Statistical Learning of Distractor Locations in Visual Search

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1 General Introduction

Visual search is a crucial skill we depend on in daily life, such as, locating the favorite chocolate in a supermarket or searching the key in the house. Given an overwhelming amount of information in the complex environment that we are constantly interacting with, an efficient selection of visual input is vital for behavior adapted to various environments and goals. In other words, we need to use our limited attentional resources on goal-related information while ignoring irrelevant information that might distract us.

However, the attentional selection is not always under volitional control and directs to relevant objects consistent with our goals, it could sometimes be involuntarily drawn to salient but goal-irrelevant objects, resulting in relevant information being processed with a delay and thereby accompanied with poor selection performance. For instance, our attention could go away to a nearby chocolate with a salient sale label on it, instead of the specific chocolate we are searching for in the supermarket, even though we don't have any intention to look for it. Related research in the visual field has been largely investigated in the last three decades using variant types of experimental tasks, the additional singleton task for example (Theeuwes, 1991), and illustrated within several theoretical accounts that attention was potentially distracted or 'captured' by the salient objects that may be completely irrelevant with regard to the action goals we pursue (Folk & Remington, 1998; Forster & Lavie, 2008; Hickey et al., 2006), however, the interference caused by the goal-irrelevant distractor can also be attenuated via attentional control in some situations (Bacon & Egeth, 1994; Folk et al., 1992; Gaspelin et al., 2017; Leber & Egeth, 2006), such as repeated exposure and practice (Kelley & Yantis, 2009; Müller et al., 2009; Zehetleitner et al., 2012; Sauter et al., 2018).

Visual search can be facilitated by exploiting the spatial distribution of objects or context in the environments. For instance, if you always put the wallet in a particular place, this prior information will help narrow down your search and make it more effective. The process that observers appear to prioritize attention selection to certain locations where relevant information is regularly encountered has been termed as the '*probability cueing effect*' (Geng & Behrmann, 2002, 2005). Likewise, locations where salient but irrelevant objects appear frequently can also be deprioritized via attention control. For example, if you regularly visit the supermarket, the salient 'on-sale' label on the advertised chocolate may not capture your attention any more. The effect that observers tend to learn the spatial distribution of salient but goal-irrelevant distractors in the visual environment from experience in order to reduce the interference from distractors in frequently occurred locations and thereby improve search efficiency has been referred to as '*distractor location probability cueing*' (e.g., Goschy et al., 2014; Sauter et al., 2018).

While emerging studies hold no dispute that the reduced distractor interference is largely attributable to better suppression of distractor in frequent locations (e.g., Ferrante et al., 2018; Leber et al., 2016; Sauter et al., 2018; Wang & Theeuwes, 2018a), concerning how the learned spatial distractor suppression is implemented (namely, which stage the suppression operates at) within the functional architecture of search guidance to reduce interference, conclusions are still in the debate (details are described below). Moreover, how the distractor suppression is processed in the brain to reduce the interference in more likely relative to less likely distractor locations remains poorly understood. The line of studies of the current dissertation, therefore, explores the cognitive and neural mechanism underlying the spatial distractor suppression based on the probability-cueing (or statistical-learning) of distractor locations. Specifically, we firstly use classical behavior investigations to conclude the locus of the spatial distractor suppression within the functional architecture of search guidance, and then probe how the learned spatial suppression of distractors is implemented at the neural level by functional magnetic resonance imaging (fMRI) techniques.

The introduction firstly (1.1) outlines potential theoretical accounts of attentional selection, specifically how attention was captured by distractors in a bottom-up fashion and how potential distractor interference can be minimized by top-down attentional control in the visual search. Then the second part of the introduction (1.2) describes the *distractor location probability cueing*, possible suppression strategies within the functional architecture of search guidance, and current theoretical conflicts with regard to the suppression strategies. The third part (1.3) introduces the visual attentional brain network and how to get rid of visual distractors at the neural level. And finally, (1.4) point to the aims of the current dissertation. Chapter 2 is the key section of the current dissertation, including three individual studies (two published articles and one submitted manuscript). A summarizing General Discussion concludes all three studies in Chapter 3.

1.1 Bottom-up and top-down attentional selection

Theoretically, the process that an object captures attention due to its physical salience is termed as ‘bottom-up’, ‘stimulus-driven, ‘exogenous’, ‘automatic’ selection. By contrast, an object that is intentionally selected based on goals of the observer is referred to as ‘top-down’, ‘goal-directed’, ‘endogenous’, ‘non-automatic control’ selection (e.g., Egeth & Yantis, 1997; Neumann, 1984; Posner et al., 1978; Shiffrin & Schneider, 1977). A so-called ‘overall-saliency’ (e.g., Wolfe & Gancarz, 1997; Wolfe & Gray, 2007) or ‘priority’ (e.g., Fecteau & Munoz, 2006) map is constituted by the dynamic convergence of these two distinct types of processes that determines where, how, and to what information within the environment is selected. In other words, attentional selection has been considered to be the integrated results of top-down and bottom-up processes.

The stimulus that stands out from the environment can generate involuntary attentional shifts, which is assumed to be an automatic process based on the salience signal of the stimulus in the visual field (Jonides & Irwin, 1981). Related research has been largely explored with defining the distractor as an abrupt onset item or a salient item within the additional singleton paradigm (Theeuwes, 1991, 1994b; Yantis & Jonides, 1984). In a typical additional singleton task, observers are instructed to search for a specific target (e.g., a green circle singleton among other green items), while another salient but task-irrelevant singleton distractor (e.g., a red item) is present occasionally. The typical finding is that when the salient but goal-irrelevant distractor is present, search performance is impaired, measured by significantly longer response time (RT) for presenting (vs. absent) a distractor, indicating that the salient but goal-irrelevant distractor caused interference. And this interference only appears when the distractor singleton is more salient than the target singleton (Theeuwes, 1991, 1992, 1994a, 1994b). For example, searching for a shape-defined target but sometimes presenting with a color-defined singleton distractor would impair behavior performance, but not vice versa. Thus, taking the increased response time as proof of attentional capture by the distractor, Theeuwes (1994b) formulated the *stimulus-driven attentional capture account*: objects with the highest feature-contrast in the visual environment would automatically capture attention, and attentional selection occurs in a purely bottom-up fashion.

However, whether the salient distractor is able to capture attention in a purely bottom-up manner is still controversial. For example, Folk et al. (1992) raised the *contingent attentional capture account* that argued for top-down (instead of bottom-up) control over the attentional selection (Folk et al., 1992; Folk & Remington, 1998). The key support behind this notion comes from one demonstration with a spatial cueing paradigm. In this task, prior to the search display, observers saw a cue with three forms of manipulations: a spatial cue in the middle of the search display where the target never appeared, a valid cue with 100 percent right indicating the upcoming target's position, and an invalid cue with 100 percent error indication of the target's location. One group of participants searched for an abrupt-onset-defined target, and another group searched for a color-defined target. They found that in the abrupt-onset detection group, the search performance was improved by valid cues but impaired by invalid cues. In contrast, in the color detection group, observers only showed search benefits from valid cues but not search costs from invalid cues. These findings suggest that the invalid cue impairs task performance only when it shares the target's defining feature. The following experiment further confirmed this conclusion with color cues: invalid color cues generated larger search costs for the color-defined target than the abrupt-onset-defined target. Therefore, they concluded whether the attentional captured by irrelevant stimuli depends on whether the irrelevant stimuli match the top-down search goal.

In addition to the purely bottom-up and top-down attentional selection accounts, some other influential theories combine the two processes. For example, the *search-mode account* (Bacon & Egeth, 1994; Leber & Egeth, 2006) posits two distinct search strategies that observers can adopt to perform the visual search task: One is the *feature search mode*, by which observers monitor the presence of the relevant feature. Observers in this search mode have a clear attentional set for the object containing the target-defining feature and can effectively filter out other items that do not share this feature, resulting in a top-down visual search. The other mode is called the *singleton detection mode*, by which observers detect the element that was different from others in the background. In this case, visual search is stimulus-driven since interference from more salient but goal-irrelevant distractors (relative to the target) is unavoidable in the search display. A typical feature search model is illustrated by the study of Bacon and Egeth (1994). Observers searched for a shape-defined target in the search display that potentially contains more than one target or other non-target items also different in shape. Such a search display puts observers to use the feature search mode, and their findings revealed that no search impairment was caused by the color-defined distractor. The well-known example of singleton detection mode is demonstrated by Theeuwes (1992) in his additional singleton capture paradigm, which shows a strong bottom-up capture effect by color-defined distractors when observers use a singleton detection mode to detect a changeable shape-defined target.

Another account, the *signal suppression hypothesis*, holds that irrelevant stimuli can generate salience signals automatically in a bottom-up way, (e.g., salient distractor produce strong signals that invoke attention shifts), but this signals can be actively suppressed by top-down attentional mechanisms (Gaspelin et al., 2015, 2017; Gaspelin & Luck, 2018b; Sawaki & Luck, 2010). This account was demonstrated by a capture-probe paradigm (e.g., Gaspelin and Luck, 2015) which is similar to the additional singleton task that observers searched for a shape-defined target (e.g., a green diamond) but presented with a salient but task-irrelevant color singleton within the search display. Differentially, on some critical trials, a letter was presented inside each item shortly, and observers were instructed to report those presented letters as many as possible. The task was tested with two conditions: the promoting capture condition (e.g., using singleton detection mode) and the discouraging capture condition (e.g., using feature search mode). Results showed that in the condition of promoting capture, relative to the letter inside non-salient distractors, the letter within the salient distractor was reported with higher accuracy. However, this is not the case in the condition to avoid capture: reporting accuracy was lower for the letter inside the salient distractor than inside non-salient distractors, which they took as an indication of active suppression implemented in the salient distractor location. These behavioral findings are consistent with the electrophysiological study observing a P_D (distractor positivity) component of the event-related potential (ERP) (an index of attentional suppression) (e.g., Gaspelin & Luck, 2019), as well as the eye-tracking study showing less first eye movements to the singleton distractor relative to nonsingleton distractors (oculomotor suppression effect) (e.g., Gaspelin et al., 2017), when the irrelevant singleton distractor behaviourally fails to capture attention.

Taken all accounts together, the salient but task-irrelevant distractor could potentially bottom-up capture our attention and impair search performance, but the interference caused by the distractor can also be reduced via top-down attentional control. Notably, instead of considering the attentional selection as a result of the interaction of top-down and bottom-up processes, Awh et al. (2012) proposed a third pillar of the functional architecture: *selection history*: the attentional selection is shaped by a combination of the past selection history, the bottom-up physical salience, and the top-down goal-related selection. Supporting evidence comes from studies with reward association as well as priming effect. The former reveals that a previous reward-associated stimulus can capture attention even the stimulus is non-salient and task-irrelevant (e.g., Anderson et al., 2011; Della Libera & Chelazzi, 2009; Raymond & O'Brien, 2009). The latter demonstrates the attentional deployments from recent selection history can lead to selection biases, even though the selection history effects were neither competing for physical salience nor aligned with current goals (e.g., Allenmark et al., 2018; Eimer et al., 2010; Geyer et al., 2007; for a review, Kristjánsson & Campana, 2010).

1.2 Probability-cueing of distractor locations

The spatial layout in the environment makes a contribution to the visual search. There is ample evidence showing that observers can learn the spatial distribution of objects in our environment, given that their locations are often relatively invariant. For example, houses and trees in our surroundings are stable and do not change their locations. Such invariant context is useful in guiding our attention selection. A classic example demonstrated of this phenomenon in laboratory studies is known as ‘contextual cueing’: a target can be detected quicker when it appears in a fixed search display that has been previously encountered compared to a new display where the target and distractors are randomly shuffled (Chun & Jiang, 1998, 1999). Another common finding from a series of studies is that targets can be identified more quickly in locations where they occur more frequently (e.g., Fecteau et al., 2009; Geng & Behrmann, 2002, 2005; Miller, 1988; Shaw & Shaw, 1977), referred to as the ‘*probability cueing effect*’ (Geng & Behrmann, 2005). That is, observers can learn to prioritize locations where targets are regularly encountered for efficient attention selection. Importantly, recently, emerging studies have also indicated that observers can learn from experience to deprioritize locations where salient but goal-irrelevant distractors appear frequently (Goschy et al., 2014; Ferrante et al., 2018; Leber et al., 2016; Sauter et al., 2018; Wang & Theeuwes, 2018a). Typically, in these studies, a salient distractor occurs with higher likelihood at one display location or in a subregion of the display (i.e., ‘frequent’ region) relative to the remaining ‘rare’ locations/region (hereafter, we refer to this as the *‘distractor-location learning task*’). The consistent finding of relevant studies is that over time search performance (measured by reaction times and accuracies) is less impaired by the salient distractor when the distractor appears at the frequent as compared to rare locations (an effect, Goschy et al., 2014, referred to as ‘*distractor location probability cueing*’).

Much evidence is gained to support the notion that search performance improvement is likely attributed to better attentional suppression of the frequent location(s) of the distractor (Sauter et al., 2020; Wang & Theeuwes, 2018b). Supporting evidence, on the one hand, comes from eye-movement studies, which have consistently shown that oculomotor capture is less likely when the singleton distractors occur at the frequent location(s) relative to the rare location(s) (Di Caro et al., 2019; Sauter et al., 2020; Wang, Samara, et al., 2019). For example, Sauter et al. (2020) used an adjusted distractor-location learning task with an orientation-defined target, and the salient distractor was either defined in the different (e.g., color) or the same (e.g., orientation) visual dimension to the target. They found that compared with salient distractors appearing at the rare region, the landing positions and latencies of the first saccades were fewer when the distractor (either the color or orientation) appeared at the frequent region. Their finding suggests that a better proactive spatial suppression is implemented for distractors in the frequent region than in the rare region. Note that Sauter et al. (2020) also provided evidence that the rapid disengagement effect also contributes to the reduced interference of distractors in the frequent region, which was reflected by shorter dwell time for the distractor when it appeared at the frequent area as compared with the rare area. However, the suppression effect potentially could be the major reason, since they found that when the search display didn't contain a salient distractor, the latencies of the first saccade for a target falling in the frequent region was longer than in the rare region, and this prolonged effect was observed only in the same- (but not different-) distractor dimension condition, consistent with the behavior RT results, showing an impaired search performance for targets occurred at the frequent region only when the distractor was defined in the same- (but not different-) dimension to the target. On the other hand, using the similar distractor-location learning paradigm with shape-defined target and color-defined singleton distractor in an electrophysiological study, Wang and van Driel et al. (2019) observed an increased alpha power in parieto-occipital that is contralateral (relative to ipsilateral) to the frequent distractor location during the pre-stimuli period, and also identified a suppression-related P_D component corresponding to the frequent distractor location no matter the salient distractor was presented in the frequent or rare location. These findings also indicated a proactive attentional suppression implemented in the frequent distractor locations (Wang, van Driel, et al., 2019).

Covering evidence from behavior, eye-movement, and electrophysiological studies described above together indicated a potential suppression of the distractor in frequent locations to reduce interference, take one step further, based on the saliency-based accounts of search guidance (from Itti & Koch, 2000, onwards), in principle, suppression could be implemented at three possible different levels: (1) Distractor suppression occurs at the level of priority or overall-saliency map (e.g., Fecteau & Munoz, 2006). The top-down global attentional bias suppresses any saliency signals at the frequent distractor location, thus it reduces distractor interference. At this level, the suppression is region-specific and dimension-unspecific. Within-the-target and different-to-the-target dimension distractors make no difference. (2) Distractor suppression occurs below the saliency map at the dimension level. In this case, according to the Dimension-Weighting Account (DWA, e.g., Found & Müller, 1996;

Müller et al., 2003; Müller et al., 1995), the feature-contrast signals relate to the distractor-defining dimension, prior to their integration with other dimensions (e.g., the target-defining dimension), is suppressed or down-weighted at the 'supra-dimensional' priority map (Müller et al., 2009; Zehetleitner et al., 2012). At this level, the suppression is dimension-specific. Singleton distractors coming from the target-related dimension cause stronger interference than the different-dimension distractors. (3) Distractor suppression occurs below the saliency map at the featural level, that is, the signal of distractor-defining feature is inhibited directly to reduce their potential to produce feature-contrast signals (Gaspelin & Luck, 2018b). At this level, suppression is feature-specific.

Using similar distractor-location learning tasks, two recent investigations (Sauter et al., 2018; Wang & Theeuwes, 2018a), however, led to different conclusions concerning at which stage (or level) the suppression operates within the functional architecture of search guidance. Specifically, in the study of Wang and Theeuwes (2018a), the target was shape-defined (e.g., a diamond among circles, or a circle among diamonds) while the salient singleton distractor was color-defined (e.g., a red salient distractor among other green items) with more likely probability (e.g., 65%) appearing in one location. Firstly, results showed the typical *distractor-location learning effect*, manifested by shorter reaction time when the distractor appeared at the high probability location as compared to low probability locations. Besides, they also found a *target location effect*: when there was no distractor in the search display, responses were slower for targets located at the more (vs. less) likely distractor location, regardless of the fact that the target was equally distributed among all locations. Based on the finding of impaired processing of targets in the high probability location, they concluded that the suppression of distractor operates at the level of priority map with inhibiting all signals (both targets and distractors) in the frequent distractor location. However, using at-surface similar task, Sauter and colleagues (2018) explored the locus of learned spatial suppression with both different-dimension singleton distractors (distractor-target in cross-dimension: color-defined distractors and orientation-defined targets) and same-dimension singleton distractors (distractor-target within dimension: both orientation-defined targets and distractors). Their results also pointed to the typical distractor-location learning effect within both types of distractors: the response was faster with less attention captured by the distractor when it was located at the frequent region relative to the rare region, and the same-dimension distractor caused larger interference than the different-dimension distractor. More importantly, they differentiated the target location effects for the within and cross distractor types. The results showed that the target processing was slowed down in the frequent relative to the rare distractor region when there was no distractor in the search display, but this reduction of target processing was only significant in the same-dimension distractor type but not in the different-dimension distractor type. The finding thus supports the notion that distractor suppression occurs below the priority map at the dimension level: when the singleton distractor is defined in the different visual dimension to the target, only the distractor-defining dimension (here, color) is suppressed, and this dimension inhibition was assigned more in the frequent distractor region than in the rare distractor region based on the statistical learning, but the distractor-defining dimension suppression did not impair the target processing due to the target in a different dimension. By contrast, when the singleton distractor is defined as the same visual dimension as the target, the dimension suppression strategy is not possible since the inhibition of the distractor-defining dimension is contradictory to the task of searching for the same-dimension-defined target. Thus, any signal in the frequent distractor region would be supressed in the priority-based level and search performance for target appearing in the frequent region is also impaired.

Thus the critical result ensuing the theoretical conflict between the above two studies is that, with different-dimension distractors, whether a target location effect accompanies the distractor-location learning effect or not. Given that there are some uncontrolled factors and a number of differences between the Wang and Theeuwes (2018a) and Sauter et al. (2018), such as the cross-trial inhibition, the probability of target locations, the specificity of the likely distractor location, display density, whether swapping color of singleton distractor and non-distractor items, the current dissertation firstly tried to examine what critical factors might be between the paradigm of Wang and Theeuwes (2018a) and the design of Sauter et al. (2018), leading to different results concerning the target location effect and thereby resulting in fundamentally different theoretical conclusions.

