, frequency analysis may also be useful for understanding statistical learning of distractor-location suppression. For example, enhanced lateralized alpha-band (8–12-Hz) oscillations have been reported over the occipital cortex contralateral to the to-be-ignored location prior to the onset of the to-be-attended target (Jensen & Mazaheri, 2010; Kelly et al., 2006; Worden et al., 2000). A recent study of distractor-location probability cueing found pre-stimulus alpha-band oscillations in the parieto-occipital visual region to be enhanced for frequent relative vs. rare distractor locations (Wang et al., 2019). It should be noted, though, that such findings consistent with anticipatory suppression have not always been replicated in other studies using a probability-cueing paradigm.In fact, several recent studies (Noonan et al., 2016; van Moorselaar et al., 2020, 2021; van Moorselaar & Slagter, 2019) failed to find any evidence that a bias in the spatial distractor distribution induces changes in pre-stimulus alpha-band activity in visual regions.

Thus, more work is needed to advance our understanding of the neural dynamics underlying statistical distractor-location learning and inhibitory intertrial effects in visual attention. Given this, the present study aimed to investigate (1) how the long-term probability of distractor location and the short-term inter-trial coincidence of the distractor and target locations modulate attentional selection across trials at the neural level, by examining the early posterior-contralateral components (N1p, Ppc, and N2pc) and the late SPCN component when the target (Trial *n*) occurs at the previous distractor (Trial *n–1*) location; and (2) whether any anticipatory suppression occurs prior to search display onset, by examining the pre-stimulus alpha activity. Concerning issue (1): Based on Kerzel and Burra's (2020) reasoning that the early components' polarity (positivity or negativity) depends on the display 'context' to which they are referenced, and on Baker et al.'s (2022) finding that these components may already be sensitive to expectations about upcoming stimulus events (see also Zinchenko et al., 2020), we hypothesized that the early posterior-contralateral components may also be determined by statistical learning (i.e., acquired 'priors') of where the most salient and behaviorally most significant items are likely to appear in the search display. In our study, the most likely location to contain the most salient display item across all (distractor-present and -absent) trials was the frequent distractor location. Examining the early components referenced to this ‘context’ location is also of interest in light of the conflicting reports (mentioned above) according to which the N2pc does (Wang et al., 2019) or does not (Moorselaar et al., 2021) differ between targets at the frequent and rare distractor locations. Further, if the behavioral *distractor-target inter-trial effect* is attributable to impaired identification of a selected target (Trial *n*) at the previous (Trial *n–1*) distractor location, we would expect the SPCN to be increased in amplitude, reflecting the increased demands to post-selectively recognize the target as the task-critical (vs. an irrelevant) item in the coincident condition. Concerning issue (2): If anticipatory suppression exists, we expect alpha power (8–12 Hz) to be increased in the contra- vs. the ipsilateral parietal-occipital region with reference to the frequent distractor location. To test these predictions, we adopted the additional singleton search paradigm (Allenmark et al., 2019; Theeuwes, 1992; Zhang et al., 2019), in which participants look for and respond to a unique shape-defined target (e.g., a circle among diamonds, or vice versa) while ignoring a salient color-defined distractor (e.g., a red or green singleton different in color from other, non-distractor items). Importantly, when present in the search display, the salient distractor singleton appeared with high probability at one ‘frequent’ location and with low probability at one of the ‘rare’ locations, providing for statistical learning of the distractor-location distribution (see Fig. 1).

2 Material and methods

2.1 Participants

Twenty-four participants (mean age 26.79 years, age range 18 to 40 years; 9 females) were recruited at Ludwig-Maximilians-University (LMU) Munich for this experiment. They were paid 9 Euro per hour for their participation or received course credits. The sample size was determined based on the crucial target-location effect reported in previous studies (Liesefeld et al., 2017; Wang & Theeuwes, 2018; Zhang et al., 2019), which is sufficient to detect effects of size $d_z = 0.65$ and above with a power of 0.8 ($\alpha = 0.05$, one-tailed).

All participants were right-handed and had normal or corrected-to-normal visual acuity and (self-reported) normal color vision. The study protocol was approved by the Ethics Committee of the LMU Faculty of Psychology and Pedagogics. Informed consent was obtained from all participants before the experiment. To reduce the COVID-19 risks for both experimenters and participants (Simmons & Luck, 2020), we filled out a short coronavirus checklist for each participant, following the approved hygiene concept of the LMU Central Administration and the Department of Psychology out laboratory-based research, and participants signed the coronavirus regulations consent form.

Four participants were excluded for further analysis because three of them had large artifacts after EEG preprocessing, and another participant had a high error rate of 49.53%.

2.2 Apparatus and stimuli.

The experiment was performed in a dimly lit, sound-attenuated, and electrically shielded experimental booth. Stimuli were generated by Psychophysics Toolbox Version 3 (PTB-3) (Brainard, 1997; Kleiner et al., 2007; Pelli, 1997) based on MATLAB R2019b (The MathWorks® Inc., Natick, MA USA). Stimuli were presented on a VIEWPixx/3D 24-inch monitor at 1920×1080 pixels screen resolution and a refresh rate of 120 Hz. Participants viewed the monitor from a distance of 60 cm (eye to screen). They were instructed to sit as relaxed as possible to minimize muscle activity and other ‘noise’ that could appear in the EEG signal during task performance. They issued manual responses by pressing the left- (‘horizontal’) or upward-pointing (‘vertical’) arrow key on the keyboard with their right-hand index or middle fingers, respectively.

The visual search display (see Fig. 1) consisted of eight colored outline shapes (circles or diamonds) equidistantly arranged around an imaginary circle (radius: 4° of visual angle). The circle shapes were 2° of visual angle in diameter, and the diamond shapes were 2° × 2° in size. The display items consisted of either one circle (the response-critical singleton-shape target) and seven diamonds (non-targets) or, alternatively, one diamond (the target) and seven circles (non-targets). Each shape contained either a vertical or a horizontal gray line (0.3° × 1.5°) inside; that is, there were four vertical and four horizontal lines randomly distributed across the eight shapes on a given trial. On some trials (see *2.3 Design and Procedure* section), one of the non-target shapes (the additional-singleton distractor) differed in color from all the other shapes, being either green (CIE [Yxy]: 29.5,0.17, 0.55) among homogeneous red shapes (CIE [Yxy]: 29.6, 0.63, 0.32) or red amongst homogeneous green shapes. All search displays were presented on a black screen background (3.58 cd/m^2), with a white fixation cross (1° × 1°) in the center.

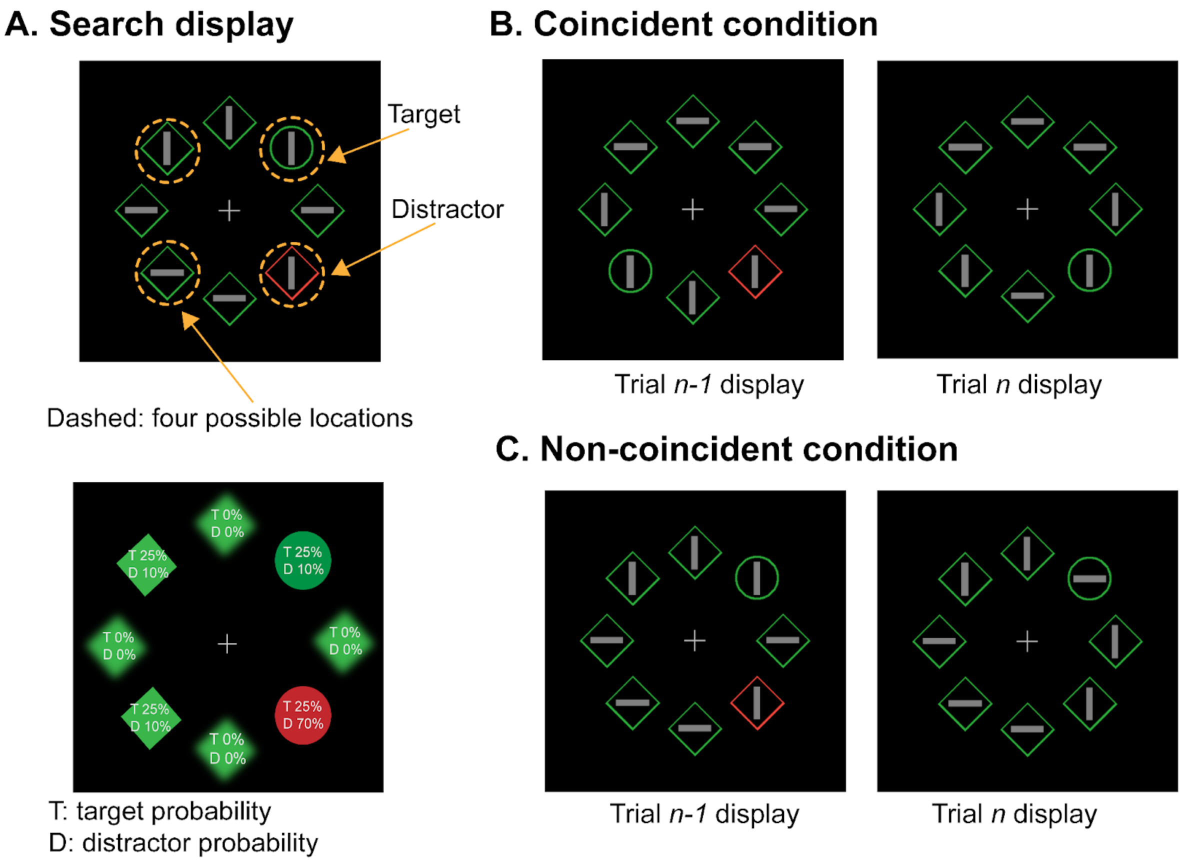

Figure 1. Visual search display and design. (A) An example of the search display with the labeled singleton-shape target, singleton-color distractor, and non-target items is shown in the upper panel. On each trial, participants had to find the shape-defined target singleton (here the circle) and discriminate (and respond to) the orientation of the line segment inside it (horizontal or vertical), while ignoring a salient but task-irrelevant color-defined singleton distractor (colored either red or green, depending on the color of the non-distractor items) of the same shape as the other non-target items. The dashed circles (not presented in the real trial displays) denote the four possible locations at which the target and distractor could appear in a given search display. The lower panel illustrates the probability of the target and distractor at each location. The high-probability location was fixed for each participant, and counter-balanced over the four possible locations across participants. **(B)** The *coincident* condition (illustrating a trial sequence with distractor-present Trial *n–1* being followed by a distractor-absent Trial *n*): critically, the target on Trial *n* appears at the same location as the singleton distractor on Trial *n–1*. **(C)** The *non-coincident* condition: the target on Trial *n* does not appear at the location of the singleton distractor on Trial *n-1*.

2.3 Design and procedure

A target – a shape-defined singleton (either a circle amongst diamond non-targets or a diamond amongst circular non-targets, equally likely and randomly assigned on each trial) – was present on all trials. A salient distractor – a color-defined singleton (either red among green or green among red non-distractors, equally likely and randomly assigned on each trial) – appeared in 50% of trials. The target and the distractor singleton could appear only at four possible locations: the top-right, bottom-right, bottom-left, and top-left positions (marked by dashed outline shapes in Fig. 1A); they never appeared on the horizontal or vertical midline positions (i.e., the 3 and 9 o'clock and, respectively, the 12 and 6 o'clock positions). If a distractor was present, it appeared with a likelihood of 70% at one consistent location (the frequent distractor location) and with a likelihood of 10% at each of the other three locations (the rare distractor locations). On distractor-absent trials, the target was equally likely to appear at all four possible locations; and on distractor-present trials, it was equally likely to appear at each of the three non-distractor locations (i.e., within a given trial display, the target and distractor never appeared at the same location). The frequent distractor location was fixed per participant and counterbalanced across participants.

To ensure sufficient cross-trial sequences of target-only (i.e., distractor-absent) displays following target-plus-distractor (i.e., distractor-present) displays – necessary for examining how a target falling vs. not falling at a previous distractor location is processed[2] –, distractor-absent and distractor-present trials (including the critical 'long-exposure' trials; see below) alternated in a row; that is, a given distractor-present trial (Trial *n-1*) with a singleton distractor appearing at one of the locations was followed by a distractor-absent trial (Trial *n*). As regards the latter (distractor-absent) trials *n*, there were then two possibilities: the target appeared either at the location of the preceding distractor (hereafter, the *coincident* condition; see Fig. 1B), or at a different location (hereafter, the *non-coincident* condition, see Fig. 1C). Thus, with the type of positional distractor-target coincidence (coincident, non-coincident) and appearance of the target at a frequent or rare distractor location as the two main factors, the present study implemented a 2 × 2 (Distractor-Target Coincidence × Target-Location) within-subject design.

Participants were instructed to search for the singleton-shape target and respond to the orientation of the line inside it (vertical or horizontal), as fast and accurately as possible. For a vertical line, participants pressed the upward-pointing arrow key on the keyboard, and for a horizontal line the leftward-pointing arrow key. Participants were told that the odd-one-out colored item (i.e., the singleton distractor) was task-irrelevant, and so could be ignored. However, they were not informed that this item would appear more frequently at one location, and they were not expressly informed that distractor-absent trials would alternate with distractor-present trials. After they had completed the experiment, participants were

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[2] In principle, this question could also be addressed by examining successive distractor-present trials (i.e., both Trial *n-1* and Trial *n* contain a distractor, but the target on Trial *n* either does or does not fall at the location of the distractor on Trial *n-1*; see also Sauter et al., 2018, for a behavioral analysis of such sequences). Arguably, however, given that the presence of a distractor calls upon various distractor-handling strategies, the carry-over of inhibitory tags is best investigated by examining pure target-only trials (uncontaminated by effects of a salient distractor in the display).

asked whether the distractors had appeared equally often at all four critical locations or more often at one location. If they noticed the unequal distractor distribution, they were further asked to indicate exactly at which location the distractor had appeared most frequently. In total, 20 participants reported the distribution of the distractor locations was unequal, but only five of them went on to indicate the correct location of the frequent distractor.

Each trial began with a fixation cross for 1300 ms, followed by the search display (with the fixation marker remaining visible). In order to balance the need for sufficient trials for the four conditions of interest (2 Distractor-Target Coincidence × 2 Target-Location) and a reasonable overall duration for conducting an EEG experiment, we split the trials into two types regarding their exposure roughly equally: long exposure (52.48% of all trials) and short exposure (47.52% of all trials) trials. The critical inter-trial sequences, which determined the four conditions that we investigated, were always presented as long-exposure trials (71.38% of the long-exposure trials), that is: a long-exposure distractor-present trial (Trial *n-1*) was followed by long-exposure a distractor-absent trial (Trial *n*). On such long-exposure trials, the search displays were presented until the participant responded or for a maximum of 2500 ms, followed by response feedback, the word 'correct' or 'error' in the display center for 300 ms. On short-exposure trials, search displays were shown for 300 ms, and the window for issuing a response was curtailed at 900 ms (measured from search-display offset)[3]; search-display termination was then followed by a feedback display with a neutral white dot in the center shown for 300 ms. The next trial started after a random inter-trial interval (ITI) varying between 0 and 350 ms. Participants were instructed to maintain fixation on the central cross throughout each trial. They could take a break of a self-determined length between blocks, starting the next block by pressing any key on the keyboard. The experiment consisted of 1920 trials in total, subdivided into 16 blocks of 120 trials each. Prior to the formal experiment, participants completed one block of 120 trials to become familiar with the task. Overall, the 1920 trials took around 80 minutes to complete.

2.4 Electrophysiological recording and preprocessing analysis

The electroencephalogram (EEG) was sampled at 1 kHz from 64 Ag/AgCl active electrodes (actiCAP system; Brain Products, Munich, Germany). Electrodes were mounted

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[3] These settings were taken over from a previous (fMRI) study, in which we obtained a significant distractor-location probability-cueing effect with a search-display exposure time limited to 300 ms and a response time window of 900 ms (Zhang et al., 2022).

on an elastic cap (Easy Cap, FMS, Munich, Germany) placed according to the international 10-20 System (American Electroencephalographic Society, 1994). To monitor for potential eye movements, horizontal eye movements were recorded from electrodes F9 and F10, and vertical eye movements from Fp1 and an electrode placed at the inferior orbit of the left eye. All electrophysiological signals were amplified using BrainAmp amplifiers (Brain Products) with a 0.1-Hz to 250-Hz band-pass filter. During data acquisition, all electrodes were referenced to FCz and re-referenced offline to the average of both mastoids. All electrode impedances were kept below 5 kΩ prior to the experiment.

Data analysis was performed using the Brain Vision Analyzer II (Brain Products, Munich, Germany). Firstly, the continuous EEG data were manually inspected to remove apparent noise, such as electromyographic (EMG) bursts or wireless signal interference. Subsequently, the raw data was band-pass filtered using a 0.1-Hz to 30-Hz Butterworth infinite-impulse-response (IIR) filter (24 dB/Oct). Next, an ocular infomax independent-component analysis (ICA) was performed to remove eye blinks and horizontal eye-movement artifacts.

After the preprocessing of the continuous EEG, data were epoched from -200 to 800 ms relative to search display onset and baseline-corrected using the prestimulus interval. Next, incorrect trials and trials with large artifacts, such as any absolute amplitude exceeding ±60 μV, bursts of electromyographic activity as defined by voltage steps larger than 50 μV per sampling point, and activity changes lower than 0.5 μV within an interval length of 500 ms (indicating dead channels), were removed on an individual-channel basis before further ERP averaging. Among the 23 participants, three had more than 30% of the total trials with large artifacts. These participants were excluded from further analysis (including the behavioral analysis). Across the remaining 20 participants, the preprocessing procedure left 90.09% of the critical – inter-trial condition – trials for analysis.

2.4.1 L-ERP analysis

To examine the three L-ERP components of interest (N1pc, N2pc, SPCN) on critical trials, EEG epochs were averaged separately for contralateral and ipsilateral parieto-occipital electrodes (PO7 and PO8) relative to the target location for each condition. These ERPs were then used to calculate the L-ERP components by subtracting the ipsilateral from the contralateral waveforms. We adopted the mean-amplitude (rather than the peak-amplitude) approach to provide a metric for the components of interest, as it is less affected by noise (e.g., Larson et al., 2013).[4] Based on the literature (Mazza et al., 2009; Tay et al., 2019; van Moorselaar & Slagter, 2019) and the L-EPRs we observed, the N1pc and N2pc were quantified by the mean amplitude of the difference waveforms (at the lateral occipital electrodes PO7/PO8) in the 120–180 ms and, respectively, 180–350 ms time windows post-stimulus onset. To quantify the SPCN, the mean amplitude was calculated across the 350–500 ms time window, following the criteria used in previous studies (Geib et al., 2020; Gokce et al., 2014; Kiss et al., 2008).

2.4.2 Time-frequency analysis

To study frequency-specific activity over time, a time-frequency analysis (Mallat, 2009) was performed on individual epochs. This was done by transforming epochs into power values using a continuous wavelet transform (CWT) in the time domain (t) to different frequencies (f). These modulated Gaussian sine functions are defined as: $W(t, f) = Ae^{\frac{-t^2}{2\sigma_t^2}} e^{i2\pi ft}$ where W denotes the complex convolution with the wavelet function, t is the time, and f is the frequency which increased from 1 to 30 Hz in 30 logarithmically spaced steps. To keep a good trade-off between temporal and frequency precision, the Morlet parameter c: $c = f_0\left(2\pi\sigma_t\right)$, or $c = f_0 / \sigma_f$, was set to 7 cycles, as suggested previously (Cohen, 2014; Rommerskirchen et al., 2021), where f_0 is the central frequency, σ_f is the width of the Gaussian shape in the frequency domain, and σ_t represents the standard deviation of the Gaussian bell function (Tallon-Baudry et al., 1998). For different f_0, time and frequency resolutions can be calculated as $2\sigma_t$ and $2\sigma_f$, respectively (Tallon-Baudry et al., 1997). We extracted wavelet layers corresponding to our interest in alpha-band (8–12 Hz) activity. The time and frequency resolution for the lowest (8-Hz) and highest (12-Hz) frequency were determined by Morlet transform functions, which yielded the center of each frequency layer of 8.26 Hz and 11.74 Hz, time resolutions of 269.85 ms and 189.81 ms, and frequency resolutions of 2.40 Hz and 3.35 Hz, respectively. To ensure a reliable analysis with sufficient temporal distance to the stimulus onset and to avoid edge and smearing effects, a 2950-ms long segmentation (i.e., –1950 to 1000 ms relative to the onset) was used for time-frequency decomposition. We assumed that any anticipatory suppression

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[4] Of note, in Appendix B, we also provide the peak-amplitude metric for the N2pc analysis.

would be detectable within the pre-stimulus time window [-1950, 0 ms]. The resulting power was baseline-corrected using a time window of −1300 to −1000 ms: a time window without any task-related processing and far from the stimulus onset. The results of the wavelet transformations were then averaged across participants and conditions to obtain a measure of total power (Cohen, 2014). Finally, the time-frequency power was quantified as mean power within 8–12 Hz for further statistical analysis.

Given that the pre-stimulus lateralized alpha power could reflect anticipatory location suppression prior to display onset (Kelly et al., 2006; Wang et al., 2019), we further calculated the lateralized alpha power from a parieto-occipital electrode cluster (O1/2, PO3/4, and PO7/8), separately for the three types of distractor condition on the previous Trial *n–1* (i.e., distractor absent, distractor present at the frequent location, distractor present at the rare location). Note that, for the lateralization index, the contra- and the ipsilateral alpha power were defined based on the side of the distractor on the preceding (distractor-present) trial; if there was no distractor on the preceding (distractor-absent) trial, the lateralization index was defined based on the side of the frequent distractor location. Further, to obtain a full picture of any anticipatory suppression based on statistical distractor-location learning, we also calculated the lateralization index solely based on the frequent distractor 'side' across all (i.e., both distractor-absent and -present) trials. That is, we calculated the lateralization index – contralateral minus ipsilateral alpha power – for the 8–12 Hz wavelet layer (with the center at 10 Hz) from the parieto-occipital cluster within the pre-stimulus window [–1950, 0] ms. According to the literature (Kelly et al., 2006; van Moorselaar et al., 2020), if the previous distractor location or the frequent distractor location is suppressed prior to display onset, we would expect alpha power to be higher over the contralateral relative to the ipsilateral parietal-occipital region.

3 Results

Given that the main manipulations were in those long-exposure trials, we reported the results on those long-exposure trials here and the results on those short trials in Appendix A.

3.1 Behavioral data

3.1.1 Error rates

On average, the error rate was 12.20%.[5] The mean error rates for three different distractor conditions (distractor absent, at frequent location, at rare location) are shown in Fig. 2A (bottom panel). A repeated-measures ANOVA revealed the Distractor-Condition main effect to be significant, $F(2, 38) = 15.9$, $p < .05$, $\eta_p^2 = .46$: the error rate was lower on distractor-absent trials relative to the two types of distractor-present ($\Delta = 5.30\%$; $ts(19) > 4.52$, $ps < .001$, Bonferroni-corrected), with numerically higher error rates caused by distractors occurring at the frequent vs. the rare locations (13.6% vs. 16.8%, $t(19) = 2.60$, $p = .05$, Bonferroni-corrected).

3.1.2 Mean RTs

For the analysis of the correct mean RTs, we excluded the error trials (12.20%) as well as outliers (1.06%), defined as RTs outside 1.5 interquartile differences above the third or below the first quartile of the respective RT distribution. The mean RTs for three different distractor conditions (distractor absent, at frequent location, at rare location) are depicted in Fig. 2A (top panel). A repeated-measures ANOVA revealed a significant main effect of Distractor Condition, $F(2, 38) = 36.1$, $p < .001$, $\eta_p^2 = .66$: responses were faster in the distractor-absent condition relative to the distractor-present conditions ($\Delta = -106.5$ ms; $ts(19) > 4.39$, $ps < .001$, Bonferroni-corrected), evidencing significant distractor interference. And, crucially, distractors that appeared at the frequent location caused substantially less interference than distractors at rare locations (873.26 ms vs. 938.83 ms, $t(19) = 4.11$, $p < .001$, Bonferroni-corrected). The error-rate pattern mirrored the RT pattern, effectively ruling out speed-accuracy trade-offs.

Of note, on distractor-absent trials (see Fig. 2A), when the target appeared at the frequent distractor location relative to the rare locations, RTs were slightly increased by 10 ms (805 vs. 795 ms), associated with a numerically lower error rate (9.6% vs. 10.2%), though this increase was not significant, $t(19) = .99$, $p = .33$. The absence of a (significant) target-location effect is at variance with, for instance, Wang and Theeuwes (2018), who found RTs to be prolonged to targets at the frequent location on trials without a competing color

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[5] This error rate is relatively high, likely owing to the pressure to respond fast was introduced by the fact that the display was presented only briefly and required a response within 900 ms in nearly 50% of the trials (the error rate was similar in Zhang et al.'s, 2022, fMRI study, under 300 ms display-presentations and 900 ms response-deadline conditions). Note that in the slowest – i.e., the distractor-at-rare-location – condition, the mean RT was around 900 ms, indicating that participants attempted to respond within the 900-ms deadline even though there was no externally imposed pressure to respond fast on long-exposure trials (on which the response deadline was extended to 2500 ms).

distractor in the display; but it is consistent with other recent studies that found no reliable target-location effect (Allenmark, Shi, et al., 2021; van Moorselaar et al., 2021).

3.1.3 Coincidence effect

Next, we examined the critical positional (inter-trial) inhibition effects induced by a distractor (on distractor-present Trial *n–1*) onto the processing of a target (on distractor-absent Trial *n*) falling either at the same (coincident) or a different (non-coincident) location relative to the distractor on the preceding trial, separately for distractors (Trial *n–1*) and targets (Trial *n*) at the frequent and, respectively, one of the rare locations. Fig. 2B depicts the corresponding RT (upper panel) and error-rate (lower panel) results. A 2 (Distractor-Target Coincidence: coincident, non-coincident) × 2 (Target-Location: frequent, rare) repeated-measures ANOVA revealed only the Coincidence main effect to be significant, F (1, 19) = 5.83, $p < .05$, $\eta_p^2 = .23$. There were no significant effects involving Target Location; Target-Location main effect, F (1, 19) = .09, $p = .76$, $\eta_p^2 = .004$; Coincidence × Target-Location interaction, F (1, 19) = .24, $p = .63$, $\eta_p^2 = .01$. The coincidence effect was due to RTs being significantly slower when the target appeared at the same location as the distractor on the preceding trial (814.93 ms), as compared to a different location (787.77 ms) – indicative of (reactive) distractor-location inhibition being carried over across consecutive trials. Interestingly, this carry-over-of-inhibition effect, of some 27 ms, was only little influenced by whether the distractor and target occurred at the frequent distractor location (23 ms) or a rare location (30 ms). In previous studies, the carry-over of inhibition had been found to be significantly reduced for frequent (vs. rare) distractor locations (Allenmark, Shi, et al., 2021).

Given that some priming effects, such as ‘priming of pop-out’ (Allenmark, Gokce, et al., 2021; Maljkovic & Nakayama, 1994, 1996), have been reported to involve longer-lasting memory traces, we also examined the Coincidence effect on Trial *n* with respect to Trial *n-2*. Neither the Coincidence effect ($F(1, 19) = 3.96$, $p = .06$, $\eta_p^2 = .17$) nor the Target-Location effect ($F(1, 19) = 3.88$, $p = .06$, $\eta_p^2 = .17$) turned out significant (interaction, $F(1, 19) = .83$, $p = .37$, $\eta_p^2 = .04$). In fact, the mean RT was numerically faster (by 16.60 ms) when the current target appeared at the location of the distractor on Trial *n-2* compared to a non-coincident location. Thus, the coincidence effect did not persist beyond one trial back.

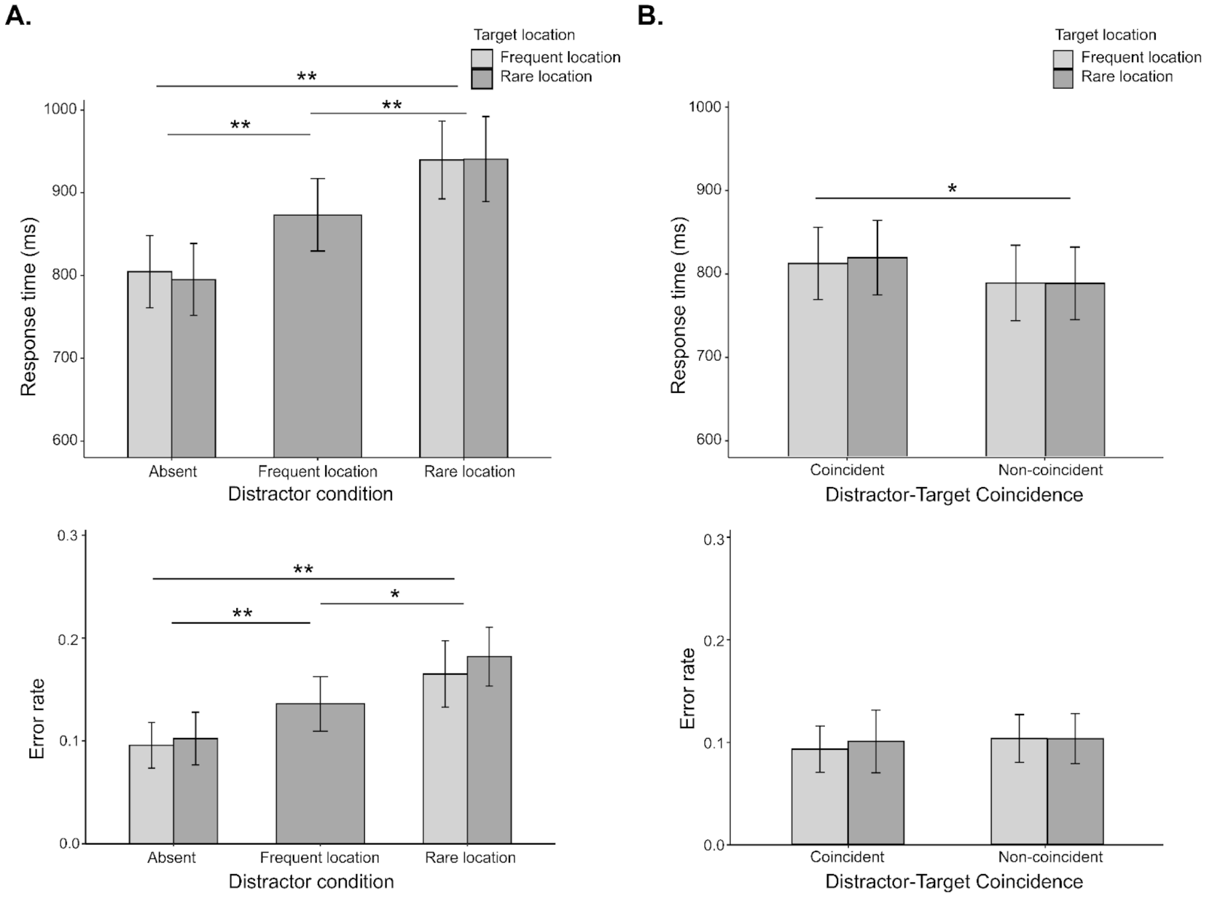

Figure 2. Behavioral results. (A) Mean RTs and error rates (on long-exposure trials) for the three distractor conditions: ‘Absent’ denotes the distractor-absent condition, ‘Frequent location’ that the distractor occurred at the frequent location, and ‘Rare location’ that the distractor occurred at one of the rare locations. **(B)** Mean RTs and error rates on (long-exposure) distractor-absent trials, separately for the Distractor-Target Coincidence (coincident vs. non-coincident location of the target relative to the preceding distractor) × Target-Location (at frequent vs. rare distractor location) conditions. Significant differences between two means are indicated by one ($p < .05$) or two asterisks ($p < .001$). Error bars depict the one standard error of the mean.

3.2 Electrophysiological data

To investigate the short-term inter-trial distractor interference, we calculated the N1pc/Ppc, N2pc, and SPCN components. For the target-only (distractor-absent, long-exposure) trials, the lateralized waveforms were calculated relative to the target side, separately for each combination of Distractor-Target Coincidence (coincident vs. non-coincident) and Target Location (frequent vs. rare). For the distractor-plus-target (distractor-present long-exposure) trials, the lateralized waveforms were calculated relative to the distractor side, but only for trials on which the target appeared on the side opposite to the distractor. We omitted trials on which the target and distractor appeared on the same side, as those trials do not allow the distractor-related L-ERPs to be distinguished from the target-related L-ERPs. Further, to obtain an unconfounded measure of the L-ERPs for distractors at rare locations, we ignored trials on which the distractor or target occurred at the one rare location on the same side as the frequent location.

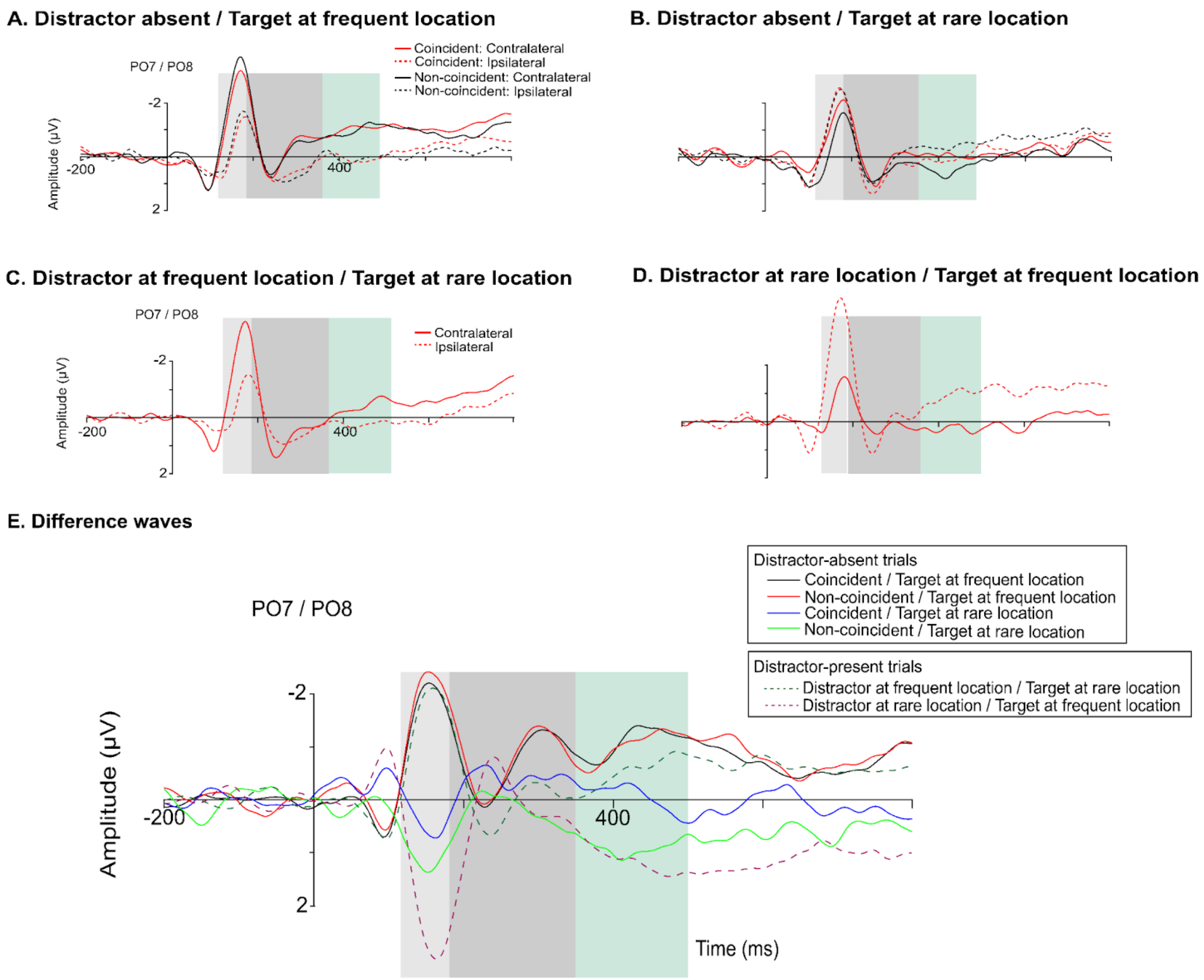

Figure 3. Grand-average ERP waveforms. Subpanels **A** and **B** show the *target-related* contra- and ipsilateral waveforms, at electrodes PO7/PO8, from 200 ms pre-stimulus to 800 ms post-stimulus for targets that appeared at the frequent location **(A)** and, respectively, a rare location **(B)**. The red waveforms indicate the coincident condition, in which the target appeared at the same location as the distractor on the previous trial; the black waveforms denote the non-coincident condition, in which the target occurred at a different location from the previous distractor. The solid lines represent the contralateral waveforms, the dashed lines the ipsilateral waveforms. Subpanels **C** and **D** show the *distractor-related* waveforms for the distractor at the frequent location, with the target at the rare location on the opposite side **(C)**; and, respectively, the distractor at a rare location, with the target at the frequent location on the opposite side **(D)**. Panel **(E)** shows the ERP difference waves (contralateral minus ipsilateral) for the six experimental conditions. The light gray, dark gray, and green areas indicate the N1pc/Ppc time window (120–180 ms), the N2pc time window (180–350 ms), and the SPCN time window (350–500 ms), respectively.

Fig. 3 shows the lateralized ERPs for the (four critical) target-only conditions (Fig. 3 A-B) and the (two) distractor-present conditions (Fig. 3 C-D). By visual inspection, all waveforms exhibit a more negative-going deflection in the 100–250 ms time window (N2) over the hemisphere contra- and ipsilateral to the target or, respectively, the distractor in all conditions. Fig. 3 shows the contralateral-minus-ipsilateral difference waveforms. As can be seen, the most salient item in the display – i.e., the target on target-only (distractor-absent) trials and, respectively, the distractor on distractor-plus-target (distractor-present) trials – elicited an early positivity if it appeared at a rare location and a negativity if it appeared at the frequent location. Similar to the N1pc/Ppc flip reported by Zinchenko et al. (2020) in statistical context learning, this complex polarity pattern is primarily driven by the reference employed in computing the difference waves. It would be simplified when the frequent location is taken as the reference: activation of the N2 was higher contralateral vs. ipsilateral to the frequent location, irrespective of the location of the most salient display item. Further, when the target appeared at the frequent location, a late N2pc component appeared to emerge. The difference waveforms then diverge in the subsequent 350–500-ms window among the various conditions. The following sections provide separate analyses of the N1pc/Ppc, N2pc, and SPCN components.

3.2.1 Early N1pc/Ppc

Target-only (distractor-absent) trials. A two-way repeated-measures ANOVA of the mean amplitude in the early, 120–180 ms time window revealed a significant main effect of Target-Location, $F(1, 19) = 5.13$, $p < .05$, $\eta_p^2 = .21$. As can be seen from Fig. 4A, this effect was due to a more negative deflection when the target appeared the frequent vs. a rare distractor location (mean difference $\Delta = 1.08$ μV). Further simple t-tests established the mean amplitude to be significantly negative (N1pc) when the target appeared at the frequent location, $t(19) = -2.22$, $p < .05$, but significantly positive (Ppc) when the target appeared at a rare location, $t(19) = 2.21$, $p < .05$. Interestingly, a comparison of the absolute mean amplitudes of the N1pc and Ppc revealed the mean amplitude to be significantly reduced when the target appeared at a rare vs. the frequent location, $t(19) = 3.68$, $p <.05$.

Of note, the early L-ERPs were uninfluenced by the Distractor-Target Coincidence (Coincidence main effect, $F(1, 19) = 1.59$, $p = .22$, $\eta_p^2 = .08$; Coincidence × Target-Location interaction, $F(1, 19) = 1.58$, $p = .22$, $\eta_p^2 = .08$).

Target-plus-Distractor (distractor-present) trials. Similar to the target-referenced early L-ERPs above, the distractor-referenced difference waves revealed a strong N1pc when the distractor occurred at the frequent location (and the target at a rare location) and a large Ppc when the distractor appeared at a rare location (and the target at the frequent location). While the amplitude difference between the two conditions was significant, due to their opposite signs ($\Delta = 3.99$ μV, $t(19) = 2.78$, $p < .05$); the N1pc and the Ppc were actually of comparable absolute mean amplitude, $t(19) = 1.05$, $p = .31$. This suggests that both lateralized target-distractor configurations elicited a similar N1pc if referenced to the frequent distractor location (rather than to the actual distractor).

Taken together, the results revealed a significant difference in the early lateralized component. When the most salient item in the display – the singleton-shape target (on target-only trials) or the singleton-color distractor (on target-plus-distractor trials) – appeared at a rare location, it engendered a strong Ppc or ‘Pd’. In contrast, a strong N1pc was elicited when it appeared at the frequent location. Note that the frequent location was overall most likely to contain the most salient singleton item in the display: the combined likelihood of the target or the distractor occurring at this location was 47.5%, which is about three times higher compared to any of the rare locations (see Fig. 1). In other words, in terms of behavioral decision making, this location was of the highest ‘significance’: it needed to be rejected if it contained a distractor or to be selected if it contained a target. Accordingly, as a result of statistical learning, participants may have acquired a strong ‘overall prior’ for processing information from that location (cf. Zinchenko et al., 2020). Thus, when this ‘prior’ was activated by the onset of the search display, whatever item was located at this position (whether the target or a non-target on target-only trials or the target or the distractor on target-plus-distractor trials) elicited an early and large negativity (N1), even when there was a competing singleton item on the opposite side of the display (see Fig. 3). In essence, similar to Zinchenko et al (2020), we take the initial L-ERP to be a negativity referenced to the display location that was learnt to be most significant behaviorally (which is also the location where the distractor is most likely to appear); in other words, it is ‘agnostic’ to the stimulus that generated it.

Interestingly, though, the amplitude of Ppc/N1pc was reduced when the target (on target-only trials) appeared at the rare location, as compared to the frequent location. This suggests there was a biased competition between the initial statistically-based prioritization towards the frequent location and the stimulus-based ‘attend-to-me’ signal generated by the target at the rare location (or, conversely, the target may have boosted the prioritization of the frequent location when it occurred at this location). When one singleton was presented at the frequent location and the other at a rare location (on the opposite side), the amplitudes of (distractor-referenced) Ppc and N1pc were comparable. This is likely attributable to the fact that the 'attend-to-me' signals from both sides neutralized the bottom-up competition, leaving the top-down probability-based prioritization of the most significant display location largely intact.

Thus, the fact that presentation of both the lateralized target (on target-only trials) and the distractor (on target-plus-distractor trials) were associated with a pronounced early N1pc/Ppc (depending on whether it occurred at the frequent or a rare location) can be taken to suggest that, as a result of overall statistical learning, a spatially uneven prioritization of attention is triggered at a very early stage of processing, which interacts with the bottom-up registration of 'attend-to-me' signals generated by the (target and distractor) singleton items.[6]

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[6] Concerning the subsequent components, there were no significant effects (see right-hand panels in Fig 4). In particular, the N2pc mean amplitudes did not differ significantly between distractors occurring at the frequent vs. a rare location ($\Delta = 1.58$ µV, $t(19) = .93$, $p = .36$); there were also no differences when the N2pc was assessed in terms of the peak-amplitude metric (amplitude, $\Delta = 1.68$ µV, $t(19) = .95$, $p = .35$; latency: $\Delta = 8.2$ ms, $t(19) = .46$, $p = .65$). Further, the SPCN, too, did not differ significantly between distractors appearing at the frequent vs. a rare location ($\Delta = 2.51$ µV, $t(19) = 1.41$, $p = .17$). Overall, the effect patterns mirror those seen with target-related effects on target-only (i.e., distractor-absent) trials (see Fig. 4 right panels), suggesting that distractors at the frequent location were processed similarly to targets at that location.

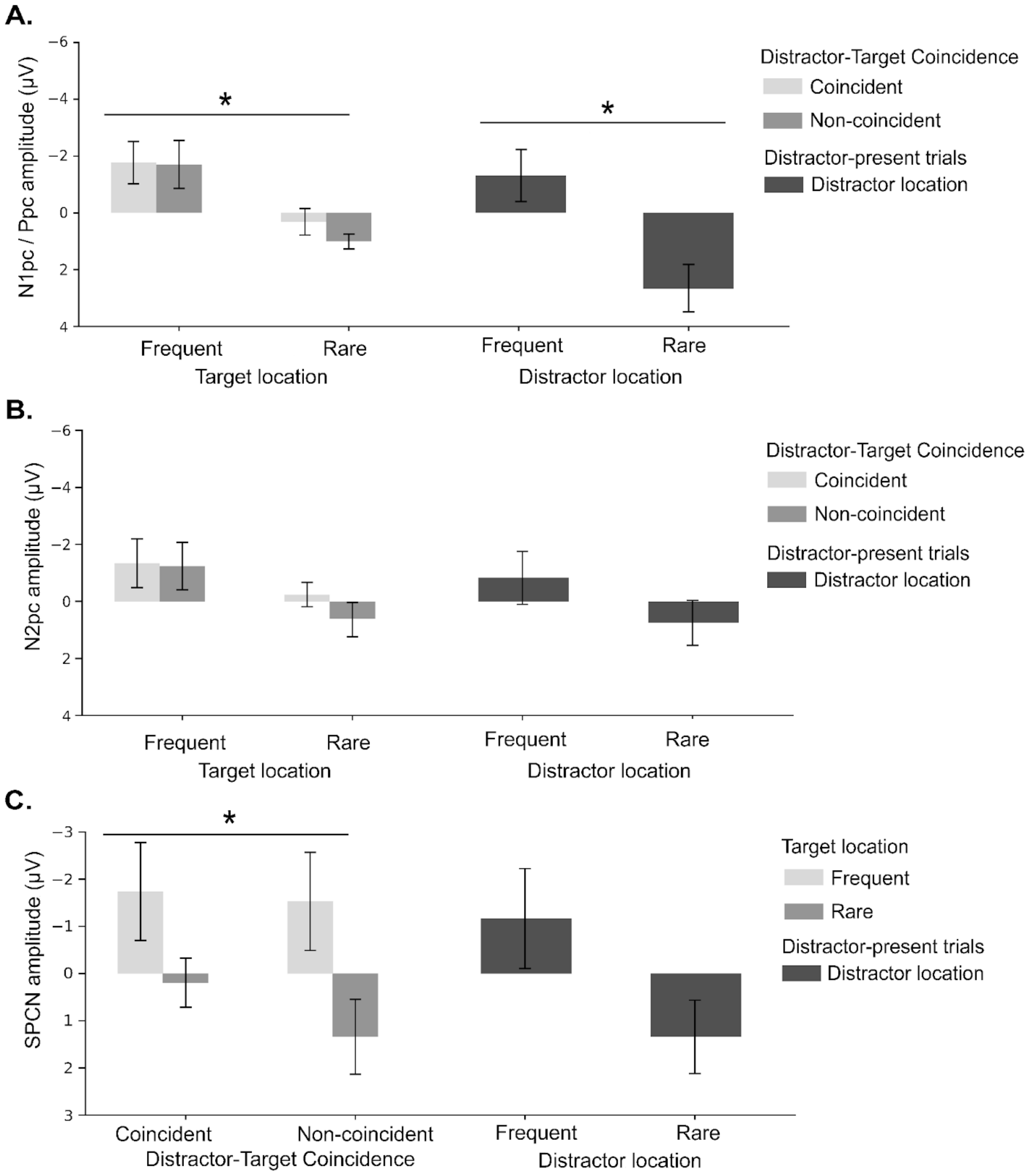

Figure 4. Mean *target-related* and *distractor-related* (i.e., left panels and right panels, respectively) N1pc mean amplitude (**A**), N2pc mean amplitude (**B**), and SPCN amplitude (**D**). The *target-related* L-ERPs are plotted as a function of the target location (target at the frequent or a rare distractor location) on (distractor-absent) Trial *n*, dependent on the coincident vs. non-coincident positioning of the target on Trial *n* relative to the distractor on Trial *n–1* (Distractor-Target Coincidence condition). The *distractor-related* L-ERPs are plotted as a function of the distractor location (at the frequent or a rare distractor location), with the target positioned on the opposite side. Error bars depict the one standard SEMs.

3.2.2 N2pc

The mean amplitudes of N2pc in the time window 180–350 ms were similar across the target-only and the target-plus-distractor conditions (see Fig. 4B). For the target-only conditions, a two-way (Target-Location × Distractor-Target Coincidence) ANOVA revealed no significant effects (Target-Location, $F(1, 19) = 1.58$, $p = .23$, $\eta_p^2 = .08$; Coincidence, $F(1, 19) = 1.21$, $p = .29$, $\eta_p^2 = .06$; interaction, $F(1, 19) = 1.20$, $p = .29$, $\eta_p^2 = .06$). Numerically, though, there was a negativity when the target occurred at the frequent distractor location (a-priori one-tailed t-test against zero, $t(19) = -1.57$, $p = .06$), but a positivity (i.e., no negativity) when it occurred at a rare location ($t(19) = .47$, $p = .67$).[7] As an alternative to the mean-amplitude approach, we also examined the N2pc using the local-peak detection method (Geib et al., 2020; Gokce et al., 2014). Based on this metric, the N2pc (peak) amplitude turned out to be significantly larger, and the (peak) latency to be slightly delayed (by 25 ms), for targets that appeared at the frequent vs. a rare distractor location (see Appendix B).

Thus, the spatially biased distractor distribution and the distractor-target inter-trial coincidence had little impact on the N2pc. Qualitatively, though, the pattern remained similar to the earlier N1pc/Ppc components (compare Fig.s 4A and 4B). If anything, attentional engagement, reflected in the N2pc (peak) amplitude and timing, was somewhat stronger and mildly delayed by targets appearing at the likely location. The timing effect may reflect some (statistically acquired) resistance to deploy attention to the likely distractor location, despite the enhanced ‘attend-to-me’ signal reflected in the N1pc/Ppc.

3.2.3 SPCN

For the target-only conditions, analysis of the SPCN component revealed a marginally significant main effect of Distractor-Target Coincidence, $F(1, 19) = 3.96$, $p = .06$, $\eta_p^2 = .17$ (see Fig. 3E and Fig. 4C); neither the main effect of Target Location, $F(1, 19) = 2.35$, $p = .14$, $\eta_p^2 = .11$, nor the Coincidence × Target-Location interaction, $F(1, 19) = 2.03$, $p = .17$, $\eta_p^2 = .10$, was significant. The Coincidence effect was due to the SPCN amplitude being more negative-going (mean difference $\Delta = 0.68$ μV) when the target location was coincident vs. non-coincident with the previous distractor location (a-priori one-tailed t-test, $t(19) = 1.99$, $p = .03$). That is, there was an enhanced sustained negativity during the post-stimulus period when the target occurred at the previous distractor location, suggesting that more attentional

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[7] Following an approach used by van Moorselaar et al. (2021), we further categorized participants into two groups, ‘learners’ and ‘non-learners’, according to whether they showed a behavioral target-location effect (i.e., slowed responding to targets appearing at the frequent vs. a rare distractor location). However, this analysis failed to reveal any differential N2pc effects between the two groups (see Appendix C for details).

vWM resources were required to analyze a target at a previous distractor location. As a result, responding to the target at the coincident location was slower compared to a non-coincident location.

In summary, the L-ERP results reveal a difference between the early N1pc/Ppc and SPCN in response to targets at the frequent and rare distractor locations and the spatial coincidence of the target on Trial *n* and the distractor on Trial *n–1*: referenced to the frequent distractor location, an early N1pc was triggered whether the target appeared at the frequent distractor location or a rare distractor location on the opposite side, while an enhanced sustained negativity (SPCN) was evident when the target appeared at the previous distractor location, both for the frequent and rare distractor locations.

3.3 Time-frequency data

As outlined in the Methods section, we further calculated the lateralized alpha-band power during the pre-stimulus period of Trial *n* across all conditions and separately for each of the three distractor conditions on Trial *n-1* (distractor absent, distractor at frequent location, distractor at rare location). Fig. 5A depicts the overall lateralized (contralateral minus ipsilateral, with reference to the frequent distractor location) alpha-band power (8–12 Hz) across all trials. Following (van Moorselaar et al., 2020), we limited the statistical analyses to the anticipatory time window (i.e. -750 ms to 0 ms). A *t*-test on the mean (contralateral minus ipsilateral) lateralization index failed to reveal any significant difference, $t(19) = -.72$, $p = .48$, $d_z = .08$; that is, there was no evidence of increased alpha-band power contra- vs. ipsilateral to the frequent distractor location, that would be indicative of pro-active suppression, before the onset of the search display. Fig.s 5 B-D show the lateralized pre-stimulus alpha-band power for Trial *n* dependent on the distractor condition on Trial *n-1* (distractor absent, at the frequent location, at the rare location). Further *t*-tests for each of these conditions also failed to reveal any difference in pre-stimulus alpha power (distractor-absent condition, $t(19) = .50$, $p = .62$, $d_z = .07$; distractor-at-frequent-location condition, $t(19) = .96$, $p = .35$, $d_z = .09$; and distractor-at-rare-location condition, $t(19) = .96$, $p = .35$, $d_z = .12$).

To rule out smearing effects, it is advisable to avoid time points around 0 ms, which may contain information from data points well after 0 ms. Accordingly, we conducted a second time-frequency analysis for the pre-stimulus window of -750 to -450 ms. Because the safety margin is half of the wavelet length of the lowest frequency of interest, a sufficient temporal distance to zero would be equal to or greater than 423.87 ms (lowest frequency of interest = 8.26 Hz, time resolution = 269.85 ms, frequency resolution = 2.40 Hz, wavelet length = 847.74 ms). However, again, there was no reliable increase in alpha-power contralateral vs. ipsilateral to the likely distractor location in any condition (*t*s(19) > .52, *p*s > .61, Bonferroni-corrected), corroborating the above results.

To search for potential anticipatory suppression that we might have missed with the above method. We adopted the cluster-based permutation tests across the 1–30-Hz frequency band between the contralateral and ipsilateral region over the whole pre-stimulus interval from -1950 to 0 ms (*p* < .05, cluster-corrected, 1000 iterations). Again, the analysis failed to find any reliable clusters exhibiting enhanced pre-stimulus oscillations among three distractor conditions (i.e., the distractor absent, at the frequent, and at the rare location). Further permutation tests among three distractor conditions also failed to reveal any reliable difference in the lateralization power among them.

Taken together, the time-frequency analyses failed to provide any evidence that the distractor-location suppression observed in the behavioral data derives from anticipatory suppression prior to the search display. This non-finding is at variance with some reports in the literature (Wang et al., 2019), but consistent with others (van Moorselaar et al., 2021).

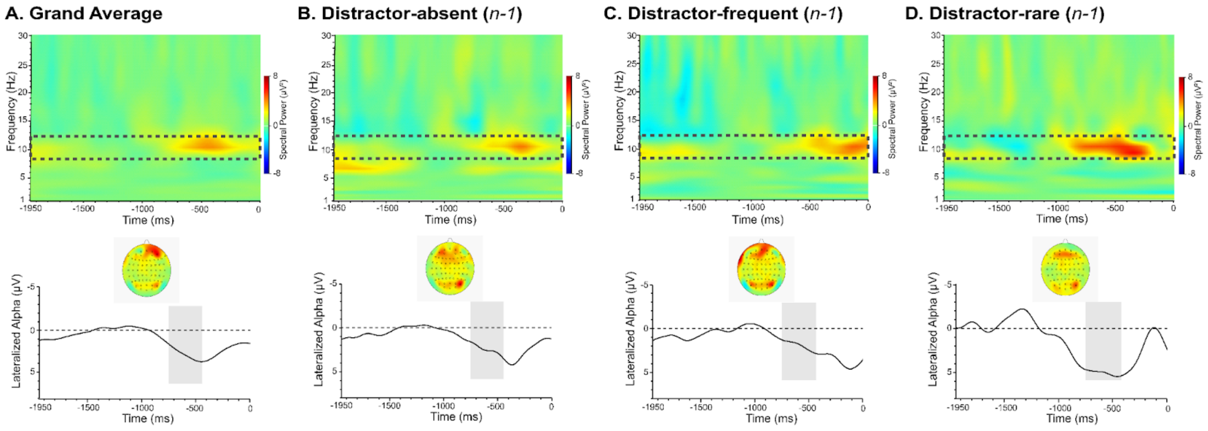
A. Grand Average
B. Distractor-absent (*n-1*)
C. Distractor-frequent (*n-1*)
D. Distractor-rare (*n-1*)

Figure 5. Grand average results for the EEG time-frequency anticipatory alpha-power. (A) The upper panel presents the lateralization index (contralateral minus ipsilateral) with reference to the frequent distractor location, for all trials. The bottom panel depicts the time series of the lateralization index waveform plotting the averaged alpha power (10 Hz) averaged across electrodes O1/2, PO3/4, and PO7/8, along with the grand-average scalp distribution of alpha power, prior to search-display onset (-1950 to 0 ms). **(B-D)** Lateralization index (contralateral minus ipsilateral) with reference to the distractor condition on the previous

Trial *n-1*: distractor absent, distractor at the frequent location, distractor at the rare location. For each condition, the upper panel shows the grand average time-frequency oscillation (time series: -1950 to 0 ms prior to the search-display onset; frequency-band: 1 to 30 Hz) at contralateral minus ipsilateral electrode clusters (O1/2, PO3/4, and PO7/8). The bottom panel presents the two-dimensional waveform plot of the central alpha power and its grand-average scalp distribution. Note that the power spectrum bars indicate the lateralization index from -8 to 8 μV^2; the black dashed boxes in the upper panels represent the alpha-band range used for statistical analysis.

4 Discussion

The aim of the present study was to investigate the neural mechanisms involved in long-term probability-based (proactive) and short-term inter-trial-based (reactive) distractor handling and related distractor suppression effects. Behaviorally, we replicated the distractor-location probability-cueing effect: distractor interference (i.e., the RT slowing on distractor-present vs. -absent trials) was reduced when the distractor appeared at the frequent location, compared to one of the rare locations. Further, on target-only trials, responding to a given target was slowed when it appeared at a location occupied by a distractor on the preceding trial, compared to a non-distractor location, and this spatial target-distractor coincidence effect was little affected whether the critical location was the frequent or a rare location. Electrophysiologically, we observed a dissociation between the early N1pc/Ppc and the late SPCN. The polarity of the early lateralized component was dependent on the target, on target-only trials, appearing at either the frequent location – in which case a target-referenced N1pc was triggered – or a rare location – in which case a target-referenced Ppc was triggered. An analogous, distractor-referenced N1pc/Ppc pattern was observed on target-plus-distractor trials. Further, the amplitude of the late SPCN was more negative-going when the target location coincided with the preceding distractor location than when it did not. Finally, time-frequency analysis failed to reveal any evidence of anticipatory suppression induced by the uneven spatial distractor distribution in terms of differential alpha-band activity contra- vs. ipsilateral to the likely distractor location.

The most robust effect observed in distractor-location probability-cueing paradigms is the generally reduced RT interference caused by distractors appearing at the frequent location compared to a rare location (Allenmark et al., 2019; Allenmark, Shi, et al., 2021; Goschy et al., 2014; Sauter et al., 2018; Wang & Theeuwes, 2018; Zhang et al., 2019). It is believed that this effect results from statistical learning across trials of where distractors are likely to occur in the display, which leads to 'proactive' suppression of the respective locations – evidenced, for instance, by distractors at frequent locations attracting fewer eye movements (e.g., Allenmark, Shi, et al., 2021; Sauter et al., 2021). In addition, when a distractor does capture attention, whether overtly or covertly, its location needs to be suppressed 'reactively' for attention to disengage and move towards the target location (e.g., Geng, 2014). This reactive inhibition carries over to the next trial, evidenced by slowed RTs to a target presented at the same location as a distractor on the previous trial (e.g., Allenmark, Shi, et al., 2021; Geyer et al., 2006; Kumada & Humphreys, 2002; Sauter et al., 2018). While this may reflect an 'inhibition-of-return' tag carried over across trials, it might also reflect an adjustment of decision criteria in post-selective 'target' decisions, that is, in deciding whether an attentionally selected item is actually the searched-for target or an irrelevant distractor (or non-target) item.[8]

Statistical long-term learning of frequent distractor locations

Our findings indicate that whether an early lateralized negativity (N1pc) or positivity (Ppc) was observed was contingent on whether the most salient display item (the target on target-only trials or the distractor on target-plus-distractor trials) appeared at the frequent distractor location (early negativity) or a rare location on the opposite side (early positivity). This polarity pattern may be best understood by inspecting the original ERP waveforms (Fig. 3 A-D). Irrespective of the side on which the most salient display item appeared, the N1 peaked earlier and more prominently contralateral vs. ipsilateral to the side of the frequent distractor location. This suggests that, as a result of statistical learning, participants acquired a strong memory 'prior' where the most salient, and in terms of behavioral decision-making, most significant item (the target on target-only trials or the distractor on target-plus-distractor trials) is likely to appear in the display, and this prior then top-down biased attentional selectivity towards this location. Previous work has linked the early N1pc and Ppc/Pd to the registration of an 'attend-to-me' signal and attentional orienting to salient display items (Dodwell et al., 2021; Donohue et al., 2018; Itthipuripat et al., 2014; Johannes et al., 1995; Sawaki & Luck, 2010; Schettino et al., 2016), or to (proactive) suppression of task-irrelevant

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[8] In fact, the globally measured behavioral distractor-location probability-cueing effect may also, to some extent, reflect such post-selective processes, evidenced by findings from studies of oculomotor capture that it takes less time to disengage the eye from a frequent vs. a rare distractor location (Sauter et al., 2021). While this may have to do with the overcoming of oculomotor 'hold' processes, it may also reflect a shift in post-selective decision criteria: if decisions are biased towards 'distractor' and away from 'target' at frequent locations, the (perceptual) signal to disengage the eye would be issued faster, expediting oculomotor disengagement from distractors at frequent locations.

distractors (Kerzel & Burra, 2020; Sawaki & Luck, 2010). In the present study, however, the initial lateralized activity is likely to reflect an (as a result of statistical) acquired bias in spatial attention. The fact that such a bias can be purely driven by statistical learning is consistent with the N1pc/Ppc polarity flip in contextual cueing reported by Zinchenko et al (2020): participants persisted in prioritizing the initially learnt target locations within repeated display arrangements even after consistent re-location of the targets to the opposite side of the displays. We suggest that, under the conditions of the present study, the search-guidance system has learned that salient stimuli at the frequent location may engender a decision 'conflict' (see, e.g., Schneider et al., 2012): 'pay special attention' to the stimulus at this location because, although it is highly likely to be a distractor, it may actually be a target.

It should be noted, however, that both the statistically acquired top-down prior and the bottom-up 'attend-to-me' signal generated by the stimulus influence the early prioritization of spatial attention: when both are spatially congruent – i.e., when the target appears at the frequent location – the N1pc is enhanced. Conversely, when the two are incongruent – i.e., when the target appears at a rare location on the opposite side and so competes with the top-down prioritized location – the Ppc amplitude is reduced. In contrast to the target-only (distractor-absent) trials, this competitive interaction is lessened on distractor-present trials, where the target signal on one side and the distractor signal on the other side already compete with each other, curtailing the influence of the top-down prior. As a result, the N1pc and Ppc are of comparable (absolute) amplitudes in the target-plus-distractor conditions (Fig. 3).

How does our finding compare to previous ERP studies of distractor-location probability cueing? Overall, the results from these studies were inconsistent. In our study, we observed statistical learning to impact the early lateralized component (N1pc/Ppc), while having little influence on the N2pc amplitude; if anything, the N2pc appeared only slightly delayed to targets at the frequent vs. a rare distractor location. In contrast, Wang et al. (2019) reported a reduced N2pc amplitude for frequent-location targets, which they attributed to a suppression-related Pd component simultaneously acting on the frequent location, rendering the target-elicited N2pc less robust (consistent with their finding of a Pd for the frequent location when the target appeared on a vertical midline position). It is worth noting that the lack of an N2pc modulation by the distractor likelihood is not an uncommon finding. For instance, van Moorselaar et al. (2021) also failed to find a difference in N2pc amplitudes between targets at frequent vs. rare locations. Similarly, Sauter et al. (2017) did not find a latency/amplitude difference in the N2pc between targets occurring in a frequent vs. a rare distractor region on distractor-absent trials: lateral targets elicited a pronounced N2pc whether they appeared in the frequent or the rare distractor region, suggesting that attention was consistently allocated to the target.

One crucial aspect that has been overlooked in the debate is the interplay between statistical learning and the bottom-up saliency in the N2pc. The majority of studies examining the N2pc have employed designs with equal (i.e., spatially unbiased) distributions of the lateralized target or distractor singletons, that is: they were not devised to study *spatial* statistical learning. Recent studies focusing on distractor-location probability cueing implemented heterogeneous display configurations: some used more and some less possible locations at which a distractor or target could occur (e.g., 8 locations in Wang et al, 2019, and van Moorselar, 2021, compared to 4 out of a total of 8 locations in the present study[9]; see also Kerzel & Burra, 2020, who used only a total of 4 locations). These differences in the display design may have contributed to the inconsistent findings in the literature. Here, we found that the early lateralized component (N1pc/Ppc) influenced by statistical-learnt attentional prioritization has implications for the subsequent N2pc component. For instance, when the target appeared at a rare distractor location (on the side opposite to the frequent location), we did not observe any posterior-contralateral negativity in the window of the N2. This may appear surprising initially, as one would have expected the rare side to be least suppressed by statistical *distractor*-location learning. However, the reason becomes clearer when taking the preceding N1pc/Ppc component into account, that is, the consistent negativity referenced to the top-down prioritized, frequent distractor location – which had the highest occurrence (47.5%) of the most salient display item (the target on target-only trials and the distractor on target-plus-distractor trials) across all trials. As a result of statistical learning, this location was prioritized for processing – either for a ‘reject’ decision or a ‘select’ decision – at the onset of the display, irrespective of any bottom-up ‘attend-to-me’ signals. As a result, when the target appeared at the rare location, it had to compete with the probability-based prioritization of the frequent location. Although the biased competition greatly reduced the early Ppc amplitude (as compared to the absolute N1pc amplitude), it remained positive, preventing the subsequent negative-going wave (‘N2pc’) from reaching the negative region.

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[9] Recall that our focusing on only 4 locations was owing to the main aim of the study, namely, to examine the pattern of Distractor-Target Coincidence effects, separately for the frequent and rare distractor locations.

Of note, while our results are reasonably clear as to how targets at the frequent location are processed on target-only (distractor-absent) trials, we cannot tell what the reduced RT interference caused by distractors at the frequent vs. one of the rare locations (which we observed, in line with a plethora of other studies) is due to on target-plus-distractor (distractor-present) trials. What we find is that, electrophysiologically, the distractor at the frequent location is handled similarly to a target at this location. In particular, it elicits an early N1pc that is as large as that generated by a target. Thus, if not due to early signaling, the cueing effect would have to originate in later processes involving attentional selection and engagement and/or post-selective processing of the selected item. Recall that the present study was designed to examine the origin of the slowed processing of targets (on target-only trials) occurring at a preceding distractor location, and so it did not incorporate conditions with lateral distractors only or, respectively, lateral distractors and targets on the vertical midline (on distractor-plus-target trials). Accordingly, it is hard to isolate distractor-related L-ERPs indexing of these later processes. In particular, we cannot examine for differential Pd effects, and how these may impact the N2pc and SPCN components, between distractors at the frequent and rare locations, limiting our conclusions as to the origin of the cueing effect.

Short-term (cross-trial) after-effects of distractor rejection

To examine the effects of short-term, inter-trial ‘inhibition’ of distractor locations, we selected sequential trial pairs with Trial *n-1* always containing a distractor that appeared at either the frequent or a rare location, followed by Trial *n* with the target only. Further, we categorized Trials *n* into coincident and non-coincident trials based on the target appearing at either the same or a different location to the distractor on Trial *n–1*. The behavioral results showed the cross-trial coincidence effect: it took longer to respond to a target at a previous distractor vs. a non-distractor location. This coincidence effect was mirrored in the SPCN component. The SPCN turned out more negative for coincident, vs. non-coincident, positioning of the target on Trial *n* with respect to the distractor on Trial *n–1* (i.e., when the target appeared at the same, vs. a different, location to the preceding distractor).