1.3 Neural mechanism of selective attention

Our visual cortex is continually processing information from external visual fields and receives signals feeding back from higher brain levels. Due to limited capacity to process all information at any given time, the brain's principal approach is to prioritize the most crucial information. One rudimental signature indicating importance is saliency (e.g., color contrast, orientation contrast, etc.). For example, a red item among multiple green items can be detected effortlessly and quickly due to its saliency, biasing the competition in favor of red stimuli. Salient signals within the visual environment involuntarily capture attention and guide attentional shifts at first glance, referred to as the bottom-up, stimulus-driven process (Kastner & Ungerleider, 2001; Nordfang & Wolfe, 2014; Kamkar et al., 2018; Krüger et al., 2016; Töllner et al., 2011). Thus it is generally assumed that the sensory inputs in the early visual cortex constitute the first pre-attentive computational stage of salience processing and develop a saliency map with the activity at each location reporting the strength of its bottom-up attentional attraction. However, there was still controversy regarding which brain area was involved in this pre-attentive computational salience processing. For instance, Li (2002) proposed that the saliency map was created in the primary visual cortex (V1) by intracortical interactions. The saliency of a given location is related to the highest neural response among all the V1 cells. One supporting evidence used EEG-MRI measurement (Zhang et al., 2012), with a short presentation of stimuli (50ms) consisting of a high-contrast orientation bar surrounding by low-luminance texture, and observed that when the contrast of the orientation bar increased (namely, increased the degree of attention attraction), the amplitude of the earliest C1 component of the ERP (assumed to be associated with V1 sensory responses) and the blood-oxygenation-level-dependent (BOLD) response in V1–V4 were also increased. Crucially, they found that degree of attention attraction in behaviour was significantly correlated with the C1 amplitude and with the BOLD signal only in V1 across individual subjects. These findings strongly suggest that neural activities in V1 create a saliency map. By contrast, other animal study and/or human neurophysiological and imaging studies argued that the extrastriate ventral area V4 (Mazer and Gallant, 2003), parietal cortex including the lateral intraparietal area (LIP) (Gottlieb et al.,1998) and the anterior intraparietal sulcus (aIPS) (Geng and Mangun, 2009) and frontal eye fields (FEF) (Thompson and Bichot, 2005) were also potentially associated with constructing the saliency map.

However, attention can also be voluntarily guided to particular parts in the visual field through intrinsic signals from high brain levels and this signal can even modulate neural activity in the visual cortex (Desimone & Duncan, 1995; Kanwisher & Wojciulik, 2000; Peck et al., 2009). In the last two decades, most neurophysiological studies of attentional control have focused on voluntary orienting to locations, features, or objects and have identified a distributed frontoparietal attention network that plays a vital role in attentional control (Corbetta & Shulman, 2002; Kastner & Ungerleider, 2000; Reynolds & Chelazzi, 2004; Szczepanski et al., 2010). Notably, Corbetta and Shulman (2002) proposed two partially separated visual attention control neural systems: the dorsal and ventral frontoparietal networks. Specifically, the dorsal system is located on the dorsal posterior parietal context (e.g., intraparietal sulcus, IPS, and superior parietal lobule, SPL) and dorsal frontal cortex (e.g., frontal eye fields, FEF), which is responsible for mediating voluntary attentional control of sensory information and responses. Supporting evidence comes from a series of functional magnetic resonance imaging studies, showing that pre-cueing (e.g., using an arrow cue) the information about the forthcoming target (e.g., the location of the target or the moving direction of the target) in the visual scene invoked consistently preparatory brain areas during the cue period, areas including the dorsal parietal cortex including the IPS extending into the SPL and postcentral sulcus, and the dorsal frontal cortex like superior frontal sulcus (FEF) (Corbetta et al., 2000; Hopfinger et al., 2000; Kastner et al., 1999; Shulman et al., 1999). In addition to those frontoparietal brain areas, some studies further showed that pre-cueing a target’s location also induced increased signals in the early visual cortex in favor of the cueing target location even in the absence of a target, and this biased visual signal during the cue period derives from the dorsal frontoparietal network (e.g., IPS, FEF, and SPL) (Kastner et al., 1999; Hopfinger et al., 2000). In contrast, the ventral system is mainly centered on the temporoparietal junction (TPJ) cortex and ventral frontal cortex (VFC) (strongly lateralized to the right hemisphere), which is involved in the detection of sensory events that are related to behavior, especially when the targeted stimuli is outside the focus of processing. The role of the ventral frontoparietal plays is assumed to be an altering mechanism or ‘circle-breaker’ for the dorsal system to monitor the unattended objects. The existence of the ventral frontoparietal network is supported by several brain imaging studies showing that the TPJ is strongly activated by target detection, especially when the target occurs at an unexpected location (e.g., Corbetta et al., 2000; Perry & Zeki, 2000).

While the frontoparietal network is identified mostly in orienting attention to targets, emerging evidence shows that this network is also involved in attentional control of reducing interference from salient distractor (de Fockert et al., 2004; de Fockert & Theeuwes, 2012; Krueger et al., 2007; Pollmann et al., 2003). Due to a difference in one or more physical factors with the surrounding background (e.g., a different orientation or color), the salient singleton distractor is assumed to calculate with peak saliency and would pop out to capture attention. And this involuntary attention capture requires top-down dorsal frontoparietal brain areas to make efforts for controlling attention. For example, de Fockert et al. (2004) demonstrated that the presence (vs. absence) of a salient but task-irrelevant color singleton distractor invoked stronger activity of the superior parietal cortex, which indicated that the singleton distractor induced spatial attention shifts toward itself, and then the superior parietal cortex needs to relocate attention from distractor to target. They also identified a strong negative correlation between the strength of the neural activation of the frontal cortex (e.g., precentral gyrus) and the magnitude of behavioral interference caused by the singleton distractor, strongly suggesting a role of frontal areas in attentional control of distractor interference.

Moreover, as top-down brain areas biased the visual cortex signals in favor of the cued attended target location during the pre-stimuli period, top-down attention control can also instigate preparatory activity on the visual cortex to minimize capture by expected distractors (Munneke et al., 2011; Ruff & Driver, 2006; Serences et al., 2004). For instance, by presenting pre-cues indicating the likely target side as well as, on critical trials, the appearance of a distractor in the opposite hemifield, Ruff and Driver (2006) observed enhanced occipital cortex activation in the hemisphere that is contralateral to the upcoming distractor during the cue period, and this was associated with reduced search costs later on. However, concerning the top-down influence on distractor coding in the early visual cortex, the evidence is mixed. For instance, Bertleff et al. (2016) found that cuing the target's position to diminish distractor interference was through increased activity in medial parietal regions that were assumed to be involved in controlling spatial attention, rather than by down-modulating distractor signals in the early visual cortex. On the contrary, Won et al. (2020) manipulated the overall likelihood with which a distractor could occur anywhere in the display, and reported distractor signaling in the visual cortex to be diminished when distractors frequently appeared, along with reduced distractor interference. Given that the evidence is somewhat mixed, the current dissertation aims to explore, based on statistical-learning of distractor locations, whether visual-cortex signals at learned distractor locations would be down-modulated to reduce distractor interference and what specific role frontoparietal attention networks play in distractor handling.

1.4 Aims of this thesis

The goal of the current dissertation is to investigate the cognitive and neural mechanisms underlying the spatial distractor suppression based on statistical learning (probability-cueing) of distractor locations in the visual search. To tackle this issue, classical behavioral investigations and fMRI techniques are employed. Firstly, 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 examines the critical factors between the paradigm of Wang and Theeuwes (2018a) and the design of Sauter et al. (2018) that potentially lead to theoretical conflicts: priority-based suppression or dimension-based suppression. In addition, combining fMRI techniques in the distractor-location learning paradigm, the dissertation further explores how the learned spatial suppression of distractors is neurally implemented in the early visual cortex and the frontoparietal attention networks to reduce the interference.

To begin with, in Chapter 2.1, by adopting and modifying the original paradigm of Wang and Theeuwes (2018a), three psychophysical experiments are performed to investigate three potentially ‘confounding’ factors that might be responsible for the target location effect observed in Wang and Theeuwes (2018a), which were systematically ruled out in the design of Sauter-et-al. (2018): (i) carry-over of positional inhibition of the distractor location from one distractor-present trial to the next distractor-absent trial; (ii) a reduced likelihood of the target appearing at the frequent location as compared to other rare distractor locations; and (iii) remove of manipulation of color swap between the distractor and non-distractor items.

Subsequently, in Chapter 2.2, by combining the distractor-location learning paradigm of Wang-&-Theeuwes and the design of Sauter-et-al, in which the singleton distractor is more likely to appear in a subregion, instead of a location, two potentially important factors that might determine the level of learned spatial suppression were further explored: display density (dense vs. sparse search display) and random color swapping between the distractor and non-distractor items (color swapping vs. no color swapping), in order to draw conclusions concerning the critical factors that decide whether observers adopt a priority-map- or a dimension-based suppression strategy.

Finally, Chapter 2.3 employes fMRI techniques with distractor-location learning paradigm in Sauter et al. (2018) with two types of distractors defined in either the same- or different- visual dimension relative to the target to examine (i) whether visual-cortex signals at learned distractor locations would be down-modulated to reduce distractor interference, (ii) what specific role the frontoparietal attention network plays in distractor handling, as well as (iii) differences in neural mechanisms mediating between the two distractor types.

2 Cumulative Thesis

The current cumulative thesis is made up of three separate studies: two peer-reviewed and published papers (2.1 and 2.2) and one manuscript that has been submitted (2.3). These three studies are included in the following chapter, each of which is followed by a brief statement about the contributions of the authors concerned.

2.1 Probability cueing of singleton-distractor locations in visual search: priority-map- vs. dimension-based inhibition?

CONTRIBUTIONS

BZ and FA share first authorship. HJM, BZ and FA conceived and designed the experiments. BZ collected and analyzed the data. BZ and FA discussed the results with ZS and HJM. BZ, FA and HJM interpreted the results and wrote the paper. ZS and HRL commented and revised the manuscript.

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Probability cueing of singleton-distractor locations in visual search: priority-map- vs. dimension-based inhibition?

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ABSTRACT

Observers can learn the likely locations of salient distractors in visual search, reducing their potential to cause interference. While there is agreement that this involves positional suppression of the likely distractor location(s), it is contentious at which stage the suppression operates: the search-guiding priority map, which integrates feature-contrast signals (e.g., generated by a red amongst green or a diamond amongst circular items) across dimensions, or the distractor-defining dimension. On the latter, dimension-based account (Sauter et al., 2018), processing of, say, a shape-defined target should be unaffected by distractor suppression when the distractor is defined by color, because in this case only color signals would be suppressed. At odds with this, Wang & Theeuwes (2018a) found slowed processing of the target when it appeared at the likely (vs. an unlikely) distractor location, consistent with priority-map-based suppression. Adopting their paradigm, the present study replicated this target location effect. Crucially, however, changing the paradigm by making the target appear as likely at the frequent as at any of the rare distractor locations and making the distractor/non-distractorcolor assignment consistent abolished the target location effect, without impacting the reduced interference for distractors at the frequent location. These findings support a flexible locus of spatial distractor suppression – priority-map- or dimension-based – depending on the prominence of distractor 'cues' provided by the paradigm.

Key words: search guidance, attentional capture, statistical (distractor location) learning, distractor suppression

INTRODUCTION

Recently, there has been a growing interest in statistical, location-probability learning in visual search. While most of this research has focused on the learning of target locations (e.g., Druker & Anderson, 2010; Geng & Behrmann, 2002, 2005; Jiang, Swallow, & Rosenbaum, 2013; Walthew & Gilchrist, 2006; see also Miller, 1988; Müller & Findlay, 1987; Shaw & Shaw, 1977), more recently, there have been various attempts to extend this to the learning of distractor locations (e.g., Ferrante, Patacca, Di Caro, Della Libera, Santandrea, & Chelazzi, 2018; Goschy, Bakos, Müller, & Zehetleitner, 2014; Leber, Gwinn, Hong, & O'Toole, 2016; Sauter, Liesefeld, Zehetleitner, & Müller, 2018; Sauter, Liesefeld, & Müller, 2019; Wang & Theeuwes, 2018a). Collectively, these studies showed that observers appear to be able to learn, from experience, the spatial distribution of salient but task-irrelevant singleton, or 'pop-out' distractors in the search array, to minimize the interference – or potential for 'attentional capture' – normally caused by such distractors (an effect Goschy et al., 2014, referred to as 'distractor location probability cueing'). This appears to be the case whether the salient distractor occurs consistently at one specific, 'most frequent' location in relatively sparse displays (e.g., 4-item displays in Ferrante et al., 2018; 8-item displays in Wang & Theeuwes, 2018a, b) or within a 'frequent' region encompassing multiple possible locations, such as a whole display half, in dense displays (39-item displays in Goschy et al., 2014, and Sauter et al., 2018). However, even though there is no dispute about the fact that observers can learn the statistical distribution of salient distractors and use this 'knowledge' to minimize the interference of distractors occurring at frequent locations, conclusions differ with regard to the locus, or processing stage, within the functional architecture of search guidance at which the observed reduction of distractor interference (for frequent vs. infrequent locations) is realized.

In principle, there are two possibilities: the level of the search-guiding 'overall-saliency' (Guided Search; e.g., Wolfe & Gancarz, 1997; Wolfe, 2007) or 'priority' (e.g., Fecteau & Munoz, 2006) map of the search array, essentially inhibiting any saliency signals at the frequent distractor location and thus preventing distractors at this location from summoning attention. Or a level below this map, for instance, the feature-contrast signals generated in the distractor-defining dimension, which – according to the Dimension-Weighting Account (DWA, e.g., Found & Müller, 1996; Müller, Heller, & Ziegler, 1995; Müller, Reimann, & Krummenacher, 2003) – may be 'down-weighted' prior to their integration with feature-contrast signals from other dimensions (e.g., that of the target) at the 'supra-dimensional' priority map (Müller, Geyer, Zehetleitner, & Krummenacher, 2009; Zehetleitner, Goschy, & Müller, 2012)[1]. Recall that saliency-based accounts of search guidance (from Koch & Ullman, 1985, onwards) assume that the priority map is 'feature-' or 'dimension-blind': due to the loss of feature- and dimension-specific information in the signal integration process, priority signals indicate only to what degree an object at a given location differs from its surround, but not in what way it differs. Accordingly, if distractor suppression operates via inhibition of the likely distractor location at the level of the priority map, this would not only impact the potential of distractor-generated signals to summon attention (reducing interference from distractors appearing at the likely, vs. an unlikely, distractor location), but necessarily also that of target-generated signals (slowing detection of and, consequently, responding to targets at the likely vs. unlikely locations). Critically, this would be the case whether the target is defined in a different dimension to the distractor (e.g., color-defined distractor vs. orientation/shape-defined target) or in the same dimension. By contrast, if distractor suppression (stronger at frequent than at rare distractor locations) operates already on signals at the level of the distractor dimension (i.e., prior to their integration on the priority map), as envisaged by the DWA, then target processing should be unaffected at least when the target is defined in a different dimension to the distractor. Thus, with target and distractor defined in different dimensions, whether or not target processing is affected by learnt suppression of the likely distractor location(s) is diagnostic as to the level, in the hierarchical architecture of search guidance, at which learnt positional distractor suppression is realized.[2]

However, two recent investigations, both using an 'additional-singleton' paradigm (Theeuwes, 1992) with a target defined by a unique shape/orientation and, additionally, a more (bottom-up) salient distractor singled out by color from the homogeneous background items, came to the opposite conclusions. Finding a target location effect (slower reaction times to

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[1] 'Down-weighting' means scaling the 'bottom-up saliency' of the distractor by some inhibitory weight, yielding the effective 'selection saliency' (see Zehetleitner, Koch, Goschy, & Müller, 2013), where the acquired inhibitory weight is greater for the frequent vs. the rare distractor locations (see Sauter et al., 2018). Accordingly, the effect of inhibiting a distractor signal depends on how bottom-up salient a distractor is, and inhibition is a matter of degree rather than ever absolute (see, e.g., Müller, Töllner, Zehetleitner, Geyer, Rangelov, & Krummenacher, 2010).

[2] Suppression of the distractor at the likely location might conceivably also operate at the featural level, that is: the coding of distractor features might be inhibited directly, reducing their potential to generate feature contrast in the distractor dimension (e.g., Gaspelin & Luck, 2018a). In this case, too, one would not expect a target location effect. We come back to the issue of dimension- vs. feature-based distractor suppression in Experiment 3 and the General Discussion. – Also note that when the distractor occurs equally likely at each display location, as is typical in studies not examining spatial biases in the distractor distribution, feature- or dimension-based down-weighting would be applied uniformly across the whole display. Both spatial and non-spatial distractor down-weighting may operate voluntarily (according to task goals) or involuntarily (e.g., driven by selection history or statistical learning), or involve a combination of both (cf. Gaspelin & Luck, 2018b).

targets appearing at likely vs. unlikely distractor locations) in their paradigm, Wang and Theeuwes (2018a) concluded that suppression operates at the level of the priority map (see also Ferrante et al., 2018). Sauter et al. (2018), by contrast, interpreted the absence of a target location effect in their paradigm (backed by Bayes factor analysis favoring the null-hypothesis) as evidence for a dimension-based locus of distractor suppression. Notably, Sauter et al.'s (2018) null-finding with 'different-dimension' distractors (color-defined distractor, orientation-defined target) contrasted with a robust target location effect in a condition with 'same-dimension' distractors, in which both distractor and target were defined by a (more or, respectively, less strong) orientation contrast to the background items. Sauter et al. (2018) interpreted this differential effect pattern in terms of a qualitative difference in the level on which distractor suppression operates: dimension-based with different-dimension distractors and priority-map-based with same dimension distractors (see Sauter et al., 2019, for confirmatory evidence from carry-over of distractor location probability cueing acquired, on day 1, as a result of sampling an uneven spatial distribution of *same*-dimension distractors [distractor more likely in frequent vs. rare region] to test, on day 2, with an even distribution of *different*-dimension distractors [distractor equally likely in both regions]).

Given this impasse (Wang & Theeuwes, 2018a, vs. Sauter et al., 2018), the present study was designed to examine why two studies, using at the surface-level similar, additional-singleton paradigms led to fundamentally different *theoretical* conclusions. Specifically, adopting and modifying Wang and Theeuwes' (2018a) original paradigm, we examined what the critical (and potentially uncontrolled or 'confounding') factors might be in their paradigm, vis à vis the Sauter-et-al. (2018) paradigm, that drive the target location effect.

Since our experiments used variations of the original Wang-and-Theeuwes (2018a) paradigm, it is befitting to describe this paradigm and the essential findings in some more detail. Wang and Theeuwes (2018a) presented observers with a ring of 8 shape stimuli (radius: 4° of visual angle), one of which was designated a 'target' item: either the only circle in the array, presented amongst 7 diamond shapes; or the only diamond in the array, presented amongst 7 circular shapes (target-to-non-target assignment was changing randomly across trials). A target was present on all trials. The task was a 'compound-search' task: observers were required to find the target shape and respond to the orientation of a line within it, where a line of the same orientation (as in the target shape) or a different orientation appeared in each of the non-target shapes. All stimuli – except for possibly one: the additional singleton 'distractor' – were either green or red on a given trial. On distractor-present trials (67% of the total number), one non-target shape appeared in an odd-one-out color: either red (when the other items were green) or green (when the other items were red).

The distractor could appear at any of the 8 possible locations, but, crucially, it was most likely to appear at one, ‘frequent’ distractor location ($p = .65$ on distractor-present trials, as compared to $p = .05$ for each of 7 the remaining, ‘rare’ distractor locations), randomly selected (and kept constant) for each observer. Although this was not expressly stated, it is clear from the analyses conducted that the distractor never coincided with the target location on distractor-present trials. On distractor-absent trials, the target appeared with equal likelihood at each location (including the frequent distractor location). The key findings were: (i) a *distractor location effect* on distractor-present trials: distractor interference was markedly reduced when the distractor appeared at the frequent (vs. a rare) distractor location (as well, to a lesser extent when it appeared at a location adjacent to the frequent location); and (ii) a *target location effect* on distractor-absent trials: responding to the target was markedly slowed when it appeared at the frequent (vs. a rare) distractor location. Although also measurable on distractor-present trials, the finding of a target location effect on distractor-absent trials is particularly diagnostic, because it is unaffected by any processes invoked to deal with an irrelevant singleton in the display. This effect pattern was obtained irrespective of the repetition versus swapping (see also Wang & Theeuwes, 2018b), across trials, of the color assignment to the distractor and non-distractor items, arguing against feature-based effects.[3] Wang and Theeuwes (2018a) took this pattern to be indicative of learnt spatial suppression of the likely distractor location on the attention-guiding priority map, thereby reducing the potential of distractors at this location to capture attention.[4]

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[3] By introducing uncertainty with regard to both the distractor- and the target-defining features, thus limiting the use of distractor and target ‘templates’ to top-down modulate search guidance (distractor templates, e.g. Woodman & Luck, 2007; target templates, e.g., Soto, Heinke, Humphreys, & Blanco, 2005), this paradigm was meant to evoke a saliency-based, ‘singleton detection’ search mode (Bacon & Egeth, 1994), producing strong ‘attentional capture’ by the distractor singletons. Going for strong capture effects to start with is reasonable, given the aim of the study was to examine for modulations of the capture effect by statistical learning of the likely distractor location. Of note, these effects are also discernible, though much weaker, when observers are induced to operate a ‘feature search’ mode (see Wang & Theeuwes, 2018b).

[4] Reduced attentional capture is a plausible explanation, especially given the observation of a P_D component (an electrophysiological index of positional inhibition; Hickey, Di Lollo, & McDonald, 2009; Sawaki, Geng, & Luck, 2012) for the likely distractor location even on distractor-absent trials, i.e., when there was actually no to-be-inhibited distractor at this (or any other) location in the display (Theeuwes, 2018). However, to date, potential influences of other mechanisms have not been ruled out, in any of the relevant studies (including Ferrante et al., 2018, and Sauter et al., 2018). We come back to this issue towards the end of the General Discussion.

The present experiments examined two uncontrolled or potentially ‘confounding’ factors that might be responsible for the target location effect in Wang and Theeuwes’ (2018a) paradigm (influences of these factors were systematically eliminated or ruled out by design in Sauter et al., 2018): (i) carry-over, into a given trial n, of inhibition placed on the distractor location on trial $n - 1$ (Experiment 1); and (ii) a reduced likelihood (on distractor-present trials) of the target appearing at the frequent as compared to any of the rare distractor locations (Experiment 2). Experiment 3 went on to examine whether making the color of the distractor, vis-à-vis that of the non-distractor items, predictable (as had been the case in Sauter et al., 2018) would abolish the target location effect. Taken together, the results indicate that learnt suppression of the likely distractor location may actually operate on either the priority map or a (dimension-specific) map of feature contrasts in the distractor dimension, with the level depending on the prominence of distractor-related ‘cues’ (spatial, feature-definitional) provided by the paradigm.

EXPERIMENT 1

Experiment 1 was designed to replicate the findings of Wang and Theeuwes (2018a) and, additionally, examine whether their pattern of result (in particular, the target location effect) is attributable to an uncontrolled variable: *positional* inter-trial effects, which had not been (or, rather, could not be systematically) examined by Wang and Theeuwes (2018a).

Recall that in Wang and Theeuwes (2018a), a distractor occurred with 65% likelihood at the frequent distractor location, generating a substantial suppression effect centered on this location(s). In our own paradigm (see Supplement in Sauter et al., 2018; see also, e.g., Geyer, Müller, & Krummenacher, 2007; Kumada & Humphreys, 2002; Maljkovic & Nakayama, 1996), such inhibition effects do carry over across trials, that is: if the target on the current trial n appears at the same location as a distractor on the previous trial $n - 1$, RTs to the target are significantly increased – owing to lingering inhibition placed on the ‘rejected’ distractor location on the previous trial (a type of cross-trial ‘inhibition-of-return’, IOR, effect); likewise, if a distractor on trial n falls at the same location as a distractor on trial $n - 1$, the interference effect caused by the current distractor is reduced.

Thus, with regard to the effect pattern reported by Wang and Theeuwes (2018a), that is, the target location effect (distractor-absent trials) as well as the distractor location effect (distractor present trials): making a distractor (65%) likely to appear at one specific location versus unlikely (5%) at one of the (seven) other locations introduces imbalances, between the frequent and rare distractor locations, in potentially critical inter-trial transitions. For instance, on a given distractor-absent trial, the likelihood for a *target* (on trial n) to follow a distractor (on trial $n - 1$) at the frequent distractor location is $.65 \times .125 = .0825$, which compares with a probability of $.05 \times .125 = .00625$ for a *target* to follow a distractor at the exact-same rare distractor location. This means that a target on distractor-absent trial n would have been more likely to fall on an inhibited (i.e., trial $n - 1$ distractor) location when it appeared at the frequent distractor location than when it appeared at one of the rare locations, which could account for the slower RTs to targets appearing at the frequent versus the rare distractor locations. Similarly, on a given distractor-present trial, the likelihood for a *distractor* (on trial n) to follow a *distractor* (on trial $n - 1$) at the frequent distractor location is $.65 \times .65 = .4225$, which compares with a probability of $.05 \times .05 = .025$ for a distractor to follow a distractor at the exact-same rare distractor location. This means that a distractor (on distractor-present trial n) would have been more likely to fall on an inhibited (i.e., trial $n - 1$ distractor) location when it appeared at the frequent distractor location than when it appeared at one of the rare locations, which could go some way to account for the reduced interference caused by distractors appearing at the frequent versus the rare locations.

Thus, it is possible that at least some, if not all, of Wang and Theeuwes' (2018a) critical effects are attributable to passive carry-over across trials of location-based inhibition, rather than to statistical learning of distractor location probabilities. This may apply especially to the target location effect, which is theoretically critical for distinguishing between priority-map- and dimension-based accounts of distractor location probability cueing (see Introduction) and, accordingly, is the critical effect examined in Experiment 1. A role of positional cross-trial inhibition in this effect would be consistent with Sauter et al. (2018), who showed that when positional inter-trial 'confounds' were eliminated, there was no target location effect with different-dimension distractors (in contrast with the distractor location effect, which survived correction for positional inter-trial confounds).

As the number of trials in the Wang and Theeuwes (2018a) experiment (720 trials) was insufficient for estimating inter-trial effects on RTs for relatively rare cross-trial transitions, the number of trials in Experiment 1 was greatly increased to 3000 overall (administered in two separate sessions). This ensured some 29 observations, on average, per participant for the rare transitions with the target on trial n appearing at the exact-same rare (distractor) location as a distractor on trial $n-1$ (yielding a reasonably reliable measure of cross-trial inhibition for the rare distractor locations). In addition, it permitted us to examine for learning/practice effects in distractor suppression (e.g., Gaspelin & Luck, 2018a; Geyer, Krummenacher, & Müller, 2008; Müller et al., 2009; Zehetleitner et al., 2012; see also Cunningham & Egeth, 2016; Töllner; Conci, & Müller, 2015). In all other respects, Experiment 1 was identical in design and procedure to the study of Wang and Theeuwes (2018a).

Method

Participants. A cohort of 24 participants (mean age: 28.33 years; age range: 18-40 years; 15 female) were recruited at Ludwig-Maximilians-University (LMU) Munich for this experiment. This sample size was determined based on the crucial target location effect reported by Wang and Theeuwes (2018a). Although they did not report effect sizes, we calculated a $d_z = .56$ based on the reported *t* test. With $\alpha = .05$, $1-\beta = .80$, and one-tailed testing (the direction of the effect was predicted: RTs to targets appearing at the inhibited, frequent-distractor location were predicted to be slowed, and not expedited!), the sample size needed to replicate this effect is 22 participants. As this is close to the 24 participants in the original Wang and Theeuwes study, we decided to collect the same number of participants, to be on the safe side. As we used a much larger number of trials, thereby reducing the measurement error in each individual average, we actually expected a much higher power. Indeed, post-hoc power calculations indicated a $1-\beta = .9997$ for Experiment 1 and $1-\beta = .99$ for session 1 of Experiment 2 (see below).

All participants were right-handed and all reported normal or corrected-to-normal vision, including normal color vision. They received 9 Euro per hour in compensation for their service. The study protocol was approved by the LMU Faculty of Pedagogics & Psychology Ethics Board. Informed consent was obtained from all participants prior to the experiment.

Apparatus. The experiment was conducted in a sound-reduced and moderately lit test room. Stimuli were presented on a CRT monitor at 1280×1024 pixels screen resolution and a refresh rate of 120 Hz. Stimuli were generated by Psychophysics Toolbox Version 3 (PTB-3) (Brainard, 1997) based on MATLAB R2016a (The MathWorks® Inc). Participants viewed the monitor from a distance of 60 cm (eye to screen) and gave their responses by pressing the leftward- ('horizontal) or upward-pointing ('vertical') arrow on the keyboard with their right-hand index or middle fingers, respectively.

Stimuli. The search displays (see Figure 1 for an example display) were composed of eight outline shapes (circles or diamonds) equidistantly arranged around a virtual circle with a radius of 4° of visual angle. The display items consisted of either one circle (target) and seven diamonds (non-targets), or, alternatively, one diamond (target) and seven circles (non-targets). The diameter of the circle shapes and, respectively, the side length of the diamond shapes was 2° of visual angle. Each outline shape contained a vertical or horizontal gray line inside (0.3° x 1.5°), with half of the internal lines being (randomly) vertical and half horizontal. In a certain percentage of trials (see below), one of the non-target shapes (the distractor) differed in color from all the other shapes, being either green (CIE [Yxy]: 22.5, 0.32, 0.55) amongst homogeneous red shapes (CIE [Yxy]: 8.82, 0.54, 0.36), 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 ($1^\circ \times 1^\circ$) in the center.

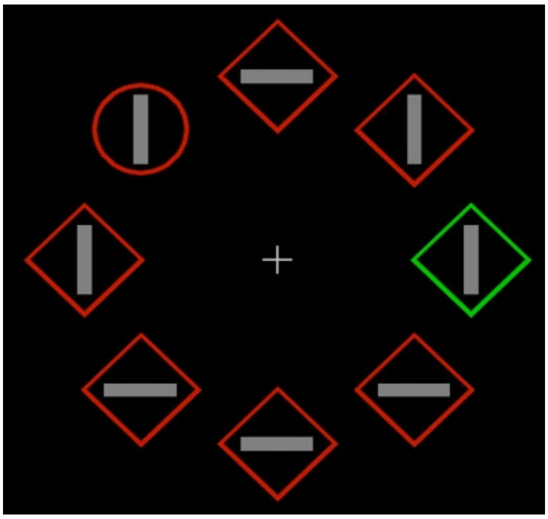

Figure 1. *Example of a visual search display. The search target is the singleton shape (here the only circle), and the distractor is a color singleton (here, the only green, diamond shape). Participants responded to the orientation of the bar inside the target shape (here vertical).*

Design. The target, which was present on all trials, was a singleton, odd-one-out shape amongst the 7 non-target shapes (either a circle or a diamond, randomly assigned on each trial). On trials without a distractor, the target was equally likely to appear at all 8 possible locations. On trials on which a distractor was present in the display, the target appeared equally frequently at all of the remaining 7 non-distractor locations. A singleton distractor, defined by a unique color (red or green, randomly assigned on each trial), appeared in 66% of the trials. If a distractor was present, it appeared with a likelihood of 65% at one, consistent location (frequent distractor location) and with a likelihood of 35%/7 at each of the other 7 locations (infrequent distractor locations). Note that the target and the distractor never appeared at the same location. The frequent distractor location remained the same for each participant, and was counterbalanced across participants. The experiment consisted of 3000 trials in total, subdivided into 2 sessions; each session was subdivided into 25 blocks of 60 trials each. Participants performed the two sessions on separate days.

Procedure. Each trial began with the presentation of a fixation cross for 500 ms, followed by the search array, which was shown until the participant gave a response. The intertrial interval (ITI) ranged between 500 and 750 ms (determined randomly). Participants were instructed to search for the target (the differently shaped item) and identify and respond to the orientation of the line inside – vertical or horizontal – as fast and as accurately as possible. For a vertical line, participants pressed the up arrow on the keyboard; and for a horizontal line the left arrow. At the end of the experiment, participants completed a post-experiment questionnaire, designed to determine whether they were aware of the frequent distractor location. This involved a two-stage procedure: first, participants had to indicate whether the distractor distribution was equal across all locations, or centered on one specific location; second, (even when they had given an equal response in stage 1) participants had to give a forced-choice response at which of the 8 locations the distractor had occurred most frequently (by marking the corresponding location on the 'display' depicted on the answer sheet). Prior to the main experiment (in each session), participants performed 60 unrecorded practice trials to re-/familiarize themselves with the task. Between trial blocks, participants could take a break of a self-determined length. Overall, each session took about one hour and 20 minutes to complete.

Bayes-Factor analysis. Bayesian analyses of variance (ANOVAs) and associated post-hoc tests were carried out using JASP 0.9.0.1 (*http://www.jasp-stats.org*) with default settings. All Bayes factors for ANOVA main effects and interactions are 'inclusion' Bayes factors calculated across matched models. Inclusion Bayes factors compare models with a particular predictor to models that exclude that predictor. That is, they indicate the amount of change from prior inclusion odds (i.e., the ratio between the total prior probability for models including a predictor and the prior probability for models that do not include it) to posterior inclusion odds. Using inclusion Bayes factors calculated across matched models means that models that contain higher-order interactions involving the predictor of interest were excluded from the set of models on which the total prior and posterior odds were based. Inclusion Bayes factors provide a measure of the extent to which the data support inclusion of a factor in the model.

Bayesian t-tests were performed using the ttestBF function of the R package 'BayesFactor' with the default setting (i.e., rscale ="medium").

Results and Discussion

All RT analyses below excluded outliers, defined as trials on which RTs were slower than 3 secs or faster than 150 ms (approximately 2% of trials, which is comparable to Wang and Theeuwes, 2018a), as well as trials on which participants made an incorrect response. In the analyses of inter-trial effects, the very first trial in each block was additionally excluded, because of the break between that trial and the last trial in the preceding block.

In the first instance, the data were analyzed analogously to Wang and Theeuwes (2018a), except that, since our experiment consisted of two sessions, we also examined for differences between the sessions reflecting practice effects. See Figures 2 (RTs and error rates as a function of target and distractor condition) and 3 (RTs and error rates as a function of the distance of the distractor from the frequent distractor location) for the results.

Distractor location effects. To examine how distractor presence at the high-frequency position compared to presence at one of the low-frequency positions affected RT performance, and whether the pattern differed between sessions, we performed a repeated-measures ANOVA with distractor condition (distractor absent, distractor at frequent location, distractor at rare location) and session (1, 2) as factors. This ANOVA revealed both main effects to be significant, distractor condition ($F(2,46) = 126.90, p < .001, \eta_p^2 = .85, BF > 100$) and session($F(1,23) = 37.80, p < .001, \eta_p^2 = .62, BF > 100$) ; the interaction was non-significant ($F(2,46) = 2.83, p = .07, BF = 0.14$). Mean RTs are depicted in Figure 2. The main effect of session reflected faster RTs in the second compared to the first session (mean RTs: 974 ms vs. 1123 ms). Concerning the main effect of distractor condition, post-hoc t-tests revealed that, relative to the distractor-absent baseline (996 ms), there was significant RT interference wherever the distractor occurred (frequent distractor location, $t(23) = 7.24, p < .001, BF > 100$; rare distractor locations, $t(23) = 14.56, p < .001, BF > 100$), but the interference was substantially reduced when the distractor occurred at the frequent location (57 [= 1053 – 996] ms) compared to a rare location (130 [= 1126 – 996] ms), $t(23) = 9.53, p < .001, BF > 100.$ The error rates (which were low overall: 3% on average) mirrored the RT pattern, effectively ruling out that the observed RT effects were driven by differential speed-accuracy trade-offs.