Previous work has shown the SPCN component, in the time interval between 350 to 500 ms post-stimulus, to be reliably observed under conditions requiring realized target stimuli to be selected and maintained in visual working memory (vWM) for ‘in-depth’ processing in order to select the appropriate response (Hilimire & Corballis, 2014; Jolicoeur et al., 2008; Kiss et al., 2008). For instance, Kiss et al. (2008) found the SPCN to be increased on target-present (vs. target-absent) trials, on which participants had to discriminate the cut-off side of a singleton target diamond in order to decide on the appropriate response. By comparison, the SPCN was attenuated on target-absent trials, on which the search arrays were perceptually homogeneous – allowing participants to rapidly reject a display as not containing an odd-one-out item, without the need for any further, in-depth processing of any response-relevant features (participants had simply to refrain from making a response on such trials). Also, the SPCN amplitude is increased when multiple odd-one-out items within a given display are to be individuated and precisely enumerated, or when a decision is to be made whether the individuated items are arranged in a particular spatial configuration (Maheux & Jolicœur, 2017; Mazza & Caramazza, 2011) – that is, in tasks posing increased demands on vWM. Similarly, in a flanker task, the SPCN is more negative when the target-flanker distance is short rather than long (Bacigalupo & Luck, 2015) – likely due to the target needing to be individuated from the flankers in vWM when attention fails to focally select it under conditions of ‘crowding’.

In the present study, the *distractor-target inter-trial effect* is defined by whether the processing of a given target (on Trial *n*) is in some way ‘inhibited’ when it occurs at the same location as the distractor on the preceding Trial *n–1*. As considered in the Introduction, there are two possible explanations of such a short-term distractor-target inter-trial effect: (i) an additional inhibitory tag may be (reactively) placed on the distractor on Trial *n–1* – which, on the next trial (Trial *n*), would make the allocation of attention to a target item at this location harder; or, (ii), attentional selection of the item at this location is itself unaffected, but the distractor on Trial *n–1* shifts the starting point of the post selective (vWM-demanding) decision process determining what the item is at this location – a task-irrelevant distractor or the response-critical target – towards a ‘distractor’ decision, so that a diffusion-type decision process would take longer to reach the target boundary, prolonging the RT. Given that the most robust coincidence effect we observed was on the vWM-related SPCN component, without an effect on the attentional-selection-related N1pc and N2pc components, would argue in favor of the coincidence inter-trial effect reflecting mainly post-selective processes, in line with alternative (ii). This is in line with our previous eye-movement study (Allenmark, Shi, et al., 2021), in which we found that even though, on some critical trials, participants made an overt eye movement to the target, they mis-identified this item and rejected it as a distractor and kept on searching other items before eventually returning to the target and making the correct decision. Erroneous rejection of the fixated target as a distractor would be in line with alternative account (ii), because, when a previous distractor shifts the starting point of the decision process towards 'distractor' (and away from 'target'), one would expect a diffusion-type process of evidence accumulation to randomly drift towards the nearer, 'distractor' boundary, resulting in the wrong decision on 'target' trials. Of note, in Allenmark et al. (2021) study, this oculomotor pattern was more marked when a target followed a distractor at a rare (distractor) location, compared to the frequent location (and it was more marked in individuals with ASD compared to healthy controls). Allenmark et al. (2021) explained this by assuming that the shift towards the 'distractor' boundary caused by a distractor appearing at a given location is more marked when distractors are unexpected, rather than highly expected, at that location. In the present study, the SPCN pattern (depicted in Fig. 3G and Fig. 4D) looks generally similar (in that the coincidence effect appears driven more by targets at rare locations), though only the Coincidence main effect was reasonably robust, that is, the Coincidence × Target-Location interaction was not significant. Further work with a larger participant sample is required to examine the existence of the analogous interaction in the SPCN.

Anticipatory suppression of distractor-location probability cueing

To date, it remains controversial whether the statistically learned (long-term) 'inhibition' of the frequent distractor location reflects a process of proactive location suppression in anticipation of search-display onset, where this process would be purely spatial (i.e., feature-blind), suppressing the allocation of attention to the learnt location whether a distractor or target appears in the search display. One recent study, by Wang et al. (2019), has reported alpha power to be enhanced contralateral to the frequent location prior to display onset. Oscillatory alpha activity (~10 Hz) has been shown to be inversely related to cortical excitability (Benwell et al., 2019; Lange et al., 2013), and lateralized alpha-band activity has been related to anticipatory suppression (Bengson et al., 2012; Jensen & Mazaheri, 2010; Kelly et al., 2006); in particular, an increase in lateral alpha-band power has been linked to the functional suppression of task-irrelevant information (Mazaheri et al., 2014). Accordingly, the finding of Wang et al. (2019) would argue in favor of proactive suppression of the frequent distractor location. However, in the present study, we failed to find any increase in pre-stimulus alpha-band power over the hemifield contralateral to the frequent distractor location within the pre-stimulus time window of [-750 to -450 ms] and [-750 to 0 ms].

It should be noted that our null-finding is not unique. Noonan et al. (2016) also failed to find any distractor-location-related anticipatory alpha lateralization in a study of distractor suppression. More recently, examining expectation-dependent distractor suppression, van Moorselaar et al. (2020) also found no differential contralateral vs. ipsilateral alpha-band activity prior to search-display onset. In the present study, we further controlled the target- and distractor-defining shape and color features by swapping them unpredictably across trials to maximize location-based and minimize feature-based statistical learning. But, again, we found no evidence of an active suppression process initiated in anticipation of the search display. Consistent with van Moorselaar et al. (2020) and Noonan et al. (2016), this points to anticipatory alpha-band modulations *not* playing a significant role in the statistical long-term learning and 'suppression' of likely distractor locations.

This leaves two possibilities. Either, distractors at likely locations are 're-actively' suppressed (preventing them from summoning attention) in the sense that suppression is invoked only once the presence of a distractor (or saliency signal) is registered at some level in the system; that is, the distractor rapidly activates some acquired suppression 'routine', and this works more efficiently for frequent as compared to rare distractor locations. Such fast-acting, phasic suppression may be evidenced by an early distractor-related Pd component (preventing the elicitation of an N2pc), as reported in some studies (Gaspelin & Luck, 2018a, 2018b, 2018c). This notion would appear to be consistent with Gaspelin and Luck's (2015; 2018a) 'signal suppression hypothesis'. Alternatively, the acquired suppression mechanism may work more tonically in that distractor-location learning down-modulates the responsivity of local neuron populations at some (higher and/or lower) level in the functional architecture of priority computation. Accordingly, any signal at such locations would be attenuated 'passively', without the need for the intervention of some '(re-)active' suppression process. This would be consistent with habituation-type accounts of statistical distractor-location learning (Allenmark et al., 2022; Turatto et al., 2018; Turatto & Pascucci, 2016; Zhang et al., 2022).

5 Conclusions

In summary, the present study investigated the mechanisms involved in distractor-location suppression through long-term statistical learning and short-term (inter-trial) adjustments. Behaviorally, we replicated the classical distractor-location probability-cueing effect, showing that participants can statistically learn to reduce the interference caused by salient distractors at frequent (vs. rare) distractor locations (Allenmark et al., 2019; Goschy et al., 2014; Müller et al., 2009; Sauter et al., 2018; Wang & Theeuwes, 2018), as well as the inter-trial coincidence effect, i.e., the slowing of RTs when the target appears at the same (vs. a different) location as a distractor on the preceding trial. Electrophysiologically, statistical learning of the likely distractor location manifested in an early N1pc/Ppc post-display onset, but not in lateralized alpha power during the pre-stimulus period. The polarity of the early lateralized component N1pc/Ppc was due to the reference used to calculate the difference wave: the Ppc turns into an N1pc when referenced to the side of the frequent distractor location, indicative of acquired top-down attentional bias towards the frequent distractor location (which contained the most salient stimulus on nearly 50% of the trials overall in our display design). This top-down attentional prioritization (activated only upon the appearance of the search display) competes with the 'attend-to-me' signals generated by the singleton target and distractor items, potentially rendering the classic N2pc unobservable in some circumstances. On the other hand, the inter-trial distractor-target coincidence effect was primarily associated with an enhanced SPCN, indicative of increased (vWM) resource demands to decide upon a response to the (selected) target at a previous distractor location. Accordingly, we attribute the coincidence cost on the RTs to a late, post-selective process, plausibly as a result of a short-term bias (induced by the distractor on Trial *n–1*) against identifying the item at the frequent distractor location (on Trial *n*) as a target, rather than a distractor. We acknowledge that these interpretations, especially of the early ERP effects, are post hoc and need to be corroborated in future research. Our study design did not allow us to isolate distractor- and target-related activity on distractor-present trials (since distractors and targets were always placed on opposite sides), so we cannot tell at which stage(s) in later processing the interference reduction originates. Future work, implementing lateralized distractors and midline targets, is necessary to answer this question.

Declaration of competing interest

The authors declare no competing interests

Data availability statement

Raw data used for analyses presented within this article will be made available upon request. If you would like to access the raw data and analysis, please email Nan Qiu at the following e-mail address: Nan.Qiu@campus.lmu.de.

Credit authorship contribution statement

Nan Qiu: Conceptualization, Formal analysis, Data collection & curation, Methodology, Project administration, Visualization, Writing – original draft, Review, and Editing.

Bei Zhang: Conceptualization, Data collection & curation, Methodology, Analysis, Validation.

Fredrik Allenmark: Conceptualization, Methodology, Analysis, Resources, Validation, Review, and Editing.

Jan Nasemann: Analysis, Methodology, Validation, Review, and Editing.

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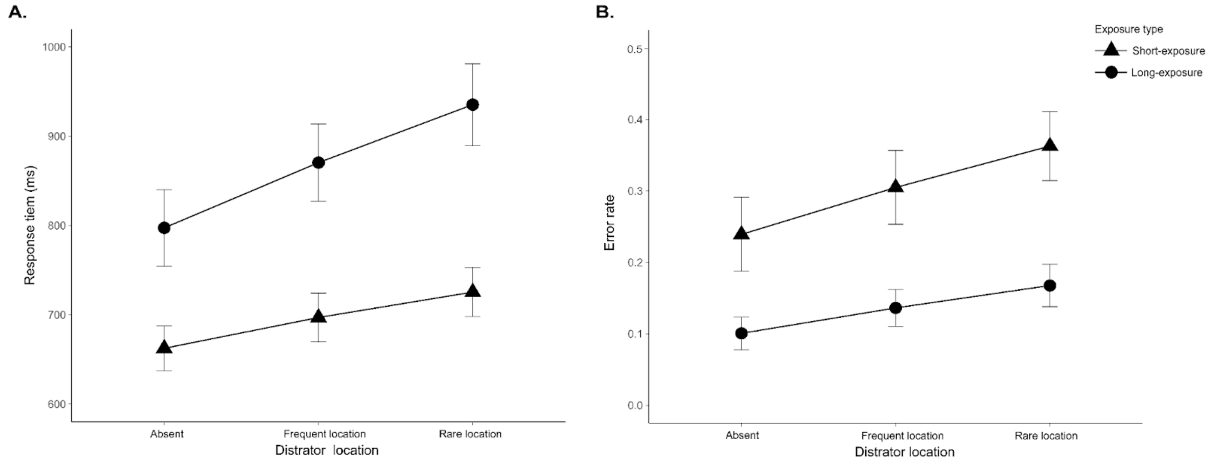
Appendix A: Distractor location effects on short-exposure trials

In order to balance the need for sufficient trials in the four critical conditions (2 Distractor-Target Coincidence × 2 Target Location) and a reasonable overall duration of the experiment involving recording of the EEG, we split the trials into two exposure-duration types: long- and short-exposure trials (52.48% and, respectively, 47.52%). Our examination of the long-term distractor-location learning and the short-term inter-trial distractor-target coincidence effects focused on successive long-exposure trials (71.38% of long-exposure trials), with the target on (distractor-absent) Trial *n* occurring at either the same or a different location relative to the distractor on (distractor-present) Trial *n-1*, and these (short-term) inter-trial coincident and non-coincident (target-distractor) placement conditions were orthogonally combined with the (long-term) frequent vs. rare distractor-location conditions. Except for these critical long-exposure trials, the remaining trials were manipulated randomly as long- or short-exposure trials, with the latter trials intended to limit the total duration of the EEG experiment. One potential problem arising from the introduction of short-exposure trials may be that they impact the long-term learning of the frequent distractor location. To examine this, here were present an analysis of the statistical learning effect on short- as well as long-exposure trials.

Appendix-Fig. 1 presents the mean RTs (left panel) and the mean error rates (right panel) for the three distractor conditions (distractor absent, at frequent location, at rare location). A two-way repeated-measures ANOVA revealed the main effect of Distractor Condition to be significant, $F(2, 38) = 43.69$, $p < .001$, $\eta p^2 = .70$: RTs were faster in the distractor-absent condition relative to the distractor-present conditions (average $\Delta = 77.86$ ms), and distractors occurring at the frequent location caused less RT interference (relative to the distractor-absent baseline) than distractors at rare locations (differential interference $\Delta = 47.16$ ms) (t's$(19) > 4.59$, p's $< .001$, Bonferroni-corrected) – evidencing a distractor-location probability-cueing effect. Further, the main effect of Exposure Type and the Exposure-Type × Distractor-Condition interaction were significant, $F(2, 38) = 28.24$, $p < .001$, $\eta p^2 = .60$, and $F(2, 38) = 8.72$, $p < .001$, $\eta p^2 = .32$, respectively. Short display exposures gave rise to overall faster responses vs. long exposures (696.22 vs. 870.54 ms, i.e., $\Delta = 174.32$ ms; $t(19) = 8.74$, $p < .001$, Bonferroni-corrected), and this was associated with reduced distractor interference on distractor-present vs. -absent trials (short vs. long exposure: $\Delta = 49.22$ ms vs. 106.51 ms; t's$(19) > 4.39$, p's $< .001$, Bonferroni-corrected) and a reduced cueing effect for distractors at the frequent vs. rare locations (short exposure: Δ = 28.75 ms, *t*(19) = 2.40, *p* = .08; long exposure: Δ = 65.57 ms, *t*(19) = 4.11, *p* < .05, Bonferroni-corrected). This effect pattern – especially the overall shorter RTs with short vs. long exposures – is expected assuming that the limited display presentation time in the short-exposure condition acts like a response deadline, forcing participants to produce fast responses, likely at the expense of increased error rates.

This was borne out by an analysis of the error rates, which are depicted in Appendix-Fig. 1B (right panel). As can be seen, the error rates increased from the distractor-absent (17.05%) through the distractor-at-frequent-location (22.30% to the distractor-at-rare-location (26.90%) condition (main effect of Distractor Condition: *F*(2, 38) = 23.46, *p* < .001, ηp^2 = .55) and were generally increased with short vs. long exposures (30.73% vs. 13.43%; main effect of Exposure type: *F*(2, 38) = 15.71, *p* < .001, ηp^2 = .45). The interaction was also significant, *F*(2, 38) = 5.66, *p* < .05, ηp^2 = .23, owing to the Distractor-Condition effect being more pronounced with short exposures. Importantly, the probability-cueing effect (the differential error rate between the distractor-at-frequent- and -rare-location conditions) was significant with both long (Δ = 3.2%; *t*(19) = 2.60, *p* = .05, Bonferroni-corrected) and short exposures (Δ = 6%; *t*(19) = 2.90, *p* = .03, Bonferroni-corrected).

Thus, the error-rate pattern mirrors the RT pattern of results: longer RTs went along with higher error rates, particularly marked in the short-exposure condition – arguing against confounding of the RT effects by speed-accuracy trade-offs. In particular, in the short-exposure condition, the reduced RT cueing effect (the reduced RTs with distractors at the frequent vs. rare locations; 28.75 ms, as compared to 65.57 ms with long exposures) was associated with an increased error rate (6% vs. 3%) – arguing in favor of a robust distractor-location probability-cueing effect when both response speed and accuracy are taken into account. In other words, participants successfully learned the frequency distribution of the distractor locations, despite the mixing of (for our study critical) long display exposures with short exposures.



Appendix-Fig. A. Behavioral results for both long- & short-exposure trials (A-B). Mean RTs and error rates for the three distractor conditions: 'Absent' denotes the distractor-absent condition; 'Frequent location' that the distractor occurred at the frequent location; and 'Rare location' that the distractor occurred at one of the rare locations. Error bars depict the one standard error of the mean.

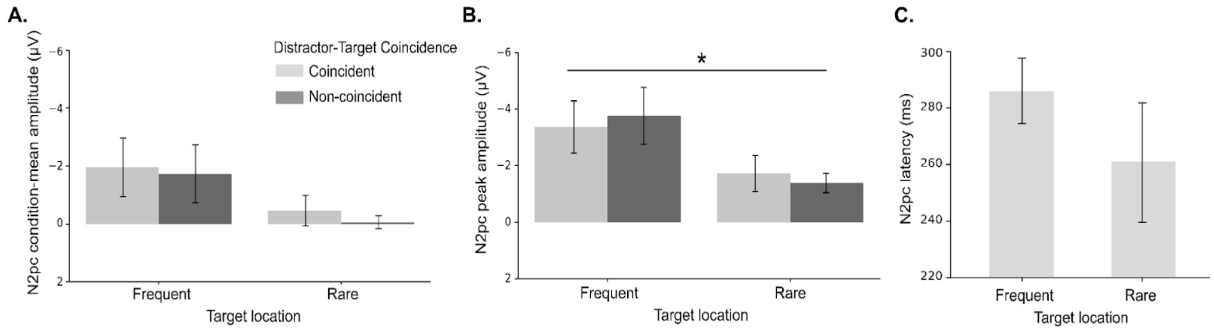
Appendix B: Analysis of target-elicited N2pc peak amplitudes and latencies

Given that previous studies of statistical distractor-location learning produced inconsistent results regarding the N2pc modulations (e.g., Wang & Theeuwes, 2019, van Moorselaar, 2021), and our mean-amplitude approach also failed to reveal any differences between targets or distractors that appeared at the frequent vs. a rare location, we analyzed the N2pc further using alternative methods.

First, we adopted the condition-specific mean-amplitude approach (van Moorselaar et al., 2020, 2021; van Moorselaar & Slagter, 2019; Wang et al., 2019). That is, N2pc epochs of interest were centered around condition-specific negative peaks in target-related waveforms, spanning a 200–400-ms window, and then averaged the amplitude values over the ±25-ms range with reference to the center point (van Moorselaar et al., 2021). The resulting mean voltages showed target-referenced N2pc components within the interval of interest (180–350 ms post-stimulus onset). An ANOVA of the respective components within this interval (305 ± 25 ms for coincident/frequent location; 230 ± 25 ms for coincident/rare location; 300 ± 25 ms for non-coincident/frequent location; 225 ± 25 ms for non-coincident/rare location) yielded no significant effects: Target-Location, $F(1, 19) = 2.05$, $p = .17$, $\eta_p^2 = .10$; Distractor-Target Coincidence, $F(1, 19) = 1.15$, $p = .30$, $\eta_p^2 = .06$; interaction, $F(1, 19) = .07$, $p = .79$, $\eta_p^2 = .003$. This is consistent with the mean-amplitude approach reported in the main text.

Next, we used a local-peak approach for determining the target-related N2pc within the (180–350-ms; ±20 ms around the peak amplitude) window, in which the most negative peak of the difference waveform was likely to occur according to prior research (Geib et al., 2020; Gokce et al., 2014; Sauter et al., 2017; Zinchenko et al., 2020). An Anova of the N2pc peak amplitudes revealed a significant main effect of Target-Location, $F(1, 19) = 4.27$, $p = .05$, $\eta_p^2 = .18$; but neither the main effect of Distractor-Target Coincidence, $F(1, 19) = .02$, $p = .90$, $\eta_p^2 = .001$, nor the Coincidence × Target-Location interaction, $F(1, 19) = 1.22$, $p = .28$, $\eta_p^2 = .06$, was significant. The N2pc showed a significantly more negative deflection when the target appeared at the frequent (-3.57 µV) vs. a rare location (-1.56 µV). Additionally, the N2pc peak latency for targets that appeared at the frequent location was marginally delayed, by 25 ms, compared to targets that occurred at one of the rare locations, $t(16) = 1.91$, $p = .07$.[10]

Overall, although the local-peak amplitude of the N2pc showed an increase in absolute terms when the target occurred at the frequent vs. a rare location, the N2pc mean amplitude did not differ significantly among the various experimental conditions, whatever analysis approach was adopted. As peak amplitudes are more susceptible to noise, relying on mean amplitudes is a more dependable approach.



Appendix-Fig. B. Target-related N2pc condition-specific mean amplitude (**A**), N2pc local-peak amplitude (**B**), and N2pc latency (**C**). The target-related L-ERPs are plotted as a function of the target location (target at the frequent or a rare distractor location) on (distractor-absent) Trial *n*, dependent on the coincident vs. non-coincident positioning of the target on Trial *n* relative to the distractor on Trial *n–1* (coincidence condition). Error bars depict the one standard SEMs.

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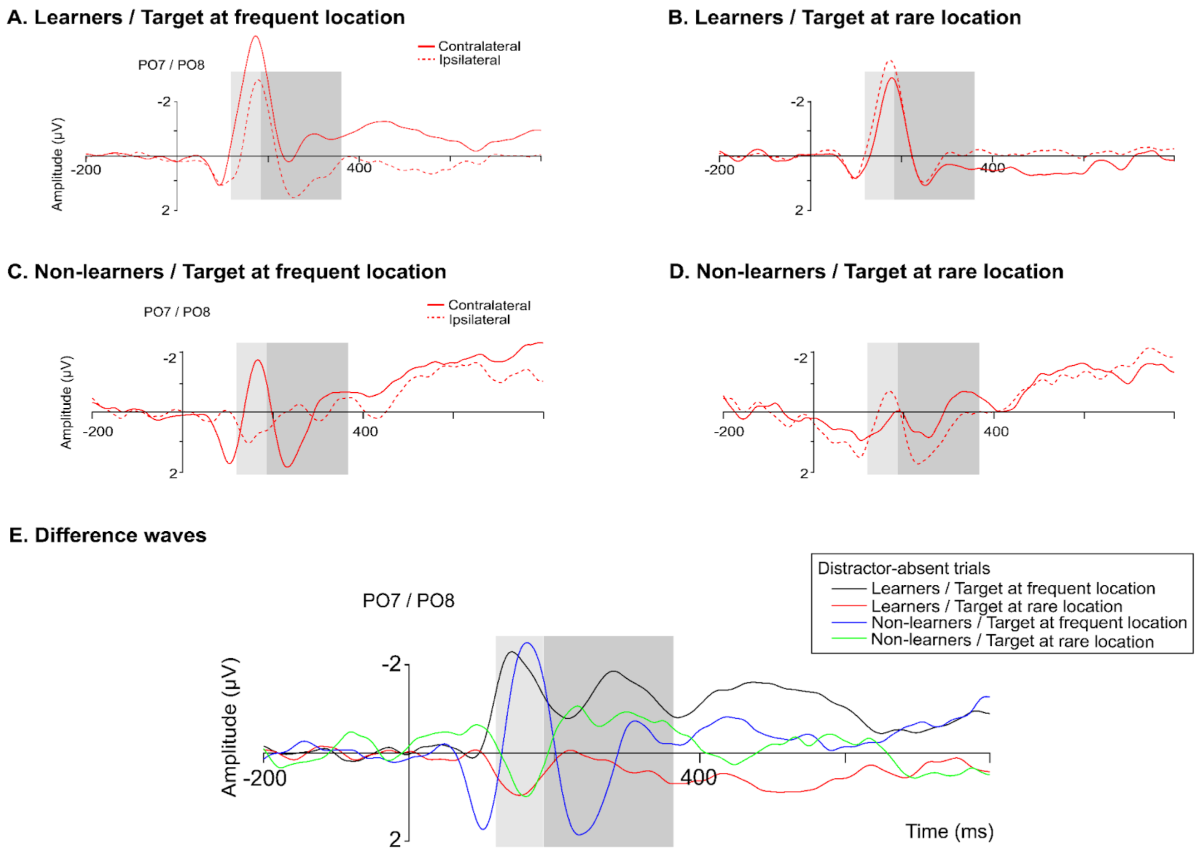
[10] The degrees of freedom were reduced to 16 here, since for three participants, the N2pc peak latency fell at the boundary of either the N1pc time window (180 ms) or the SPCN window (350 ms). Therefore, we excluded the N2pc peak latency data from these three participants as outliers.

Appendix C: Analysis of target-elicited early components for learners vs. non-learners

The absence of an N2pc modulation by statistical learning remains elusive. According to van Moorselaar et al. (2021), the inconsistent outcomes might be attributable to inter-individual differences: for some participants, suppression of the likely distractor location may be driven largely by long-term statistical learning, while for others, short-term inter-trial processes may have a greater influence.

To examine individual differences, here we likewise classified each participant as either a "learner" or "non-learner" based on whether the difference in RTs between the target at frequent and rare distractor locations was greater or equal to/smaller than zero. Thus, 12 participants were identified as "learners" and eight as "non-learners". Our initial analysis focused on determining whether target processing was impaired at either the frequent or the rare location for the "learner" group. As visualized in Appendix-Fig. C, for "learners", the N1pc was significantly negative for targets at the frequent location (simple t-test against 0) $t(11) = -2.34$, $p < .05$; and the Ppc was significantly positive for targets at the rare location, $t(11)= 2.40$, $p < .05$. However, a target-elicited N2pc was observed neither at the frequent location, $t(11) = -1.94$, $p = .08$, nor at the rare location, $t(11)= .77$, $p = .46$.

Subsequently, we included the between-subject factor Group ("learners" vs. "non-learners"), together with the within-subject factor Target Location (frequent vs. rare), to examine whether the N1pc/Ppc and N2pc were selectively elicited by the learners. For the early N1pc/Ppc component, the main effect of Target-Location was significant, $F(1, 18) = 5.11$, $p < .05$, $\eta_p^2 = .22$, simply reflecting the differential polarities of the N1pc for frequent-location and the Ppc the rare-location targets. However, there was no effect of Group: main effect, $F(1, 18) = .68$, $p = .42$, $\eta_p^2 = .04$; interaction, $F(1, 18) = .92$, $p = .35$, $\eta_p^2 = .05$. For the N2pc component, again, we failed to find any effects (all F's < 1.51, all p's > .64). In short, the polarity pattern shown in the N1pc/Ppc was comparable between "learners" and "non-learners". And there was no prominent N2pc for "learners".



Appendix-Fig. C. Grand-average ERP waveforms. Subpanels **A**-B show the *target-related* contra- and ipsilateral waveforms, calculated at electrodes PO7/PO8, from 200 ms prestimulus to 800 ms post-stimulus period for "learners", on distractor-absent trials, the target at the frequent location **(A)** and at the rare location **(B)**. Subpanels **C** and **D** show the *target-related* waveforms for "non-learners", on distractor-absent trials, the target at the frequent location **(C)** and at the rare location **(D)**. The solid lines represent the contralateral waveforms, and the dash lines the ipsilateral waveforms. Panel **(E)** shows the ERP difference waves (contralateral minus ipsilateral) for the four conditions. The light gray and dark gray areas indicate the N1pc/Ppc time window (120–180 ms), and the N2pc time window (180–350 ms), respectively.

2.2 The underlying processes of distractor spatial suppression in volatile environments: Evidence from behavior and oculomotor capture

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The underlying processes of distractor spatial suppression in volatile environments: Evidence from behavior and oculomotor capture

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Abstract

Past selection experience greatly affects the deployment of attention, which enables people to learn to ignore salient distractors frequently occurring at particular locations to reduce attentional capture. Numerous studies on attention have focused on mechanisms that result in stationary-based probability cueing of distractor locations, but much less investigate whether our brain can attenuate distractor interference by learning trial-to-trial transitions of distractor occurrences in a volatile environment. Here, we created two volatile environments where distractor-present trials and distractor-absent trials would alternatively occur in the typical visual search task with different transition probabilities (high-volatility vs. low-volatility), thereby the consecutive distractor-present trials structured with different lengths of subsequent repetitions of distractor location. Our findings show that the high-volatility session resulted in slower response times than the low-volatility session. However, the attentional capture effect measured by the reaction time (RT) cost between distractor presence and absence was larger in the low-volatility session, indicating distractor interference more with search performance in the low-volatility environment. Moreover, distractor interference was significantly reduced with increasing numbers of distractor-repeated in the same location, evidenced by reduced RTs and the proportion of the first saccade to the distractor. We conclude that the across-trial sequences of distractor-repeated locations can attenuate interference in complex and volatile environments.

Keywords: visual search, attentional capture, distractor location suppression, statistical learning, volatility, across-trial regularities, oculomotor capture

1 Introduction

In everyday life, visual search is one of the most essential and ubiquitous tasks wherein we interact with complex and ever-changing surroundings. Such interactions usually involve voluntarily selecting relevant information while filtering task-irrelevant information (Duncan, 1984; Jonides & Yantis, 1988). Theoretically, selective attention processes are guided by endogenous, current goals of the observer (i.e., top-down attentional control; (Egeth & Yantis, 1997; Folk et al., 1992) or exogenous, physical saliences of search stimuli (H. J. Müller et al., 2010; Theeuwes, 2010; i.e., bottom-up control; Yantis & Egeth, 1999). However, there is a growing consensus that a strict dichotomy of attentional control between top-down and bottom-up does not hold, as there is another contributing source: prior experience with lingering attentional biases about past episodes of selection (Anderson et al., 2021; i.e., selection history control; Awh et al., 2012; Kadel et al., 2017; H. J. Müller et al., 2010; Wolfe et al., 2003) also affects the efficiency of current visual search.

Selection history assumes that visual search could be facilitated by exploiting the statistical learning of spatial regularities of objects in the environments (Chun & Jiang, 1998; Theeuwes, 2018). For instance, if you frequently visit a particular shopping mall, it may become easier to find desired items in the areas you have visited before and avoid distracting advertisements on the way. The (implicit) process, known as the 'probability cueing effect' (Geng & Behrmann, 2002, 2005), involves prioritizing attention to locations where task-relevant information is often found based on learned spatial patterns. An eye-tracking study has shown that eye movements were more likely to land on the target when it appeared at a frequent location than other locations in the search display (Walthew & Gilchrist, 2006). More recently, studies have emerged that people can also use past experience with the spatial distribution of irrelevant but salient singleton distractors to de-prioritize those locations and minimize interference (Gao & Theeuwes, 2019; Goschy et al., 2014; Leber et al., 2016; Sauter et al., 2018; B. Wang & Theeuwes, 2018). In typical distractor-location probability cueing experiments, people can use their prior experience with uneven spatial distributions of distractors to reduce the attentional capture of statistical learning about distractor locations, resulting in faster reaction times (RTs) when a salient singleton distractor is more likely to appear at a specific location with high probability compared to other locations with low probability. Most studies on statistical learning have focused on spatial regularities of feature-based targets and distractors (e.g., one location or color being more likely compared to others), while fewer studies have examined the extent to which the visual system can bias attention across trials based on statistical learning of visual temporal sequences (e.g., the location of a distractor on one trial predicting its location on the next trial or(e.g., trial-to-trial transitions of distractor locations where the location of a distractor on Trial *n-1* predicts its subsequent location on Trial n, mentioned in a review of Theeuwes et al. 2022). The latter case is the focus of our current work to gain more insight into how statistical learning of across-trial sequences of distractor locations can attenuate the impact of distractors.

Recently, Yu et al. (2022) have shown the ability of participants to extract trial-to-trial statistical learning of target locations. Participants had to respond to a shape-defined singleton target among seven other items in this visual search task. The target could appear at any of eight locations with equal probability, but researchers manipulated the location of the target across trials by following clockwise or counter-clockwise in 80% of the trial, and randomly placing the target in the nonregular condition. The results suggested that across-trial regularities affected attentional selection: faster RTs for the dynamic predicted trials than non-predictable trials. However, such dynamic regularity for a singleton distractor failed to form any proactive suppression. Another study by Bogaerts et al. (2022) found that manipulating the frequency of color singleton distractors over a longer time scale can reduce the impact of distractors on attentional capture. Specifically, repeating identical four-trial sequences of distractors (e.g., "P-A-P-A" or "A-A-P-P") was more effective at reducing attentional capture in the high-frequency condition (i.e., three to nine distractor-present filler trials between four-trial sequences) than in the low-frequency condition (i.e., distractor-absent filler trials). EEG studies have shown that repeating distractor locations in across-trial sequences can help the brain resolve attentional capture. For instance, van Moorselaar and Slagter (2019) found that repeating distractors at the same location in subsequences over 1 to 12 trials resulted in reduced reaction times and a repetition-related reduction in the Pd component, as measured by EEG. Other studies have also shown that repeating target or distractor properties (such as location or features) on consecutive trials can improve visual search performance (e.g., Allenmark, Gokce, et al., 2021; Geyer et al., 2006; Kabata & Matsumoto, 2012; Maljkovic & Nakayama, 1994, 1996; Won et al., 2019). Likewise, these intertrial repetition effects have been explained by selection history theories, which propose that visual search can be facilitated not only by the statistical learning of stimuli, but also by the intertrial repetition priming of stimulus properties in the environment (Kadel et al., 2017; Sauter et al., 2018; Theeuwes, 2018). Particularly, in terms of the distractor suppression modulations, a similar demonstration has also been proposed by Goschy and colleagues

(2014), who showed the probability cueing effect (for distractor locations) would be attributable to both statistical learning of spatial distractor locations and intertrial facilitation due to distractor location repetitions on consecutive trials.

Consequently, in line with recent studies (Ferrante et al., 2018; Liesefeld & Müller, 2019; Turatto & Valsecchi, 2022; Valsecchi & Turatto, 2021; van Moorselaar & Slagter, 2019; e.g., B. Wang & Theeuwes, 2018; Zhang et al., 2019), we propose that distractor-location probability cueing reflects the modulation of spatial priority maps. The reduced interference regarding the most probable location of a distractor would attenuate the weight of saliency signals at this specific location in attentional-priority computations and thus reducing attentional capture, termed *proactive* distractor-location suppression (Geng, 2014; Luck et al., 2021; Sauter et al., 2021; Theeuwes et al., 2022); Alternatively, there is also a mechanism of *reactive* suppression implies that if a distractor captures attention, its location needs to be suppressed ‘reactively’ on consecutive trials so as to disengage attention from the distractor and reallocate it to the target location, and this carry-over suppression was gradually adjusted on a trial-by-trial basis and eventually affect priority maps so that it gave rise to lower costs in search performance (Allenmark, Shi, et al., 2021; Geng, 2014; Theeuwes & Failing, 2020; Won et al., 2019). In other words, observers would be better able to actively suppress distractors occurring at spatial locations that in the past had been repeatedly associated with salient irrelevant events and quickly reorient attention to the target items. Previous research has shown that the attentional weight (i.e., the level of neural activity determining the processing efficiency within the corresponding input module) allocated to task-relevant and task-irrelevant features carry over to subsequent trials in an automatic manner (Feldmann-Wüstefeld & Schubö, 2016; H. Müller et al., 2004). These changes reflected the dynamic activation and adjustment of spatial priority maps, or neural representations of the visual field throughout networks of cortical and subcortical nodes that exhibit properties of priority maps of space (e.g., frontal eye field, lateral intraparietal area, inferotemporal cortex, the superior colliculus) and indirectly (via the aforementioned nodes) in lower-order areas with the strong retinotopic organization (Hikosaka et al., 2000; Theeuwes et al., 2022; Zhang et al., 2022).