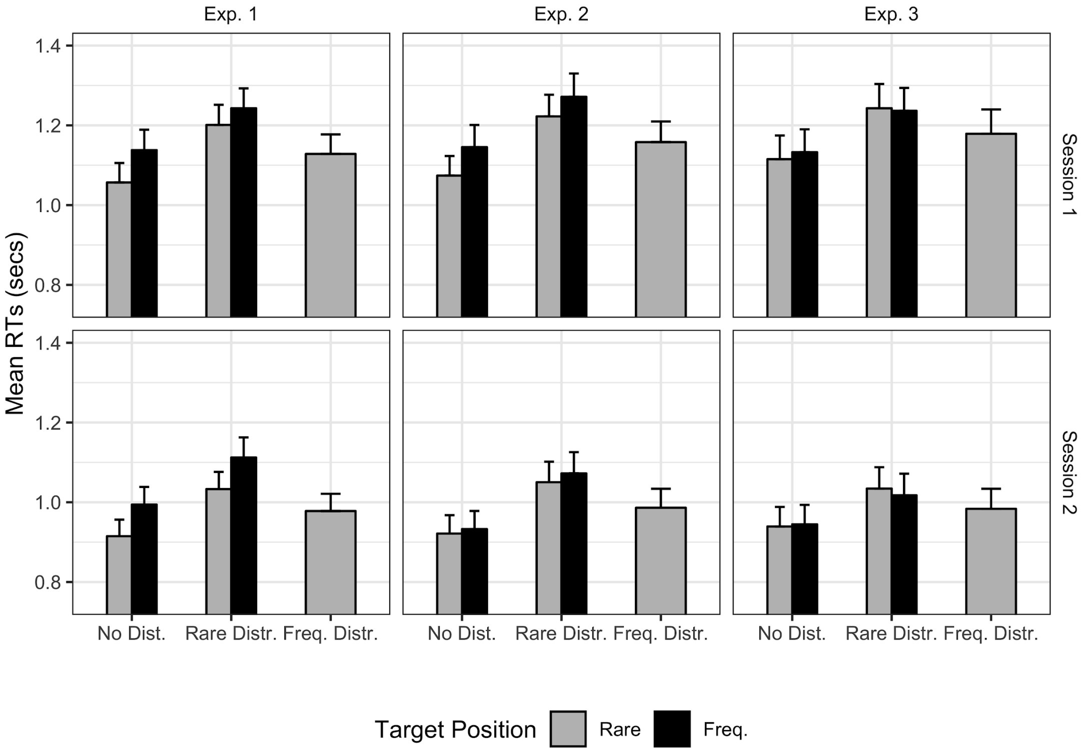

Figure 2. *Mean response times (RTs) for the distractor conditions (No Dist.: distractor absent; Rare Dist.: distractor at rare location; Freq. Distr.: distractor at frequent location), separately for the target positions (grey: target at rare distractor location; black: target at frequent distractor location). The top and bottom panels present the first and the second experimental session, respectively. Error bars denote one standard error. Note that the factor target position is defined only for distractor-absent trials and trials with a distractor at a rare location (on both of which the target could occur at either the frequent or one of the rare distractor locations); on trials with a distractor at the frequent location, the target could appear only at one of the rare locations (as the target and distractor positions never coincided).*

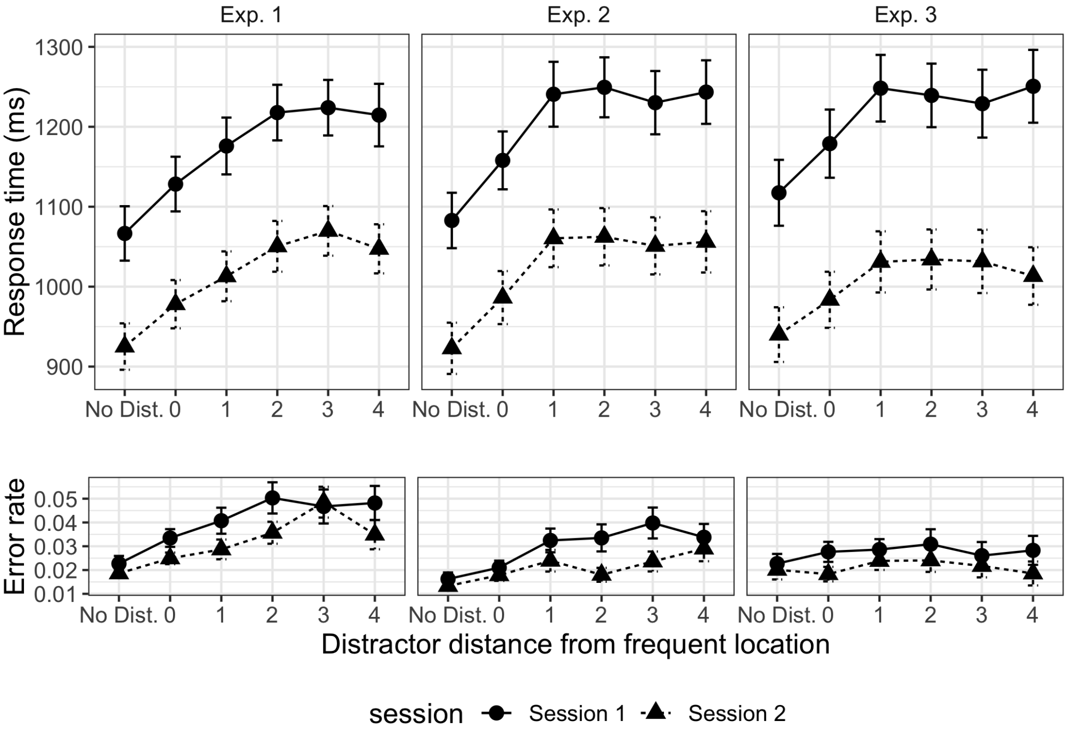

Figure 3. *Mean response times (RTs, upper panels) and mean error rates (lower panels) as a function of the distance of the distractor from the frequent distractor location, separately for the first and the second experimental session. Error bars denote one standard error. Distractor distances 0–4 denote the distance of the distractor from the frequent location (0 = distractor at frequent location; 1 = distractor at location adjacent to frequent location; etc.); 'No Dist.' denotes the distractor-absent baseline.*

Further, RTs to the target increased as the distractor on a given trial was presented further away from the frequent distractor location: an ANOVA with the factors 'distance of distractor from frequent distractor location' (ranging from distance 0 to distance 4) and session revealed the main effect of distance to be significant,$(F(4,92) = 19.60, p < .001, \eta_p^2 = .46, BF > 100)$, without interacting with session $(F(4,92) = 0.38, p = .82, BF = 0.03)$. Importantly, the main effect of distance remained significant when distance 0 (i.e., the frequent location itself) was removed from the analysis: when the distractor was located adjacent to the frequent distractor location (distance 1), the interference effect (99 ms) was larger compared to distance 0 (57 ms) but smaller compared to greater distances (e.g., 141 ms for distances 2, 3, and 4 combined, which showed little difference amongst each other). This pattern was again mirrored in the error rates. Thus, a distractor appearing in close proximity to the frequent distractor location produced less interference than a distractor further away, consistent with a gradient of inhibition centered on the frequent distractor location.

Taken together, these effect patterns replicate those reported by Wang and Theeuwes (2018a).

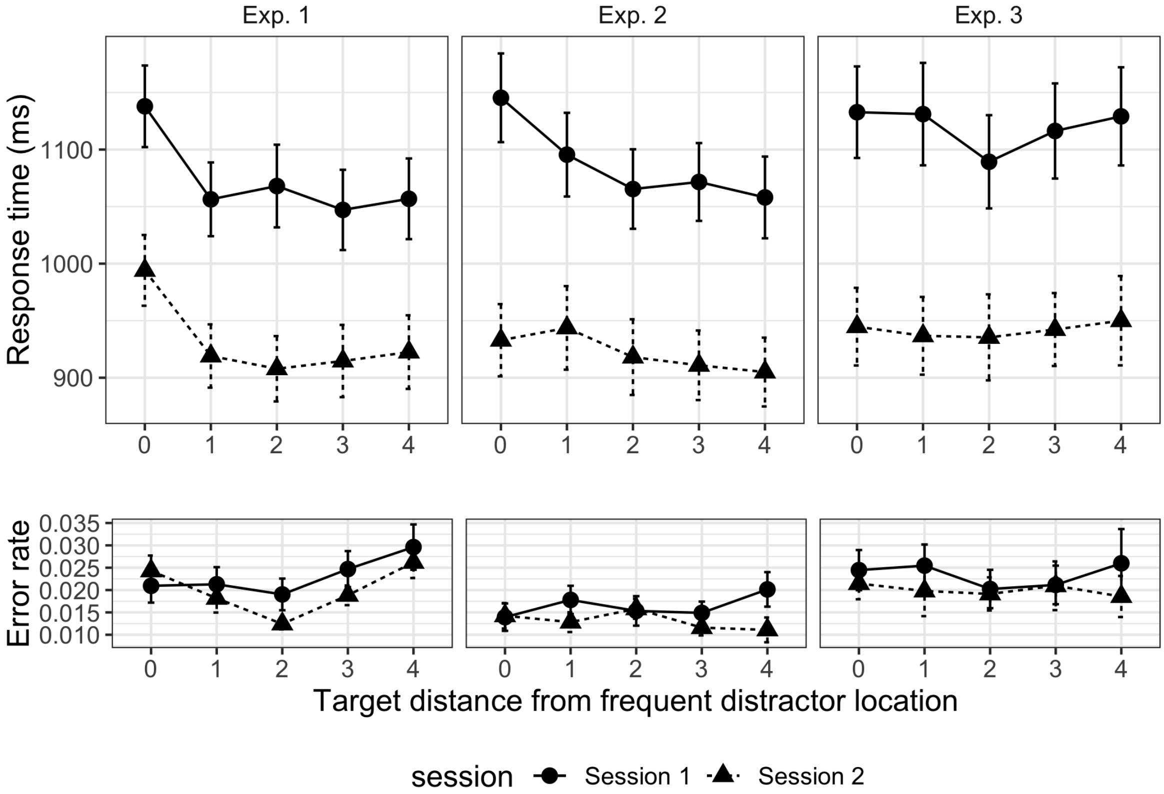

Figure 4. *Mean response times (RTs, upper panels) and mean error rates (lower panels) as a function of the distance of the target from the frequent distractor location, separately for the first and the second experimental session. Error bars denote one standard error. Target distances 0–4 denote the distance of the target from the frequent location (0 = target at frequent location; 1 = target at location adjacent to frequent location; etc.).*

Target location effects. Following Wang and Theeuwes (2018a), to examine for target location effects unaffected by any (processes to deal with the) interference caused by a distractor anywhere in the display (as well as by any unevenness in the target distribution on distractor-present trials; see introduction to Experiment 2), we focused on distractor-absent trials. This analysis revealed that responding to the target was significantly slower, by some 70 ms, when it appeared at the frequent distractor location compared to a rare location (see Figure 4), $t(23) = 5.79$, $p < .001$, $BF > 100$. [This effect was also evident on distractor-present trials (see Figure 2): there was a significant RT disadvantage, of 60 ms, for targets at the frequent versus a rare location, $t(23) = 4.99, p < .001, BF > 100$]. Figure 4 depicts the RTs (on distractor-absent trials) as a function of the distance between the target location and the frequent distractor location. Although there was a significant effect of distance ($F(4,92) = 12.56, p < .001, \eta_p^2 = .35$, $BF > 100$), which did not differ between sessions ($F(4,92) = 0.63$, $p = .64$, $BF = 0.04$), there was little evidence of a gradient effect: while RTs were slower for distance 0, they differed little between the larger distances; there was actually no significant effect of distance after removing distance 0 ($F(3,69) = 0.21$, $p = .89$, $BF = 0.03$), and the RTs for distance 1 and distance 4 were virtually the same: 988 ms and 990 ms, respectively.

Again, the slowing of RTs to targets at the frequent distractor location replicate the effect reported by Wang and Theeuwes (2018a). As Wang and Theeuwes (2018a) did not report a distance analysis for distractor-absent trials, we cannot tell whether there was a significant gradient effect in their experiment. In any case, even for distractor-present trials (for which Wang and Theeuwes reported a distance effect), based on Bayesian statistics, the evidence for a distance effect in Experiment 1 was also only weak when distance 0 was removed: $BF = 1.21$.

Positional inter-trial effects. Next, having replicated the presence of a target location effect in the Wang-and-Theeuwes (2018a) paradigm, we examined whether this effect would be (partly) driven by the imbalances in the frequency, between the frequent and rare locations, with which a distractor on trial *n-1* occurred at the exact-same location as the target on trial *n* (i.e., carry-over across trials of inhibition placed on the distractor location, which, as outlined in the introduction to Experiment 1, would occur more often at the frequent distractor location). This analysis – of the effect of the distractor-to-target transition (same vs. different location) from trial *n-1* to trial *n* – again focused on distractor-absent trials *n*, which is the condition that would reveal any carry-over (into trial *n*) of inter-trial inhibition of the distractor location on trial *n-1* in its purest form.

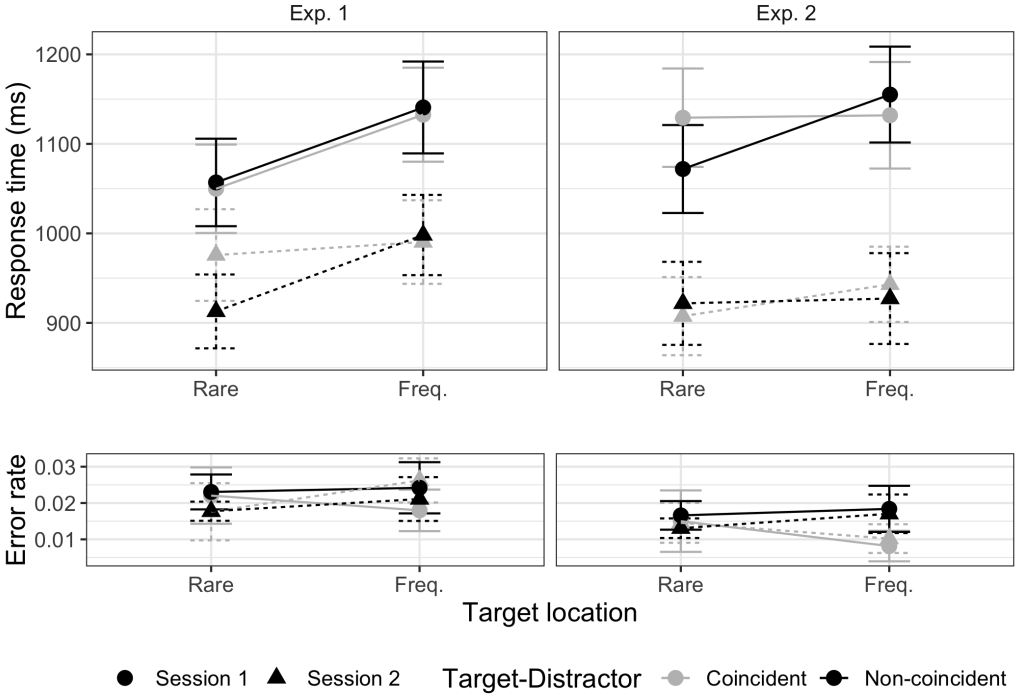

Figure 5. *Mean response times (RTs, upper panels) and mean error rates (lower panels) as a function of the target position (at frequent distractor location, at rare distractor location) and coincidence/non-coincidence of the target position with the previous distractor position, separately for the first and the second experimental session.*

With a distractor absent on a given trial *n*, the target on this trial could appear either at the frequent distractor location or at one of the rare locations. As regards the distractor condition on the previous trial *n-1*, there are then three possibilities: the target and distractor locations are either coincident (i.e., target *n* appears at the same location as the distractor on trial *n-1*) or non-coincident, that is, target *n* appears at a location different to that of the distractor on trial *n-1* or there was no distractor on trial *n-1* (i.e., there were two consecutive distractor-absent trials). As the latter two conditions revealed little difference, we collapsed them into one, 'non-coincident' condition. Figure 5 shows how RTs and error rates depend on target-distractor coincidence for each target condition (target at frequent, at rare distractor location) and session. Overall, there appeared to be some effect of target-distractor coincidence – indicative of cross-trial inhibition – for targets on trial *n* appearing at the location of a rare distractor on trial *n-1* (1013 vs. 985 ms), $t(23) = 1.85$, one-tailed $p = .039$, $BF = 0.93$, but there was no effect whatsoever for targets appearing at the frequent distractor location (1061 vs. 1069 ms, $t(23) = 0.52$, one-tailed $p = .70$, $BF = 0.24$). The effect for rare distractor locations appeared to be driven mainly by the second session (second session, coincident vs. non-coincident: 976

vs. 913 ms; $t(23) = 3.15, p = .0045, BF = 9.50$): an ANOVA with the factors target condition (target at frequent, at rare distractor location), target-distractor coincidence, and session suggested the pattern of RTs as a function of target condition and target-distractor coincidence to differ across sessions (three-way interaction: $F(1,23) = 5.66, p = .026, \eta_p^2 = .20, BF = 0.57$). However, this interaction is put into question by the Bayes factor. In any case, the (if anything) larger inter-trial inhibition associated with rare distractor locations is at variance with the hypothesis that the strong overall-inhibition of the frequent distractor location arises as a result of stronger positional (inhibitory) cross-trial dynamics for the frequent location.

Color repetition effects. Because it is conceivable that participants attempt to suppress the distractor based on its color as well as its position, even though the target (i.e., non-distractor) and distractor color changed randomly from trial to trial, we also examined for an effect of repeating versus switching the color assignment between trials. Like Wang and Theeuwes (2018a), we first examined whether the amount of interference caused by a distractor at the frequent distractor location was different when color assignment was repeated compared to when it changed. Contrary to Wang and Theeuwes (2018a), we found the interference effect to be significantly reduced when the color assignment was repeated compared to when it changed (46 ms vs. 70 ms, $t(23) = -3.19$, $p = .0041$, $BF = 10.40$). This color-repetition benefit is indicative of some additional, color-feature-specific component of distractor suppression.

Given this finding, we went on to perform a more detailed analysis of the color-repetition benefits, more precisely: of the color repetition benefit as a function of the distractor condition (distractor absent, at rare location, at frequent location) on the current trial *n*, dependent on the distractor condition of *trial n-1*. As this analysis is exploratory and somewhat tangential to the question at issue in the present study, the results are detailed in a *Supplementary* section. In brief, this analysis revealed a color-repetition benefit on the current trial *n* only when a distractor appeared at one of the rare locations on the preceding trial *n-1* (not when there was no distractor or when a distractor appeared at the frequent location), and a benefit was evident both when the current distractor appeared at a rare location and when it appeared at the frequent location (but not when there was no distractor on the current trial). – This pattern is consistent with the idea that when a distractor at a rare location captures attention (which is more likely to occur in comparison with a distractor at the frequent, i.e., ‘spatially’ suppressed, location), the distractor color is inhibited in order to disengage attention from the rare distractor and re-allocate it to the target. If this color set (inhibition of the distractor color) is carried over across trials, it would diminish the potential of a distractor defined by the same color, wherever it appears in the display, to attract attention.

Summary. Thus, overall, our results provide a near-perfect replication of those reported by Wang and Theeuwes (2018a). In particular, there was a significant target location effect (on distractor-absent trials), with targets being responded to slower when they appeared at the frequent distractor location compared to one of the rare locations. Going beyond Wang and Theeuwes (2018a), our analyses of positional intertrial effects revealed that, while there was evidence of cross-trial inhibition (IOR) for the rare distractor locations, there was no evidence of such an effect whatsoever for the frequent location. This pattern is at variance with an account of the target position effect in terms of asymmetric carry-over of inhibition (IOR) across trials between the frequent and rare distractor locations, and it is in line with the interpretation put forward by Wang and Theeuwes (2018a), namely, that there is strong (acquired) positional suppression of the frequent distractor location operating at the level of the priority map. In fact, at least judging from the distractor-absent trials (on trial *n*), suppression appeared to be 'near-saturated' for this location, leaving little room for passive positional inter-trial inhibition to assert itself! Also, there was no evidence that this pattern changed as a result of practice on the task: cross-trial inhibition was essentially absent for the frequent distractor location in both sessions/halves of the experiment (whereas it increased from session 1 to session 2 for the rare locations).

Also, unlike Wang and Theeuwes (2018a), we found a significant benefit of repeating (vs. switching) the color of the distractor (relative to that of the other display items) across consecutive trials, though only when there was a distractor at a rare location (not when there was one at the frequent location) on the previous trial. This points to an element of color-based suppression of distractors at the frequent location, on top of space-based suppression. However, as color-based suppression works equally for all (potential distractor) locations (i.e., both the frequent and the 7 rare locations), this component cannot account for the overall reduced interference with distractors at the frequent versus the rare locations.

EXPERIMENT 2

Experiment 1 showed that the result pattern of Wang and Theeuwes (2018a) cannot be reduced to positional inter-trial effects. Nevertheless, it still remains a question whether the (near-saturated) suppression of the frequent distractor location can be attributed solely to distractor position learning, that is, learning to ignore the frequent distractor location. This does remain an open question because, in the paradigm of Wang and Theeuwes, not only was a distractor more likely to appear at the frequent distractor location (on 65% of the distractor-present trials), but a target was also, at the same time, less likely to appear at this location. In number terms: on distractor-present trials, while a target appeared with a likelihood of 95%/7 (= 65%/7 + 30%/7) = approx. 14% at an infrequent distractor location, it appeared only with a likelihood of 35%/7 = 5% at the frequent distractor location; in other words, it was nearly three times less likely to appear at the frequent distractor location on distractor-present trials, and almost twice as likely across all trials combined. Accordingly, learning of the likely distractor location is potentially ‘confounded’ with learning of an unlikely target location, so that we cannot tell whether the suppression effect is due to one or the other or a combination of both. Experiment 2 was designed to examine for this, by making the frequent distractor location as likely to contain a target as any of the infrequent locations not only on distractor-absent trials, but also on distractor-present trials. Note that there was no negative target location bias in the Sauter-et-al. (2018) paradigm, in which the target was as likely to appear in the frequent as in the rare distractor region on both distractor-present and -absent trials.

Method

Methodologically, Experiment 2 was essentially the same as Experiment 1, the only exception being that, on distractor-present trials, a target was equally likely to appear at the frequent distractor location as at any one of the infrequent locations, by increasing the likelihood of a target appearing at the frequent distractor location on the 35% of trials on which a distractor occurred at an infrequent location. On distractor-absent trials, the target appeared equally likely at all locations, in any case. 24 new volunteers (mean age: 24.96 years; age range: 19-34 years; 16 female) participated in Experiment 2, on the same terms and procedural conditions as in Experiment 1. Overall, participants performed 3000 trials in two sessions, which again allowed us to examine for any changes in performance as a function of practice (session effects).

Results and Discussion

Analogously to Experiment 1, we first examined the RTs (and error rates) by a repeated-measures ANOVA with distractor condition (distractor absent, at frequent location, at rare location) and session as factors. See the middle panels of Figure 2 for a depiction of the results. This ANOVA revealed both main effects to be significant: distractor condition ($F(1.5,34.2) = 122.60, p < .001, \eta_p^2 = .84, BF > 100$), and session ($F(1,23) = 45.20, p < .001, \eta_p^2 = .66, BF > 100$); the interaction failed to reach significance ($F(2,46) = 2.83, p = .07, BF = 0.13$).

Distractor location effects. The session effect again reflected faster RTs in the second compared to the first session (mean: 973 ms vs. 1146 ms). Concerning the effect of distractor condition, post-hoc t tests revealed that relative to the distractor-absent baseline (1003 ms), there was significant RT interference wherever the distractor occurred (frequent distractor location, $t(23) = 11.99, p < .001, BF > 100$; rare locations, $t(23) = 12.98, p < .001, BF > 100$), but the interference was significantly reduced when the distractor occurred at the frequent location (69 [= 1072 – 1003] ms) compared to one of the rare locations (146 [= 1149 – 1003] ms), $t(23) = 7.63, p < .001, BF > 100$. The error rates (which were low overall: 2% on average) mirrored the RT pattern, effectively ruling out that the observed RT effects were merely driven by speed-accuracy trade-offs. Essentially, this replicates the pattern seen in Experiment 1.

However, different to Experiment 1, in Experiment 2 there was no evidence of increased distractor interference with distance of the current distractor from the frequent location (see middle panels of Figure 3): an ANOVA with the factors ‘distance of distractor from frequent distractor location’ (distances 1–4, i.e., excluding distance 0) and session revealed neither a significant main effect of distance nor a significant interaction with session (main effect: $F(3,69) = 1.01, p = .39, BF = 0.03$; interaction: $F(3,69) = 0.09, p = .97, BF = 0.06$).

Target location effects. To determine whether, on distractor-absent trials, there is any effect of target condition (at frequent distractor location vs. rare distractor location) after accounting for carry-over effects from distractor inhibition on the previous trial, we analyzed the effect of target condition after removing trials on which the target appeared in the previous distractor position (i.e., we considered the non-coincident condition; see right panel of Figure 5) in an ANOVA with target condition and session as factors. Unlike in Experiment 1, the effect of target condition differed between sessions ($F(1,23) = 6.11, p < .01, \eta_p^2 = .21, BF = 1.71$). In session 1, RTs were slower when the target appeared at the frequent distractor location compared to any other location (1141 ms vs. 1057 ms; $t(23) = 3.50$, $p < .01$, $BF = 19.60$) – which mirrors the pattern seen in Experiment 1 and in Wang and Theeuwes (2018a). In session 2, by contrast, the difference was not statistically significant (927 ms vs. 922 ms; $t(23) = 0.36, p = .72, BF = 0.23$) – that is, there was no longer a target location effect – a pattern consistent with Sauter et al. (2018a). [Essentially the same pattern was seen for distractor-present trials (see Figure 2): an RT disadvantage, of 49 ms, for targets at the frequent vs. a rare location was evident in session 1 ($t(23) = 3.43$, $p = .002$, $BF = 17$), but not in session 2 (disadvantage of 22 ms; $t(23) = 1.34$, $p = .19$, $BF = 0.47$).] – Like in Experiment 1, there was no evidence of a graded effect of the distance of the target location from the frequent distractor location on distractor-absent trials (see middle panels of Figure 4), not even in session 1, where there was a significant target location effect (an ANOVA including only session 1 and removing distance 0 yielded no significant effect of distance: $F(3,69) = 1.48$, $p = .23$, $BF = 0.27$).

Positional inter-trial effects. The pattern of positional inter-trial effects (carry-over of inhibition of the distractor location on distractor-present trial *n-1* to distractor-absent trial *n*) was overall similar to that seen in Experiment 1 (see right-hand side of Figure 5): collapsed across the two sessions, there was evidence of a carry-over of inhibition (RT coincident > RT non-coincident) for the rare locations (22-ms inhibition), but not the frequent location (3-ms difference in the opposite direction to inhibition). However, there was no significant interaction between coincidence and location (interaction coincident/non-coincident x target at frequent/rare location, $F(1,23) = 1.26$, $p = .27$). This time, though, the effect appeared to be arising in the first session ($F(1,23) = 3.48$, $p = .08$, $\eta_p^2 = .13$, $BF = 1.75$; the three-way, session×coincidence×location, interaction was significant: $F(1,23) = 7.36$, $p = .01$, $\eta_p^2 = .24$, $BF = 1.08$); in the second session, the frequent and rare locations appeared equally (un-)affected by positional cross-trial inhibition. However, looked at in terms of the Bayes factor, the evidence for an interaction involving the factor session is not convincing.

Color repetition effects. As for Experiment 1, we first examined whether the amount of interference caused by a distractor at the frequent distractor location differed depending on the repetition versus change of the color assignment across consecutive trials. Again, and contrary to Wang and Theeuwes (2018a), there was a significant color-repetition (vs. -change) benefit

(78 ms vs. 60 ms, $t(23) = 2.57$, $p = .02$, $BF = 3.10$). A follow-up analysis of the color repetition benefit as a function of the distractor condition (distractor absent, at rare location, at frequent location) on trial *n*, dependent on the distractor condition of *trial n-1* (see *Supplementary* section for details), revealed a similar picture to that seen in Experiment 1: there was a (numerical) color-repetition benefit on the current trial only when a distractor appeared at one of the rare locations on the preceding trial, and a benefit was evident when the current distractor appeared at a rare location (significant) and when it appeared at the frequent location (numerical), but not when there was no distractor on the current trial). By and large, this is in line with the account sketched for Experiment 1: when a distractor appears at a rare location on trial *n-1* (in which case it is likely to summon attention), its color may be noted and suppressed (to aid re-allocation of attention to the target location); this inhibitory set is then carried over across trials and benefits performance when the color assignment is repeated (by down-modulating the color feature contrast of the distractor on trial *n*, making it less potent to attract attention).

Summary. Overall, Experiment 2 in many respects replicates the findings of Experiment 1: observers do come to learn, and apply strong inhibition to the frequent distractor location. However, there appears to be a major shift between the two sessions in how this inhibition operates. In session 1 (as in the whole of Experiment 1), it involves a robust target location effect, that is: targets are responded to slower when they appear at the frequent compared to one of the rare distractor locations – consistent with inhibition being applied (to the frequent distractor location) at the level of the supra-dimensional priority map. In session 2, by contrast, the target location effect is no longer evident (in fact, the Bayes factor, $BF = 0.23$, favors the null hypothesis of no target location effect!), and this is so despite the fact that the magnitude of the distractor location effect (i.e., the difference in interference between distractors at the frequent vs. the rare locations) is virtually unchanged (72 ms in session 2 vs. 82 ms in session 1; $BF = 0.13$ for the distractor condition × session interaction). The lack of a target location effect mirrors the results of Sauter et al. (2018) for conditions in which the distractor is defined in a different dimension to the target: it is inconsistent with spatial inhibition of the distractor location operating at the level of the priority map, but consistent with inhibition operating at a dimension-based level, such as the map of (color-) dimension-specific feature contrast signals (which are then integrated across dimensions in the search-guiding priority map).

We propose that this reflects an adaptive shift of the processing level at which distractor inhibition is applied, which is adaptive to the distractor and target location probabilities prevailing in particular task scenarios. Of note, the beginning of a shift can be discerned already within the first session (see Figure 6): splitting the first session of Experiment 2 in halves, the target location effect on distractor-absent trials turns out smaller in the second compared to the first half (first vs. second half of session 1: 91 vs. 51 ms; $t(23) = 2.69$, $p = .013$, $BF = 3.85$[5]; the 51-ms effect in the second half is significantly different from zero: $t(23) = 3.03$, $p = .006$, $BF = 7.51$), without a corresponding decrease of the interference reduction for distractors at the frequent versus the rare locations (first vs. second half: 78 vs. 85 ms; $t(23) = 0.50$, $p = .62$, $BF = 0.24$). That is, the transition from priority-map- to dimension-based suppression of the likely distractor location occurs more gradually, but may need some 1500-plus trials to be completed.

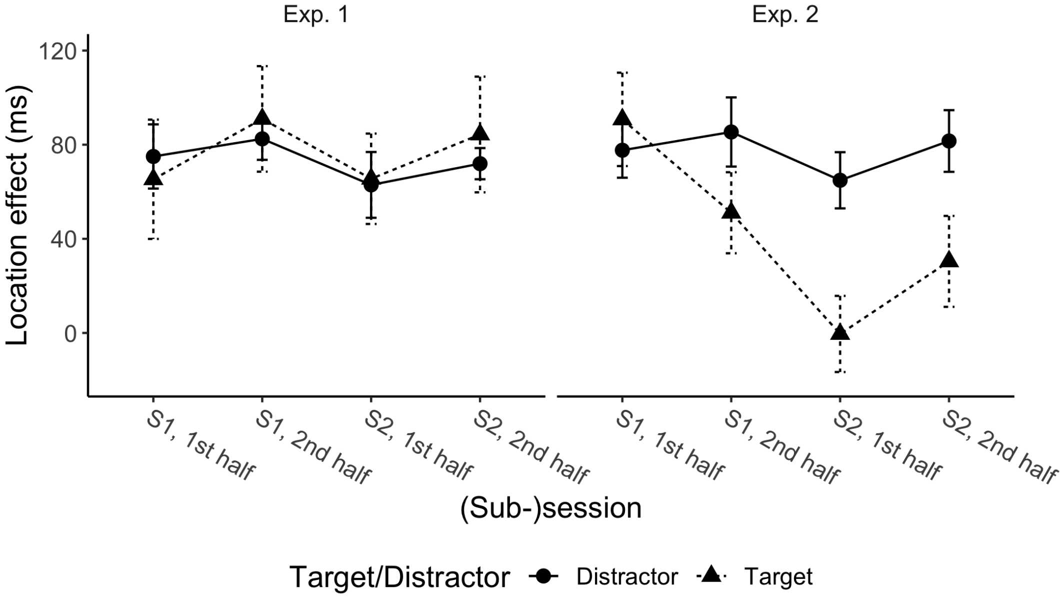

Figure 6. *Distractor location effect (RT difference between conditions with a distractor at a rare vs. the frequent distractor location), and target location effect (RT difference between conditions with the target at the frequent vs. a rare distractor location) on distractor-absent trials, across the course (first and second half of each session) of Experiment 1 and Experiment 2. In Experiment 2 the target location effect reduces towards zero, while the distractor location*

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[5] The reduction of the target location effect is numerically similar when removing trials from the analysis on which the target position on trial *n* coincided with the distractor position on trial *n-1* (first vs. second half: 100 vs. 62 ms), but not statistically significant, $t(23) = 1.44$, $p = .16$, $BF = 0.53$. Note though that estimating the carry-over of inhibition of the previous distractor location to the current target location is inherently more noisy (especially for the rare locations) when the estimates are based on only two thirds of the trials.

effect remains virtually unchanged. (Data uncorrected for cross-trial inhibition of distractor locations.)

EXPERIMENT 3

The results of Experiment 2 may be taken to be indicative of an adaptive shift – in response to the (relative to Experiment 1 unbiased) target location probabilities – of the processing level at which distractor location inhibition is applied, from a priority-map-based level to a dimension-based level. One reason why this shift was seen to develop fully only in the second session (while emerging already in the first session) may be as follows: Under the conditions of Experiment 2 (and 1), with the constant (random) swapping of the distractor and non-distractor colors across trials (which participants reported, in post-experimental debriefing, to be ‘irritating’) and with the target appearing at a non-predictable location, the most ‘salient’ regularity that observers would come to extract first is the likely location of the distractor. In response to this (and lacking other ‘cues’), they start inhibiting this location at a global spatial level: the priority-map. However, over time they come to realize that this actually harms processing of the target when it appears at the likely distractor location – especially since, in Experiment 2, the target was equally likely to occur at the frequent distractor location on distractor-present trials (whereas this was less noticeable in Experiment 1, in which the target was much less likely to occur at the frequent compared to any of the rare distractor locations). This, together with the eventual realization that, despite the color swapping, the distractor is invariably color-defined[6], drives the shift to a dimension-based suppression strategy: inhibit the frequent distractor location within the color dimension.

On this account, any ‘cue’ that would help observers realize the definition of the distractor – namely, as being defined in a different dimension to the target – before (more gradually) learning its frequent location of appearance would encourage them to (more or less immediately) adopt an *efficient* inhibitory strategy, that is, one that minimizes distractor interferences *without* harming target processing. This would be the case in the Wang-and-Theeuwes (2018a) paradigm when there is no unpredictable color swapping between the

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[6] Of course, participants were told, in the instruction, that one, task-irrelevant item would differ from the others by being the only red amongst green items or the only green amongst red items. However, expressly realizing this regularity and translating it into an effective dimension-based inhibitory strategy would take time – given that, compared to a direct feature-based suppression strategy (e.g., suppress ‘red’), implementing a dimension-based strategy (suppress any color difference signal) involves a level of abstraction. This is in line with (and motivated by) informal reports of subjects complaining that the permanent color swapping was perceived as “irritating”.

distractor and non-distractor items in the display, that is, when the color assignment is kept constant. Müller et al. (2009) have shown that with a just few trials of distractor practice under these conditions, distractor interference is very substantially reduced, to a barely significant level. These are also the very conditions under which Sauter et al. (2018; see also Sauter et al., 2019) failed to observe a target location effect in distractor location probability learning, that is: with a constant, color-defined distractor, RTs to the orientation-defined target were not slowed when the target occurred in the frequent versus the rare distractor region. Accordingly, we predicted that by making the color assignment constant in the Wang-and-Theeuwes (2018a) paradigm (with a single likely distractor location), we would observe a robust distractor location learning effect (reduced interference of a distractor occurring at the frequent vs. an infrequent distractor location) without any (substantial) target location effect (slowed RTs to targets at the frequent vs. a rare distractor location) even in the first session of the experiment. This hypothesis was tested in Experiment 3.

Method

Experiment 3 was virtually the same as Experiment 2, except that the distractor/non-distractor color assignment was kept constant throughout the experiment: for half the participants, the singleton distractor was red and the non-distractor items green, and vice versa for the other half. Twenty-four new volunteers (mean age: 24.96 years; age range: 19-34 years; 16 female) took part in Experiment 3, on the same terms and procedural conditions as in the previous experiments. Overall, participants performed 1920 trials in two sessions, which (although fewer than the 3000 trials in Experiments 1 and 2) again allowed us to examine for any changes in performance as a function of practice (session effects). The trial number was reduced because our focus was no longer on the positional inter-trial dynamics, which had been conclusively ruled out to be a factor (in the target location effect) in Experiments 1 and 2.

Results and Discussion

Distractor location effects. As for the previous experiments, we first examined the RTs (and error rates) by a repeated-measures ANOVA with distractor condition (distractor absent, at frequent location, at rare location) and session as factors. See the right-hand side of Figure 2 for a depiction of the results. This ANOVA revealed both main effects to be significant: distractor condition ($F(1.5,34.2) = 80.9, p < .001, \eta_p^2 = .78, BF > 100$), and session

($F(1,23) = 84.30, p < .001, \eta_p^2 = .79, BF > 100$); the interaction was also significant($F(2,46) = 6.19, p = .004, \eta_p^2 = .21, BF = 0.23$).

The session effect again reflected faster RTs in the second compared to the first session (mean: 979 ms vs. 1173 ms). Concerning the effect of distractor condition, post-hoc t-tests revealed that relative to the distractor-absent baseline (1029 ms), there was significant RT interference whether the distractor occurred at the frequent ($t(23) = 6.37, p < .001, BF > 100$) or one of the rare locations ($t(23) = 10.93, p < .001, BF > 100$), but the RT cost (relative to the distractor-absent condition) was significantly lower for the frequent (vs. the 'rare') location(s) (52 [= 1081 – 1029] ms vs. 105 [= 1134 – 1029] ms, $t(23) = 7.89, p < .001, BF > 100$). The error rates (which were low overall: <3% on average) were near-equivalent for the two distractor location (and the distractor-absent) condition, arguing against the differential interference effect being confounded by differential speed-accuracy trade-offs. When the distractor occurred at one of the rare locations, RTs did not differ as a function of its distance to the frequent location($F(3,69) = 1.011, p = .39, BF = 0.03$), that is: reduced interference was confined to the frequent distractor location. Thus, the essential distractor location (probability learning effect) is exactly the same as in the previous experiments.

Also, note that the overall RT speed, the strength of distractor interference, and the magnitude of the learning effect differ only little from Experiments 1 and 2 (see Figure 2). While an ANOVA with the factors experiment (1, 2, 3) and distractor condition (distractor absent, at frequent location, at rare location) failed to reveal a significant main effect of experiment, ($F(2,69) = 0.063, p = .94$), the interaction turned out significant ($F(3.6,125) = 2.93$, $p = .027$, $\eta_p{}^2 = .078$): both the distractor interference and the distractor location probability-cueing effects were somewhat smaller in Experiment 3 (interference from distractor at rare location: 105 ms in Experiment 3 vs. 130 and 146 ms in Experiments 1 and 2; cueing effect: 53 ms in Experiment 3 vs. 73 and 77 ms in Experiments 1 and 2), but the interaction was not supported by the Bayes factor analysis ($BF = 0.06$). That is, the task as such did not become much easier by the constant color assignment in Experiment 3.