So far, our discussion of distractor suppression patterns merely focused on a stationary likely distractor location based on statistical learning and simple intertrial repetitions such that de/prioritization at a given location was easily described through local weight changes in a priority map. In fact, real visual environments are much more dynamic and volatile, as is the account of the Predictive-coding framework of perception (Friston, 2010; Friston & Kiebel, 2009): the brain continually makes predictions, based on prior knowledge, about the environmental causes of the sensory inputs it receives. If a discrepancy between the top-down prediction and the actual sensory input (i.e., a prediction error) occurs, the brain attempts to reduce this mismatch by integrating the top-down prior information and the sensory input and adjusting its internal generative model accordingly. Previous studies showed that learning speed can depend on the volatility of the environment: a highly volatile environment where unexpected uncertainty caused by changes of different contingencies may be more difficult to predict a distractor in a given context (Behrens et al., 2007; Ferrari et al., 2022; Jungerius et al., 2022). For instance, in larger set-size search displays (i.e., larger contextual uncertainty), less precision or weight may be given to sensory input, and predictable distractors cease to capture attention when increased contextual volatility in the higher set-size displays (Slagter and van Moorselaar; Jungerius et al. 2022). Additionally, some studies supposed that the priority maps could be tuned flexibly across trials by continuously adjusting weights, which dynamically controls the deployment of covert attention and gaze (Theeuwes et al., 2022; L. Wang et al., 2021).

For instance, observers did learn across-trial target-target regularities to facilitate search, even when the search task changed dramatically from a parallel search mode (i.e., searching for a red T-target among gray Ls displays) to a serial search mode (i.e., searching for a gray T-target among gray Ls displays). This indicates a flexible priority map, whereby the selection of a predicted location results in the up-weighting of that location on the next trial, even when the search task changes significantly (Li et al., 2022). However, while such across-trial statistical learning for sequence pairs suggests a flexible priority map of attentional selection that can up-weight or down-weight predicted locations based on past experience, little is known about how the volatility of the overall search environment can influence the speed of learning of distractor inhibition.

To date, however, less evidence tells us whether we can adaptively adjust learning rates of distractor suppression based on environmental volatility. This issue is a well noteworthy aspect of the experience-driven attention topic, and moreover, whether our brains are able to learn across-trial sequences of distractor locations in more complex volatile environments. In the current study, we specifically set out to examine the influence of environment volatility on the statistical learning of distractor locations to minimize the attentional capture by salient distractor singleton. To do this, we used the Markov-chain function (Hamilton, 1990) and the classical visual search paradigm (Goschy et al., 2014) to create a high- and a low-volatility environment, which differed in terms of the frequency of alternation between distractor-present and distractor-absent trials in the search display. This resulted in consecutive distractor-present trials with different lengths of subsequent repetitions (i.e., 0, 1, 2, 3, 4, and above times) of distractor location. We manipulated the probability of repeating the same distractor state ("present" or "absent") from one trial to the next, with a 30% probability in the high- and 70% probability in the low-volatility session, See *Method* section for details. To better understand overt attentional selection, we examined oculomotor capture and disengagement during the visual search task, as the attentional and oculomotor systems are known to be associated (Deubel & Schneider, 1996; McPeek et al., 1999; B. Wang et al., 2019).

Given this, this experiment was designed to examine (1) whether salient distractors capture attention and whether volatile environments affect the learning speed of distractor suppression; (2) Crucially, whether observers can also make use of local trial-to-trial regularities of distractor locations to reduce attentional capture. If so, the longer subsequence of distractor location repetitions increasingly speeded up RTs, with more first saccades towards the target and/or shorter dwell times to the distractor due to decreasing the interference of the distractor at this location. Also, if this were the case, distractors in the global low-volatility environment should cause less interference compared to distractors in the global high-volatility environment; (3) Since the volatile environment caused by contextual contingencies when the distractor states changed, it would generate switching costs at the beginning of a new context period (Ferrari et al., 2022; Koch, 2008; Lien & Ruthruff, 2008). This study aimed to investigate whether distractor suppression effects can be implemented through inter-trial transitions of distractor states. It was hypothesized that search performance would be better when the distractor did not switch conditions from Trial *n-1* to Trial *n* (i.e., AA, PP), as there is an advantage to repeating the same state across trials. In contrast, it was expected that search performance would be slowed when the distractor switched conditions from Trial *n-1* to Trial *n* (i.e., AP, PA), as the transitional states across trials may impair target selection processing.

2 Methods

2.1 Participants.

We recruited 24 healthy adults (age range: 18-40 years, mean age = 26.5 years,12 females and 12 males) to take part in two experimental sessions (i.e., high-volatility and low-volatility). Using G*Power (Faul et al., 2007), sample size was predetermined based on the effect size of significant distractor suppression (i.e., the significant difference between high-probability and low-probability location) based on Wang and Theeuwes (2018), with an effect size of 1.83, alpha = .001, and power for the critical effect should be > 0.99, yielded a sample size of 16 participants. We increased to 24. All participants reported normal or corrected-to-normal vision. They gave prior informed consent and received course credits or financial reimbursement (9 € per hour) for their participation. The study was approved by the ethics committee of the Department of Psychology and Pedagogics at LMU.

2.2 Apparatus and Stimuli

The experiment was performed in a dimly lit, sound-attenuated, and electrically shielded experimental cabin. Movements of the dominant eye of participants were monitored using an Eyelink 1000 desktop-mounted system (SR Research, Canada), set at a sampling rate of 1 kHz. Stimulus generation, response recording, and eye-movement sampling were controlled via a customized Matlab program using the Psychtoolbox and the Eyelink Toolbox based on the MATLAB R2019b environment (Brainard, 1997). Stimuli were presented on a VIEWPixx/3D (VPixx Technologies Inc., Saint-Bruno, QC Canada) 24-inch monitor (diagonal) with 1920×1080 pixels resolution at a refresh rate of 120 Hz. Responses were collected via the computer keyboard. A chin-rest was used to set the viewing distance at approximately 65 cm from the monitor.

For each trial, stimuli were gray bars (0.18 × 0.81°) against a black background (RGB = 0 0 0). Each bar contains a notch (~0.25° in height) in its upper or lower part, and the position of the notch is random and balanced within each block (Figure. 1A). Search displays consisted of 40 bars arranged around four concentric circles (radii of 1.1°, 2.2°, 3.3°, and 4.4°, respectively) centered on the fixation cross. Most of the bars (homogenous background / non-targets) were vertical (0°) in orientation and at 20% (of maximum) intensity in luminance. The target was tilted by 12° to the right and presented at non-target intensity. The orientation distractor was tilted 45° to the left, with two notches and at non-target intensity. Targets and distractors always appeared at 8 possible locations of the second concentric circle (Figure. 1A).

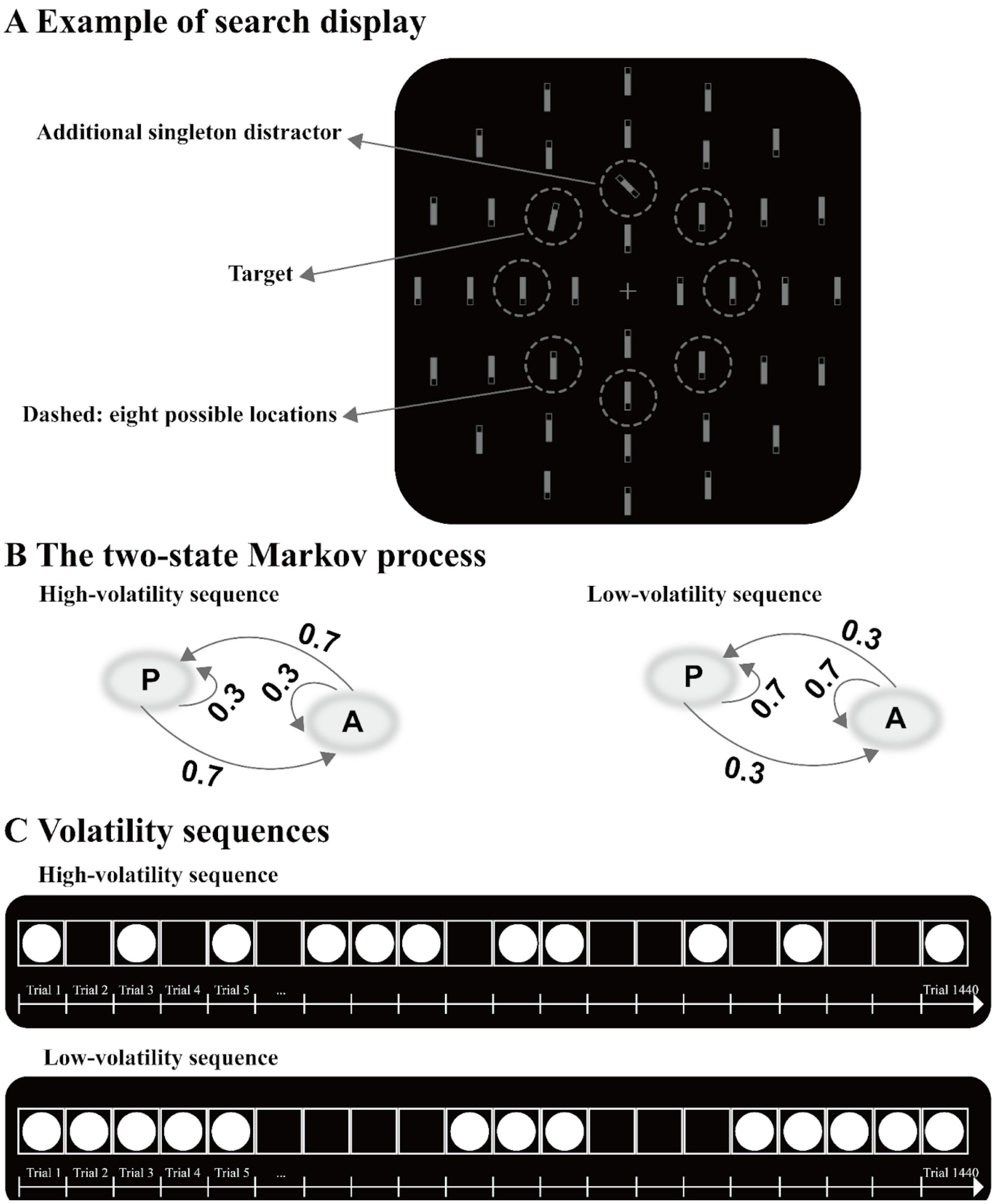

Figure. 1. Search displays and volatility sequences. **A.** Observers had to find a bar tilted 12° to the right and indicate the position of the notch (top or bottom) on the (orientation) target bar. In some trials, the displays additionally contained a 45°-tilted (same-dimension as the orientation-defined target) distractor. Distractors were

always completely irrelevant and should therefore ideally be ignored. Targets and distractors could appear at one of eight locations on the second ring layer. **B.** The two-state Markov process (high-volatility vs. low-volatility) is based on if the distractor is present or absent across trials. It represents the relationship between the distractor on Trial *n* and the distractor on Trial *n-1*: 'present-present', 'present-absent', 'absent-present', and 'absent-absent', respectively, abbreviated as 'PP', 'PA', 'AP', and 'AA', correspond with different transition probability. **C.** The trial sequence of high-volatility and low-volatility sessions. Every participant completed each of the two sessions (with a time interval of 5-7 days in between). The trial sequences were randomly generated by the Markov switching model. In a sequence, the squares represent trials, and a white disk inside a square means the distractor was present, while an empty black square means the distractor was absent in the search display.

2.3 Design

2.3.1 Session 1 (spatial bias on high-volatility distractor) design

In the current study, we manipulated the volatility chain between 'distractor absent' and 'distractor present' states via the 'Markov-chain' package in R. The volatility chain denoted a sequence of states from a given discrete Markov-chain. That is to say, the whole sequence of 1440 trials was used as a finite number of values, with a fixed 2 × 2 transition probability matrix, *P*. The 'distractor absent' state represents the search display containing no distractor (which occurred on 1/2 of all trials), and the 'distractor present' state means the search display contained a distractor (the remaining 1/2 of all trials). The state variable s_n of trial *n* is assumed to evolve according to the two-state Markov-probability transition matrix between trial *n* and trial *n-1*. For example, the probability of being in state 1 at trial *n* decided by state 1 obtained at trial *n-1* equals p_{11}, as notationally shown below,

$$\begin{aligned} p(s_n = 1 \mid s_{n-1} = 1) &= p_{11} \\ p(s_n = 2 \mid s_{n-1} = 1) &= 1 - p_{11} \\ p(s_n = 1 \mid s_{n-1} = 2) &= 1 - p_{22} \\ p(s_n = 2 \mid s_{n-1} = 2) &= p_{22} \end{aligned}$$

These conditional probabilities are collected together into the transition matrix, *P*, such that,

$$P = \begin{bmatrix} p_{11} & 1 - p_{22} \\ 1 - p_{11} & p_{22} \end{bmatrix}$$

In the high-volatility session, state '1' equals the 'distractor present' condition, state '2' equals the 'distractor absent' condition. The fixed transition probabilities for each condition: p_{11} = 0.3, 1- p_{11} = 0.7, p_{22} = 0.3, and 1- p_{22} = 0.7, according to our previous probability cueing studies (cites). Therefore, there are four types of inter-trial switching conditions based on distractor states across trials to represent the relationship between the distractor on trial *n* and the distractor on trial *n-1*: 'present-present', 'present-absent', 'absent-absent', and 'absent-present', respectively, abbreviated as 'PP', 'PA', 'AA', and 'AP', with the corresponding Markov-probabilities p_{11} = 0.3, 1- p_{11} = 0.7, p_{22} = 0.3, and 1- p_{22} = 0.7, resulting in the high-volatility sequence (Figure. 1B). In the current study, we randomly draw from one different high-volatility sequence for each participant, each generated by the general Markov switching model (Figure. 1C).

In the whole high-volatility sequence, there are different lengths of subsequence including only distractor present displays. That is, in the subsequences of distractor present displays, the distractor was repeated at the same location on several consecutive trials. Since each randomly generated high-volatility sequence has a different count of subsequence lengths, we did not use any randomly generated sequence, only those that fulfilled certain constraints, where the constraints were related to how many times distractor present subsequences of different lengths (...APA..., ...APPA..., ...APPA..., etc) occur in the sequence. In the current study, we analyzed the length of distractor-repeat subsequences as 0, 1, 2, and 3 trials to establish whether repetition of distractor location could modulate the attentional capture. To get enough repetitions of subsequences of different lengths, we will ensure that each high-volatility sequence included 350-359 sets of 1-trial distractor-repeat subsequence, 100-109 sets of 2-trial distractor-repeat subsequence, and 31-39 sets of 3-trial distractor-repeat subsequence. Participants completed 80 (non-analyzed) practice trials followed by 9 blocks of 160 trials each in the formal study, thus yielding 1440 analyzed trials that matched the high-volatility sequence overall.

2.3.2 Session 2 (spatial bias on low-volatility distractor) design

In the low-volatility session, we used the same design as in Session 1 except that the transition probability of inter-trial switching conditions is different. That is, in the low-volatility environment, state '1' equals the 'distractor present' condition, and state '2' equals the 'distractor absent' condition. The relationship between the distractor on trial *n* and the distractor on trial *n-1*: ‘present-present’, ‘present-absent’, ‘absent-absent’, and ‘absent-present’, respectively, abbreviated as ‘PP’, ‘PA’, ‘AA’, ‘AP’, correspond with the Markov-probability $p_{11} = 0.7$, $1 - p_{11} = 0.3$, $p_{22} = 0.7$, $1 - p_{22} = 0.3$, resulting in the low-volatility sequence (Figure. 1B). In the current study, we randomly draw from a separate low-volatility sequence for each participant, each generated by the general Markov switching model, and we kept each low-volatility sequence including 51-59 sets repeated 1-trial subsequence, 50-58 sets repeated 2-trial subsequence, and 31-51 sets repeated 3-trial subsequence (Figure. 1C).

2.4 Procedure

Participants performed a classic visual search task in which they had to find the target (a bar tilted 12° to the right) on every trial and indicated the orientation of the notch (top or bottom) inside it by pressing a mouse button with either their right or left thumb. Participants were instructed to fix their eyes at the fixation cross as soon as possible once they finished searching for the target on the display.

Every trial began with the presentation of the fixation cross randomly 0.8 to 1.6s. After that, the visual search display was shown until a response or 4s (maximum). Participants were told to respond as fast as possible without sacrificing accuracy. In case of an incorrect or delayed response, the fixation cross changed color for 1s, turning red if the answer was wrong and, respectively, blue if it was too slow. The inter-trial intervals, which contained the fixation cross, jittered randomly at 0.8 to 1.6s before the start of the next trial.

After finishing two sessions of the experiment, participants were asked the awareness question, “Do you think the irrelevant tilted-left 45-degree bar changes the location more frequently from trial to trial?” Given 5 options: (1) The irrelevant bar changed its present location more frequently in Session 2 than in Session 1. (2) The irrelevant bar changed its present location more frequently in Session 1 than in Session 2. (3) In both Sessions 1 and 2, the location of the irrelevant bar did not change obviously in consecutive trials. (4) In both Sessions 1 and 2, the location of the irrelevant bar frequently changed in consecutive trials. (5) Unsure. In total, eleven participants answered 'Unsure', three selected the fourth option, and three selected the third option. Of note, seven participants selected the first or second option, 6 of them answered wrong, and only one participant answered correctly, but we excluded this participant because the eye-tracking dataset couldn't be transformed.

3 Results

3.1 Manual response times

3.1.1 Distractor interference on RTs

All RTs analyses were performed on the group mean response times after excluding trials on which participants made an incorrect response and outliers defined as RTs outside 1.5 interquartile differences above the third or below the first quartile of the respective RT distribution (approximately 8.7% of all trials on average).

To examine the distractor interference effect in different volatility environments, we conducted a 2 (Distractor Condition: absent vs. present) × 2 (Volatility Type: high vs. low) repeated-measures ANOVA on RTs. The Distractor Condition main effect showed that search with the singleton distractor present significantly slowed down RTs, relative to the distractor absent condition (1115 ms vs. 958 ms), $F\,(1, 20) = 178.07, p < .001, \eta_p^2 = .90$. Also, the main effect of Volatility Type was significant, $F(1, 20) = 4.15$, $p = .05$, $\eta_p^2 = .17$, suggesting the high-volatility environment with distractors that caused slower search performance, compared to the low-volatility environment (1075 ms vs. 983 ms), see Figure. 2A. No interaction effect: $F(1, 20) = .68$, $p = .42$, $\eta_p^2 = .03$. Of note, a 2 (Distractor Condition: absent vs. present) × 2 (Volatility Type: high vs. low) repeated-measures ANOVA on error rates revealed the main effect of Volatility Type to be significant, $F(1, 20) = 6.83, p < .05$, $\eta_p^2 = .25$, which was consistent with the RTs result. But neither the main effect of Distractor Condition, $F(1, 20) = .71, p = .41$, $\eta_p^2 = .03$, nor the interaction effect: $F(1, 20) = .89, p = .37$, $\eta_p^2 = .04$.

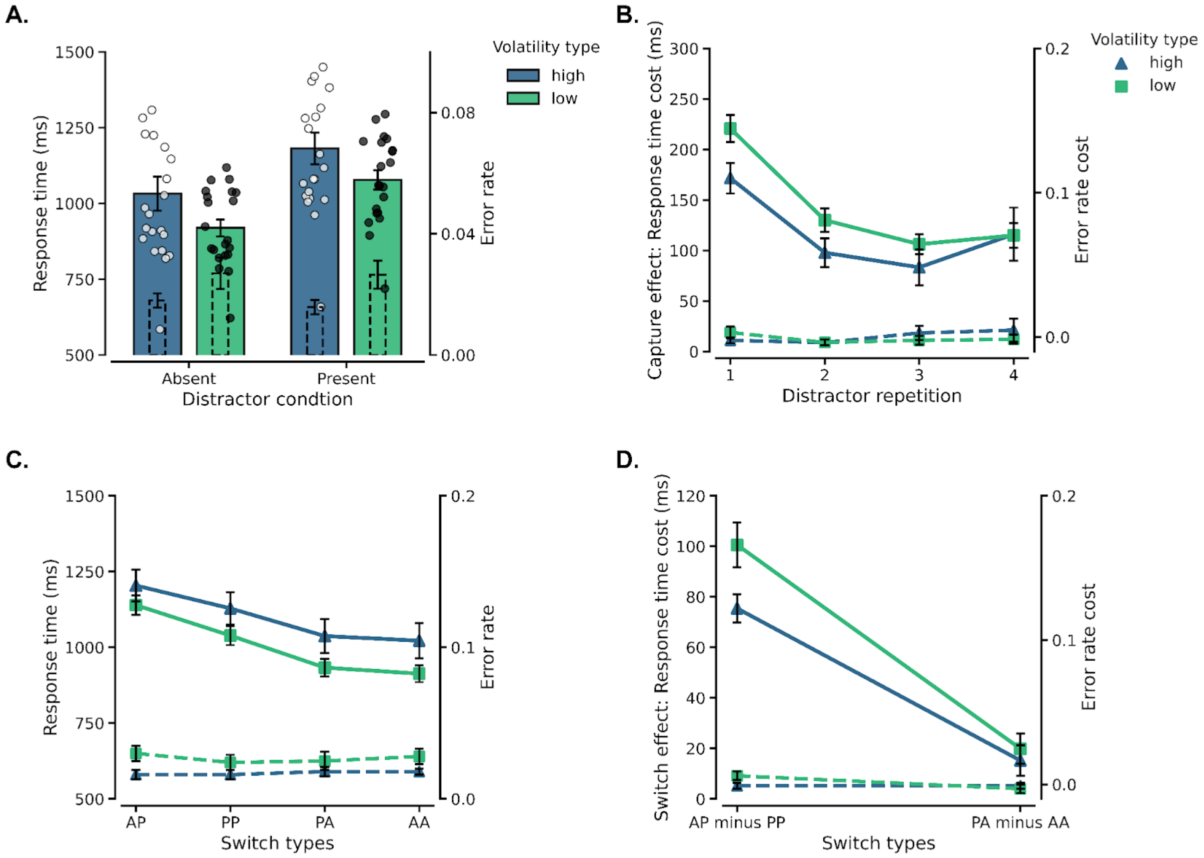

Figure 2. Manual results. (A) Mean RTs and error rates (dashed bars) as a function of Distractor Condition (x-axis; absent vs. present) and Volatility Type (high vs. low). **(B)** Mean RTs and error rates (dashed lines) on distractor-present trials, as a function of Distractor Repetition and Volatility Type. Line plots showing the benefits of distractor location repetition in four subsequences (i.e., repetition 1, repetition 2, repetition 3, and repetition 4) contrasted to distractor-absent trials for the high-volatility and low-volatility sessions. **(C)** Mean RTs and error rates for Switch Type: AA, AP, PA, and PP, separately for the Volatility Type (high vs. low). **(D)** Mean RTs cost and error rates cost as a function of Volatility Type (high vs. low) × Switch-cost ('AP minus PP' vs. 'PA minus AA'). Error bars depict the one standard error of the mean.

3.1.2 Distractor-repetition inhibition effect on RTs cost

After establishing that the averaged RTs were significantly overall longer in the high-volatility session relative to the low-volatility session, we explored whether the size of the attentional capture effect would decrease for each subsequence of distractor repetition in different volatile environments. Given this, we investigated the impact of volatility conditions on distractor-present subsequences in more detail. That is, we calculated the cost in RTs due to distractor presence (i.e., the difference in RTs between the distractor-present and the distractor-absent conditions) was calculated in four different subsequences where distractors repeated at the same location on consecutive trials (i.e., repetition 1, repetition 2, repetition 3, and repetition 4).

Following this rationale, we conducted an ANOVA with the Distractor Repetition subsequences (repetition 1, repetition 2, repetition 3, and repetition 4) and the Volatility Type (high- vs. low-volatility) as factors. The main effect of Distractor Repetition, $F(3, 60) = 33.01$, $p < .001$, $\eta_p^2 = .62$. As visualized in Figure. 2B, RTs cost for repetition 1 was greater than, repetition 2, repetition3, repetition 4, respectively, and RTs cost for repetition 2 was greater than repetition 3 (all t values > 2.60, all p values < .05, Bonferroni–Holm corrected). It demonstrated that the attentional interference was more attenuated when the distractor location was more repeated. That is, the distractor was more repeated at a particular location on consecutive trials, and RTs were faster. The main effect of Volatility Type was significant, $F(1, 20) = 4.15$, $p = .05$, $\eta_p^2 = .20$. There is a larger RT cost with distractors in the low- compared to the high-volatility environment. But this did not interact with the two factors, $F(3, 60) = 2.40$, $p = .08$, $\eta_p^2 = 0.11$.

3.1.3 Inter-trial Switch-cost effect on RTs cost

In addition, we looked at the inter-trial transitions when the distractor switched the states between distractor absent and distractor present conditions. The rationale is as follows: (1) if the distractor didn’t switch the condition from Trial *n-1* to Trial *n* (i.e., AA, PP), the response performance would be better since there was an advantage of repeating the same state across trials. (2) if the distractor did switch the condition from Trial *n-1* to Trial *n* (i.e., AP, PA), the response performance would be slowed down since the transitional states across trials probably impaired target selection processing. To better understand the transitional inhibition effect, we calculated RTs cost for the two types of switch conditions: 'AP minus PP', and 'PA minus AA'. An ANOVA on Volatility Type (high- vs. low-volatility) × Switch-cost ('AP minus PP' vs. 'PA minus AA') of RTs cost revealed two main effects to be significant: the main effect Volatility Type, $F(1, 20) = 10.55$, $p < .05$, $\eta_p^2 = 0.35$; the main effect of Switch-cost, $F(1, 20) = 148.35$, $p < .001$, $\eta_p^2 = 0.88$; but a non-significant interaction effect between Volatility Type and Switch-cost: $F(1, 20) = 3.58$, $p = .07$, $\eta_p^2 = 0.15$. RT costs were increased in the low-volatility than the high-volatility environment (60.21 ms vs. 45.31 ms), and RTs cost was higher in the 'AP minus PP' condition compared to the 'PA minus AA' location (88 ms vs. 17.52 ms), see Figure. 2C-D.

3.2 Eye movements

Attentional capture and Distractor-repetition suppression effects

3.2.1 First saccades to the target

Previous eye-movement studies have found that fast saccades initiated soon after search display onset are more likely to be directed toward salient items (Di Caro et al., 2019; van Zoest et al., 2004). Accordingly, we first examined whether distractors interfered with visual detection after the search array onset, measured by oculomotor capture in terms of the likelihood with first saccades on the target on distractor-present and -absent trials. Figure. 3A depicts the proportion of first saccades on the target as a function of the Distractor Condition (absent vs. present), separately for the two types of Volatility (high- vs. low-volatility). A repeated-measures 2 × 2 ANOVA revealed the significant main effect of the Distractor Condition, $F(1, 20) = 43.54$, $p < .001$, $\eta_p^2 = 0.69$. Indeed, the proportion of first saccades landed on the target was very high when the distractor was absent (51%), but it decreased significantly when the salient distractor was present (28.5%), suggesting that there was a generalised detrimental effect on target-directed saccades, reducing the percentage of initial saccades landed on the target due to the distractor appearance. But neither the main effect of Volatility Type, $F(1, 20) = 2.22$, $p = .15$, $\eta_p^2 = 0.10$, nor the interaction effect of Distractor Condition × Volatility Type, $F(1, 20) = 2.78$, $p = .11$, $\eta_p^2 = 0.12$, was significant.

Second, we were interested in understanding whether attentional capture was modulated by distractor location repetitions to give rise to significant suppression effects in oculomotor capture, so that facilitating manual responses in subsequences in which distractors appeared at the same location across consecutive trials to attenuation interference. As visualized in Figure. 3D, these values were then submitted to a 2 × 4 ANOVA, with the Distractor Repetition subsequences (1–4) and Volatility Type (high- vs. low-volatility) as statistical factors. The main effect of Distractor Repetition is significant, $F(3, 60) = 23.76$, $p < .001$, $\eta_p^2 = 0.54$, suggesting that the proportion of first saccades landing on the target increased after the repeated appearance of the distractor at the same location across consecutive trials, due to decreasing the interference of distractor at this location. Neither the main effect of Volatility Type, $F(1, 20) = 0.98$, $p = .33$, $\eta_p^2 = 0.05$, nor the interaction effect of Distractor Condition × Volatility Type, $F(3, 60) = .22$, $p = .80$, $\eta_p^2 = .01$, was significant.

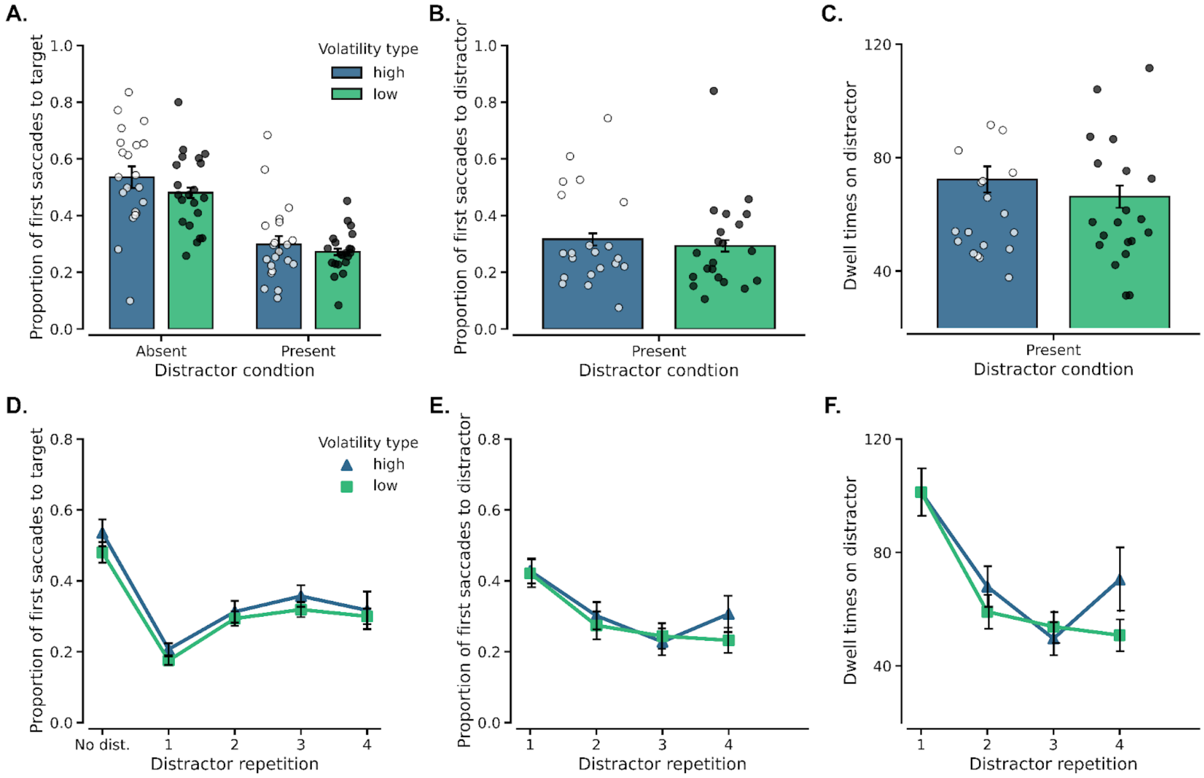

Figure 3. Eye movements results. (A & D) Proportion of first saccades to the target when the target was presented in the high- vs. low-volatility sessions and when the distractor was on conditions (absent vs. present); the x-axis of line plots showed the distractor location repetition in five subsequences (i.e., distractor absent, repetition 1, repetition 2, repetition 3, and repetition 4). **(B & E)** Proportion of first saccades to the distractor when the distractor was present in the high- vs. low-volatility sessions; the x-axis of line plots showed the distractor location repetition in four subsequences (i.e., repetition 1, repetition 2, repetition 3, and repetition 4). **(C & F)** Dwell times when the distractor was presented in the high- vs. low-volatility sessions; the x-axis of line plots showed the distractor location repetition in four subsequences (i.e., repetition 1, repetition 2, repetition 3, and repetition 4). Error bars depict the one standard error of the mean.

3.2.2 First saccades to the distractor

In order to reveal directly whether the learned suppression effect from distractor location repetitions would emerge on eye movements, we computed the proportion of first saccades directed toward the distractor. A 2 × 4 ANOVA was conducted on these values, with the Distractor Repetition subsequences (1–4), and Volatility Type (high- vs. low-volatility) as statistical factors, see Figure. 3B&E. The main effect of Distractor Repetition was significant, $F(3, 60) = 34.57$, $p < .001$, $\eta_p^2 = 0.63$. It revealed that if the salient distractor was present, the number of first saccades landing on the distractor decreased when the distractor repeatedly appeared at the same location across consecutive trials, suggesting that the distractor captured attention less when reappearing in the same location as on previous trials. The main effect of Volatility Type was not significant, $F(1, 20) = 1.51$, $p = .23$, $\eta_p^2 = 0.07$. But the interaction effect of Distractor Condition × Volatility Type, $F(3, 60) = 3.42$, $p = .04$, $\eta_p^2 = .15$, was significant, showing a lower percentage of first saccades landed on the distractor at repetition 2–4 relative to repetition 1, respectively [$t(19) = 6.38$, $p < .001$, $d = .82$; $t(19) = 7.82$, $p < .001$, $d = 1.03$; $t(19) = 6.28$, $p < .001$, $d = 1.10$, Bonferroni-Holm corrected] in the low-volatility environment, and also a lower percentage of first saccades landed on the distractor at repetition 2–3 relative to repetition 1 subsequence, respectively, in the high-volatility environment [$t(19) = 5.19$, $p < .001$,$d = .75$, $t(19) = 8.12$, $p < .001$, $d = 1.19$, Bonferroni-Holm corrected]. Together, these findings showed that the learned distractor suppression effect was a spatial trial-by-trial basis suppression in distractor-present displays, and this effect was more pronounced in low-volatility session from the subsequence repetition 1 to repetition 4, but only from the subsequence repetition 1 to repetition 3 in high-volatility session.