Target location effects. Next, and critically for the question at issue in Experiment 3, we examined for the presence of an effect of target condition (i.e., the target appearing at the frequent vs. a rare distractor location) on distractor-absent trials. A preliminary analysis of positional inter-trial effects revealed no evidence for carry-over of distractor location inhibition from a previous (*n-1*) distractor to a current (*n*) no-distractor trial for either the frequent or the rare locations (if anything, RTs were faster, rather than slower, to targets at the previous distractor location). Accordingly, the critical analysis was conducted on the uncorrected (for cross-trial inhibition) data. An ANOVA with the factors target condition and session failed to reveal any significant effects; in particular, there was no evidence of slower RTs (on distractor-absent trials) to targets occurring at the frequent versus one of the rare distractor locations (overall: 1039 ms vs. 1027 ms; main effect of target location,$F(1,23) = 1.03, p = .32, BF = 0.26$), in either session (session 1: 1133 ms vs. 1115 ms, $t(23) = 1.28$, $p = .21$, $BF = 0.44$); session 2: 945 ms vs. 939 ms, $t(23) = 0.45$, $p = .66$, $BF = 0.24$). [The same was true for distractor-present trials (see Figure 2): overall, 1127 ms vs. 1139 ms; main effect of target location, $F(1,23) = 1.09$, $p = .31$, $BF = 0.27$; session 1, 1237 ms vs. 1243 ms, $t(23) = -0.42$, $p = .68$, $BF = 0.23$; session 2, 1017 ms vs. 1034 ms, $t(23) = -1.25$, $p = .22$, $BF = 0.43$.] Note also that (on distractor-absent trials) there were no effects of the distance of the target to the frequent distractor location in either session 1 or session 2 (ANOVA of the distance effect, with distance 0 = target at frequent distractor location, and the additional factor session: main effect of distance, $F(2.4,55.3) = 0.733$, $p = .51$, $BF = 0.034$; distance × session interaction, $F(4,92) = 1.16$, $p = .33$, $BF = 0.05$). In other words, the distance functions for the target are essentially flat (see Figure 4), whereas those for the distractor (distance of current distractor from the frequent distractor location) show a narrow trough for the frequent distractor location (see analysis above and Figure 3).

Summary. Thus, when the distractor is defined by a constant color relative to the non-distractor items (in contrast to the random color assignments in Experiments 1 and 2), although we observe the development of the ‘standard’ distractor location probability cueing effect (of a similar magnitude as in Experiments 1 and 2), this effect is *not* accompanied by a target location effect in either session 1 (in contrast to both Experiments 1 and 2) or session 2 (in contrast to Experiment 1). The lack of a target location effect in Experiment 3 replicates Sauter et al. (2018) using the Wang-&-Theeuwes paradigm and implies that the frequent location was not inhibited at the global level of the priority map: if it had been, processing should have been slower when the target appeared at the frequent as compared to a rare distractor location – in addition to distractor interference being reduced when the distractor appeared at the frequent versus a rare location. The fact that only distractor processing, but not target processing, was impacted argues in favor of the idea that the distractor location was inhibited at some level below the priority map, such as a color-based level, leaving target (i.e., shape) signals unaffected. Based on the present data alone, it is not clear whether this level is dimension-specific (inhibit any color difference signals) or feature-specific (inhibit blue or, respectively, red signals). However, given that the result pattern is the same as in the second session of Experiment 2 (in which the distractor color was non-predictable), dimension-based inhibition is more likely than feature-based inhibition. Also, it is not clear from Experiment 3 whether, and to what extent, the immediate 'abolishment' of the target location effect was due to the constancy of the distractor (vis-à-vis the non-distractor) color or the balanced target location probabilities (on distractor-present as well as -absent trials). Given that many trial samples are required for observers to learn and utilize the target distribution (see Experiment 2), it is likely that the constant color assignment was the more decisive factor, which was then secondarily reinforced by the even target distribution.

GENERAL DISCUSSION

Three experiments designed to examine the target location effect in Wang and Theeuwes' (2018a) paradigm revealed their pattern of effects to be highly replicable. In particular, in all experiments, there was strong suppression of the frequent distractor location: a distractor at this location caused substantially less interference than a distractor at a rare location (on distractor-present trials). In addition, in Experiment 1 (which was an exact replication of Wang and Theeuwes', 2018a, experiment, the only difference being an increased number of trials), we also found a target location effect on distractor-absent trials: RTs were substantially slowed when the target appeared at the frequent distractor location compared to a rare location. Going beyond a mere replication, we also examined for a potential confound: carry-over of positional inhibition of the distractor location from one (distractor-present) trial to the next (distractor-absent) trial. Contrary to our initial hypothesis, however, the target location effect could not be reduced to positional inhibition being cumulatively stronger for the frequent (i.e., statistically frequently inhibited) distractor location compared to the rare locations. If anything, the effect pattern was the other way round: the frequent distractor location was inhibited (tonically) to such a degree that cross-trial positional inhibition made little difference. This overall effect pattern was essentially the same in both experimental sessions – thus ruling out a potential confound and supporting Wang and Theeuwes' (2018a) conclusion that suppression of the frequent distractor location operated at the level of the priority map.[7]

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[7] This is supported by a complementary analysis of distractor location repetition effects on distractor-present trials: while a distractor falling at a previous distractor location causes reduced interference overall, the distractor-location probability-cueing effect survives correction for positional inter-trial inhibition (see Supplementary 2 for details.)

Experiment 2 went on to examine whether this strong inhibition was influenced not only by the distractor location probability, but also by the target location probability. In Wang and Theeuwes' (2018a) original paradigm, the frequent distractor location was actually nearly three times less likely to contain a target than any of the rare locations on distractor-present trials (and some two times less likely across all trials), providing participants with a secondary incentive to ignore the frequent distractor location. This target location bias was removed in Experiment 2. The results revealed that in the first experimental session (averaged across the two session halves), the effect pattern essentially mirrored that obtained in Experiment 1. In particular, a distractor at the frequent (vs. one of the rare) location(s) caused less interference, and responding was significantly slowed when the target appeared at the frequent (vs. a rare) distractor location on distractor-absent trials. This pattern was changed in the second session: while distractor interference was still reduced – by an equal amount! – on distractor-present trials, there was no longer a target location effect on distractor-absent trials (in fact, the Bayes factor argues in favor of a null effect). This is the very pattern observed by Sauter et al. (2018) for conditions with a distractor defined in a different dimension (color in both studies) to the target (shape in the present study, orientation in the Sauter-et-al. study). Experiment 3, which was identical to Experiment 2 except that there was no random swapping, across trials, of the color assigned to the distractor and non-distractor items, yielded essentially the same result pattern as that seen in session 2 of Experiment 2 – however, this time, this pattern was obtained right from the start, in session 1: while there was a significant distractor location probability-cueing effect (of a comparable magnitude to Experiments 1 and 2), this was not associated with a target location effect: RTs were not slowed to targets at the frequent as compared to the rare distractor locations (again, the Bayes factor argues in favor of a null effect).

The effect pattern seen in Experiment 1 and session 1 of Experiment 2 is consistent with the notion, advocated by Wang and Theeuwes (2018a; see also Ferrante et al., 2018), that (spatial) suppression of the frequent distractor location operates at the level of the search-guiding priority map.[8] This is beneficial in that it brings about a substantial reduction of distractor interference; at the same time, it is costly in that targets appearing at the frequent distractor location fall into the inhibitory trough: they take much longer to be detected and processed. By contrast, the effect pattern seen in session 2 (and already emerging during the

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[8] A similar, 'spatial-filtering' account was recently proposed by Ruthruff and Gaspelin (2018), to explain the lack of interference caused by a salient onset 'pre-cue' stimulus presented at one of two invariable, i.e., known, non-target locations in a variant of the 'contingent-capture' paradigm (cf. Folk & Remington, 1996).

second half of session 1) of Experiment 2 and in both sessions of Experiment 3 is consistent with the notion of dimension-based (spatial) inhibition, advocated by Sauter et al. (2018): strongly inhibiting color signals at the frequent distractor location effectively reduced the interference of (color-defined) distractors at this location, while leaving the processing of shape/orientation-defined (target) signals unaffected. Thus, the present results argue that removal of the target location bias in Wang and Theeuwes' (2018a) paradigm (Experiment 2) and making the distractor/non-distractor color assignment consistent (Experiment 3) can bring about an adaptive shift from priority-map-based to dimension-based suppression.

There are at least two questions to be discussed as regards this interpretation: (i) Why was the target location effect fully abolished only in session 2 of Experiment 2, but not already in session 1 (even though it started to decrease in the second half of session 1; see Figure 6), whereas the effect was never evident, in any session, in Experiment 3? (ii) Is the mode of suppression applied (i.e., the level, in the functional architecture, at which suppression operates) flexible, a matter of strategic set?

Concerning question 1, one plausible answer is that, in Wang and Theeuwes' (2018) original paradigm, observers first pick up the more striking distractor location 'regularity' (as also evidenced by the fact that most observers become consciously aware of the likely distractor location[9]), and this makes them operate a purely spatial, priority-map-based inhibitory strategy: suppress any stimulus at this location because it is likely to be a distractor. However, over time, they come to realize that this strategy harms detection of (and responding to) the target when it appears at the frequent distractor location, especially when they come to learn more slowly, in Experiment 2, that the target is (actually) not less likely to be located at the frequent distractor position as at any of the rare locations. In this situation, switching to dimension-based inhibition is adaptive: it minimizes distractor interference while not harming target processing at the frequent location.

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[9] In Experiments 1, 2, and 3, 12 (of 24), 6 (of 24), and, respectively, 11 (of 24) participants correctly pointed to the likely distractor location in an eight-alternative forced-choice test at the end of the second session. Thus, overall, more than three times as many participants had precise knowledge of the likely distractor location (40.28%) than would be expected by random guessing (12.50%). This is indicative of a degree of above-chance knowledge of the likely distractor location, consistent with Wang and Theeuwes (2018a). However, Wang and Theeuwes (2018a) had found no difference in performance between observers who could vs. could not correctly tell the frequent distractor location. That is, suppression of the likely distractor location reflects, by and large, an implicit learning effect (see also Sauter et al., 2018).

In Experiment 3, by contrast, the most immediately apparent regularity is that the distractor is distinguished by a constant color from the other, themselves consistently colored items. Accordingly, participants adopt a color-based suppression strategy right from the start – that is, even before they learn more slowly that the distractor is most likely to appear at one particular location, in response to which they come to focus color-based suppression on this location over time. According to Sauter et al. (2018, 2019), this is the default strategy to deal with 'different-dimension' distractors, which minimizes (color) distractor interference without harming (shape/orientation) target processing. However, while the absence of a target location effect (supported by Bayes factor analysis) strongly argues against a priority-map-based account, we cannot tell from Experiment 3 alone at what level the inhibition of the color distractor was implemented: a feature-specific level (inhibition of a specific color feature, e.g., red) or a dimensional level (inhibition of any color feature contrast signal). However, there are at least two pieces of evidence in favor of the latter account. First, the result pattern for the whole of Experiment 3 is the same as for the second session of Experiment 2 – an experiment in which the distractor (and non-distractor) color was completely unpredictable, so that observers could not have developed a consistent 'distractor feature template' (e.g., Woodman & Luck, 2007). Under these conditions, to effectively reduce distractor interference, observers would have had to resort to a color-, that is, dimension-based inhibition strategy. Second, while (some) feature-based effects were resolvable in Experiments 1 and 2, they contributed only very little to the probability-cueing effect (see below and *Supplementary* section). This is broadly consistent with Wang and Theeuwes (2018a) as well as Experiments 3 and 4 of Wang and Theeuwes (2018b): in these experiments, the distractor was made more likely to appear in one versus the other color (80% vs. 20%), and yet there was no feature-specific effect. Note, though, that these experiments were set up to make observers operate in 'feature search', as opposed to 'singleton detection', mode (cf. Bacon & Egeth, 1994). As a result, the distractor interference and distractor location probability-cueing effects were greatly reduced compared to Wang and Theeuwes' (2018a) original study (e.g., overall interference: 27 ms vs. 117 ms), which would have made it harder to resolve any feature-based effects. – Thus, given the evidence from Experiments 1 and 2, there is no reason to assume that a different (namely: feature-based) suppression strategy was at work in the present Experiment 3 than in Experiment

2.[10] In any case (whatever the precise level): both feature- and dimension-based inhibition would act on signal coding processes *below* the priority map.

Concerning question 2, it appears that observers adapt their mode of suppression to the prevailing positional distractor *and* target probabilities. When target and distractor colors swap randomly across trials, as in Wang and Theeuwes' (2018a) paradigm, the default set appears to be priority-map-based, which immediately brings about a strong reduction of distractor interference; a shift to dimension-based suppression is set in motion only later, when it is realized (over the course of the first session) that this set is associated with a substantial cost in processing targets at the frequent location. In contrast, in the paradigm of Sauter et al. (2018), the distractor color stays constant and is therefore perfectly predictable. In this case, the default may be dimension-based suppression. The random swapping of the (distractor, non-distractor) color assignment across trials in Wang and Theeuwes' (2018a) original paradigm (in contrast to the consistent assignment in the Sauter-et-al., 2018, paradigm and our variation of Wang & Theeuwes', 2018a, paradigm in Experiment 3) may also retard adoption of a dimension-based set, as observers could not tell by the color of a stimulus that it is likely a distractor, rather than a target (they could tell this more reliably based on its position at the frequent location). Thus, if spatial information is perceptually dominant over dimensional (or featural) information, observers may (first) come to operate a purely spatial (priority-map-based) distractor inhibition set.

More generally, this is to say that different default sets, or strategies, may be suggested by specifics of the individual paradigms, and overcoming these default sets may take time and additional learning of more subtle (e.g., target location) probability cues entailed in these paradigms. Thus, the mode of suppression applied is in principle flexible. This does not necessarily mean that adopting a specific set or changing set involves a conscious decision; rather, it may simply be an adaptive process, driven by the availability of various distractor- (and target-) related probability cues. Also, it is conceivable that the two sets do not operate in an all-or-nothing fashion; rather (as suggested by the roughly halved, though still significant target location effect in the second compared to the first half of session 1 of Experiment 2), priority-map-based suppression may coexist with dimension-based suppression. However,

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[10] This is consistent with Won, Kosoyan, and Geng (2019), who – in the absence of color swapping (similar to Experiment 3) – found the interference reduction in a high vs. a low distractor prevalence condition (cf. Müller et al., 2009) to be equally effective when the distractor could be defined, variably across trials, by 192 different colors (randomly chosen from the CIE Lab color wheel) as compared to one, fixed color.

more work is necessary to examine how this ‘mixture’ comes about: do the two sets operate in parallel within a given trial, or can only one set be effective on a trial (yielding a statistical mixture of the two sets across trials)?

In any case, the ‘locus’ of inhibition is flexible: priority-map- or dimension-based. And: just because one finds a distractor location effect, one cannot conclude from this finding alone that inhibition operates at the level of the priority map. Ultimately, of course, it is the priority map via which the inhibition is always expressed in search guidance, but the true level, at which it is instantiated at least in certain conditions, may be below the priority map. This is as envisaged by the Dimension-Weighting Account, according to which selection is ultimately based on the priority map which, however, is itself shaped by the weighting applied to the various, target- and distractor-defining feature dimensions (e.g., Liesefeld, Liesefeld, & Müller, 2019a; for a recent review, see Liesefeld, Liesefeld, Pollmann, & Müller, 2019b).

Finally, a few remarks are in order concerning other influences in the present paradigm, in particular, inter-trial effects as well as spatial gradient effects.

The first concerns *positional cross-trial inhibition of (previous) distractor locations*. We did find evidence of passive carry-over of inhibition, however the effect tended to be small and relatively larger for rare distractor locations. The fact that there was hardly any effect for the frequent location supports the argument that distractors at this location are effectively prevented from capturing attention by other means, limiting the room for passive cross-trial inhibitory effects to influence performance: the less often a distractor occurring at this location captures attention, the less often would this location have to be inhibited (e.g., in order to re-allocate attention to the target location), and the less often would such inhibition be carried over across trial. Thus, with strong persistent inhibition, (cross-trial) transient inhibition becomes rare and therefore, contrary to our initial hunch, the latter has next to no influence in the present paradigm – which may not be entirely surprising given that transient inhibition tends to be small with cross-dimensionally defined targets and distractors to begin with (see Sauter et al., 2018, who found these effects to be larger by a factor of 4 with distractors defined in the same vs. a different dimension to the target).

The second concerns *color-based cross-trial repetition effects*. We did find *color-based repetition effects* (see Figure 7, which presents the effect pattern combined across Experiments 1 and 2), which were however relatively weak and tended to reflect, in the main, carry-over of (inhibition) of the distractor color from the previous trial, which aids performance if a same-colored distractor is present on the current trial (while it makes little difference with regard to where the current distractor appears, at the frequent vs. the rare locations).[11] This contrasts with Wang and Theeuwes (2018a), who probably did not have the power to resolve these effects (due their smaller number of trials). In any case, the fact that there is a significant color repetition benefit also for (current) trials with a distractor at the frequent location would indicate that the suppression of the distractor at this location is not entirely space-based, but involves some element of color-based suppression. However, given that such an effect is seen only in the relatively infrequent event that there is a distractor at a rare location on the preceding trial (i.e.,$p = .66 \times .35 \times .66 \times .65 \approx .10$, and $p = .05$ for color repetition trials), and also given that the effect is equally seen when the distractor on trial *n* occurs at a rare location (i.e., it is a spatially non-specific, parallel effect), carry-over of inhibition of the distractor color (from trial *n-1* into trial *n*) cannot account for the interference reduction with distractors at the frequent versus one of the rare locations. This is the reason why we also find no difference (or only a numerical difference) when we compare simply the interference reduction for the frequent versus the rare locations between trials with a color repetition versus a switch (from the preceding trial): Experiment 1, 78 versus 67 ms, $t(23) = 1.27$, $p > .05$, $BF = 0.44$; Experiment 2, 70 versus 83 ms, $t(23) = -1.34$, $p > .05$, $BF = 0.48$. Overall, this is also consistent with Wang and Theeuwes's (2018b) recent report that making one specific distractor color more likely than the alternative color (80% vs. 20%) in their Experiments 3 and 4 failed to produce a significant main effect of color feature (numerically, there was a small effect, of the order of 5 to 10 ms, in both experiments), or interaction of color feature with distractor location.

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[11] It should be noted that it could conceivably also, or in addition, reflect carry-over of 'facilitation' of the target color from the previous trial – though, arguably, given there are 7 items of the same color (including the target in the display) in the display, carry of inhibition of the unique distractor color would represent a more effective strategy. More work, varying distractor and target colors independently across trials, would be necessary to dissociate these alternatives.