3.2.3 Attention dwell times on the distractor

Interestingly, this distractor suppression effect described above was also observed in the pattern of attentional dwell times. This eye movement indicator allowed us to check whether the reduction of distractor interference may be driven by rapid disengagement from the distractor location learning repeatedly in subsequences, we expected that dwell times (durations) of first saccades on the distractor would be shorter when the length of subsequence was longer. Therefore, dwell times fixated on the distractor were also evaluated via a 2 × 4 ANOVA with the Volatility Type (high vs. low) and Distractor Repetition (1–4), see Figure. 3C&F. It yielded a significant main effect of Distractor Repetition, $F(3, 60) = 40.89$, $p < .001$, $\eta_p^2 = 0.67$, suggesting that there were shorter dwell times accompanied by increasing the length of distractor location repetitions from 1 to 4 times, but no a significant main effect of Volatility Type, $F(1, 20) = 2.83$, $p = .11$, $\eta_p^2 = .12$. An interaction effect of Distractor Repetition × Volatility Type, $F(3, 60) = 4.29$, $p = .03$, $\eta_p^2 = .18$. Further, paired *t*-tests confirmed that the reduced dwell times were specific to the same distractor repetition conditions as obtained suppression effects from the first saccades to the distractor. That is, there were faster dwell times of first saccades fixated on the distractor at repetition 2–4 relative to the repetition 1 subsequence, respectively [$t(19) = 8.12, p < .001, d = 1.26$; $t(19) = 8.75, p < .001, d = 1.44$; $t(19) = 6.86, p < .001, d = 1.54$] in the low-volatility environment; and also shorter dwell times landed on the distractor at the repetition 2–3 relative to repetition 1 subsequence, respectively, [$t(19) = 6.25, p < .001, d = .93$, $t(19) = 9.66, p < .001, d = 1.56$] in the high-volatility environment. Thus, dwell times analyses showed that distractor location repetitions resulted in first saccades to the distractor being indeed shorter significantly when the length of distractor repetition subsequences increased from 1 to 4 times. These results were associated with faster attentional and oculomotor disengagement.

Volatility effect

As described above, behavior results have already shown that the high-volatility environment with the salient intervening distractor caused slower search performance relative to the low-volatility environment. We were especially interested in any effects of environmental volatility on task-relevant processing.

3.2.4 Total number of fixations

Consistently with what emerged from the analysis of manual RTs, a 2 × 2 ANOVA for the Distractor Condition (distractor-absent, distractor-present) × Volatility Type (high vs. low) on the average number of fixations showed that participants required overall fewer eye movements to acquire the response-critical target information in the low-volatility environment compared to the high-volatility environment (fixations: 2.41 vs. 2.75), $F(1, 20) = 4.81, p < .05, \eta_p^2 = .19$; it also showed that more items were fixated before the response in the distractor present condition, consistent with attentional capture by the salient distractor (2.85 vs. 2.31 fixations), $F(1, 20) = 4.04, p = .058, \eta_p^2 = .17$; no interaction effect: $F(1, 20) = 2.93, p = .10, \eta_p^2 = .13$, see Figure. 4A. Further, the volatility effect was strongly held when we ran a 2 × 4 ANOVA that was similar to the one described above, with the factors of Volatility Type (high vs. low) and Distractor Repetition (1–4), see Figure. 4D. Both main effects of Volatility Type and Distractor Repetition were significant, $F(1, 20) = 6.24, p < .05, \eta_p^2 = .24$, $F(3, 60) = 9.32, p < .001, \eta_p^2 = .32$, respectively. The latter repetition effect indicated clearly that in both volatility sessions, participants needed fewer eye movements to arrive at a response decision when the distractor location was repeated 2–4 times, relative to om the first repetition, respectively [$t(19) = 4.37$, $p = .001$, $d = .32$; $t(19) = 6.07$, $p < .001$, $d = .47$; $t(19) = 2.80$, $p < .05$, $d = .33$]. Interestingly, while participants were more likely to decrease the average number of fixations to make a response decision on repetition 2–4, relative to repetition 1 subsequences in the low-volatility session [$t(19) = 6.13$, $p = .001$, $d = .37$; $t(19) = 7.02$, $p < .001$, $d = .47$; $t(19) = 6.55$, $p < .001$, $d = .48$], but there were no significant results except for the repetition 3 compared to repetition 1 in the high-volatility session [$t(19) = 3.75$, $p < .05$, $d = .37$]. However, the interaction between Distractor Repetition and Volatility Type was not reliable, $F(3, 60) = 2.14$, $p = .15$, $\eta_p^2 = .10$.

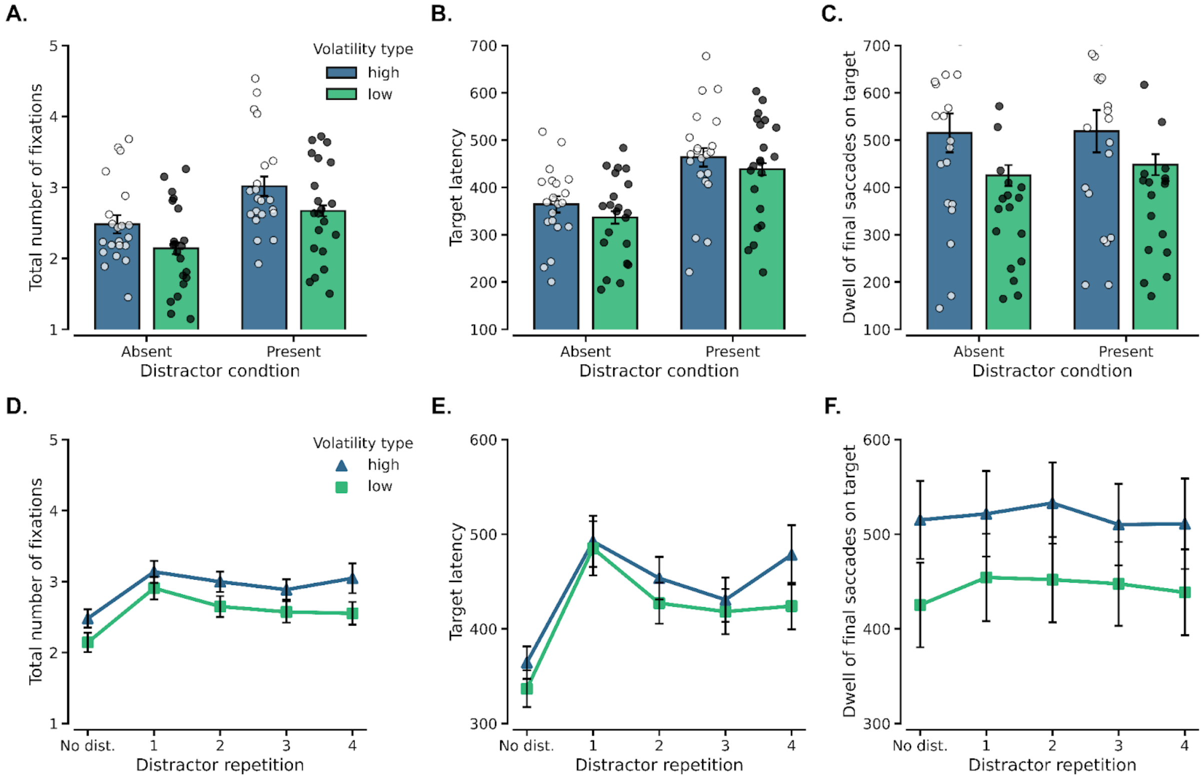

Figure 4. Eye movements results. (A & D) Total number of fixations when the target was presented in the high- vs. low-volatility sessions when the distractor was on absent vs. present conditions. **(B & E)** Target latency was when the target was presented in the high- vs. low-volatility sessions when the distractor was on absent vs. present conditions. **(C & F)** Dwell times of final saccades landed on the target when the target was presented in the high- vs. low-volatility sessions when the distractor was on absent vs. present conditions. In all line plots, the x-axis showed the distractor location repetition in four subsequences (i.e., distractor absent, repetition 1, repetition 2, repetition 3, and repetition 4). Error bars depict the one standard error of the mean.

3.2.5 Target latency

Further, we examined the timing of oculomotor capture to arrive at a response decision when the salient distractor facilitated search performance in different lengths of repetitions. Thus, saccadic latencies to the target were submitted to a 2 × 2 ANOVA with the Distractor Condition (absent vs. present) and the Volatility Type (high vs. low-volatility) as factors, see Figure. 4B&E. The main effect of Distractor Condition was significant, $F(1, 20) =149.01$, $p < .001$, $\eta_p^2 = .88$, and so was the main effect of Volatility Type, $F(1, 20) = 5.01$, $p < .05$, $\eta_p^2 = .20$. Their interaction, however, was not reliable, $F(1, 20) = .18$, $p = .68$, $\eta_p^2 = .01$. Thus, on the one hand, saccadic latency was longer to distractor present- as compared to absent condition (451.17 ms vs. 350.56 ms), suggesting a detrimental interference effect on target-directed saccades when a distracting onset appeared in the search display; on the other hand, searching the target was slower in the high as compared to the low-volatility environment (443.87 ms vs. 418.23 ms), reflecting the high-volatility series causes lower effective searching performance. We also examined saccade latencies towards the target when the distractor repeated at the same location in different lengths of subsequences. A 2 (Volatility Type: high, low) × 4 (Distractor Repetition: 1–4) ANOVA on the target latency revealed a main effect of Distractor Repetition, F (1, 20) = 11.36, $p < .001$, $\eta_p^2 = .36$. It showed that saccades were initiated faster to targets when the distractor occurred at the same location repeatedly over 2 or 3 times, compared to it only occurring once time (ts(20) > 6.11, Bonferroni–Holm corrected). However, neither the main effect of Volatility Type nor the interaction effect, F (1, 20) = 3.44, $p = .08$, $\eta_p^2 = .15$, F (1, 20) = 2.18, $p = .10$, $\eta_p^2 = .10$, respectively.

3.2.6 Dwell times of final saccades on the target

Next, the current study employed the dwell times (durations) of final saccades landed on the target to test whether any contribution of post-selective processes to the volatility influence. Looking at the dwell times of final saccades on the target as a function of the Distractor Condition (absent vs. present) and the Volatility Type (high vs. low) trials Figure 4C&F. This ANOVA yielded both main effects to be significant, the Distractor Condition, F (1, 20) = 4.04, $p = .058$, $\eta_p^2 = .17$, and the Volatility Type, F (1, 20) = 4.81, $p < .05$, $\eta_p^2 = .19$, but the two factors did not significantly interact, F (1, 20) = 2.93, $p = .10$, $\eta_p^2 = .13$. As visualized in see Figure. 4C, participants required overall longer dwell times to identify the target item when distractor occurred in the search display as compared to distractor absent condition (483.52 ms vs. 470.17 ms). Also, final fixaitons on the target were indeed longer in the highly volatile searching session than the lowly volatile session (518.16 ms vs. 443.54 ms). Similarly, as shown in Figure. 4F, an ANOVA on the dwell times of final fixations on targets with Distractor Repetition (1–4) and Volatility Type (high vs. low) as factors revealed a significant main effect of Volatility Type, F (1, 20) = 4.14, $p = .055$, $\eta_p^2 = .17$, but not for repetition, F (1, 20) = 1.35, $p = .26$, $\eta_p^2 = .06$. The interaction between Distractor Repetition and Volatility Type was not reliable, F (1, 20) = 0.67, $p = .54$, $\eta_p^2 = .03$, suggesting that even the post-selective processing time of the task-relevant target was slower in the high- versus low-volatility environment, but this identification processing of target items did not change over the length of distrctor repetition subsequences.

Inter-trial Switch-cost effect

3.2.7 Total number of fixations

With the same analysis as manual RTs, we looked at the inter-trial transitions effect when the distractor switched the states between absent and present conditions to examine the oculomotor capture events, see Figure. 5A. A 2 (Volatility Type: high, low) × 4 (Switch Type: AA, PP, AP, PA) ANOVA on the total number of fixations revealed there were significant main effects of Volatility Type, F (1, 20) = 6.33, $p < .05$, $\eta_p^2 = .24$, and Switch Type, F (3, 60) = 160.10, $p < .001$, $\eta_p^2 = .89$. Specifically, participants typically make more saccades in the high-volatility session than the low-volatility session (fixations: 2.76 vs. 2.46). In addition, we found that 'AP' type needed a larger number of saccades during the target selection processing, relative to the other three types (fixations: AA = 2.27, PP = 2.79, AP = 3.02, PA = 2.35, all t values > 5.24, all p values < .001, Bonferroni-Holm corrected). There was also an interaction between Volatility Type and Switch Type, F (3, 60) = 3.92, $p < .05$, $\eta_p^2 = .16$. Post-hoc t-tests provided some evidence for the interactive relationship of volatility-driven attention capture and switch states of distractor can affect the impact of target selection. That is, there was a larger number of fixations in PP, PA, and AA transition conditions, respectively, under the high-volatility circumstance than under the low-volatility circumstance to finish the search performance (all t values > 2.71, all p values < .05, Bonferroni-Holm corrected).

When we submitted the Switch-cost value to a 2 × 2 ANOVA, with Volatility Type (high vs. low) × Switch-cost ('AP minus PP' vs. 'PA minus AA') revealed two significant main effects of Volatility Type, F (1, 20) = 21, $p < .001$, $\eta_p^2 = .51$, and Switch-cost, F (1, 20) = 6.50, $p < .05$, $\eta_p^2 = .25$. As visualized in Figure. 5A, participants required more switch-cost of fixations to identify the target item when a distractor occurred in the search display (on Trial *n*) as compared to distractor absent condition on consecutive trials (on Trial *n-1*). Also, it reflected a higher cost when the search sequence is low-, compared to the high-volatility session to filter distractors from the remaining non-switch type to changed switch type on constant trials across the whole experimental sequence. There was also an interaction between the Volatility Type and Switch-cost, F (1, 20) = 4.68, $p < .05$, $\eta_p^2 = .19$. Further, there was a larger switch-cost of fixations in the 'AP minus PP' condition rather than 'PA minus AA' condition; compared to the high-volatility session, the low-volatility session significantly reduced the number of fixations to search the target with the 'AP minus PP' condition; also we only found there was a significantly larger cost of number saccades with the 'AP minus PP' condition rather than 'PA minus AA' condition in the low-volatility session (all t values > 2.55, all p values < .05, Bonferroni-Holm corrected), but no any significant difference in the high-volatility session, see Figure. 5A.

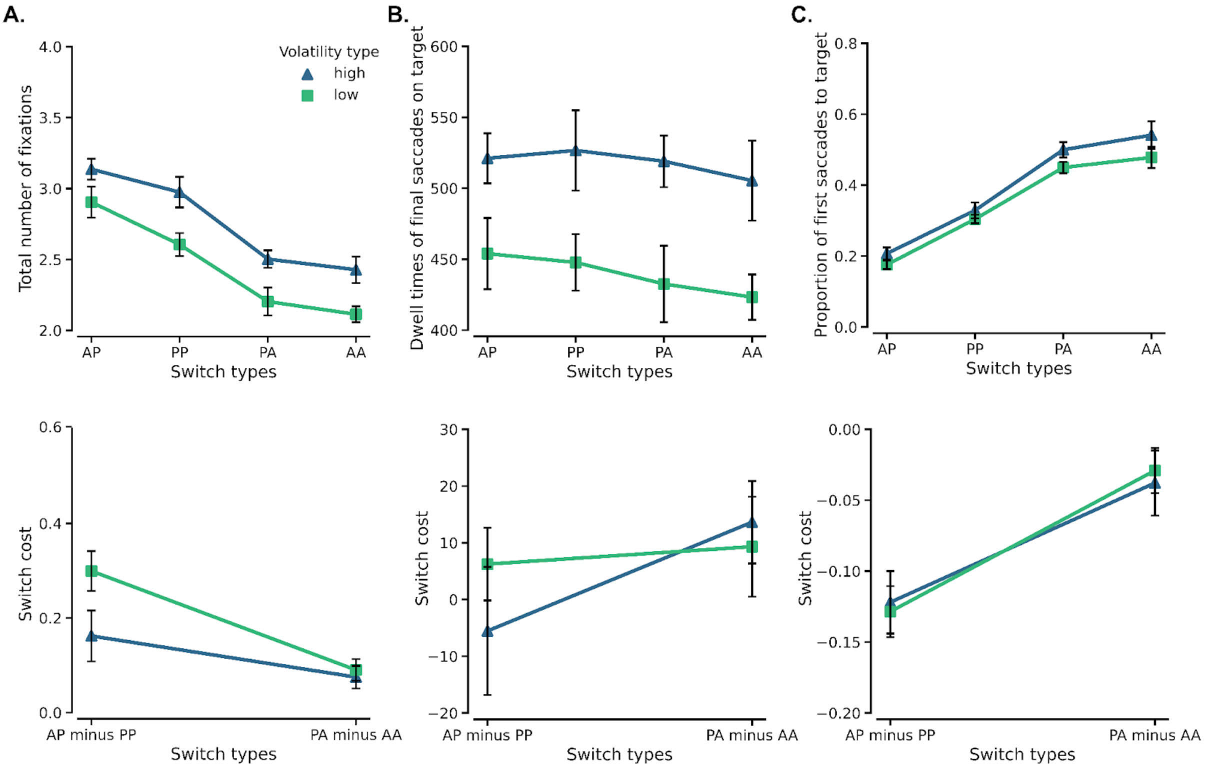

Figure 5. Eye movements results. (A) Total number of fixations as a function of Switch Type (AA, AP, PA, and PP) and the Volatility Type (high vs. low). **(B)** Dwell times of final saccades landed on the target as a function of Switch Type (AA, AP, PA, and PP) and Volatility Type (high vs. low). **(C)** Proportion of first saccades landed on the target as a function of Switch Type (AA, AP, PA, and PP) and Volatility Type (high vs. low). For all line plots in the bottom panels, the x-axis showed the oculomotor capture cost as a function of Volatility Type (high vs. low) × Switch-cost ('AP minus PP' vs. 'PA minus AA'). Error bars depict the one standard error of the mean.

3.2.8 Dwell times of final saccades on the target

A similar analysis was conducted on the dwell times of final saccades towards the target, see Figure. 5B. A 2 (Volatility Type: high, low) × 4 (Switch Type: AA, PP, AP, PA) ANOVA revealed there were significant main effects of Volatility Type, F (1, 20) = 4.65, $p < .05$, $\eta_p^2 = .19$, and Switch Type, F (3, 60) = 4.68, $p < .05$, $\eta_p^2 = .19$, indicating that final fixations on the target were indeed longer when it appeared at the high-volatility session than at the low-volatility session location (518 vs. 439.33 ms). What's more, dwell times were significantly longer when distractors presented rather than distractors absent consecutively carry-over across trials (PP vs AA: 173 vs. 123 ms), $t(20) = 3.67$, $p < .05$, $d = .13$. The interaction between volatility and switch was not statistically significant, F (3, 60) = 1.09, $p = .36$, $\eta_p^2 = .05$. Interestingly, with the Switch-cost value to a 2 × 2 ANOVA on Volatility Type (high vs. low) × Switch-cost ('AP minus PP' vs. 'PA minus AA') showed that none of the main effects was significant (Volatility Type: F (1, 20) = .22, $p = .64$, $\eta_p^2 = .01$; Switch-cost: F (1, 20) = 1.35, $p = .26$, $\eta_p^2 = .06$), nor was the interaction between the two (Volatility by Switch-cost: F (1, 20) = 1, $p =.33$, $\eta_p^2 = .05$.

3.2.9 Proportions of first saccades on the target

In terms of the oculomotor capture effect evidenced above, a similar analysis measured the proportion of first saccades going to the target on a 2 (Volatility Type: high, low) × 4 (Switch Type: AA, PP, AP, PA) ANOVA found that no main effect of Volatility Type, F (1, 20) = 3.04, $p = .10$, $\eta_p^2 = .13$. But a significant main effect of (Switch Type, F (3, 60) = 47.29, $p < .001$, $\eta_p^2 = .70$, suggesting that the reduced proportion of first saccades going to the target on AP vs. PP trials, PA vs. PP trials, AP vs. AA trials, PA vs. AA trials (all t values > 2.64, all p values < .05, Bonferroni-Holm corrected), respectively. Further, with the

Switch-cost value to a 2 × 2 ANOVA on Volatility Type (high vs. low) × Switch-cost ('AP minus PP' vs. 'PA minus AA') revealed that the main effect of switch-type was significant, F (1, 20) = 40.90, $p < .001$, $\eta_p^2 = .67$), but neither main effect of Volatility Type, F (1, 20) = .003, $p = .96$, $\eta_p^2 = .00$, nor was the interaction between the two (Volatility by Switch-cost: F (1, 20) = .22, $p =.64$, $\eta_p^2 = .01$, see Figure. 5C.

4 Discussion

The present study investigated intermediate-term statistical learning to suppress a visual distractor based on its dynamic probability of appearing in a particular location across multiple trials, and how this statistical learning is influenced by the volatility of distractor occurrence. We found that reaction times (RTs) were slower overall in the high- relative to low-volatility session, likely because higher uncertainty in the high-volatility session led participants to make more conservative decisions (e.g. being more careful about whether an item was the target or distractor), trading speed for accuracy. This was evidenced by lower error rates and longer target viewing in the high-volatility session (see Figures 2A and 4C). At the same time, the distractor probability cueing, measured by mean RTs difference between distractor present and absent, was larger in the low-volatility session, indicating that the singleton distractor interfered more in a less volatile environment.

Importantly, the overall frequency of distractor present trials was the same (50%) in both sessions, so the effect of volatility on distractor interference found here is distinct from the reduction of distractor interference with increased overall distractor frequency as well as with increased local frequency in a location or region found in several previous studies (e.g. Allenmark et al., 2022; H. J. Müller et al., 2009; B. Wang & Theeuwes, 2018; Won et al., 2019; Zhang et al., 2019). Instead, it was the probability of a transition from a distractor absent trial to a distractor present trial that was lower in the low-volatility session. Consequently, the average number of distractor absent trials between two distractor present subsequences was larger in the low-volatility session, and a distractor, once it appeared, may have been less expected (or more surprising). Therefore, theories which propose that salience depends on Bayesian surprise or prediction error (e.g. Baldi & Itti, 2016; Horstmann, 2015; Itti & Baldi, 2009; Spratling, 2012) could potentially explain at least why the first distractor in a distractor present subsequence would have caused more interference in the low-volatility session (however, somewhat inconsistent with this explanation, proportions of first saccades to the distractor were no more frequent in the low-volatility session).

We found that distractor interference decreased with increasing number of repetitions of the distractor in the same location, replicating a closely related finding by van Moorselar and Slagter (2019). However, we did not find any significant difference in the rate at which interference was reduced across repetitions between the high- and low-volatility sessions. In the high-volatility session the probability of a repeated distractor present trial was lower than the probability of a distractor present trial after a distractor absent trial, so purely based on this repeated distractor should have been, if anything, more unexpected than the first distractor in a distractor present subsequence. However, since a repeated distractor present trial always had a distractor in the same location as the first one in the subsequence, the probability of a repeated distractor in the same location (30%) was higher than the probability of a distractor in that particular location after a distractor absent trial (70%/8=9%), but still much lower than the probability of a repeated distractor in the same location in the low-volatility session (70%). Based on this, if observers had adapted their distractor suppression strategy to the different statistics in each session, there should have been less reduction of distractor interference between the first and second distractor repetition in the high-volatility session. Since we did not find such a difference, it could be taken to suggest that the decreased distractor interference across distractor location repetitions is not a result of learning to expect distractor occurrence in a particular location, but could instead be similar to priming of pop-out. Early priming of pop-out study by Maljkovic and Nakayama found that RTs are slower in a condition of 100% predictable change of the target feature from trial to trial than in the maximally unpredictable condition with equal probability of repetition and change (Maljkovic and Nakayama 1994), which the authors took as evidence that the short term memory of the target feature primes and facilitates performance when the feature repeats regardless of any expectations based on the statistics of the stimulus sequence. Similarly, short-term memory of a previous distractor location could “prime” suppression of that location, relatively independently of any statistical expectations learned from the sequence of distractor locations. Alternatively, the pattern of results is also consistent with local habituation (e.g. Allenmark et al. 2022; Thompson 2009; Sokolov 1963; Turatto and Valsecchi 2023). That is, after a distractor appears in a particular location, this may lead to updating of an internal model of the environment, such that on the following trials, a distractor in that location is less unexpected and attracts less attention.

While we did not find any significant interaction between the volatility condition and the number of distractor repetitions in the overall RTs, we did find such an interaction for the proportion of trials on which the first saccade went to the distractor and on distractor dwell times. In both cases, there was virtually no difference on the first distractor repetition, but on the second and fourth repetitions, there were numerically more and longer fixations on the distractor. This hints at a somewhat slower increase in distractor suppression across repetitions in the high-volatility environment. Overall, it seems that learning to better ignore the irrelevant distractor as the distractor location was repeated, one or multiple times, was influenced relatively little by the volatility of the stimulus sequence, but with some evidence of slower learning in the high-volatility session. This seems unlikely to be a result of an adaptation of overall learning rate to the statistics in the environment, since Bayesian theories of optimal learning predict a difference in the opposite direction, i.e. a higher learning rate in the high-volatility environment (e.g. Behrens et al. 2007; Mathys et al. 2011). Instead, the slower increase in distractor suppression in the high-volatility session is in the direction predicted by optimal learning of the transition probabilities of the Markov chain, i.e. in the high-volatility session there is a lower probability of repeating the same distractor location, so it makes sense to apply less suppression to that location.

In addition to the decreased distractor interference with increasing repetitions of the same distractor location we found switch costs when switching from a distractor absent to a distractor present trial or vice versa compared to when the distractor condition was repeated. These switch costs were particularly large when switching from absent to present, which is probably, at least in part, a consequence of our design where the same distractor location was repeated across repeated distractor present trials, but there was also a switch cost in the other direction. This could potentially also be explained by the habituation account, discussed above, since after a sequence of distractor present trial with a repeated distractor location, the participant would have updated their model to expect a distractor in that location, and the absence of such a distractor may then have been surprising and attracted attention. However, it could also be a consequence of the suppression of the previous distractor location, resulting in slower RTs when the target appears in that location.

5 Conclusion

In sum, the present study reveals not only the influence of distractor-repeat sequences on location suppression but also the influence of environmental volatility on adjusting learning rates of distractor suppression. We found that the high-volatility session resulted in slower response times than the low-volatility session. However, in the low-volatility session, the attentional capture RTs cost between distractor presence and absence was larger, which indicates distractor interference more with search performance in the less volatile environment. Moreover, we found that distractor interference reduced with increasing number of repeats of the distractor in the same position, and speculated that priming of pop-out may be responsible for this reduced interference across distractor location repetitions. Additionally, it seems plausible that habituation may play a role in learned distractor suppression because our results showed that switch costs were higher when switching between distractor absent and distractor present trials than when repeating distractor states. These results are consistent with the notion of selection history: due to the spatial priority map being highly flexible, volatile environments could affect the learning speed of distractor suppression, and observers could also make use of local trial-to-trial regularities of distractor locations to reduce attentional capture. While future studies will need to reveal the neural mechanisms supporting such attentional bias in volatile environments.

Declaration of competing interest

The authors declare no competing interests.

Data availability statement

Raw data used for analyses presented within this article will be made available upon request. If you would like to access the raw data and analysis, please email Nan Qiu at the following e-mail address: Nan.Qiu@campus.lmu.de.

Credit authorship contribution statement

Nan Qiu: Conceptualization, Formal analysis, Data collection & curation, Methodology, Project administration, Visualization, Writing – original draft, Review, and Editing.

Fredrik Allenmark: Conceptualization, Formal analysis, Methodology, Project administration, Validation, Writing – original draft, Review, and Editing.

Hermann J. Müller: Funding acquisition, Methodology, Resources, Supervision, Validation, Writing, Resources, Review, and Editing.

Zhuanghua Shi: Conceptualization, Funding acquisition, Analysis, Methodology, Supervision, Validation, Writing, Project administration, Resources, Review, and Editing.

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2.3 Impacts of distractor volatility on statistical learning of distractor suppression

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Impacts of distractor volatility on statistical learning of distractor suppression

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Abstract

Statistical learning to suppress the location(s) of where a salient distractor is likely (vs. unlikely) to occur can enhance visual search efficiency, an effect termed distractor-location probability cueing. However, whether this effect is influenced by the volatility of distractor occurrence (i.e., of the sequence of distractor-present and -absent events) remains poorly understood. Here, we investigated this question by contrasting two volatility regimens in a distractor-location probability-cueing paradigm: a low-volatility environment (distractor-present and -absent trials likely streaked) and a high-volatility environment (two trial types changing frequently). The distractor prevalence was 50% in both conditions, with the distractor appearing 13 times more often at the frequent vs. any rare distractor location. We replicated the distractor-location probability-cueing effect: faster responding when the distractor appeared at the frequent vs. a rare location. Although responses were generally slower in the high-volatility environment, the distractor-location and the intertrial distractor-repetition effects were similar in both conditions. Interestingly, the target-location effect – slowed responding to a target at the frequent vs. a rare distractor location on distractor-absent trials (reflecting proactive location suppression) – remained robust across repeated distractor-absent trials in the high-volatility environment, but disappeared after the first distractor-absent event in the low-volatility environment. This pattern suggests that, while statistical learning of the spatial distractor distribution as such is unaffected by the volatility of distractor occurrence, the engagement of proactive suppression is dynamically adjusted according to the expectancy that a distractor event will occur on the next trial.

Keywords: visual attention, distractor location suppression, statistical learning, volatility, across-trial regularities

Introduction

Visual search is a vital and ever-present task by which we navigate complex and ever-changing environments. Whether looking for our car key on a cluttered desk or searching for a friend in a crowded street, our attentional system must work hard to filter out task-irrelevant information and pinpoint the relevant target. However, even with filtering processes in place, some salient irrelevant objects may still intrude into the ongoing search by capturing attention. It is well established that the presence of a salient distractor can considerably impact the search process (e.g., Theeuwes, 1992). In fact, the first saccade, or rapid eye movement, is often directed toward the salient distractor rather than the less salient target (e.g., Allenmark et al., 2021; Sauter et al., 2021). Despite this initial disruption, when the distractor happens to appear regularly at a certain location, the attentional system is capable of learning its statistical regularity and 'suppressing' (in the sense of down-modulating) potentially interfering stimuli at this location to enhance search performance. This phenomenon, referred to as distractor-location probability cueing, has been demonstrated in numerous recent studies (e.g., Allenmark et al., 2022; Goschy et al., 2014; Leber et al., 2016; Sauter et al., 2018; Wang & Theeuwes, 2018).

In a typical distractor-location probability-cueing search paradigm, participants may be asked to search for, say, an orientation-defined target bar while ignoring any salient distractors, which might be defined within either the same dimension as the target (in the example: orientation) or in a different dimension (such as color or luminance), and identify and respond to some response-critical attribute of target, such as the position of a notch in an oriented target bar. Critically, the salient distractor appears more frequently at one specific location or a contiguous region of the search display. A typical finding is the so-called 'distractor-location effect', that is: distractor interference – measured in terms of reaction times (RTs) to the target in the presence vs. the absence of a distractor in the display – is significantly reduced when the salient distractor appears at the frequent distractor location compared to one of the other, rare locations – evidencing statistical learning and attendant probability cueing of the likely distractor location(s) (Goschy et al., 2014). This distractor-location effect is commonly explained in terms of some down-modulation of the selection weight assigned to salient stimuli in the computation of the attentional-priority map, which integrates the signals across all feature dimensions and determines the allocation of visuo-spatial attention (Allenmark et al., 2019; Chelazzi et al., 2019; Ferrante et al., 2018; e.g., Sauter et al., 2019; Theeuwes et al., 2022; Zhang et al., 2019). While there are different views on where in the system of priority computation the down-modulation occurs, there is wide (though not universal) agreement that it occurs at the level of the priority map when the salient distractor is defined within the same dimension as the target (Allenmark et al., 2022; Zhang et al., 2019, 2022). Critically, this notion is supported by the fact that a 'target-location effect' on distractor-absent trials, in addition to a 'distractor-location effect' on distractor-present trials, is most consistently observed under within-dimension distractor conditions. The target-location effect refers to the fact that processing of a target appearing at the frequent (vs. a rare) distractor location is compromised (even) on trials on which there is no competing distractor in the display (Liesefeld & Müller, 2021; e.g., Wang & Theeuwes, 2018; Zhang et al., 2019). It is important to note that, compared to the distractor-location effect, the target-location effect is relatively weak, and not reliably observed when salient distractors are defined in a different dimension to the target (Allenmark et al., 2019; Sauter et al., 2018; Zhang et al., 2019) – in which case the down-modulations of distractor signals may be attributed to a level below the integrative attentional-priority (Allenmark et al., 2019).[11]

While it has been demonstrated that statistical learning can lead to the suppression of the likely distractor location(s) through the acquisition of local and global probability distribution of the distractor (Allenmark et al., 2022; Turatto et al., 2019; Turatto & Valsecchi, 2023), its connection to short-term inter-trial positional priming and suppression is less clear. Intertrial priming refers to the phenomenon that the processing of a target on a given trial is influenced by the nature of the previous trial. For instance, participants tend to respond faster and more accurately to a given target when critical target features, including its location, are inherited from the previous trial (e.g., Found & Müller, 1996; Maljkovic & Nakayama, 1994, 1996; Müller et al., 2010). Of note, the nature of intertrial priming is transient and temporary, and not typically regarded as an instance of 'statistical learning' (Lamy & Kristjánsson, 2013; Theeuwes et al., 2022; Wolfe et al., 2003). Regarding distractor-location probability cueing, Goschy and colleagues (2014) have shown that the probability-cueing effect cannot be solely attributed to inter-trial priming. They found that when the distractor repeated at the same location, search performance was transiently raised to a similar level as when the distractor was absent. However, even after carefully removing

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[11] In fact, Zhang et al. (2019) observed that, with such cross-dimension distractors, observes may at first show a target location effect, but then completely lose this effect over the course of training (while maintaining the the distractor-location effect) – indicative to a change of strategy from initial priority-map-based distractor suppression to suppression of distractor- (but not target-) generated signals below the priority map.

all cross-trial repetitions of the distractor location, a significant probability-cueing effect remained.

Statistical learning of distractor locations occurs gradually over multiple trials. Quite possibly, initially, when a distractor captures attention, its location needs to be *reactively* suppressed to disengage attention from the distractor and reorient it to the target location – where such reactive suppression would occur more often for locations at which distractors appear frequently. The immediate effect of reactive suppression may last only for a short period of time, affecting distractor and target processing on the next trial (for a detailed analysis, see, e.g., the Appendix in Sauter et al., 2018). However, in the longer run, it may foster statistical long-term learning of the spatial distractor distribution by trial-by-trial updating of the weights assigned to the various locations in the computation of attentional priorities – giving rise to *proactive* suppression of the likely distractor location (Allenmark et al., 2021; Geng, 2014; Theeuwes & Failing, 2020; Won et al., 2019). Trial-by-trial updating, however, is affected by the sequential structure of distractor prevalence, as shown by Müller et al. (2009). Adopting Theeuwes' (1992) additional-singleton paradigm (in which distractors, on distractor-present trials, were equally likely to appear at all display locations), Müller and colleagues (2009) compared search performance between a 'run-up' and a 'run-down' groups. Observers in the run-up group started with a pure distractor-absent (i.e., 0% distractor-prevalence) condition, and the distractor prevalence then increased in stages up to a condition with a distractor on every trial (100% prevalence); conversely, the run-down group began with a 100% distractor-present condition and the distractor prevalence then decreased down to a condition with no distractors. Müller et al. (2009) found that the degree of distractor interference was generally (in both groups) the lower the higher the distractor prevalence (2009). Interestingly, however, the run-down group displayed less distractor interference than the run-up group. In fact, when both groups were presented with a block of trials containing 50% distractors halfway through the experiment, the run-down group showed no reliable distractor interference, in contrast to the run-up group which showed robust interference. This suggests that general learning to mitigate distractor interference is dependent on the sequential trial structure associated with a given level of distractor prevalence.

A more recent study by van Moorselaar and Slagter (2019) indicates that location-based distractor suppression is acquired gradually: they found that repeating distractors at the same location in a sequence of 12 (consecutive) trials resulted in increasingly faster responses and a repetition-dependent reduction in the lateralized event-related P_D component (i.e., a positivity in the 280–360 ms time window contralateral to the distractor location, with the target positioned at a location on the vertical midline), which is taken as an electrophysiological signature of distractor suppression (hence, the name P_D, ‘distractor positivity’). However, their manipulation represents a special case of intertrial repetition, with a fixed distractor location across the critical trial sequence. Accordingly, evidence as to the extent to which the weight of the distractor location is down-modulated over the time course of ‘standard’ *statistical* learning remains scarce. In other words, it remains an open question whether the cross-trial sequential structure of distractor occurrence matters for statistical learning of the likely distractor location(s), or whether the biased probability distribution of distractor occurrence is the sole determining factor.

Recent work has shown that the volatility of the sequential structure of events in the environment may influence the way people update their prior knowledge and integrate this in perceptual decision-making (e.g., Behrens et al., 2007; Ferrari et al., 2022; Glasauer & Shi, 2022). Applied to visual search: in situations where the environment is highly uncertain and unexpected uncertainty is caused by the shifting of various contingencies, it can be challenging to anticipate the presence of a distractor within a specific setting (Jungerius et al., 2022). Examining the effect of intertrial feature repetition, Feldmann-Wüstefeld and Schübo (2016) varied distractor colors either randomly or repeated the same distractor color in a chunk of three trials in a row (with a distractor present on every trial at some randomly selected location). They found that when the search context was heterogeneous, with the non-target items being randomly oriented horizontal and vertical bars and the target item the only 45° left- or right-tilted bar, the predictive sequence greatly enhanced the intertrial distractor-suppression effect. But this enhancement was absent when the search context was homogeneous, with the non-target items being either all horizontal or all vertical bars. This suggests that cross-trial distractor volatility (in Feldmann-Wüstefeld and Schübo’s study: color volatility) might impact the statistical learning of distractor handling (at least) in certain, relatively challenging search scenarios.

In any case, to our knowledge, there has been no systematic investigation of whether the volatility of distractor occurrence across trials (i.e., the sequential structure of distractor-present and -absent trials) influences the acquisition and operation of location-based distractor suppression (i.e., the distractor- and target-location effects), and how this relates to the intertrial repetition (benefit) and switch (cost) effects. The present study was designed to address these questions, to gain a better understanding of the role of sequential distractor volatility in learning to suppress locations where distractors are likely to occur. To this end, we adopted a distractor-location probability-cueing paradigm (e.g., Goschy et al., 2014; Liesefeld et al., 2019) to compare statistical learning of distractor suppression between two, high- and low-volatility environments, determined by differential Markov-chain transition-probability matrices (Hamilton, 1990). Critically, we kept global distractor prevalence and the global spatial distractor distribution the same between the two environments: distractors were presented in 50% of the trials and (on distractor-present trials) appeared at one location with a higher probability (65%) than at the other seven possible locations (35%/7). In the high-volatility sequence, distractor presence and absence were more frequently switched (70%), whereas the low-volatility sequence consisted of more concentrated bursts of distractor-present (and -absent) trials (see Figure 1). Distractors were defined in the same dimension as the target, namely, orientation and generated a greater degree of (orientation) feature contrast relative to the homogeneous background than the target. Liesefeld and Müller (2021), among others, had shown this scenario to produce both robust distractor-location and robust target-location effects – that is, the very effects 'targeted' by our volatility manipulation.

To preview the results, we found response speed to be generally slower in the high- vs. the low-volatility environment, but the distractor-location effect – indicative of statistical learning of the spatial distractor distribution – was comparable between the two environments, including showing a similar decrease across (identical) streaks of repeated distractor-present trials. Interestingly, however, there was a sustained target-location effect across repeated distractor-absent trials only in the high-volatility condition (where, in fact, the effect tended to increase with the trial repetition after an initial decrease). In the low-volatility condition, by contrast, the target-location effect effectively vanished after the first occurrence of a distractor-absent trial in the streak. This pattern suggests that the target-location effect is dynamically adjusted to the 'local' likelihood with which a distractor occurs on the next trial.

Methods

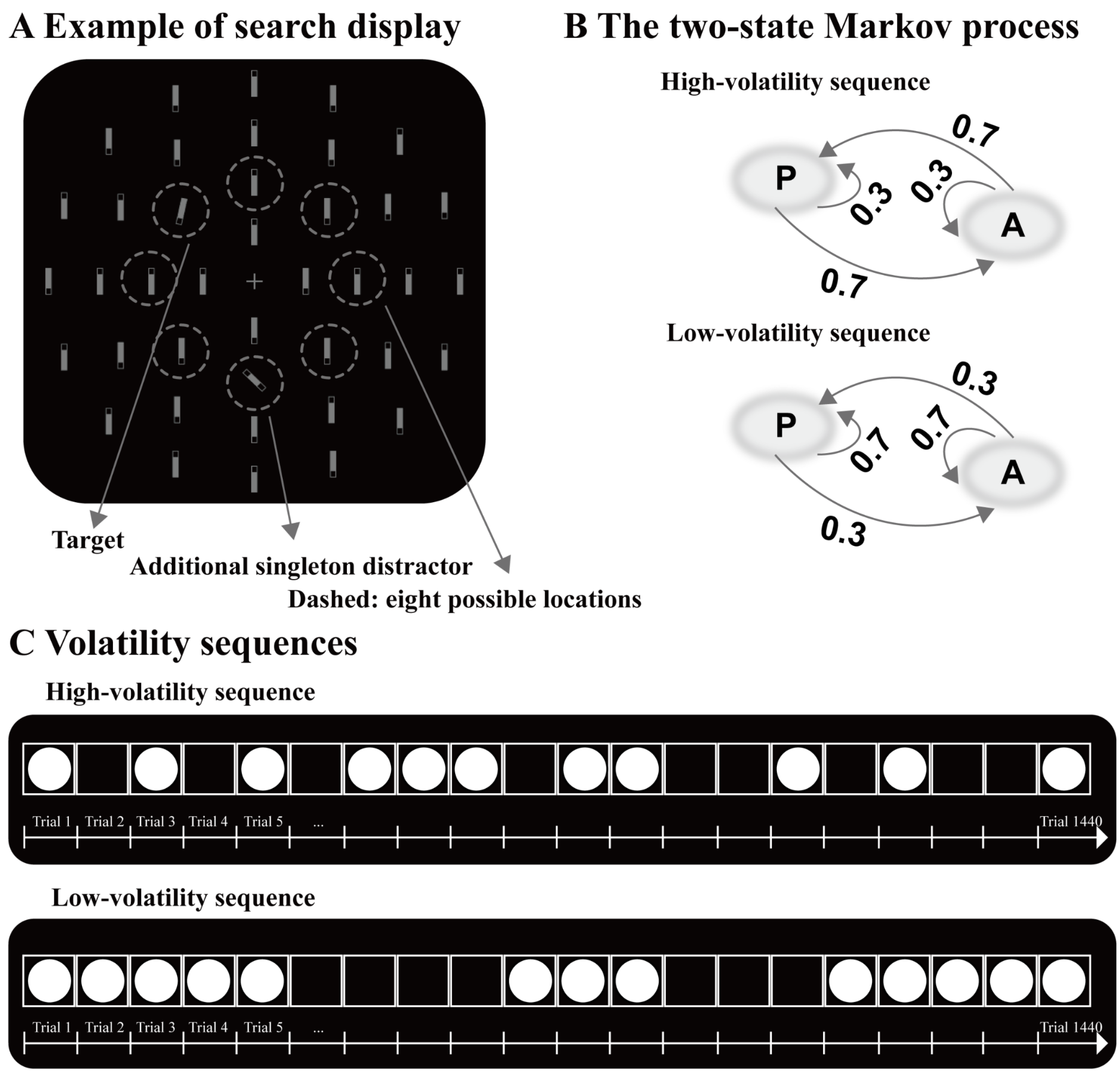
Participants.

24 healthy adults (mean age of 26.5 years, range 18–40 years, 9 males and 15 females) were recruited to participate in the experiment. This sample size was the same as in Liesefeld et al. (2019), who used the same visual-search paradigm. All participants reported normal or corrected-to-normal vision. They gave informed consent prior to the experiment and received course credits or were paid 9 € per hour for their service. The study was approved by the Ethics Committee of the LMU Faculty of Psychology and Pedagogics.

Apparatus and Stimuli

The experiment was conducted in a dimly lit and sound-attenuated laboratory cabin. Visual stimuli and response acquisition were controlled via a customized Matlab code using Psychtoolbox (Brainard, 1997). Visual stimuli were presented on a 24-inch ASUS monitor (mode: VG248QE) with 1920 × 1080 pixels screen resolution, at a refresh rate of 144 Hz. Responses were collected via the mouse buttons. The viewing distance was fixed to 65 cm, maintained with the aid of a chin-rest.

Visual search items were gray bars (subtending 0.18° × 0.81° of visual angle) presented against a black background. Each bar contained a notch (~ 0.25° in height) in either its upper or lower part (randomly determined per item), except for a singleton distractor which had both upper and lower notches (Figure. 1A). Each search display included 40 bars arranged around four concentric circles (radii of 1.1°, 2.2°, 3.3°, and 4.4°, respectively) centered on a central fixation cross (0.49°). All bars were set at 20% (of maximum) intensity in luminance, and, except for the target and the distractor, the bars were vertical (0° orientation), providing a homogeneous orientation (and luminance) background. The target (present on all trials) and the distractor (on distractor-present trials) were both singled out by orientation contrast to their background surround. The target was tilted 12° to the right, and the distractor (if present) was tilted 45° to the left. Accordingly, the distractor had a higher feature contrast relative to the background than the target (i..e, it was more bottom-up salient); nevertheless, a 12° tilted target bar still pops out from the homogenous array of vertical background items (i.e., search for 12° orientations among vertical orientations is spatially parallel; see Liesefeld et al., 2016). The target and the singleton distractor only appeared at the eight possible locations of the second concentric circle (Figure. 1A).



A Example of search display

B The two-state Markov process

C Volatility sequences

Figure. 1. Search displays and volatility sequences. (A) Participants' task was to locate a bar tilted 12° to the right and identify (and respond to) whether the notch in the bar was at the top or the bottom. In half of the trials, there was an 'additional-singleton' distractor bar tilted 45° to the left (with two notches), which was task-irrelevant. The target appeared in any of the eight possible positions on the second ring with equal probability, while the distractor bar (if presented) appeared more frequently at one of the eight positions (65%) than at any of the other seven positions (35%/7). (**B)** Two-state (distractor **P**resence vs. **A**bsence) Markov chains with different transitional probabilities generating the trial sequences for the two, high- and low-volatility sessions (upper and lower panel, repanel). High-volatility sequences had a high probability (70%) of switching states; conversely, low-probability sequences had a high probability (70%) of remaining in the same state. The probability of the distractor presence was the same in both types of sequence (50%). (**C)** Illustration of the two types of sequence. Each square with a disk represents a distractor-present trial (squares without a disk represent distractor-absent trials). As illustrated, compared to the low-volatility sequence, the high-volatility sequence is more likely to switch (distractor presence vs. absence) states. Participants performed both sessions, separated by 5 to 7 days.

Design and Procedure

Volatility of trial sequences

In each (high- and, respectively, low-volatility) session, the sequence of distractor-present and -absent trials was generated by a Markov transition matrix, with the matrices differing between the two sessions (illustrated in Figure 1B). In high-volatility sequences, the states of distractor presence vs. absence were 70% likely to be switched (i.e., 30% likely to remain the same), as compared to a switch probability of 30% (i.e., a non-switch probability of 70%) in low-volatility sequences (see Figure 1C for an illustration). We used the Markov-chain package in R to generate the two sequences, each of 1440 trials, individually for each participant. When the distractor bursts in a row, it appears at the same location. Owing to the nature of the volatility structure, the low-volatility sequence was more likely to have long streaks of distractor-present (or, respectively, distractor-absent) trials. Accordingly, in order to allow the distractor-repetition effect to be compared between the two volatility conditions, we selected high-volatility sequences for inclusion in the experiment that contained at least 31 sub-sequences of three consecutive distractor-present (PPP) trials (the number of such sub-sequences ranged between 31 to 51 across participants).

Spatial distribution of the singleton distractor

For both volatility sessions, the target, presented on all trials, was equally likely (and across trials randomly) assigned to one of the eight possible locations on the second (virtual) ring (Figure 1A). The singleton distractor appeared in 50% of trials. If the distractor was present, it appeared at one (fixed) location with a likelihood of 65% (the ‘frequent’ distractor location) and a likelihood of 5% at each of the other seven locations (the ‘rare’ distractor locations). Given the long-term persistence of distractor-location learning (e.g., Sauter et al., 2019), the location that was frequent to contain a distractor was fixed per participant for both volatility sessions, and counterbalanced across participants. On distractor-absent trials, the target was equally likely to appear at all eight possible locations; and on distractor-present trials, it was equally likely to appear at each of the seven non-distractor locations (i.e., within a given trial display, the target and distractor never appeared at the same location).

Procedure

A trial began with a central fixation cross for a randomly selected time between 800 ms to 1600 ms, prompting participants to fixate their eyes on it. Then the visual search display was shown until a response was made or for a maximum of 4 seconds. Participants were told to find the (12° right-tilted) target bar – while ignoring any (45° left-tilted) distractor – in the display and report the (upper vs. lower) notch position within it as fast as and accurately as possible, by pressing either the left or right mouse button with their left or right index finger, respectively. In case of an incorrect or delayed response, the fixation cross changed color for one second, turning red if the answer was wrong and blue if it was too slow. The inter-trial intervals, which presented a blank screen, were jittered randomly between 800 to 1600 ms. Prior to the formal experiment, participants received 80 practice trials (not analyzed), in which the distractor occurred equally likely at all locations (i.e., the spatial distractor distribution was unbiased) and the volatility regimen was neutral (i.e., each distractor-present trial was equally likely to be followed by a distractor-present or -absent trial, and vice versa). The formal session consisted of 9 blocks, each of 160 trials, yielding a total of 1440 (analyzed) trials for each session. The two sessions were conducted on separate days 5 to 7 days apart. A random half of the participants performed the high-volatility session first and the low-volatility second, and vice versa for the other half.

Awareness test

After each experimental session, participants complete to assess their general awareness of the uneven spatial distractor distribution (“did distractors occur equally often at all locations or more frequently at some vs. other locations?”) and their explicit knowledge of likely distractor location (“if you had to make a choice, to which location would you point where the distractor occurred most frequently?), along with their confidence in the answers. At the end of the second session, participants were also asked to compare the volatility regimens in the two sessions (“In the two experimental sessions you performed, how frequently did displays with and without distractors change across trials?” – answer alternatives: “more frequently in session 1”, “more frequently in session 2”, “equally frequently in both sessions”, “unsure”).

Results

All response-time (RT) analyses were performed on mean RTs after removing trials on which participants gave an incorrect response (1.63% of trials) and produced an outlier response (RTs outside 1.5 times the interquartile range below the first quartile or above the third quartile of the RT distribution; 5.72%). On average, 7.35% (sum of response-error and outlier-RT trials) of all trials were removed. For statistics, we carried out repeated-measures ANOVAs on mean RTs and error rates, plus further (post-hoc) comparisons, if necessary.

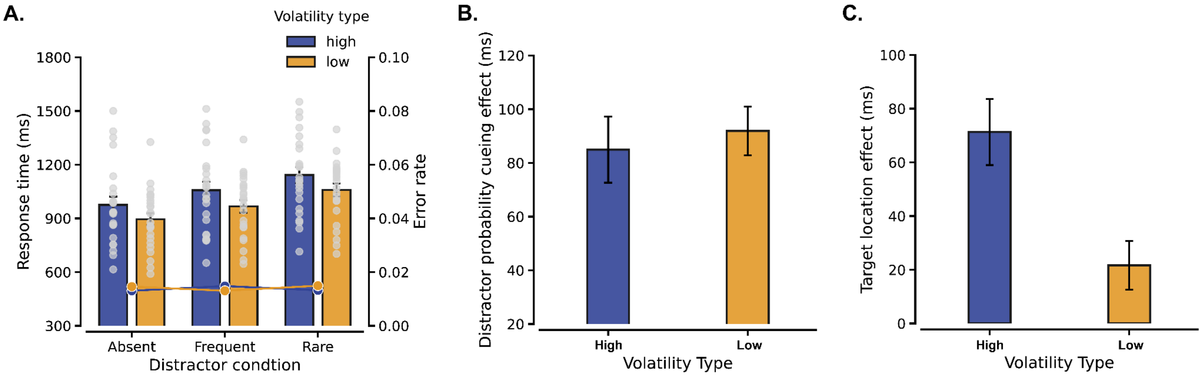


Figure 2. **Distractor interference effects. (A)** Mean RTs (bars) and error rates (lines) as a function of Distractor Condition (distractor absent, at the frequent location, and at a rare location), separately for the two Volatility Types (high vs. low). **(B)** Distractor-location probability-cueing effects (i.e., RT difference between trials with a distractor at a rare vs. the frequent location), separately for the high- and low-volatility conditions. (**C**) Target-location effect (i.e., RT difference between distractor-absent trials with the target at the frequent vs. a rare distractor location), separately for the high and low-volatility conditions. Error bars depict the one standard error of the mean.

A two-way repeated-measures ANOVA of the error rates, with the factors Distractor Condition (distractor absent, at frequent location, at rare location) and Volatility Type (high, low), revealed no significant effects: Distractor Condition, $F(2, 46) = 0.02$, $p = .98$, $BF_{10} = 0.05$, $\eta_p^2 = 0.001$; Volatility Type, $F(1, 23) = 0.05$, $p = .83$, $BF_{10} = 0.13$, $\eta_p^2 = 0.002$; interaction, $F(2, 46) = 1.46$, $p = 0.25$, $BF_{10} = 0.008$, $\eta_p^2 = 0.06$. Given the absence of error effects, we focused on the differences in correct mean RTs in the following analysis.

Figure 2A displays the correct mean RTs, categorized by the Distractor Condition and Volatility Type/Session. Upon visual inspection, it appeared that participants responded generally slower in the high- compared to the low-volatility session, and that RTs increased as the distractor condition progressed from absent distractors to distractors appearing at the frequent location to distractors at a rare location. A repeated-measures ANOVA revealed both main effects to be significant: Distractor Condition, *F* (2,46) = 162.72, $p < 0.001$, $BF_{10} > 1000$, $\eta_p^2 = 0.88$; Volatility Type, *F*(1, 23) = 8.86, $p < 0.05$, $BF_{10} > 1000$, $\eta_p^2 = 0.28$. The interaction was non-significant, *F*(2, 46) = 0.36, $p = 0.69$, $BF_{10} = 0.49$, $\eta_p^2 = 0.02$.

Volatility effect

On average, RTs were 85 ms slower when participants performed the task under high- vs. low-volatility trial-sequence conditions (1058.31 ms vs. 973.67 ms).

Distractor-location (probability-cueing) effect

Post-hoc comparison confirmed robust, and significant, distractor-interference effects (relative to the distractor-absent baseline) both when the distractor occurred at a rare location ($\Delta = 165.79$ ms, *t*(23) =18.01, $p < 0.001$, $BF_{10} > 100$, $d = 0.89$, Bonferroni-corrected) and when it appeared at the frequent location ($\Delta = 77.38$ ms), *t*(23) = 8.20, $p < 0.001$, $BF_{10} > 100$, $d = 0.41$, Bonferroni-corrected). Importantly, the interference effect was substantially reduced when the distractor appeared at the frequent location relative to a rare location (RT reduction of 88.41 ms; *t*(23) = 9.88, $p < 0.001$, $BF_{10} > 100$, $d = 0.47$, Bonferroni-corrected), confirming the standard distractor-location probability-cueing effect. However, the probability-cueing effects were comparable between the two, high- and low-volatility conditions (high: 85 ms, low: 92 ms, *t*(23) = -0.57, $p = 0.57$, $BF_{10} = 0.25$, $d = -0.13$; see Figure 2B).

Target-location effect

Following previous studies (Wang & Theeuwes, 2018; Zhang et al., 2019), we also analyzed the target-location effect (target at frequent vs. a rare distractor location) on distractor-absent trials to determine whether target selection was impacted by statistical learning of the distractor locations. Previous studies had shown that (even without a distractor in the display) observers would respond more slowly toward a target singleton presented at the frequent vs. a rare distractor location, especially if the distractor is defined within the same as the target (as was the case in the present study). For the present study, the target-location effect (RT difference between distractor-absent trials with the target at the frequent vs. a rare distractor location) are depicted in Figure 3C, separately for the two volatility types (high vs. low). Interestingly, the target-location effect turned out to be 71.28 ± 22 ms for the high-volatility condition, which was significantly higher than the effect in the low-volatility condition (21.65 ± 20.95 ms), *t*(23) = 3.37, $p < 0.01$, $BF_{10} = 14.9$, $d = 0.46$. And while the effect was significantly positive in the high-volatility condition, *t*(23) = 3.25, *p* <

0.05, BF_{10} = 11.64, d = 0.66, it did not differ reliably from zero in the low-volatility condition, $t(23) = 1.03$, $p = 0.31$, $BF_{10} = 0.35$, $d = 0.21$. To control for the potential impact of baseline RT differences, we further calculated the relative target-location effect by dividing the RT difference (target at frequent vs. rare location) by the RT for the distractor-absent baseline, separately for the high- and low-volatility conditions. Again, the relative target-locations effects differed significantly between the two volatility conditions, $t(23) =$ 3.02, $p < 0.05$, $BF_{10} = 7.39$, $d = 0.51$.

Repetition-suppression effects

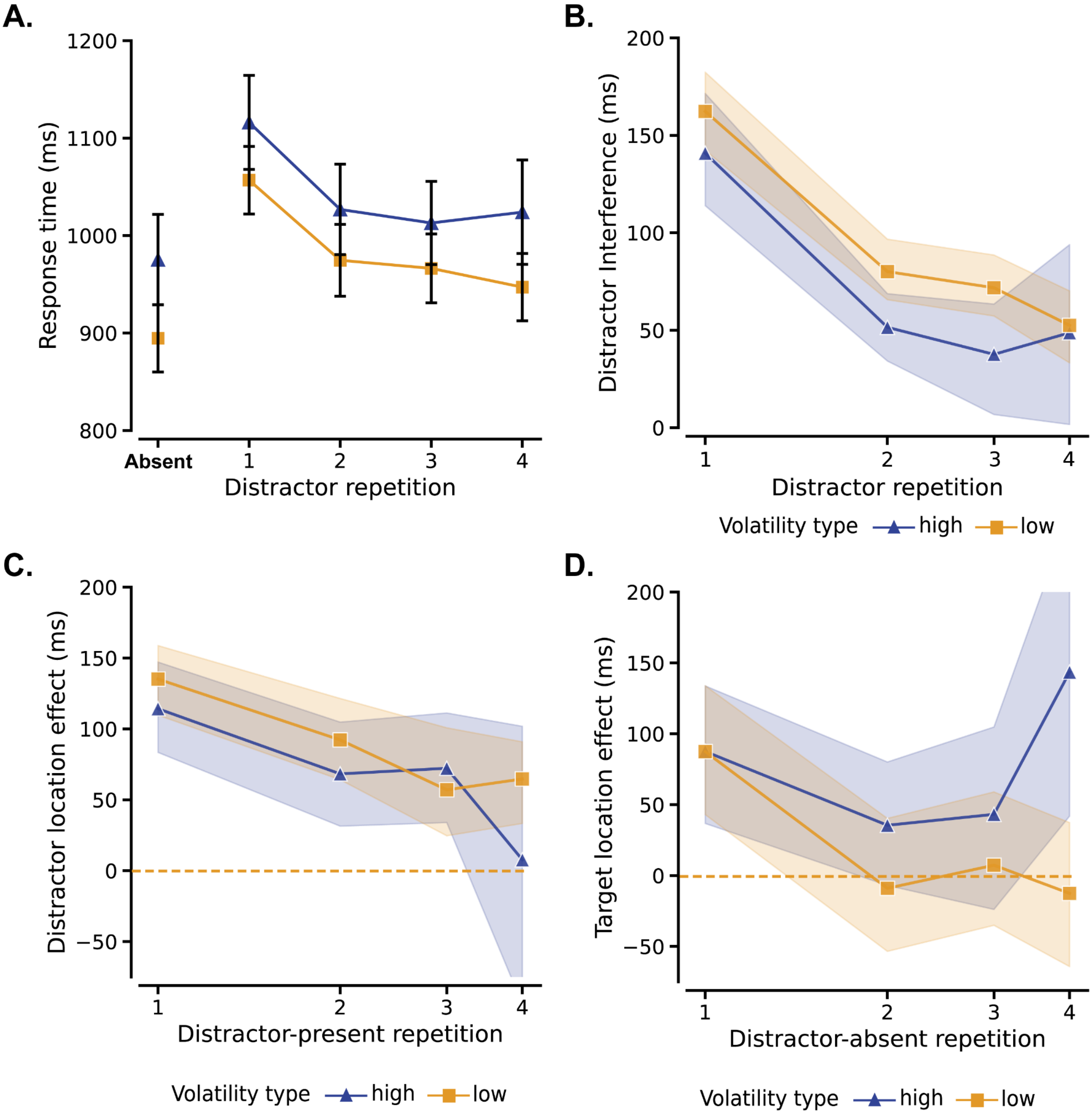


Figure 3. **Distractor-repetition effects. (A)** Mean RTs as a function of the number of consecutive distractor occurrences ('repetitions'), separately for the high- and low-volatility conditions. Error bars depict one standard

error of the mean. **(B)** Distractor interference (i.e., RT difference between distractor-present trials and the distractor-absent baseline) as a function of distractor repetition (in log scale), separately for the high- and low-volatility conditions. (**C**) Distractor-location effect (RT difference between distractor-present trials with a distractor at the frequent vs. a rare distractor location) as a function of distractor-*present*-trial repetition (in log scale), separately for the high- and low-volatility conditions. (**D**) Target-location effect (RT difference between distractor-absent trials with a target at the frequent vs. a rare distractor location) as a function of distractor-*absent*-trial repetition (in log scale), separately for the high- and low-volatility conditions. The shade areas indicate 95% confidence intervals.

In the low-volatility session, distractor-absent trials and, respectively, distractor-present trials, were more likely to appear in (uninterrupted) streaks. To examine whether there were any differences in short-term inter-trial distractor-repetition effects between the two volatility conditions, we marked the number of distractor occurrences leading up to and including the current trial as the number of consecutive distractor repetitions. We had more than 30 streaks of three repetitions in a row for both volatility conditions, providing sufficient statistical power for comparison. Figure 3A depicts the RTs (collapsed across trials with a distractor at the frequent and rare distractor locations) as a function of the number of distractor repetitions within streaks of four trials (1 being the first distractor in the streak and 4 being the last), along with the distractor-absent baseline, per volatility condition. As can be seen, RTs decreased with increasing numbers of distractor repetitions, with the most marked decrease occurring from the first to the second distractor; however, (even at the end of the streak) the RTs were still slower compared to the distractor-absent baseline. A repeated-measures ANOVA of the mean RTs with factors Distractor Repetition and Volatility Condition revealed both main factors to be significant: Distractor Repetition, $F(3, 69) = 39.96$, $p < 0.001$, $BF_{10} > 1000$, $\eta_p^2 = 0.64$, reflecting the decrease in RTs with increasing repetitions; and Volatility Condition, $F(1, 23) = 4.30$, $p < 0.05$, $BF_{10} > 1000$, $\eta_p^2 = 0.16$, reflecting consistently slower responding (by 58.75 ms) in the high- vs. the low-volatility condition. However, the interaction was not significant, $F(3, 69) = 0.73$, $p = 0.54$, $BF_{10} = 0.29$, $\eta_p^2 = 0.3$.

Next, using the distractor-absent condition as the baseline, we calculated the distractor interference as a function of distractor repetition, which is plotted (with repetition in log-scale) in Figure 3B. As can be seen, interference dropped markedly after the first repetition and decreased more gradually thereafter, evidencing ‘repetition suppression.’

Given that the relation between the distractor interference and the log-scaled distractor repetition is approximately linear[12], we further estimated the learning rate of 'repetition suppression' using linear regression (with the log-scaled distractor repetition). The regression slopes were -70.9 and -77.6 for the high- and low-volatility conditions, respectively, without a significant difference between the two conditions, $t(23) = 0.34$, $p = 0.73$, $BF_{10} = 0.23$, $d = 0.1$. In other words, the repetition-suppression rate, indicated by the slope, was comparable between the two volatility regimens. We also estimated the interference generated by the first occurrence of a distractor by taking the intercept of the log-scaled regression. A paired *t*-test revealed the intercept to be significantly higher in the low- (153.3 ± 9.5 ms) vs. the high-volatility condition (126.0 ± 13.8 ms), $t(23) = -2.09$, $p = .049$, $BF_{10} = 1.34$, $d = -0.47$ – likely due to the first occurrence of a distractor was preceded by a streak of distractor-absent trials in the low-volatility condition (see Figure 3A).

Figure 3C depicts the distractor-location effect (i.e., the differential RT interference between trials with a distractor at a rare vs. the frequent location) as a function of the number of (successive) repetitions of distractor-present displays. Note that triple and, in particular, quadruple sub-sequences of successive distractor-present trials (with a distractor appearing consistently at the same, frequent and, respectively rare type of location) were reduced in number after splitting between the 'distractor-at-frequent-location' and 'distractor-at-rare-location' conditions (so each of the respective data points was based on even fewer observations, particularly for the condition of four repetition). For this reason, we calculated individual participants' median RTs for the distractor-location effect (rather than the mean RTs, which are more affected by outliers) and submitted these to a two-way, Repetition × Volatility, repeated-measures ANOVA. This analysis only yielded a significant main effect of Repetition, $F(3, 69) = 5.26$, $p < 0.05$, $BF_{10} = 10.48$, $\eta_p^2 = 0.19$. Neither the main effect of Volatility, $F(1, 23) = 1.67$, $p = 0.21$, $BF_{10} = 0.27$, $\eta_p^2 = 0.07$, nor the interaction, $F(3, 69) = 0.78$, $p = 0.47$, $BF_{10} = 0.15$, $\eta_p^2 = 0.03$, was significant.[13] Thus, consistent with the initial analysis of the distractor-location effect, which disregarded the effects of sequential distractor occurrence (see above), the distractor-interference effect as such did not differ between the two volatility conditions. However, it decreased (by an, in log-scale, approximately equal amount) with each additional repetition of a distractor in a row.

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[12] We chose not to apply a log-scale transformation to the distractor interference, as individual interference values could potentially be negative.

[13] Note that in the high-volatility condition, there were only very few trials per participant with a fourth occurrence of a distractor-present display in a row, increasing the variance associated with the respective data point.