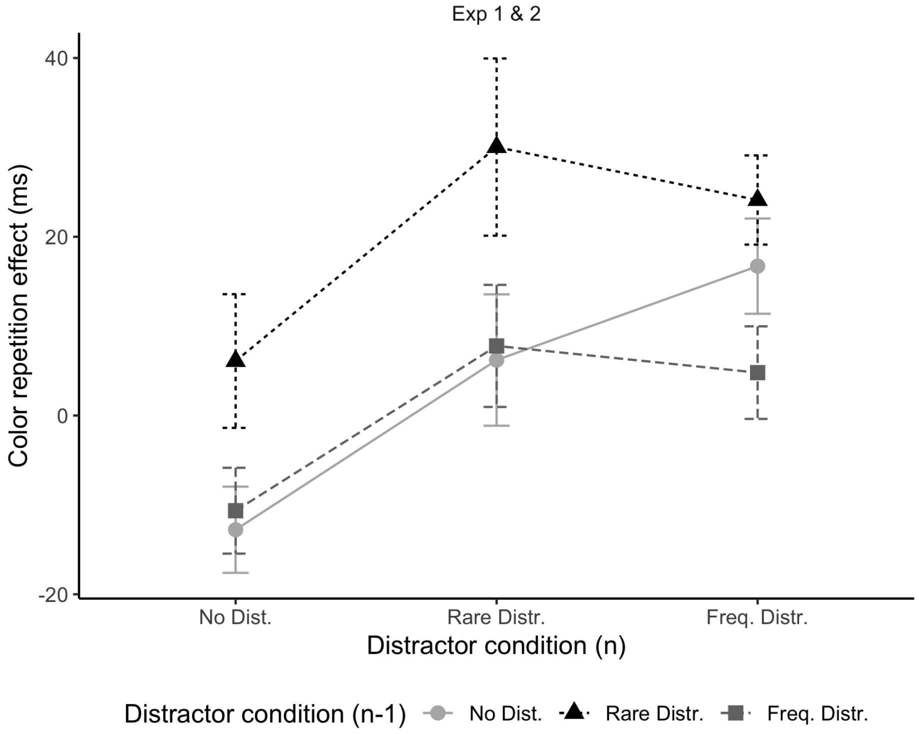

Figure 7. *Color repetition effects (mean difference in RT between trials with a cross-trial change vs. repetition of the color assignment) as a function of the distractor condition on trial n, dependent on the distractor condition on trial n-1, combined across Experiments 1 and 2. Positive values mean RTs were faster when the same color was repeated (color repetition benefits).*

With regard to the dimension-weighting account, one interesting issue in this context is why a color-feature-based modulation (spatially parallel carry-over of inhibition of the distractor color from the previous trial) appears to coexist with a dimension-based modulation (dimension-based suppression of the likely distractor location) in the second session of Experiment 2. As argued elsewhere (see, e.g., Sauter et al., 2018a), the two may not be incompatible: one may de-prioritize (down-weight) some specific feature at a feature-based level, while also de-prioritizing (down-weighting) the respective feature dimension at a higher level, prior to the integration of the dimension-specific feature contrast signals into the search-guiding (feature-less and supra-dimensional) priority map. Alternatively, different colors might effectively be treated as different (though related) dimensions (see Liesefeld et al., 2019b).

In sum, our finding (in two experiments) of a feature-based component of distractor suppression provides evidence in favor of all three levels – the featural, dimensional, and priority-map level (see Gaspelin & Luck, 2018a, for a similar distinction) – being of importance.

However, the feature-based color repetition effect is additive to the distractor location effect (affecting the frequent and rare distractor locations equally), that is, it cannot explain the distractor location probability-cueing effect.

A third point concerns the notion of an inhibitory gradient centered on the frequent distractor location, which Wang and Theeuwes (2018a) took to be indicative of the inherently 'spatial' nature of the distractor location learning effect. While we found some evidence of a gradient of inhibition (on distractor-present trials) in Experiment 1 (consistent with Wang & Theeuwes, 2018a, 2018b), there was little evidence of a gradient effect on either distractor-present or -absent trials in Experiments 2 and 3 – despite the fact that the respective distractor location effects (the difference in RTs between frequent and rare locations) were comparable in magnitude to those of Experiment 1 and those reported by Wang and Theeuwes (2018a). This is not problematic for their (and our) conclusion, however: it might simply mean that the suppression is tightly centered on, rather than being fuzzily distributed around, the frequent distractor location.

Last, but not least, there is a more general point to be addressed: Although the present (as well as previous) results on distractor-location probability cueing are all coherently interpretable in terms of learnt suppression of the likely distractor location(s) at some level in the architecture of saliency computation, there are other, conceivable mechanisms that could also underlie the distractor location and target location effects, which have not been systematically investigated as yet. In particular, rejection of distractors and, consequently, disengagement of attention might be expedited at the frequent distractor location (Geng & Diquattro, 2010), and/or selection of responses to targets at the likely distractor location might be slowed (Huang, Holcombe, & Pashler, 2004). For instance, assume that what observers learn in distractor-location probability-cueing paradigms is a decision bias towards an item occuring at the likely distractor location being a distractor and against it being a target. In terms of a drift-diffusion model (Ratcliff & McKoon, 2008), the starting point of evidence accumulation might be shifted towards the 'distractor' boundary and away from the 'target' boundary. This would generate both a distractor location effect (faster disengagement from distractors at frequent vs. rare locations), and, on the flipside, a target location effect (slower responses to targets at the frequent vs. rare locations). However, while this account has the virtue of simplicity, it could not explain why the target location effect vanishes under certain conditions, while the distractor location effect remains fully intact. Of course, other accounts assuming differential 'attentional-disengagement' and 'response selection' processes may be feasible, but these would have to be more complex. These possibilities need to be examined in future work. However, given the finding of a P_D component (Hickey et al., 2009; Sawaki et al., 2012) for the likely distractor location even on distractor-absent trials (Theeuwes, 2018, March, TeaP; see Footnote 4), we would expect these processes to operate alongside the modulation of attentional capture envisaged by saliency-based accounts.

CONCLUSION

We conclude that in the Wang and Theeuwes' (2018a; see also Wang & Theeuwes, 2018b) paradigm, the learnt distractor location inhibition is not necessarily based on the priority map (as assumed by Wang & Theeuwes, 2018a; see also Ferrante et al., 2018). Instead, it may also be implemented at (or, over the course of learning, shifted to) a lower, dimension-based level in the functional architecture of saliency computation – especially when the featural predictability of the distractor (vis-à-vis the non-distractor items) and/or the target location distribution affords a dimension-based inhibitory set: implementing inhibition at a dimension-based level would leave target processing unaffected in scenarios in which the distractor is defined in a different dimension to the target (see Sauter et al., 2018). On the other hand, observers do not mandatorily operate a dimension-based suppression strategy with different-dimension distractors (as implicitly assumed by Sauter et al., 2018). Rather, at least when the distractor and non-distractor (including the target) colors swap randomly across trials, suppression at the level of the priority map may provide a ready 'default' strategy which is only slowly adapted in response to more subtle target location probability cues. Thus, both strategies are feasible in principle, and which one is adopted depends on the various, distractor and target probability cues acquired over the course of practice on the task.

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SUPPLEMENT 1: Color-Repetition Benefits

Figure S1 depicts the RT benefit for repeated versus switched color assignments averaged across sessions, more precisely: the color repetition benefit as a function of the distractor condition (distractor absent, at rare location, at frequent location) on the current trial *n*, dependent on the distractor condition of *trial n-1*, for Experiments 1 and 2 (left and right panels), respectively.

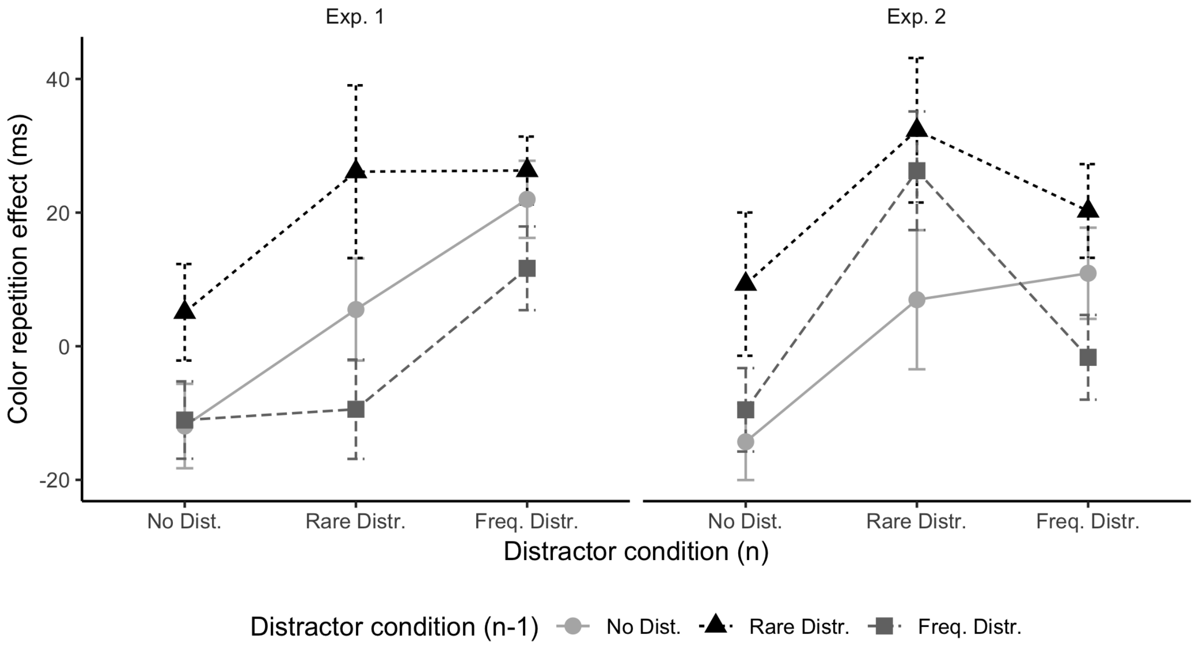

Figure S1. *The effect on RTs of repeating minus switching the target/distractor color between consecutive trials as a function of the distractor condition on trial n, dependent on the distractor condition on trial n-1. Positive values indicate that RTs were faster when the color was repeated.*

Color-repetition effects in Experiment 1. As can be seen from the left panel of Figure S1, there was an RT benefit of repeating (vs. changing) the color assignment (distractor and non-distractor colors) from the previous trial when a distractor was present (vs. absent) on the current trial *n*, and this color repetition benefit was most marked when there was a distractor on the preceding trial *n-1*. A repeated-measures ANOVA revealed both main effects to be significant: distractor condition on trial *n* (*F*(1.7, 38.8)=4.01, *p*=.032, η_p^2 =.15, *BF*=2.5, Hyunh-Feldt corrected degrees of freedom) and distractor condition on trial *n-1* (*F*(2,46)=5.28, *p*=.009, η_p^2 =.19, *BF*=3.1); the interaction was not significant (*F*(3.1, 70.3) = 0.40, *p*=.76, *BF*=0.057, Hyunh-Feldt corrected degrees of freedom). For interpreting the data, though, it should be borne in mind that some of the (cross-participant) condition means are likely to be beset by noise because the individual participants' estimates (means) are based on very few observations (e.g., trials on which a distractor occurred at a rare location twice in a row (same or different rare location) were relatively infrequent, p=.054, i.e., p=.027 for color repetition and switch trials). Overall, it appears that a (positive) color repetition manifested consistently (only) on a given trial *n* when, on the preceding trial *n-1*, a distractor had occurred at a rare location (explaining the main effect of the distractor condition on trial n-1). This produced a benefit especially when a distractor was also present on the current trial *n* at the frequent location (26-ms benefit, $t(23)$=3.51, p=.02 (Bonferroni-corrected for multiple comparisons), *BF*=20.3), though there was also a numerical effect, of near-equal magnitude (30 ms), when a distractor was present at a rare location (though this benefit was statistically non-reliable: $t(23)$=1.72, p>.05 (Bonferroni-corrected), *BF*=0.77).

Color-repetition effects in Experiment 2. Similar to Experiment 1, there was an RT benefit of repeating the color assignment from the previous trial when a distractor was present on the current trial *n*, and (judging from the right panel of Figure S1) this color repetition benefit appeared to be most marked when there was a distractor on the preceding trial *n-1*. However, a repeated-measures ANOVA of the color repetition effect, with the factors distractor condition on trial *n* and distractor condition on trial *n-1*, revealed only the main effect of distractor condition on trial *n* to be significant ($F(2, 46)$=5.78, p=.006, η_p^2 =.201, *BF*=6.7), while the effect of distractor condition on trial *n-1* failed to reach significance: $F(2, 46)$=2.00, p=.15, *BF*=0.34) (interaction: $F(2.7, 63.1)$=0.41, p=.80, *BF*=0.056). The significant main effect of distractor condition on trial *n* was due to the color repetition benefit being significantly larger than zero only when the distractor occurred at one of the rare locations (23 ms, $t(23)$=2.61, p=.047 (Bonferroni corrected), *BF*=3.3), but not when it occurred at the frequent locations (12 ms, $t(23)$=1.67, p>.1, *BF*=0.72). Note that when no distractor was present on trial *n*, there was not even a numerical benefit (if anything, there was a numerical, 7-ms cost; $t(23)$=-1.17, p=.25, *BF*=0.39), consistent with Experiment 1 (5-ms cost; $t(23)$=-1.10, p=.28, *BF*=0.37). Although this pattern looks the other way round to that seen in Experiment 1 (where the benefit was significant for the frequent location, but not for the rare locations), it should not be over-interpreted given the noise in the data (see above).

Thus, a possible account for the pattern common to both experiments (see also Figure 7 in the main text, which presents the data combined across the two experiments) may be as follows: When a distractor at a rare location captures attention (which is more likely to occur in comparison with a distractor at the frequent, i.e., ‘spatially’ suppressed, location), the distractor color is inhibited (and perhaps the non-distractor color enhanced) in order to disengage attention from the rare distractor and re-allocate it to the target. If this color set (inhibition of the distractor color, and perhaps facilitation of the target color) is carried over across trials, it would diminish the potential of a distractor defined by the same color, wherever it appears in the display, to attract attention (and a positive bias for the non-distractor color would help guide attention towards the target). Assuming a positive bias towards the non-distractor color (in addition to a negative bias towards the distractor color) would explain the slight numerical benefit seen even if there is no distractor present on the current trial. Also in line with this account is the fact there is no significant color-repetition benefit with a distractor at the frequent location on trial *n-1*: as such distractors (at the spatially suppressed location) are unlikely to capture attention, their color is not encoded (and inhibited), thus not giving rise to a color repetition effect. – This, arguably, makes sense of key features of the pattern seen in Figure S1, although this pattern appears to be richer than the post-hoc account sketched here. Further, dedicated work would be required to explore these more subtle effects.

SUPPLEMENT 2: Distractor-Distractor Location Repetition Effects in Experiments 1 to 3

For distractor-present trials, Figure S2 shows the distractor-distractor location repetition effects (coincidence vs. non-coincidence of the distractor locations on trial n-1 and trial n), with the current distractor occurring either at the frequent or a rare distractor location. To increase power, the data were collapsed across Experiments 1, 2 and 3.

As can be seen from Figure S2 there is a significant coincidence effect ($F(1,71) = 12.1$, $p < .001$, $\eta_p^2 = .145$, $BF = 8.53$): RTs are significantly faster overall with co-incident than with non-coincident distractor locations on consecutive trials, though this effect differs little between the frequent and rare distractor locations (numerically, it is somewhat larger for the latter, as we had expected, but the interaction is not significant: $F(1,71) = 0.67$, $p = .42$, $BF = 0.23$).

This pattern shows that while a distractor falling at a previous distractor location causes reduced interference overall (indicative of carry-over, into the current trial, of inhibition placed on the distractor location on the preceding trial), this carry-over effect is not a significant factor in the distractor-location (probability-cueing) effect, it survives correction for positional inter-trial inhibition (i.e., it is evident even on non-coincident trials). This is consistent with Sauter et al. (2018).

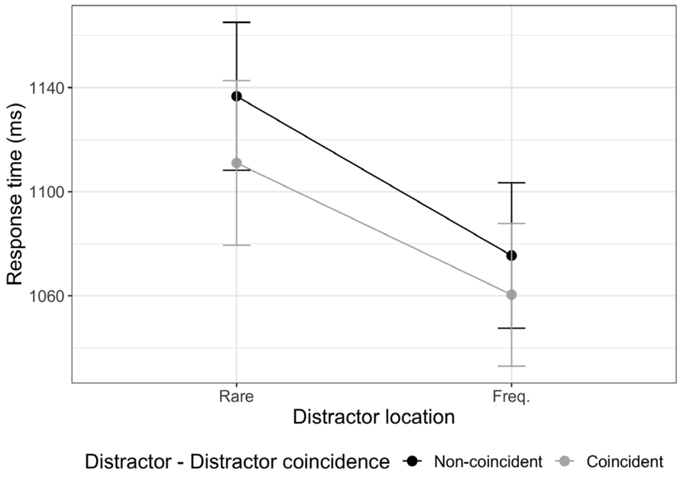

Figure S2: *Distractor-distractor location repetition effects (coincident vs. non-coincident distractor locations on trials n-1 and n): RT to the target on trial n with a distractor* *occurring at the frequent distractor position vs. a rare position. Error bars show the standard error of the mean.*

For comparison, Figure S3 shows the distractor-target location repetition effects on distractor-absent trials (collapsed across Experiments 1 and 2). For this data set, while there was no significant main effect of coincidence ($F(1,47) = 1.30$, $p = .26$, $BF = 0.27$), the interaction between coincidence and target location was marginally significant ($F(1,47) = 3.98$, $p = .052$, $\eta_p^2 = .078$, $BF = 0.65$). For targets on trial *n* at one of the rare distractor locations, RTs were slower when it was preceded by a distractor at the same vs. a different location (1016 ms vs 991 ms, $t(47)=-2.38$, $p=.022$, $BF=2.0$), while there was no such difference for targets at the frequent location (1049 ms vs 1055 ms, $t(47)=.44$, $p=.66$, $BF=0.17$). See the sections on „positional inter-trial effects" in the main document for a more detailed analysis of distractor-target location repetition effects.

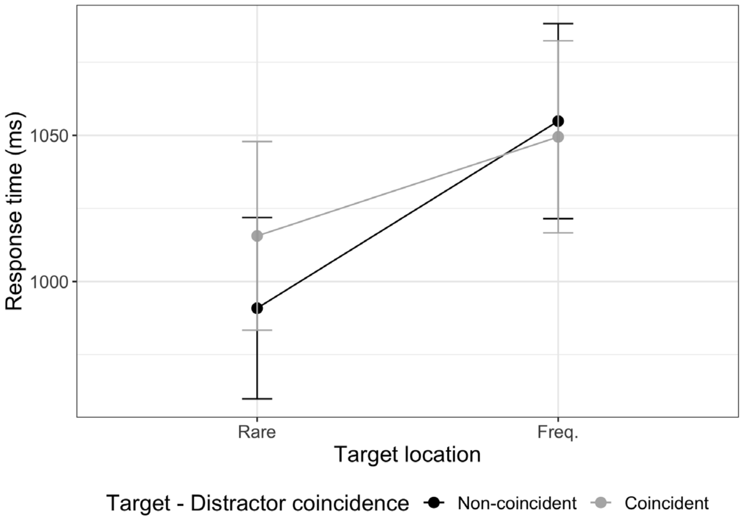

Figure S3: *Distractor-target location repetition effects (coincident vs. non-coincident distractor location on trial n-1 and target-location on trial n) on distractor-absent trials: RT to the target on trial n appearing at the frequent vs. a rare distractor position. Error bars show the standard error of the mean.*

2.2 Probability cueing of singleton-distractor regions in visual search: the locus of spatial distractor suppression is determined by color swapping

CONTRIBUTIONS

BZ and FA share first authorship. HJM, BZ and FA conceived and designed the experiments. BZ collected and FA analyzed the data. FA and BZ discussed the results with ZS and HJM. FA, BZ and HJM interpreted the results and wrote the paper. ZS and HRL commented and revised the manuscript.