Finally, we conducted a similar analysis for the target-location effect as a function of the number of (successive) repetitions of distractor-absent displays (with the target consistently appearing at either the frequent or a rare location). Figure 3D reveals different patterns for the high- and low-volatility conditions: the target-location effect diminished to zero after the second repetition in the low-volatility session, while it persisted across repetitions in the high-volatility session. A two-way repeated-measures ANOVA of the target-location effect on individuals' median RTs yielded significant main effects of both Repetition, $F(3, 69) = 4.59$, $p < 0.05$, $BF_{10} = 8.22$, $\eta_p^2 = 0.17$, and Volatility, $F(1, 23) = 7.44$, $p < 0.05$, $BF_{10} = 58.19$, $\eta_p^2 = 0.24$. The interaction was also significant, $F(3, 69) = 3.97$, $p < 0.05$, $BF_{10} = 11.08$, $\eta_p^2 = 0.15$. Of note, the target-location effect for the first distractor-absent trial (i.e., a switch from a distractor-present to an -absent trial) did not differ between the high- and low-volatility conditions, post-hoc $t(23) = 0.006$, $p = 0.99$, $BF_{10} = 0.22$, $d = 0.001$. However, in the low-volatility session, starting from the second distractor-absent trial onwards, there were no reliable target-location effects (tested against 0, all ts< 0.30, all ps > 0.77, Bonferroni-Holm corrected). In the high-volatility session, by contrast, the target-location effect did not only remain significantly positive for the second, third, and fourth distractor-absent trial in a row (one-tailed t values > 1.36, p values < 0.05, Bonferroni–Holm corrected), but in fact it also tended to increase again as the number of repetitions increased (with a marked increase for the fourth distractor-absent trial) – explaining part of the interaction. This – intriguing – pattern suggests that proactive distractor-location suppression was quickly 'turned off' after the first occurrence of a distractor-absent trial in the low-volatility condition, in which the next (and subsequent) trial(s) were also likely (i.e., could be predicted) not to contain a distractor, as there was likely a longer streak of distractor-absent trials. In the high-volatility condition, by contrast, proactive location suppression not only remained in place, but showed a tendency to increase as the (subjective) expectancy of yet another distractor-absent trial decreased and that of a distractor-present trial increased.[14]

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[14] Objectively, of course, the likelihood of the next (distractor-present/-absent) event was fixed by the Markov process.

Inter-trial switch costs

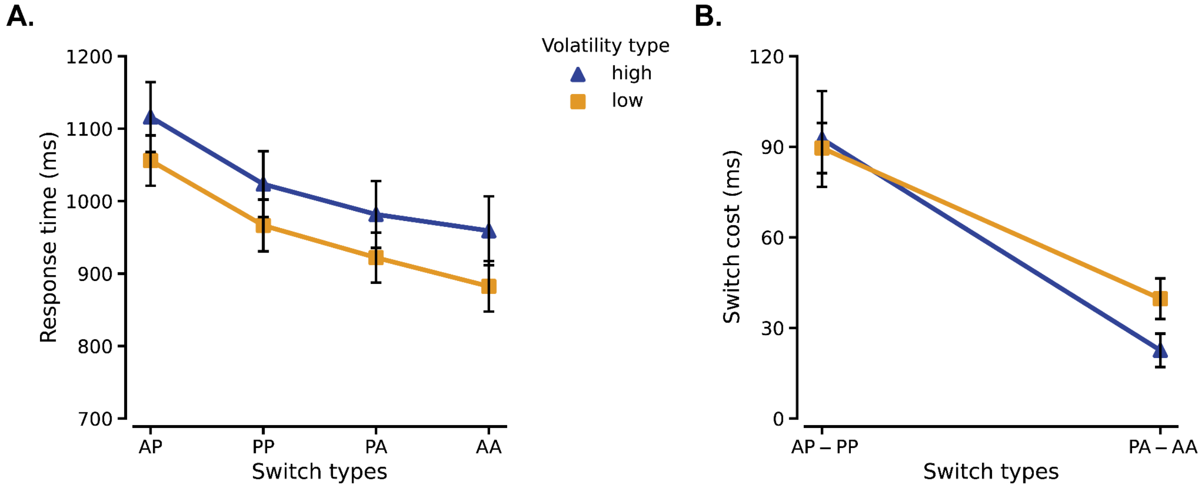

Figure 4. Switch types and switch costs. (A) Mean RT as a function of Switch Type (progress from AA, AP, PA, to PP), separated for high- and low-volatility sessions. A represents the distractor-absent, and P the distractor-present. Two letters correspond to the preceding and the current trial types. **(B)** Mean switch cost as a function of Switch Type ('AP - PP' vs. 'PA - AA'), separated for high- and low-volatility sessions. 'AP-PP' represents the switch cost for the current distractor-present trials, while 'PA - AA' represents the switch cost for the current distractor-absent trials.

Finally, we also examined the pattern of inter-trial switch effects. Considering distractor presence (Present vs. Absent) on the preceding trial (*n-1*) and the current trial (*n*), there were four types of inter-trial switches: Absent-Present (AP), Present-Present (PP), Present-Absent (PA), and Absent-Absent (AA). Figure 4A depicts the mean RTs for this 'progression' of inter-trial switches, separately for the high- and low-volatility conditions. A repeated-measures ANOVA on mean RTs with factors Switch Type and of Volatility Type revealed both main to be significant: Volatility, F (1, 23) = 4.81, $p < 0.05$, $BF_{10} > 1000$, $\eta_p^2 = 0.17$, and Switch Type, F (3, 69) = 134.21, $p < 0.001$, $BF_{10} > 1000$, $\eta_p^2 = 0.85$. But the interaction was non-significant, F (3, 69) = 0.92, $p = 0.40$, $BF_{10} = 0.27$, $\eta_p^2 = 0.04$. The main effect of volatility was mainly due to the generally slower responses in the high- vs. the low-volatility condition, as already reported above.

To better understand the main effect of Switch Type, we further calculated switch costs for the current distractor-present and -absent trials (*n*) by using subtraction 'AP-PP' and 'PA-AA', respectively. Figure 4B illustrates two types of switch costs for the high- and low-volatility sessions. Upon visual inspection, the switch cost was larger for a current distractor-present trial than a current distractor-absent trial. Both the switch costs of 'AP-PP' and ‘PA-AA’ were reliably larger than zero value (tested against 0, all t values > 6.95, all p values < 0, Bonferroni–Holm corrected). A repeated-measures ANOVA on the switch costs with the factors Switch Type (AP-PP vs. PA-AA) and Volatility Type (high vs. low) revealed the switch cost to be significantly higher for current distractor-present trials (91.1 ms) vs. current distractor-absent trials (31.1 ms), $F(1, 23) = 69.23, p < 0.001$, $BF_{10} > 1000$, $\eta_p^2 = 0.75$. However, neither the main effect of Volatility Type, $F(1, 23) = 0.43, p =0.52$, $BF_{10} = 0.28$, $\eta_p^2 = 0.02$, nor the interaction, $F(1, 23) = 1.33, p =0.26$, $BF_{10} = 0.43$, $\eta_p^2 = 0.06$, was significant. That is, short-term inter-trial switch costs were comparable between the high- and low-volatility conditions, though with asymmetric costs for switching to a current distractor-present trial (large cost) vs. a current distractor-absent trial (smaller cost).

Awareness report

Recall that participants completed a questionnaire after each experimental session to assess their general awareness of the uneven spatial distractor distribution (“did distractors occur equally often at all locations or more frequently at some vs. other locations?”) and their explicit knowledge of likely distractor location (“if you had to make a choice, to which location would you point where the distractor occurred most frequently”). In the high-volatility session, 10 (out of the 24) participants reported having noticed a spatial bias, but then gave the wrong answer about the frequent distractor location; of the other 14 observers, one indicated the frequent location correctly. In the low-volatility session, 7 (out of the 24) participants reported they were aware of a bias, but again none of them pointed correctly to the frequent distractor location; of the remaining 17 observers, 7 were able to indicate the frequent location correctly, with modest confidence in their choice (average confidence score of 3.29, where 1 = highly certain and 5 = highly uncertain). The latter finding points to the low-volatility condition fostering an element of explicit awareness of the spatial distractor distribution (i.e., 29.17% of the total sample chose the likely location correctly, which compares to a chance level of ⅛ locations or 12.5%).

At the end of the second session, participants were also asked to compare the volatility regimens in the two sessions (“In the two experimental sessions you performed, how frequently did displays with and without distractors change across trials?” – answer alternatives: “more frequently in session 1”, “more frequently in session 2”, “equally frequently in both sessions”, “unsure”). The majority of participants chose either the “unsure” option (10 participants = 41.67%) or the “equal change-frequency” option (8 participants =

33.33%). Of the remaining 6 participants, only 2 (8.3% of the total sample) were able to tell correctly in which of the two sessions the two types of trial changed more frequently.

Overall, the 'awareness' results suggest that participants had little, if any, explicit awareness of the critical experimental manipulations, to some extent excepting (limited) knowledge of the frequent distractor location in the low-volatility condition. Accordingly, the effects of these manipulations are more likely to be implicit in nature, rather than reflecting consciously adopted strategies.

Discussion

The aim of the present study was to investigate how the volatility of distractor presence influences statistical learning of space-based distractor suppression. We adopted the classic probability-cueing search paradigm and compared distractor suppression in two different, high- and low-volatility sessions, each with the same 50% distractor prevalence. In the high-volatility session, the presence and absence of a salient distractor frequently switched, whereas the distractor often appeared in a row in the low-volatility session. We found that in both conditions, participants were able to learn the spatial distractor regularity to minimize interference from distractors occurring at the frequent location – as evidenced by comparable distractor-location probability-cueing effects in the two sessions. Inter-trial switch costs were also comparable between the two sessions. However, a differential pattern emerged on distractor-absent trials: on such trials, there was evidence of suppression of the frequent location – in terms of a target-location effect – only in the high-volatility, but not the low-volatility condition. In addition, response speed was overall slower in the high-volatility condition, suggesting that maintaining proactive suppression across trials brings about a general cost to search performance.

Despite different volatilities in the distractor-event sequences, the present study confirmed the robust distractor-location probability-cueing effect reported in (by now) a plethora of previous studies (Allenmark et al., 2019; Sauter et al., 2018; Wang et al., 2019; Zhang et al., 2019). That is, the statistical regularity of where the within-dimension distractor is likely to appear can be learned and used to reduce potential attentional capture by distractors occurring at the likely location. Recently, systematically manipulating distractor prevalence and the ratio of distractors occurring at frequent/rare locations, Allenmark et al.

(2022) showed that the *local* probability of the distractor occurrence is a major determining factor in distractor-location probability cueing, regardless of differences in distractor prevalence. Although Allenmark et al. (2022) did not directly manipulate the volatility of distractor presence, their manipulation of distractor prevalence indirectly impacted volatility: with increasing distractor prevalence, distractor-present trials become increasingly more likely, and distractor-absent trials less likely, to repeat.[15] From this perspective, our findings align with theirs, as distractor volatility had little influence on statistical learning of location-based distractor suppression, as long as the regional distractor probability remained the same across sessions.

According to the functional architecture of attentional-priority computation (Ferrante et al., 2018; Liesefeld & Müller, 2019; Theeuwes et al., 2022; Wolfe, 2021) and the dimension-weighting account (Found & Müller, 1996; Müller et al., 1995), learning to proactively suppress salient distractors defined within the same dimension as the target can only occur at the level of the integrative, supra-dimensional priority map, by reducing (or 'down-weighting') the integration weight of any (feature-contrast) signal – whether generated by a distractor or a target singleton – at the likely distractor location (Liesefeld & Müller, 2021). This was confirmed by the manifestation of a target-location effect in the high-volatility condition, that is, an RT cost incurred when the target appeared at the frequent distractor location compared to other locations in the absence of the distractor in the search display. Given that on distractor-absent trials, the target singleton was the only salient item in the display, the target-location effect would be indicative of proactive (capture-preventing) – rather than reactive (post-capture) – suppression of the likely distractor location.[16] Of note, according to the dimension-weighting account, learnt proactive suppression may also be implemented at the dimensional (feature-contrast) level below the supra-dimensional priority map) is not limited to spatial-based suppression if the distractor is defined in a different dimension to the target (Allenmark et al., 2019; Sauter et al., 2018, 2019; Zhang et al., 2019). The key diagnostic feature of distractor suppression operating below the priority map is that,

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[15] This is, of course, unlike in the manipulation implemented in the present study, where both these probabilities were higher in the low- vs. the high-volatility condition.

[16] Eye-movement studies of 'oculomotor' capture (e.g., Sauter et al., 2021) show that the total distractor-location effect involves not only a proactive component, reducing capture of the eye by (i.e., saccades to) the distractor at the likely location in the first instance, but also a reactive component: expedited disengagement from (reflected in a shorter fixation on) a distractor that had captured the eye at the likely distractor location. Given that this reactive component does not come into play on distractor-absent trials (on which there is no need to disengage attention from the target), the target-location effect on such trials would provide a relatively pure measure of proactive distractor-location suppression (while also explaining why it is typically smaller than the distractor-location effect).

while the distractor-location effect (which beneficial for performance) remains intact, the (harmful) target-location effect disappears – even though it may take time for participants to ‘discover’ this optimal strategy (see Allenmark et al. 2019; Zhang et al. 2019; Sauter et al. 2018; Sauter et al. 2019).

Intriguingly, here we found that in the *low-volatility* condition, the target-location effect unexpectedly diminished even with the within-dimension distractor introduced in the present study, in particular: the target-location effect completely disappeared on the second occurrence (i.e., the first repetition) of a distractor-absent display in a row (Figure 3C). This suggests that when the volatility of distractor occurrence is low, attentional selection of a target occurring at the frequent-distractor location is no longer subject to learnt suppression of this location (upon the repetition of a distractor-absent trial). The distinctive feature of the low-volatility environment is its temporal predictability, where upcoming events are likely to continue in the same state as the current event. As illustrated in Figure 1C, in the low-volatility condition, distractor-present and, respectively, -absent trials are likely to occur in a row (70%). Therefore, maintaining proactive location suppression for predictable (sequences of) distractor-absent trials would be detrimental to search performance. Accordingly, participants likely turned off proactive suppression after encountering the first distractor-absent trial in the low-volatility condition (see Figure 3C). In contrast, in the high-volatility condition, following a drop in proactive suppression after the first encounter of a distractor-absent display, proactive suppression tended to increase again upon the second and, particularly, the third repetition of a distractor-absent display – likely reflecting increasing anticipation (or subjective expectancy) of a distractor event occurring on the next trial (though see Footnote 4).

Another important issue concerns the connection between the long-term sequential volatility structure and short-term inter-trial repetition priming and switch costs. Our analysis of inter-trial repetition effects revealed the interference from the distractor (measured against the distractor-absent baseline) to decrease as the number of repetitions of the distractor increased – which is consistent with a previous report by van Moorselar and Slagter (2019). While the decreasing rate was similar between the high- and low-volatility conditions, distractor interference was overall higher in the low- vs. the high-volatility condition (Figure 3B). On the other hand, the distractor-location (probability-cueing) effect turned out comparable between the two sessions. To understand these seemingly contradictory findings, recall the nature of the low- and high-volatility trial sequences. In the low-volatility condition, distractor-present trials were more likely to occur in a row, increasing the likelihood of the distractor occurring at the frequent location during such trial streaks. In the high-volatility condition, by contrast, distractor-present trials – and thus trials with a distractor at the frequent location – were more likely to be randomly interleaved with distractor-absent trials. Our inter-trial switch-cost analysis revealed the mean RT on distractor-present trials to be larger when preceded by distractor-absent (AP) rather than distractor-present (PP) trials, with the short-term switch costs being comparable between the two conditions. Accordingly, even though the distractor-interference curve appeared higher in the low- relative to high-volatility condition (Figure 3B), the distractor-location effect was comparable between the two conditions. In other words, despite short-term fluctuations of distractor suppression, long-term distractor suppression was primarily determined by the regional probability of distractor occurrence (Allenmark et al., 2022).

Apart from the finding that distractor interference decreased with increasing number of distractor repetitions at largely the same, frequent location, we also observed asymmetric inter-trial switch costs. Specifically, the cost was significantly higher for switching to a distractor-present trial than for switching to a distractor-absent trial (i.e., AP - PP > PA - AA). The high switch cost for distractor-present trials (AP vs. PP) suggests that proactive distractor suppression did not fully operate after distractor-absent trials, resulting in a capture effect on the following distractor-present trial (consistent with the general, location-unspecific distractor-probability effects observed by Müller et al., 2009). In contrast, proactive suppression remained active following distractor-present trials. Interestingly, the short-term switch cost was not affected by the volatility of the trial sequence, which is consistent with previous findings (Goschy et al., 2014). Compared to the distractor-absent repetition (AA), the current distractor-absent trial with a preceding distractor-present (PA) was about 31 ms slower. Given that the distractor-absent trial did not have a salient distractor, the cost carried over from the preceding distractor-present trial can be mostly attributed to short-term proactive distractor suppression.

Combining both types of switch cost effects, we obtain a better understanding of the short-term dynamics of distractor suppression. When encountering a distractor, regardless if it is proactively or reactively suppressed, proactive suppression is activated afterwards. When a distractor occurs in the following trial, this proactive suppression facilitates target selection. However, when a distractor does not occur in the subsequent trial, maintaining such proactive suppression can be detrimental, leading to the subsequent winding down of the proactive suppression. The winding down process was very quick in the low-volatility session, as shown by the diminished (effectively, absent) target-location effect from the second distractor-absent trial onwards (Figure 3D). Conversely, when switching from distractor-absent to distractor-present trials, the reduced proactive suppression makes it more likely that the distractor will capture attention, and so must be suppressed reactively for attention to be disengaged and oriented towards the target location, incurring a significant switch cost (e.g., Geng, 2014). The dynamics of distractor suppression is thus tuned to the spatial distribution of the distractor as well as the volatility of its occurrence through statistical learning, as evidenced by the distinct patterns of distractor-location probability-cueing and target-location effects.

Perhaps the theoretically most significant, and challenging, finding concerns the differential pattern of the target-location effect between the high- and low-volatility conditions. Assuming that proactive suppression of the likely distractor location is a purely passive effect – simply reflecting the acquired weights, in priority computation, of signals at the frequent and, respectively, rare distractor locations –, then the fact that the target-location effect effectively vanished after the first encounter of a distractor-absent trial in the low-frequency condition is surprising; and similarly unexpected is the finding that, following the drop after the first encounter of a distractor-absent trial, the target-location effect tended to increase again with further repetitions of distractor-absent trials in the high-volatility condition. These effect patterns would suggest that proactive suppression may be dis-engaged when the expectancy of a distractor occurring is low (in the low-volatility condition) and be engaged again as the occurrence of a distractor is increasingly anticipated (in the high-volatility condition). It is not clear (from our awareness-test results) whether this ‘expectancy-dependence’ of the target-location effect is due to participants actively, or consciously, predicting what is going to happen on the upcoming trial (based on what has been going on on the preceding trials), or whether these predictions are more implicit in nature, based on participants having established some dynamic ‘prior’ of how distractor-present/-absent events unfold sequentially over time. Consistent with an element of awareness, a good number of participants could tell (upon being forced) the spatial distractor distribution at least in the low-volatility condition (in which events were likely to occur in longer streaks), and it is known that the simple kind of awareness test employed here (as well as in virttually all other studies of distractor-location probability cueing) is highly likely to underestimate the true level of awareness (Giménez-Fernández et al., 2020; e.g., Vicente-Conesa et al., 2023). Whatever the answer, it would appear that some kind of executive, ‘expectancy-dependent’ signal is required for proactive distractor-location suppression to be triggered or ‘engaged’. Further – likely empirical and theoretical – work is necessary to elucidate how this expectancy-dependence of the target-location effect is to be squared with the notion that proactive distractor-location suppression is essentially an automatic, hard-wired process. One way towards resolving this may be to conceive of proactive distractor-location suppression as an acquired ‘template’, which needs to be retrieved from spatial long-term memory and maintained in an available state to be optimally applicable. This could explain the differential target-locations effects between the two volatility conditions: assuming that it normally suffices for the routine to be rendered inactive that it is not called upon on a given (i.e., the first distractor-absent) trial, this would explain why there was no longer a target-location effect from the next distractor-absent trial onwards in the low-volatility condition. In the high-volatility condition, by contrast, the routine was being called upon relatively unpredictably, and so it needed to be prevented from becoming inactive by active retrieval processes – explaining the maintenance of the target-location effect over repeated distractor-absent trials.

Conclusion

In summary, participants exhibited similar ability to learn to mitigate the interference of within-dimension salient distractors at the frequent location under both high- and low-volatility conditions – indicating that statistical distractor-location learning is robust to changes in volatility. However, the high-volatility condition involved greater uncertainty about distractor presence on the upcoming trial(s), resulting in overall slower target selection. This high uncertainty also led participants to engage in proactive suppression more continuously, as evidenced by a sustained target-location effect on successive distractor-absent trials. In the low-volatility session, by contrast, the predictability of distractor-absent trials occurring in a trial streak allowed observers to quickly abandon proactive suppression after encountering the first distractor-absent trial, to boost search performance. Despite short-term fluctuations of distractor interference in both conditions, long-term distractor suppression was primarily determined by the local probability of distractor occurrence.

Declaration of competing interest

The authors declare no competing interests.

Data availability statement

Raw data used for analyses presented within this article will be made available upon request. If you would like to access the raw data and analysis, please email Nan Qiu at the following e-mail address: shirleyqiunan@gmail.com.

Credit authorship contribution statement

Nan Qiu: Conceptualization, Formal analysis, Data collection & curation, Methodology, Project administration, Visualization, Writing – original draft, Review, and Editing.

Fredrik Allenmark: Conceptualization, Methodology, Validation, Resources, Review, and Editing.

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Zhuanghua Shi: Conceptualization, Funding acquisition, Analysis, Methodology, Supervision, Validation, Writing, Project administration, Resources, Review, and Editing.

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3 General Discussion

The present dissertation sought to investigate behavioral and neural mechanisms of statistical learning of distractor-location suppression in visual search. I focused on the locus of the spatial statistical regularities and inter-trial distractor inhibitory effects, measuring by behavioral, eye-tracking and electrophysiological evaluations. I will briefly synopsis the main results for each quantitative-empirical study and discuss how they contribute to the present dissertation. The next step will be to present a perspective on potential future research directions, followed by a conclusion.

3.1 Summary of results

3.1.1 Distractor-location probability and inter-trial suppression effects: behavioral and electrophysiological evidence

To briefly review the first study (Chapter 2.1), by manipulating the classical additional singleton search paradigm(Allenmark et al., 2019b; Theeuwes, 1992; Zhang et al., 2019), The participants should find and respond to a unique shape-defined target (such as a circle among diamonds) while ignoring a salient color-defined distractor (such as a red or green singleton that is different in color from other, non-distractor items). Statistical learning of the distractor-location distribution can be obtained by observing if the salient distractor singleton appeared with a high probability at one "frequent" location and with a low probability at one of the "rare" locations in the search display.

It is well-known and established by numerous behavioural studies, as we introduced before (see General Introduction, Chapter 1.3), that distractors occurring at frequent (distractor) locations cause less interference than distractors occurring at rare locations. Additionally, this reduction of interference by distractors occurring at likely locations is partly attributable to short-term inter-trial effects (Goschy et al., 2014; Sauter et al., 2018; B. Wang & Theeuwes, 2018a). For instance, search RTs are slower when a target (on the current Trial *n*) occurs at the same location as a distractor on the preceding trial (*n*–1), as compared to a different location (*distractor-target* inter-trial effect; for a detailed analysis of this effect pattern, including target-distractor and target-target effects, see the Supplementary in Sauter et al., 2018). Nevertheless, to what degree such a distractor suppression effect depends on the long-term probability of the distractor and short-term inter-trial distractor-target coincidence remains elusive, particularly absent information concerning neural mechanisms. This study set out to investigate (1) how the long-term probability of distractor location and the short-term inter-trial coincidence of the distractor and target locations modulate attentional selection across trials at the neural level, by examining the early posterior-contralateral components (N1p, Ppc, and N2pc) and the late SPCN component when the target (Trial *n*) occurs at the previous distractor (Trial *n–1*) location; and (2) whether any anticipatory suppression occurs before search display onset, by examining the pre-stimulus alpha activity.

Behaviorally, in line with growing studies on the *distractor-location probability cueing effect*, we also demonstrated that distractor interference (faster RTs) was significantly decreased when the distractor occurred in the frequent- compared to a rare distractor location, revealing the statistical learning of uneven distribution of distractor locations brings performative benefits in the visual selection processing (Allenmark et al., 2019a; e.g., Goschy et al., 2014; Liesefeld & Müller, 2020; Sauter et al., 2018, 2021; B. Wang & Theeuwes, 2018b). This effect arises as a result of statistical learning, across trials, of where distractors are likely to occur in the display, which is thought to lead to 'proactive' suppression of the respective locations – evidenced, for instance, by distractors at frequent locations attracting fewer eye movements(e.g., Allenmark, Shi, et al., 2021; Sauter et al., 2021). On the other hand, when a distractor does capture attention (whether overtly or covertly), its location needs to be suppressed 'reactively'(e.g., Geng, 2014) for attention to be disengaged and reallocated to the target location. The effect of this reactive inhibition carries over to the next trial – as evidenced by slowed RTs to a target on a given Trial *n* falling at the location occupied by a distractor on the previous Trial *n-1(e.g., Allenmark, Shi, et al., 2021; Geyer et al., 2006; Kumada & Humphreys, 2002; Sauter et al., 2018)*. While this may reflect an 'inhibition-of-return' tag carried over across trials, it might also reflect an adjustment of decision criteria in post-selective 'target' decisions, that is, in deciding whether an attentionally selected item is actually the searched-for target or an irrelevant distractor (or non-target) item[17].

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[17] In fact, the globally measured behavioral distractor-location probability-cueing effect may also, to some extent, reflect such post-selective processes, evidenced by findings from studies of oculomotor capture that it takes less time to disengage the eye from a frequent vs. a rare distractor location(Sauter et al., 2021). While this may have to do with the overcoming of oculomotor 'hold' processes, it may also reflect a shift in post-selective decision criteria: if decisions are biased towards 'distractor' and away from 'target' at frequent locations, the (perceptual) signal to disengage the eye would be issued faster, expediting oculomotor disengagement from distractors at frequent locations.

Electrophysiologically, we found a dissociation between the early N1pc/Ppc and the late SPCN. On target-only trials, the polarity of the early lateralized component was dependent on the location of the target, with the frequent location triggering the target-referenced N1pc component, and the rare location triggering the target-referenced Ppc component. Target-plus-distractor trials also showed the equivalent N1pc/Ppc pattern. Moreover, the late SPCN amplitude was more negative-going when the target location coincided with the preceding distractor location than when it did not. Finally, for question (2), no reliable evidence was found of anticipatory suppression induced by the uneven spatial distribution of distractor locations in terms of differential activity in the alpha band (8-12 Hz) contra- vs. ipsilateral to the likely distractor location.

This study revealed that the statistical learning of the likely distractor location manifested in an early N1pc/Ppc post-display onset, but not in lateralized alpha power during the pre-stimulus period. Depending on the reference used to calculate the lateralized components, the Ppc reversed along the x-axis to become the negative-gong component (e.g., N1pc) towards the frequent distractor location (which contained the most salient stimulus on nearly 50% of the trials overall in our display design). It may indicate an acquired top-down attentional bias towards the frequent distractor location where it contained the most salient object (i.e., the shape-defined salient target or the color-defined salient distractor). This top-down attentional prioritization (activated only upon the appearance of the search display) competes with the ‘attend-to-me’ signals generated by the singleton target and distractor items, potentially rendering the classic N2pc unobservable in some circumstances. A second effect associated with the inter-trial distractor-target coincidence was enhanced SPCN, suggesting that there were more (vWM) resources needed to decide upon a response to a previous distractor at the same location. That is, we observed that the SPCN amplitude turned out more negative for the coincident vs. non-coincident condition, positioning of the target on Trial *n* with respect to the distractor on Trial *n–1* (i.e., when the target appeared at the same, vs. a different, location to the preceding distractor). Supporting by the behaviroal RTs evidence from the coincidence condition and the SPCN component, we suggested that the inter-trial distractor-target coincidence effect attributed to a late, post-selective process, plausibly as a result of a short-term bias (induced by the distractor on Trial *n–1*) against identifying the item at the frequent distractor location (on Trial *n*) as a target, rather than a distractor.

Another interesting finding of the present study is we didn’t find any increase in pre-stimulus alpha-band power over the hemifield contralateral to the frequent distractor location within the pre-stimulus time window. Until recently, enhanced lateralized alpha-band (8–12 Hz) oscillations have been reported over the occipital cortex contralateral to the to-be-ignored location before the onset of the to-be-attended target(Jensen & Mazaheri, 2010; Kelly et al., 2006; Worden et al., 2000). However, it has been debated whether the statistically learned (long-term) inhibition of the distractor occurring at a likely location reflects a proactive suppression in anticipation of the beginning of a search display, where this process would be purely spatial (i.e., feature-blind), suppressing the allocation of attention to the learnt location regardless of whether there are distractions or targets in the search display. As a result of one recent study that examined distractor-location probability cueing, pre-stimulus alpha-band oscillations in the parieto-occipital visual region were found to be enhanced in the case of the frequent distractor location as compared to a rare distractor location(B. Wang, van Driel, et al., 2019). However, other studies utilizing a probability-cueing paradigm have not always replicated Wang’s findings consistent with anticipatory suppression. As a matter of fact, several recent studies have failed to find any evidence that statistical learning of the frequent distractor location could bias visual attention prior to search display onset by pre-stimulus alpha-band activities in the visual region (Noonan et al., 2016; van Moorselaar et al., 2020, 2021; van Moorselaar & Slagter, 2019). In the end, the current result of alpha oscillations supports the findings of van Moorselaar et al.(2020) as well as Noonan et al.(2016) that anticipatory alpha-band modulations not playing a significant role in the statistical long-term learning and ‘suppression’ of likely distractor locations.

3.1.2 Across-trial volatility of distractor suppression: from behavioral and oculomotor evidence

In the second study (Chapter 2.2), an understudied factor of spatial distractor suppression effects, namely the volatility environment, has been examined and its influence has been evaluated. Due to past selection experiences, people are able to ignore salient distractors frequently occurring at certain locations to reduce attentional capture. Many studies have examined the mechanisms that result in stationary-based probability cueing of distractor locations, but far fewer studies have examined whether our visual system can be trained to minimize distractor interference caused by trial-to-trial transitions of distractor occurrences in volatile environments.

To do this, this study adopted the Markov-chain function (Hamilton, 1990) and the classical visual search paradigm (Goschy et al., 2014) to create volatile environments where distractor-present trials and distractor-absent trials would alternatively occur in the typical visual search task with different transition probabilities (high-volatility vs. low-volatility), thereby the consecutive distractor-present trials structured with different lengths of subsequent repetitions of distractor location. This manipulation resulted in consecutive distraction-present trials with different lengths of subsequent repetitions of distractor location (i.e., 0, 1, 2, 3, 4, and above times). The probability of repeating the same distractor state ("present" or "absent") from trial to trial was manipulated with a 30% probability for the high-volatility session, and 70% for the low-volatility session. Furthermore, we examined oculomotor capture and disengagement during the visual search task, since the attentional and oculomotor systems are known to be connected (Deubel & Schneider, 1996; McPeek et al., 1999; B. Wang, Samara, et al., 2019).

Study 2 of this dissertation has demonstrated that attentional capture by a singleton distractor significantly slowed down RT compared to the distractor-absent trials, suggesting attentional capture by a salient distractor. Likewise, the proportion of first saccades landed on the target was very high when the distractor was absent (51%), but it decreased significantly when the salient distractor was present (28.5%), suggesting that there was a generalized detrimental effect on target-directed saccades as the distractor appeared to reduce the percentage of initial saccades toward the target. In addition, the high-volatility session resulted in slower response times than the low-volatility session. However, in the low volatility session, the attentional capture RTs cost between distractor presence and absence was larger, which indicates distractor interference more with search performance in the less volatile environment.

Furthermore, distractor interference was reduced (less RTs) as distractor position repetitions increased. As evidenced by oculomotor evidence, the proportion of first saccades landing on the target increased after repeated appearances of the distractor at the same location across consecutive trials due to attenuation interference. There was a decrease in the number of first saccades landing on the salient distractor when it repeatedly appeared at the same location across consecutive trials. In short, study 2 of the dissertation suggested attentional capture was modulated by distractor location repetitions to give rise to significant suppression effects in oculomotor capture, replicating a closely related finding by van Moorselar and Slagter (2019). However, there is no difference in the rate at which interference was reduced across repetitions between the high- and low-volatility sessions. It could be taken to suggest that the decreased distractor interference across distractor location repetitions is not a result of learning to expect distractor occurrence in a particular location, but could instead be similar to priming of pop-out. We speculated that priming of pop-out may be responsible for this reduced interference across distractor location repetitions. An early priming of pop-out study, by Maljkovic and Nakayama, found that RTs are slower in a condition of 100% predictable change of the target feature from trial to trial than in the maximally unpredictable condition with equal probability of repetition and change (Maljkovic & Nakayama, 1994), which the authors took as evidence that the short term memory of the target feature primes and facilitates performance when the feature repeats regardless of any expectations based on the statistics of the stimulus sequence. Similarly, short-term memory of a previous distractor location could “prime” suppression of that location, relatively independently of any statistical expectations learned from the sequence of distractor locations. Alternatively, the pattern of results is also consistent with local habituation (e.g. Allenmark et al., 2022; Sokolov, 1963; R. F. Thompson, 2009; Turatto & Valsecchi, 2023). It means that an internal model of the environment may be updated after a distractor appears in a particular location, such that on the following trials a distractor in that location is less unexpected and attracts less attention.

It was not found that the volatility condition and the number of repetitions of the distractor had a significant interaction in overall RTs, but such an interaction did exist for the proportion of trials where the first saccade went to the distractor and the dwell time of the distractor. In both cases there was virtually no difference on the first distractor repetition, but on the second and fourth repetitions there were numerically more and longer fixations on the distractor. This hints at a somewhat slower increase in distractor suppression across repetitions in the high-volatility environment. Overall, it seems that learning to better ignore the irrelevant distractor as the distractor location was repeated, one or multiple times, was influenced relatively little by the volatility of the stimulus sequence, but with some evidence of slower learning in the high volatility session. This seems unlikely to be a result of an adaptation of the overall learning rate to the statistics in the environment, since Bayesian theories of optimal learning predict a difference in the opposite direction, i.e. a higher learning rate in the high volatility environment (e.g. Behrens et al., 2007; Mathys et al., 2011). Instead, the slower increase in distractor suppression in the high-volatility session is in the direction predicted by optimal learning of the transition probabilities of the Markov chain, i.e. in the high-volatility session there is a lower probability of repeating the same distractor location, so it makes sense to apply less suppression to that location.

Additionally, switching between distractor absent and distractor present trials seemed to generate higher switching costs than when repeating distractor states. It seems plausible that supporting habituation as a possible explanation for learned distractor suppression. These high switch costs when switching from distractor-absent to distractor-present trials, which was probably due to the repeated repetition of the same distractor location across repeated distractor-present trials, but there was also a switch cost in the other direction. As discussed above, the habituation account could potentially explain this since after a sequence of distractor-present trials with a repeated distractor location, the visual system needs to update its search model to expect a distractor in that location, and the absence of such a distractor may then have been surprising and attracted attention. However, it could also be a consequence of suppression of the previous distractor location, resulting in slower RTs when the target appears in that location.

In summary, the above results are in line with the account of selection history: since spatial priority maps are highly flexible, volatile environments could affect the learning rate of distractor suppression, and observers could also reduce attentional capture by observing local trial-to-trial regularities of distractor locations. Therefore, unlike previous studies, this study reveals both the effect of distractor-repeat sequences on location suppression and the effect of environmental volatility adjusting learning rates of distractor suppression.

3.1.3 Combination of probability cueing and volatility suppression mechanisms

In the third study (Chapter 2.3), we concentrated on the underlying mechanism of the statistical learning of spatial-based distractor suppression in a sequential-based volatile environment, because the influence of the volatility of distractor presence helps to understand further the learning rate of distractor suppression in more complex and dynamic search environment in the near past. By adopting a distractor-location probability cueing search paradigm and a Markov chain transition matrix, we created volatility sequences that compared the statistical learning of distractor-location suppression under high- and low-volatile search environments, each with the same 50% distractor prevalence, while maintaining a consistent global spatial distribution of distractors - one location with the high occurrence of the distractor.

Firstly, we reproduced the distractor probability cueing effect, evidenced by faster responses when the within-dimension distractor appeared at the frequent location relative to the rare location on distractor-present trials. Secondly, as results showed in both high- and low-volatility sessions, participants were able to learn the distractor regularities to minimize interference when a distractor onset appeared in the display, as manifested by comparable distractor-location probability cueing effects in two sessions. Thirdly, participants were able to learn implicitly distractor regularities in both high- and low-volatility sessions to minimize interference when distractors appeared, as evidenced by comparable distractor location probability cueing effects in two sessions. Intriguingly, responses were slower when the target appeared at the frequent distractor location on distractor-absent trials in the high-volatility but not in the low-volatility, sessions, revealing the differential target-location effects between two volatility search environments. This pattern may be due to the high-volatility session leading to greater uncertainty about upcoming distractor presence, resulting in generally impaired target selection. In addition, the high-volatile session showed overall slower responses than the low-volatility session, suggesting that keeping proactive suppression across trials may cause a general cost. While in the low-volatility session, observers quickly abandoned proactive suppression upon encountering the first distractor-absent trial to facilitate search performance.

Lastly, our analysis of short-term inter-trial repetition revealed that interference from the distractor decreased as the repetition of the distractor increased at the same location across trials. While the decreasing rate was similar between the high- and low-volatility sessions, the interference effect was generally higher in the low-volatility session compared to the high-volatility session. It means that using the distractor-absent condition as the baseline, we calculated the distractor interference, which showed a significant drop after the first repetition and gradually decreased afterwards. The difference was likely due to the fact: the baseline RT in the low-volatility session was significantly lower than that in the high-volatility session. We demonstrated that albeit short-term fluctuations of distractor suppression, long-term distractor suppression was primarily determined by the regional probability of distractor occurrence. In summary, statistical learning of distractor suppression is relatively unaffected by distractor volatility, but location-based proactive suppression depends on the volatility of the distractor occurrence.

3.2 Future research directions

The current findings of the dissertation have at least two significant implications for future research. On the one hand, Study1 provides strong empirical evidence to understand the neural mechanisms involved in distractor-location suppression based on long-term statistical learning and short-term (inter-trial) adjustments. On electrophysiological measures, statistical learning of the most likely distractor location was manifested in a post-display onset N1pc/Ppc, but not in lateralized alpha power pre-stimulus. Early lateralized components N1pc/Ppc had a polarity that was determined by the reference used in the difference wave calculation: the Ppc turns into an N1pc if referenced to the side of the frequent distractor location, indicating a top-down attentional bias towards the frequent distractor location in our display design (which contained the most salient stimulus on nearly 50% of trials). It is possible that this top-down attentional prioritization (active only upon the appearance of the search display) might make the N2pc unobservable in certain circumstances due to the competition with the attentional signals generated by the singleton target and distractor items. While the inter-trial distractor-target coincidence effect was predominantly associated with an enhanced SPCN, suggesting increased (vWM) resource demands to respond to the target (selected) at a previous distractor location. Accordingly, we attribute the coincidence cost on the RTs to a late, post-selective process, possibly a consequence of short-term bias (induced by the distractor on Trial *n–1*) against identifying an item at the frequent distractor location (on Trial *n*) as a target, rather than a distractor. Our interpretations, especially those of the early ERP effects, are post hoc and need to be confirmed in future studies. On distractor-present trials, we were unable to isolate distractor- and target-related activity (since distractors were always placed on the opposite side of targets), so we cannot identify where interference reduction occurs in later processing. A further investigation into this question would require lateralized distractions and midline targets to be implemented in order to provide a definitive answer.

On the other hand, this dissertation (Study 2 and Study 3) is very much concerned with investigating the cognitive functions of distractor suppression in more dynamic and volatile search environments. Although we concluded that spatial regularities of distractor suppression are relatively unaffected by statistical volatilities of the distractor occurrence, but location-based proactive suppression depends on the volatility level. Yet, we still need more future work to study the influence of volatility factors. For example, the question is if the dimension of salient distractor singleton changed, there would be different cognitive functions generated in statistical volatility environments. From a clinical perspective, how can we use these statistical regularities of features/locations of the salient distractor/target to help cognitive recovery in patients with attention deficit hyperactivity disorder (ADHD) or autism? To date, little information exists about the neural mechanism underlying the statistical learning of distractor suppression in a volatile environment. Although an fMRI study (Ferrari et al., 2022) also used a volatility environment in which two alternating contexts had different sequences of object images by transition probabilities, resulting in context-dependent expectations that must be revised as context changes. They suggested that our complex and dynamic visual environment may benefit from an insular and frontoparietal executive control network such that flexibly deploys contextual sensory expectations. While overlapping neural systems may help to extract and adapt to statistical regularities in different cognitive domains (e.g., complex visual attention, context learning, learning and memory, and so on), when and how the distractor suppression mechanism of statistical learning in a volatile environment will happen still an open question. Further studies are recommended to track the neural processing of statistical learning in more complex volatility environments, such as EEG, eye movements, and fMRI measurements.

3.3 Conclusions

This dissertation provided strong empirical evidence to understand the behavioral and neuropsychological mechanisms involved in distractor-location suppression. On the other hand, by creating a novel volatile environment, the current dissertation has studied how across-trial statistical regularities dynamically modulate distractor-location suppression effects to facilitate visual selection. The volatility factor provides a novel way to expand our understanding of how the visual system learns to reduce the interference caused by the salient distractor for adaptive behavior in the ever-changing environment. These findings have demonstrated that search performance can be improved by introducing the spatial probability distributions of distractor locations and the critical volatility factor. To conclude, the current dissertation highlighted the significant role of across-trial statistical learning of distractor locations in visual selection, and enriched our understanding of its cognitive mechanisms to better resolve attentional capture.

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Deutsche Zusammenfassung

In unserem täglichen Leben werden wir ständig mit visuellen Informationen bombardiert. Ein Beispiel wäre es, wenn wir zur Arbeit mit dem Bus fahren und an der Bushaltestelle warten, halten wir Ausschau nach passenden Informationen. Gleichsam kann uns ein ähnlich gefärbter, aber anderer Bus ablenken. Ein anderes Beispiel ist die gezielte Suche eines Freund in der Menschenmenge, der zusätzlich einen roten Hut trägt. Dabei kann unsere Aufmerksamkeit ungewollt von den auffälligen roten Blumen am Straßenrand abgelenkt werden. Es besteht kein Zweifel daran, dass die visuelle Aufmerksamkeit allgegenwärtig und im Alltag von entscheidender Bedeutung ist. Jedoch kann die Interaktion mit einer komplexen, sich ständig verändernden Umwelt unser Gehirn schlichtweg überfordern, sodass nicht alle Informationen verarbeitet werden. Dabei sind es besonders auffällige, aber für die Aufgabe irrelevante Objekte (sogenannte Distraktoren), die in einer visuellen Szene besonders hervorstechen und unsere Aufmerksamkeit erregen. Diese Ablenkung unserer Aufmerksamkeit auf plötzliche Reize kann mitunter schädlich, sogar lebensbedrohlich sein und beispielsweise einen Unfall während des Autofahrens zur Folge haben. Kurzum, es besteht ein Interesse daran, unsere limitierten Aufmerksamkeitsressourcen hinsichtlich der Priorisierung wichtiger Informationen (*Targets*) und der Ablenkung (*Distraktoren*) genauer zu untersuchen.

Die visuelle Aufmerksamkeit ermöglicht es uns, die sensorische Verarbeitung selektiv auf Informationen (*Targets*) zu lenken, die für unsere Ziele relevant sind, und zu verhindern, dass die Aufmerksamkeit auf Ablenkungen (*Distraktoren*) gelenkt wird, die nichts mit den anstehenden Aufgaben zu tun haben (Chun & Marois, 2002; Egeth & Yantis, 1997; Folk et al., 1992; Geyer et al., 2006; Mazza et al., 2007; Treisman & Gelade, 1980; Wolfe & Horowitz, 2004). Daher ist die Aufmerksamkeitsverarbeitung vom dualen Mechanismus der *Target*-Selektion und der Distraktor-Suppression abhängig (Chun & Marois, 2002). Traditionell wird angenommen, dass die aufmerksame Selektion aus der Interaktion zweier Kontrollmechanismen resultiert, die *top-down* Kontrolle (zielgesteuert: z. B. das bekannte Gesicht in der Menschenmenge), und die *bottom-up* Kontrolle (reizgesteuert: z. B. das Hören und Sehen des Blaulichts) (Egeth & Yantis, 1997; Folk et al., 1992; Orchard-Mills et al., 2013; Wolfe et al., 2003; Yantis & Egeth, 1999). Diese Theorie ist weit verbreitet und hat breite Akzeptanz gefunden. Trotz widersprüchlicher Vorhersagen beider Theorien (*top-down* vs. *bottom-up*) darüber, wann selektive Aufmerksamkeit stattfindet, haben sie sich jedoch schon seit längerem nicht weiterentwickelt. Klar ist aber folgendes, während top-down *Targets* einen prominenten Einfluss auf die Aufmerksamkeit haben, gibt es eine Vielzahl von Szenarien, in denen irrelevante aber hervorstechende (saliente) Informationen (*Distraktoren*) die Aufmerksamkeit ebenso zu erregen scheinen. Immer mehr Studien verweisen jedoch darauf, dass die anerkannte Dichotomie zwischen *top-down* und *bottom-up* nicht ausreichend ist um die Aufmerksamkeitskontrolle zu beschreiben, und weitere Faktoren wie die Vorerfahrung (*selection history*) unsere Aufmerksamkeit sowie die Selektion und Effizienz während der visuellen Suche beeinflussen und verzerren können (Anderson et al., 2021; d.h. die Kontrolle der Selektionsgeschichte Awh et al., 2012; Kadel et al., 2017; H. J. Müller et al., 2010; Wolfe et al., 2003). Die Selektionsgeschichte umfasst viele Quellen der Aufmerksamkeitsverzerrung, wie statistisches Lernen von Merkmalen / räumlicher Positionen (z. B. Fiser & Aslin, 2002; Sauter et al., 2021; Turk-Browne et al., 2005; van Moorselaar & Slagter, 2019; Won et al., 2019; Zellin et al., 2013), Priming-Effekte für Farben / räumlicher Positionen / oder wiedeholenden Geräuschen über den Zeitverlauf hinweg (auch intertrial priming effects) (Allenmark et al., 2018; Feldmann-Wüstefeld & Schubö, 2016; Geyer et al., 2007; Lamy & Yashar, 2008; z. B. Maljkovic & Nakayama, 1994).

Immer mehr Studien zeigen, dass Beobachter aus früheren Erfahrungen anhand räumlich verteilter Information lernen können, die Selektionspriorität bestimmte Positionen (oder Orte) abzuwerten, an welchen häufig irrelevante singuläre Distraktoren auftauchen, um (implizit) den Einfluss dieser Störungen zu minimieren (Gao & Theeuwes, 2019; Goschy et al., 2014; Leber et al., 2016; Sauter et al., 2018; B. Wang & Theeuwes, 2018a). Dieser Befunde werden durch weitere Studien mittels Augenbewegungen (eye tracking) bestätigt, insofern weniger Augenbewegungen (oder okulomotorische Aktivität) gemessen wurden wenn Distraktoren an erwartbaren Positionen auftauchten im Vergleich zu unerwartbaren (Allenmark, Shi, et al., 2021; Di Caro et al., 2019; Sauter et al., 2021; B. Wang, Samara, et al., 2019). Die Auswertung der statistischen Verteilung salienter Distraktoren zeigte, dass Beobachter räumliche Regelmäßigkeiten salienter Distraktoren ausnutzen können, um Interferenzen (geringere RTs) zu reduzieren (intertrial facilitation), wenn Distraktoren an häufigen im Vergleich zu seltenen Orten (oder Positionen) auftreten, was in Goschy et al.(2014) als der "*distractor-location probability cueing effect*" (Der Häufigkeitseffekt zur räumlichen Verteilung von Distraktoren) bezeichnet wird. Darüber hinaus lieferten Goschy et al. (2014) in deren Studie überzeugende Belege dafür, dass sich statistisches (und räumliches) Lernen sowie die beschleunigte Selektion oder effektive Suppression (intertrial facilitation) als zugrundeliegende Mechanismen des *probability cueing effect* sich nicht notwendigerweise gegenseitig ausschließen:

Der *distractor-location probability cueing effect* wäre sowohl auf statistisches Lernen der Distraktorpositionen als auch auf die effektive Suppression (intertrial facilitation) zurückzuführen, die durch die Wiederholung der Distraktoren bei aufeinanderfolgenden Versuchen hervorgerufen wird. Doch wie wird der Distraktor im Laufe der Zeit gelernt und unterdrückt? In der vorliegenden Dissertation wird untersucht, inwieweit das visuelle System gelernt hat, die durch den auffälligen Distraktor induzierten Störungen in Abhängigkeit der gegebenen räumlichen Häufigkeitsverteilung, sowie deren kurzfristigen effektiver Suppression über den Versuchsablauf hinweg zu minimieren. Ebenso stellt sich die Frage, wie dies innerhalb der kognitiven Architektur der visuellen Suche hinsichtlich bestimmter neuronaler Marker umgesetzt wird?

Bisher wurde eine Vielzahl von Studien zu den Auswirkungen des Häufigkeitspriming (oder auch Häufigkeitscueing) durchgeführt, die sich jedoch meist auf stationäre räumliche Regelmäßigkeiten beschränken (z. B. Orte mit hoher Wahrscheinlichkeit im Vergleich zu Orten mit geringer Wahrscheinlichkeit), wobei die Regelmäßigkeiten sequenzieller Natur sind. Das bedeutet, dass das tägliche Erlebnis von Regelmäßigkeiten meist auf dem beruhen, was zuvor geschehen ist, d. h. auf ein bestimmtes Ereignis A folgen in der zeitlichen Abfolge die Ereignisse B und C (für einen Review siehe Theeuwes et al., 2022). Allerdings haben wir bisher nur ein geringes Verständnis der zugrundeliegenden Mechanismen, wie statistisches Lernen in Form von versuchsübergreifenden Sequenzen den Einfluss von Distraktoren abschwächen kann. Diese Frage ist ein durchaus beachtenswerter Aspekt des Themas der erfahrungsgesteuerten Aufmerksamkeit, so dass sich die vorliegende Dissertation damit befasst hat. In dem Experiment von Li & Theeuwes (2020) konnte beispielsweise gezeigt werden, dass Teilnehmer ein trial-to-trial (auf deutsch von Versuch-zu-Versuch) statistisches Lernen von Zielorten extrahieren können. In dieser visuellen Suchaufgabe sollten die Beobachter auf ein Target mit einer bestimmten Form (z.B. Diamant) unter sieben anderen Objekten reagieren. In diesem Fall wurden zwei Bedingungen für die räumlichen Regelmäßigkeit der Targetpositionen in den Versuchen manipuliert: ein Target ganz rechts im vorhergehenden Trial (Versuch *n-1*) und ein Target ganz links im aktuellen Trial (Versuch *n*) für die reguläre Bedingung und andereseits Versuche oder Trials, deren Targetpositionen nicht mit dem Trail n-1 übereinstimmten, für die nicht reguläre Bedingung. Das Ergebnis ist, dass die RTs in der Bedingung der Regelmäßigkeit schneller waren als in der Bedingung der

Nicht-Regelmäßigkeit, und zwar nicht nur bei Trials (Versuchen) ohne Distraktoren, sondern auch bei Trials mit Distraktoren - was darauf hindeutet, dass die selektive Aufmerksamkeit durch versuchsübergreifende (oder intertrial) Regelmäßigkeiten beeinflusst wurde. Eine weitere Studie zu Verhalten und Elektroenzephalogramm (EEG) zeigte, dass die Vorteile der Wiederholung beim Erlernen der Position des Distraktors in der Trialsequenz dem Gehirn dabei helfen, die Aufmerksamkeitssteuerung zu lösen, wenn der Distraktor in Teilsequenzen über 1 bis 12 Trials an derselben Position wiederholt wird, was sich in den reduzierten RTs und ebenso der Reduzierung der Pd-Komponente widerspiegelt (van Moorselaar & Slagter, 2019).

Tatsächlich sind reale visuelle Umgebungen sehr viel dynamischer und unbeständiger, wie es das "predictive-coding framework" der Wahrnehmung beschreibt (Friston, 2010; Friston & Kiebel, 2009): Das Gehirn trifft auf der Grundlage von Vorwissen kontinuierlich Vorhersagen über die Umweltursachen der sensorischen Eingaben, die es erhält. Während eines solchen statistischen intertrial Lernens der Sequenzpaare (Targets und Distraktoren) entsteht eine flexible Priorisierung der räumlichen Positionen durch die Auf- und Abwertung aufgrund früherer Erfahrungen (intertrial history). Jedoch wird der Frage, inwiefern die Volatilität der räumlichen Suche von der Geschwindigkeit des Lernens (d.h. der effektiven Distraktorsuppression) beeinflusst wird, bisher zu wenig Aufmerksamkeit geschenkt. In der vorliegenden Studie wurde speziell der Einfluss der Umgebungsvolatilität auf das statistische Lernen von Distraktorpositionen untersucht, um die Aufmerksamkeitserfassung durch auffällige Distraktoren zu minimieren.

Ziel dieser Arbeit ist es, unser Verständnis der kognitiven und neuronalen Prozesse zu verbessern, die dem statistischen Lernen von Distraktorpositionen und den inhibitorischen Intertrial-Effekten in der visuellen Aufmerksamkeit zugrunde liegt, und herauszufinden, wie man intertrial Regelmäßigkeiten von Distraktorpositionen nutzen kann, um die Aufmerksamkeitserfassung in volatilen Umgebungen zu reduzieren. Um diese Fragen zu klären, werden klassische Verhaltensexperimente, Eye-Tracking und EEG-Techniken eingesetzt.

In Kapitel 2.1 wird zunächst die Position der erlernten Unterdrückung von Distraktoren innerhalb der funktionalen Architektur der (visuellen) aufmerksamen Suche untersucht, welche Interferenzen an häufigen Positionen reduzieren, um das zu erreichen, wurde in dieser Dissertation das zusätzliche Singleton Paradigma (*additional singleton* *paradigm*) von Wang und Theeuwes (2018a) verwendet: Die Teilnehmer suchen und reagieren auf ein eindeutiges, formdefiniertes Target (z. B., ein Kreis unter Rauten oder umgekehrt), während sie einen auffälligen, farblich definierten Distraktor ignorieren (z. B. ein rotes oder grünes Singleton, das sich farblich von anderen, nicht ablenkenden Elementen unterscheidet). Wichtig ist, dass der auffällige Distraktor, wenn er in der Suchanzeige vorhanden war, mit hoher Wahrscheinlichkeit an einem "häufigen" Positionen und mit geringer Wahrscheinlichkeit an einem der "seltenen" Positionen auftauchte, was ein statistisches Lernen der räumlichen Distraktorverteilung ermöglichte. Durch die Kombination des EEG-Ansatzes mit dem *additional singleton paradigm* konnten wir zeigen, dass die Interferenz des Distraktors (schnellere RTs) signifikant geringer war, wenn der Distraktor an einer häufigen anstatt einer seltenen Position auftrat, was zeigt, dass das statistische Lernen der ungleichmäßigen Verteilung der Distraktorpositionen leistungsfähige Vorteile bei der visuellen Selektionsverarbeitung mit sich bringt (Allenmark et al., 2019a; z. B., Goschy et al., 2014; Liesefeld & Müller, 2020; Sauter et al., 2018, 2021; B. Wang & Theeuwes, 2018b). Wenn andererseits ein Distraktor die Aufmerksamkeit auf sich zieht (ob offen oder verdeckt), muss seine Position "reaktiv" unterdrückt werden (z. B., Geng, 2014), damit die Aufmerksamkeit auf die Targetposition neu zugewiesen werden kann. Der Effekt dieser reaktiven Unterdrückung überträgt sich auf den nächsten Versuch, was sich in verlangsamtem RTs für ein Ziel in einem bestimmten Versuch *n* zeigt, das sich an der Stelle befindet, die im vorherigen Versuch *n-1* von einem Distraktor besetzt war (z. B. , Allenmark, Shi, et al., 2021; Geyer et al., 2006; Kumada & Humphreys, 2002; Sauter et al., 2018). Elektrophysiologisch fanden wir eine Unterscheidung zwischen der frühen N1pc/Ppc und der späten SPCN. Bei reinen Target Trials (d.h. nur Targets innerhalb eines Durchlaufs) war die Polarität der frühen lateralisierten Komponente von der Position des Target abhängig, wobei die häufige Position eine Target N1pc-Komponente und die seltene Position eine Target Ppc-Komponente auslöste. Trials mit gemeinsamen Target und Distraktor zeigten ebenfalls das gleiche N1pc/Ppc-Muster. Darüber hinaus war die späte SPCN-Amplitude negativer, wenn die Targetposition mit der vorangehenden Distraktorposition zusammefiel, als wenn dies nicht der Fall war. Ebenso zeigte sich, dass Alpha Oszillationen in Form von antizipatorischen Modulationen keine signifikante Rolle beim statistischen und andauernden (long-term) Lernen zur “Suppression” wahrscheinlicher Distraktorposition spielen, und was somit vorangegangene Studien von van Moorselaar et al. (2020) sowie Noonan et al.(2016) unterstützt.

Anschließend untersuchten wir in Kapitel 2.2, ob Beobachter die Lernrate der Distraktorenunterdrückung adaptiv an die Volatilität der Umgebung anpassen können. Dazu verwendeten wir die Markov-Ketten-Funktion (Hamilton, 1990) und das klassische visuelle Suchparadigma (Goschy et al., 2014), um eine Umgebung mit hoher und eine mit niedriger Volatilität zu schaffen, die sich durch die Häufigkeit des Wechsels zwischen Trials (oder Versuchen) mit und ohne Distraktor in der Suchanzeige unterscheidet. Dies führte zu aufeinanderfolgenden Trials mit vorhandenem Distraktor mit unterschiedlich langen Wiederholungen der Distraktorposition (d.h. 0, 1, 2, 3, 4 und öfter). Wir manipulierten die Wahrscheinlichkeit der Wiederholung desselben Distraktors ("anwesend" oder "abwesend") von einem Trial zum nächsten, mit einer Wahrscheinlichkeit von 30 % in der Sitzung mit hoher und 70 % in der Sitzung mit niedriger Volatilität. Darüber hinaus untersuchten wir die okulomotorische Aktivität (d.h. die Augenbewegungen) und deren suppressiver Anpassung (position detachment) während der visuellen Suchaufgabe, da bekannt ist, dass Aufmerksamkeits- und Okulomotorik miteinander verbunden sind (Deubel & Schneider, 1996; McPeek et al., 1999; B. Wang, Samara, et al., 2019). Unsere Ergebnisse zeigen, dass die Sitzung mit hoher Volatilität zu langsameren Reaktionszeiten führte als die Sitzung mit niedriger Volatilität. Die aktive Aufmerksamkeitsleistung (*attentional capture effect*), gemessen an den Kosten für die Reaktionszeit (RT) zwischen Anwesenheit und Abwesenheit eines Distraktors, war jedoch in der Sitzung mit niedriger Volatilität größer, was darauf hindeutet, dass der Distraktor die Suchleistung in einer Umgebung mit niedriger Volatilität stärker beeinflusst als in einer Umgebung mit hoher Volatilität. Darüber hinaus wurde die Störung durch den Distraktor mit zunehmender Anzahl von Wiederholungen an der gleichen Stelle signifikant reduziert, was sich in reduzierten RTs und dem Anteil der ersten Sakkade zum Distraktor zeigte. Daraus können wir schlussfolgern, dass die intertrial Sequenzen von Distraktorwiederholungen die Interferenz in komplexen und volatilen Umgebungen abschwächen können.

Schließlich sollte in Kapitel 2.3 untersucht werden, ob (1) auffällige Distraktoren die Aufmerksamkeit auf sich ziehen, und wenn ja, ob ein Effekt der Ablenkungswahrscheinlichkeit nachgewiesen werden konnte. Wir stellten die Hypothese auf, dass, wenn die Teilnehmer in der Lage sind, diese räumlich basierten Regelmäßigkeiten zu extrahieren und zu lernen, Distraktoren an häufigen Positionen weniger Interferenzen (d.h. schnellere RTs) verursachen als Distraktoren an seltenen Orten. Ebenso untersuchten wir (2) wie man die intertrial Regelmäßigkeiten der Distraktorenpositionen nutzen kann, um die

Aufmerksamkeitserfassung (*attentional capture*) in unbeständigen Umgebungen zu reduzieren und vor allem (3), ob unbeständige Umgebungen die Lerngeschwindigkeit der Distraktorenunterdrückung beeinflussen. Gemäß den beiden obigen Fragen beschleunigte eine längere Subsequenz von Wiederholungen der Distraktorposition zunehmend die RTs, da die Interferenz des Distraktors an dieser Position abnahm. Wenn dies der Fall wäre, sollten Distraktoren in der globalen Umgebung mit niedriger Volatilität weniger Interferenzen verursachen als Distraktoren in der globalen Umgebung mit hoher Volatilität. (4) Es sollte untersucht werden, ob die Distraktorsuppression durch die intertrial Bedingungen der Distraktoren realisiert werden kann. Die Hypothese war, dass die Suchleistung besser sein würde, wenn der Distraktor nicht von Trial n-1 zu Trial n wechselt (d.h. 2 x abwesend AA, oder 2 x anwesend PP), da es von Vorteil ist, denselben Zustand über mehrere Versuche hinweg zu wiederholen. Im Gegensatz dazu wurde erwartet, dass die Suchleistung verlangsamt wird, wenn der Distraktor die Bedingungen von Trial n-1 zu Trial n wechselt (d.h. AP, PA), da die Übergangszustände zwischen den Versuchen und der selektiven Targetverarbeitung beeinträchtigen können. Zu diesem Zweck verwendeten wir die Markov-Ketten-Funktion, um eine Umgebung mit hoher und eine mit niedriger Volatilität zu schaffen, die sich durch die Häufigkeit des Wechsels zwischen Trials mit und ohne Distraktor in der Suchanzeige unterschieden. Dies führte zu aufeinanderfolgenden Versuchen mit vorhandenem Distraktor mit unterschiedlich langen Wiederholungen der Distraktorpositionen (d.h. 0, 1, 2, 3, 4 und öfter). Wir manipulierten die Wahrscheinlichkeit der Wiederholung desselben Distraktorzustands ("anwesend" oder "abwesend") von einem Versuch zum nächsten, mit einer Wahrscheinlichkeit von 30 % in der Sitzung mit hoher und 70 % in der Sitzung mit niedriger Volatilität. Zusätzlich haben wir das Häufigkeitscueing von Distraktorpositionen in das klassische visuelle Suchparadigma (Goschy et al., 2014) implementiert, bei dem die Teilnehmer nach einem Targetobjekt unter mehreren Nicht-Targetobjekten suchen mussten. Infolgedessen war die Fähigkeit des Lernens zur Unterdrückung von Distraktoren (mit einem Kontrast in der Dimension, z.B. rote Farbe) an der wahrscheinlichen Positionen in beiden Sitzungen, mit hoher und niedriger Volatilität, ähnlich, was darauf hindeutet, dass das statistische Lernen der ortsbezogenen Unterdrückung von Distraktoren robust gegenüber Veränderungen der Volatilität ist. Die Sitzung mit hoher Volatilität führte jedoch zu einer größeren Unsicherheit über das Vorhandensein eines bevorstehenden Distraktors, was die Auswahl des Targets generell beeinträchtigte. Interessanterweise verstärkte diese hohe Unsicherheit auch die proaktive Unterdrückung, was sich in einem signifikanten Targetpositionseffekt in der Sitzung mit hoher Volatilität manifestierte. In der Sitzung mit niedriger Volatilität erlaubte die Vorhersagbarkeit der Häufung von Trials ohne Distraktoren den Beobachtern jedoch, die proaktive Unterdrückung schnell aufzugeben, nachdem sie auf den ersten Versuch ohne Distraktoren gestoßen waren, um die Suchleistung zu steigern. Trotz kurzfristiger Schwankungen der Störung durch Distraktoren in beiden Sitzungen wurde die langfristige Unterdrückung von Distraktoren hauptsächlich durch die lokale Wahrscheinlichkeitsverteilung des Auftretens von Distraktoren bestimmt. Wir vermuten, dass die Aufmerksamkeitserfassung nicht nur durch statistische räumliche Regelmäßigkeiten beim Lernen abgeschwächt wird, sondern auch durch dynamische Übergangswahrscheinlichkeiten von Trial zu Trial. Diese Ergebnisse tragen zu einem besseren Verständnis des kognitiven Mechanismus bei, der der "Selektionsgeschichte" (*intertrial history*) zugrunde liegt.

Diese Dissertation soll zusammengenommen mit den drei oben genannten Studien unser Verständnis der kognitiven und neuronalen Prozesse verbessern, die dem statistischen Lernen von Distraktorpositionen und den hemmenden intertrial Effekten bei der visuellen Aufmerksamkeit zugrunde liegen. Darüber hinaus soll herausgefunden werden, wie man trialübergreifende Regelmäßigkeiten von Distraktorpositionen nutzen kann, um die Aufmerksamkeitserfassung in volatilen Umgebungen zu reduzieren.

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Curriculum Vitae

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Education

2019 — Present	**Ph.D. in Psychology (Experiment, Neuropsychology)**, Ludwig Maximilian University of Munich, München, Germany Thesis project: “The neural and behavioral basis of statistical learning of distractor suppression in visual search” Supervised by Prof. Dr. Zhuanghua Shi; Prof. Dr. Hermann J. Müller
2016 — 2019	**M.Sc. in Psychology (Cognitive neuroscience),** University of Electronic Science and Technology of China, Chengdu China Thesis project: “An Electrophysiological Research: Short-term Effects of Action Video Gaming Experience Related to Visual Selective Attention.” Supervised by Prof. Dr. Dezhong Yao
2012 — 2016	**B.Sc. in Psychology,** Chengdu University of Traditional Chinese Medicine, China

Professional Experience

2019 — Present	Research Fellow (as a Ph.D. student) in Department of Psychology, Ludwig-Maximilian University of Munich, München, Germany
2022	Participate in 12th IMPRS NeuroCom Summer School, at MPI CBS Leipzig, Germany **Content:** "A Journey through Cognitive Neuroscience"
2022	Participate in Academic Summer School of Radboud University, Nijmegen Netherlands **Content:** Mike Cohen’s EEG Bootcamp “Analyzing Neural Time Series Data”
2022	Participate in Academic Summer School “The European Summer School: Visual Neuroscience,” Hessia, Germany **Content:** lectures, discussion and exercise in brain monitoring and visual stimulation to boost the capabilities of technological vision systems.
2022	Talk of own project at “European Conference on Visual Perception 2022,” Nijmegen, Netherlands **Title:** Electrophysiological Markers of the probability cueing suppression: statistical learning of distractor locations and inter-trial modulation
2022	Poster presentation at “TEX2022: Bringing together Predictive Processes and Statistical Learning”, SISSA (International School for Advanced Studies), Italy

2022	Poster presentation at “International Symposium on Visual Search and Selective Attention,” Bayern, Germany
2017 ─ 2019	Research Assistant in Mental Health Education Center University of Electronic Science and Technology of China, Chengdu China
2015	Participate in Academic Summer School “Psychology and Brain Science,” Faculty of Psychology, Southwestern University, Chongqing China

Academic Skills

- **Neuropsychology Methods:** Psychophysics (intermediate), Event-related potentials (intermediate), EEG Signal Processing (basic), Eye-tracking (basic), functional Magnetic Resonance Imaging (basic).
- **Programming Skills:** BrainVision Analyzer (intermediate), SPSS (intermediate), Python (intermediate), R (basic), JASP (intermediate), MATLAB (basic), E-Prime 2 (basic).
- **Other Skills:** Adobe Illustrator (intermediate), Presentation (basic), Writing and Oral English fluently, Collaborating effectively with colleagues on research work.

Scholarships and Awards

State Scholarship Fund for LMU-CSC program, China Scholarship Council	Sep.2019 - Aug.2023
Outstanding Graduates for Postgraduates	Jun.2019
National Scholarship for Postgraduate students, China	Oct. 2018
First Prize of Graduate Scholarship in Master degree period	All-Academic 3 Years
Outstanding postgraduate students in Master degree period	Oct. 2017
Excellent postgraduate student cadre, in Master period	All-Academic 3 Years
Outstanding Graduates Awards of Sichuan Province, China	Jun. 2016
Received Honors for Outstanding Achievement for Bachelor thesis	Jun. 2016
Prosperous and innovative talents scholarship, in Bachelor degree period	Jun. 2016
National Scholarship, China	Oct. 2015
First Prize of Graduate Scholarship, in Bachelor degree period	Oct. 2015
First-class Certificate for All-round Development of College Students in Sichuan Province	Jun. 2015
Outstanding students, in Bachelor degree period	Dec. 2014 - Dec. 2015
Excellent Student Cadres, in Bachelor degree period	Dec. 2013 - Dec. 2014

List of Publications

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