REFERENCE

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Probability cueing of singleton-distractor regions in visual search: the locus of spatial distractor suppression is determined by color swapping

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ABSTRACT

Observers can learn the likely locations of salient distractors in visual search, reducing their potential to cause interference. While there is agreement that this involves positional suppression of (statistically) frequent distractor location(s), the results are mixed as to the stage at which the suppression operates: the search-guiding *priority map*, which integrates *feature-contrast* signals across dimensions (e.g., Wang & Theeuwes, 2018a), or the distractor-defining dimension (Sauter et al., 2018). Critical for deciding this question is whether or not a distractor-position effect (reduced interference by distractors at frequent vs. rare locations) is accompanied by a target-position effect (slowed response times to targets at frequent vs. rare locations) when the distractor is defined in a different dimension to the target: priority-map based suppression would impact the processing of (e.g., *shape*) target as well as (*color*) distractor signals; distractor-dimension-based suppression would impact only (*color*) distractor signals. To help identify the factors that are critical for one or the other effect pattern, the present study adopted a paradigm in which the distractor was likely to appear in a larger sub-region of the display (Sauter et al., 2018) and orthogonally varied display density (i.e., singleton saliency) and random color swapping between the distractor and non-distractor items (swapping vs. no swapping). The results generalized previous findings from a single-distractor-location (Zhang et al., 2019) to a distractor-region 'cueing' paradigm: Both effect patterns are found consistently, with the critical factor being color swapping: with unpredictable color swapping, observers tend to adopt a priority-map-based suppression strategy, likely because spatial distractor cues dominate over dimensional cues; with color consistency, they adopt a dimension-based strategy, because cues to the distractor dimension dominate over spatial cues.

Key words: search guidance, attentional capture, statistical (distractor location) learning, distractor suppression

INTRODUCTION

Recently, there has been a surge of interest in statistical, location-probability learning in visual search – initially, in the learning of to-be-attended target locations (e.g., Druker & Anderson, 2010; Geng & Behrmann, 2002, 2005; Jiang, Swallow, & Rosenbaum, 2013; see also Miller, 1988; Müller & Findlay, 1987; Shaw & Shaw, 1977; Walthew & Gilchrist, 2006), and increasingly the learning of to-be-ignored distractor locations (e.g. Ferrante et al., 2018; Goschy, Bakos, Müller, & Zehetleitner, 2014; Leber, Gwinn, Hong, & O'Toole, 2016; Sauter, Liesefeld, & Müller, 2019; Sauter, Liesefeld, Zehetleitner, & Müller, 2018; Wang & Theeuwes, 2018a). The latter studies have produced consistent evidence that observers can learn, from experience, the spatial distribution of salient but task-irrelevant singleton ('pop-out') distractors in the search array, to minimize the *distractor interference* (or potential for 'attentional capture') normally caused by such distractors. Goschy et al. (2014) referred to this as '*distractor location probability cueing*'. In a typical distractor-location probability-cueing experiment, the distractor occurs with an increased likelihood at one ('frequent') display location or in a ('frequent') sub-region of the display, compared to the remaining 'rare' locations or the 'rare' region. The typical finding is that, compared to (baseline) trials without a distractor in the display, reaction-time (RT) performance is less compromised when distractors appear at a frequent as compared to a rare location – evidencing statistical learning of the likely distractor location or region.

The additional-singleton paradigm. The relevant studies on the statistical learning of (likely) distractor locations have all used variants of Theeuwes' (1992) *additional-singleton paradigm* (see the left panel of Figure 1 for an illustration of the 'classical' version of this paradigm). Reduction of interference has been observed whether the salient (additional-singleton) distractor occurred consistently at one specific, 'most frequent location' in relatively sparse displays – for instance, 8-item displays in Wang and Theeuwes (2018a, 2018b) – or within a larger 'frequent region' encompassing multiple possible locations, such as a whole display half, in dense displays – for instance, 39-item displays in Sauter et al. (2018, 2019). However, at least with a singleton distractor defined in a different dimension to the target (*different-dimension distractor*; namely, color-defined distractor and shape- or orientation-defined target), the two types of paradigm, while producing similar *distractor-position effects* (reduced interference of distractors at frequent vs. rare distractor locations), gave rise to differential *target-position effects*: In the Wang-&-Theeuwes paradigm, processing of the target was impeded (i.e., slowed) when it appeared at the frequent distractor location.

Importantly, this target-location effect was manifest even on trials without any distractor in the display – that is: it must be a by-effect of the statistical learning of the distractor distribution, rather than being attributable to any dynamics introduced by the physical presence of a distractor in the display. In the Sauter-et-al. paradigm, by contrast, the distractor-location effect was *not* accompanied by such a target-location effect when the additional singletons were defined in a different dimension to the target (different-dimension distractors).[1]

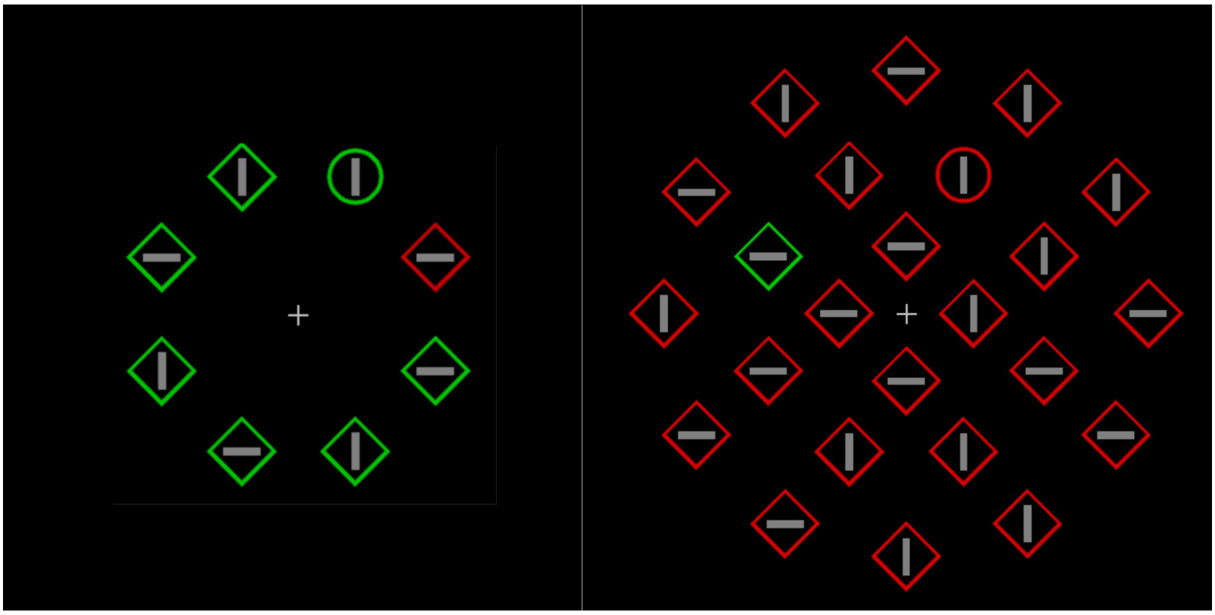

Figure 1. *Example of the visual search displays used in Group 1 and 2 (left-handed panel, sparse displays) and Group 3 and 4 (right-handed panel, dense displays). The search target is the singleton shape (here a circle shape), and the distractor is a color singleton (here, left: the only red item, right: the only green item). Participants responded to the orientation of the bar inside the target shape (here vertical).*

Locus of learned distractor suppression. These differential effect patterns led to different conclusions with regard to the processing stage, within the functional architecture of search guidance, at which the observed reduction of distractor interference (for frequent vs. infrequent locations) is realized. Wang and Theeuwes (2018a, 2018b) concluded that observers learn to inhibit the frequent distractor location at the level of the search-guiding 'overall-saliency' (Müller, Heller, & Ziegler, 1995), 'activation' (Guided Search; e.g., Wolfe & Gancarz,

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[1] However, there was a target-location effect (on distractor-absent trials) when the additional singleton was defined in the same dimension as the target (*same-dimension distractors*). Sauter et al. (2018, 2019) took this dissociation to argue that learned distractor suppression is implemented at different levels in the hierarchical architecture of search guidance with different- vs. same-dimension-distractors – see below.

1997; Wolfe, 2007), or ‘priority’ (e.g., Fecteau & Munoz, 2006) map of the search array, thus reducing the potential of any singleton stimulus– that is, a target or a distractor – at this location from summoning attention (see also Ferrante et al., 2018). By contrast, Sauter et al. (2018, 2019) proposed that, with different-dimension distractors, inhibition of the frequent distractor region occurs at an earlier stage, prior to the priority map. The priority map integrates feature-contrast signals coded in the various stimulus dimensions. Sauter et al. (2018, 2019) proposed that inhibition occurs already at the level of the distractor dimension, by reducing the contribution of feature-contrast signals from this dimension to the priority map. Specifically, in line with the Dimension-Weighting Account (DWA) of Müller and colleagues (e.g., Found & Müller, 1996; Müller, Heller, & Ziegler, 1995; Müller, Reimann, & Krummenacher, 2003; for recent reviews, see Liesefeld, Liesefeld, Pollmann, & Müller, 2019; Liesefeld & Müller, 2019a), feature-contrast signals generated in the distractor-defining dimension (color) may be selectively ‘down-weighted’[2] – leaving signals generated in the target-defining dimension (shape, orientation) unaffected. Thus, selective down-modulation of color (distractor) signals in the frequent distractor region would explain why interference is reduced for distractors appearing there, without influencing shape or orientation (target) signals.[3]

Factors (potentially) influencing the locus of distractor suppression. As mentioned above, there are a number of differences between the Wang-&-Theeuwes and the Sauter-et-al. paradigms that could have been responsible for the differential results – that is, the distractor-location effect being or not being accompanied by a target-location effect (with different-dimension distractors) – and the ensuing theoretical conflict, in particular:

(i) *specificity of the likely distractor location*: one specific location was most frequent to contain a distractor in Wang and Theeuwes, whereas a whole region (encompassing several locations in one half of the display) was most likely in Sauter et al.

(ii) *display density*: display density was relatively sparse in Wang and Theeuwes (8 items arranged around a ring), whereas it was dense in Sauter et al. (36 items arranged around three concentric rings);

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[2] ‘Down-weighting’ means scaling the ‘bottom-up saliency’ of the distractor by some inhibitory weight, yielding the effective ‘selection saliency’ (see Zehetleitner, Koch, Goschy, & Müller, 2013), where the acquired inhibitory weight is greater for the frequent vs. the rare distractor locations (see Sauter et al., 2018). Accordingly, the effect of inhibiting a distractor signal depends on how bottom-up salient a distractor is, and inhibition is a matter of degree rather than ever absolute (see, e.g., Müller et al., 2010).

[3] Suppression of the distractor at the likely location might conceivably also operate at the featural level, that is: the coding of distractor features might be inhibited directly, reducing their potential to generate feature contrast in the distractor dimension (e.g., Gaspelin & Luck, 2018a). In this case, too, one would not expect a target-location effect. We come back to the issue of dimension- vs. feature-based distractor suppression in the General Discussion.

(iii) *predictability of the distractor (vis-à-vis the non-distractor) color(s)*: the color singling out the distractor from the non-distractor items was swapped randomly with that of the non-distractor items (including the target) across trials in Wang and Theeuwes (e.g., the distractor was red amongst green non-distractor items on some trials and green amongst red on other trials), whereas the color assignment was constant in Sauter et al.;

(iv) *the target-defining dimension*: the target was defined by a relatively complex shape difference in Wang and Theeuwes (which could also change from trial to trial: the target was either a circle amongst diamond non-targets – including the distractor –, or a diamond amongst circle items), whereas it was defined by a relatively simple orientation difference in Sauter et al. (a left- or rightward tilted bar amongst invariant vertical distractor bars).

In a recent investigation examining for some of these factors, we (Zhang, Allenmark, Liesefeld, Shi, & Müller, 2019) adopted the Wang-&-Theeuwes paradigm, with a single frequent distractor location and conditions with and without random swapping of the distractor/non-distractor color assignment. The results revealed that, under the exact-same conditions as in Wang and Theeuwes (2018a), observers did show a target-location effect coupled with a distractor-location effect – indicating that they used a priority-map-based spatial 'strategy' of suppressing the likely distractor location (consistent with the conclusions drawn by Wang & Theeuwes, 2018a).[4] However, when the color swapping was abolished (by fixing the distractor and non-distractor colors)[5], they developed a dimension-based suppression strategy, characterized by the absence of a target-location effect in the presence of a nearly undiminished distractor-location effect (consistent with the conclusions of Sauter et al., 2018). We took this pattern to indicate that even with a distractor defined in a different dimension to the target, observers do not invariably come to use a dimension-based strategy (contrary to Sauter et al.'s, 2018, assumption); rather, a priority-map-based suppression strategy is equally available. Further, which strategy observers tend to adopt depends on the prominence, or conspicuity, of positional as compared to dimension- or feature-related cues about the distractor:

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[4] This was the case at least initially. However, after extended practice on the task, they changed to a dimension-based suppression strategy, characterized by a distractor-location effect unaccompanied by a target-location effect.

[5] In addition to abolishing color swapping, another difference between the present experiment and that of Wang and Theeuwes (2018a) was that the target appeared equally often at each position even on distractor-present trials. A recent study by Failing, Wang, and Theeuwes (2019) showed that, while the target position distribution does not influence the distractor position effect, an unequal target distribution can result in a target position effect: slower RTs when the target appears at a rare location. The target position distribution could therefore have been another factor potentially explaining why Wang and Theeuwes (2018a) found a target position effect. We showed, in a separate experiment (Zhang et al., 2019), that when this distribution was made equal without abolishing color swapping, there was still a significant target position effect in the first session (of 1500 trials), but not in the second session.

with color swapping, the latter cues are less conspicuous, so that participants may come to rely on the more 'salient' positional regularity (of the distractor being highly likely to appear at the frequent location) and develop a purely space-based 'global saliency' suppression strategy. By contrast, without color swapping, the consistent color definition of the distractor relative to the non-distractor items might be more immediately noticed, making observers adopt a dimension-based inhibition strategy that becomes then spatially focused on the frequent distractor location once the spatial regularity is extracted.

However, while we have reasonable evidence for such dynamics when a single location is most frequent to contain a distractor (as in the Wang-&-Theeuwes paradigm), it remains unclear whether similar dynamics would govern cue extraction and inhibitory learning with region-related distractor location probability cues, as in the Sauter-et -al. (2018) paradigm. Also, recall that Sauter et al. used dense displays, whereas Wang and Theeuwes employed comparatively sparse displays. Display density has been shown to exert a profound influence on singleton 'pop-out' (Rangelov, Müller, & Zehetleitner, 2017), so that this factor may well play a role, too (in addition to color swapping and the number of probable distractor locations). In particular, positional cues may be harder to extract in dense as compared to sparse displays, because the latter would appear to the observer to (potentially) contain a greater number of locations where a distractor may appear (even if the precise number of locations is equated between dense and sparse displays; see Method section for how this was achieved in the present study).[6]

Goal of the present study. Thus, the present study set out to explore the locus of (spatial) distractor suppression – priority-map- versus dimension-based – in a paradigm in which a whole region was (statistically) cued to be likely to contain a distractor (as in Sauter et al., 2018, 2019), orthogonally varying two factors potentially important for determining the level of (learned) suppression: swapping versus consistency of the distractor/non-distractor color assignment, and low versus high display density (while controlling for the number of locations at which a distractor was likely to appear). And we examined this implementing the 'traditional'

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[6] Note the target definition was also more complex, and less certain, in the Wang-&-Theeuwes paradigm, with random swapping, across trials, of the target and non-target shapes (the latter including the distractor); this compares with an unpredictable (left vs. right) target tilt, but with reference to constant vertical non-targets. However, we did not have any intuition as to why this factor might be important. That said, given that target swapping is known to increase distractor interference (e.g., Pinto, Olivers, & Theeuwes, 2005; Lamy & Yashar, 2008; Burra & Kerzel, 2013), a reviewer surmised that the high interference might be responsible for the target-location effect. At variance with this, however, Wang and Theeuwes (2018b) observed target-location effects even with minimal distractor costs.

design introduced by Theeuwes (1992) and used by Wang and Theeuwes (2018a). Thus, in a sense, our study combined Sauter-at-al.-type distractor location probability cueing with the Wang-&-Theeuwes paradigm, in order to examine the relationship between the distractor-location effect (if it does emerge under these conditions) and the target-location effect, in order to draw conclusions with regard to the factors that determine whether observers adopt a priority-map- or a dimension-based suppression strategy.

Note that, although the main focus of the present study was on distractor location probability cueing and its effect on target processing in the frequent distractor region, examining the effects of color swapping and display density on distractor handling is interesting per se. Previous studies have reported that distractor suppression works only if the distractor color is predictable (see Gaspelin & Luck, 2018b; Graves & Egeth, 2015; Kerzel & Barras, 2016). In line with this, Zhang et al. (2019) observed that distractor interference was somewhat reduced when colors stayed constant in their Experiment 3, compared to color swapping in their Experiments 1 and 2, though this effect was weak and not well supported by Bayesian tests. Of note, studies of the effect of color swapping on distractor interference all used relatively sparse displays, with the largest set size being 9 items (Kerzel & Barras, 2016). Here, we intended to examine whether the effect of color swapping would generalize to dense displays, with target and distractor singletons being completely surrounded by non-singleton items (maximizing local feature contrast). It is well known that display density impacts the ease to find a target, because denser displays produce stronger local contrast, resulting in higher target saliency (Liesefeld, Moran, Usher, Müller, & Zehetleitner, 2016; Nothdurft, 2000; Rangelov et al., 2017). If so, display density should not only impact target saliency – thus expediting responses to the target generally –, but also distractor saliency – thus keeping the difference in saliency between distractor and target relatively constant.

Study design. To this end, the present study implemented a 2 × 2 design, orthogonally varying color swapping and display density in four independent groups (detailed description in Table 1). That is, two groups performed the task with sparse displays, one with random color swapping of the distractor and non-distractors colors across trials and one without color swapping; analogously, one color-swapping and no-swapping group performed the task with dense displays (see Figure 1, right panel). Dense displays consisted of 24 items arranged around three (virtual) concentric rings: 4 items on the inner ring, 8 on the middle ring, and 12 on the outer ring. Sparse displays (see Figure 1, left panel), replicating the Wang-&-Theeuwes (2018a) arrangement, consisted essentially only of the (8 items of the) middle ring. The shape-defined target and the color-defined distractor appeared ever only on the middle ring (irrespective of display density). In all four groups, the target (present on each trial) was equally likely to appear in each display half (i.e., the upper four or the lower four locations on the middle ring), whereas the distractor was more likely to appear in either the upper half (one of the four upper locations on the middle ring; 90% of distractor-present trials) or in the lower half (one of the four lower locations; 90% of distractor-present trials), counterbalanced across participants in a specific group. The respective four likely locations will be referred to as the frequent distractor region (as opposed to the four locations in the respectively rare region, at which the distractor appeared in 10% of the trials). The target never appeared at the distractor location, but distractor location was not predictive of the display half in which the target appeared.

Table 1. Manipulation of color swapping and display density across four experimental groups.

	Groups			
Manipulation	1	2	3	4
color swapping	swapping	no swapping	swapping	no swapping
display density	sparse	sparse	dense	dense

METHOD

Participants. A total of 120 participants (mean age: 24.87 years; age range: 18-40 years; 85 female) were recruited at Ludwig-Maximilians-University (LMU) Munich, with 30 participants in each of the four groups. The sample size was determined based on previous studies of ‘distractor location probability cueing’ in visual search (Goschy et al., 2014; Zhang et al., 2019), which had established significant cueing effects. All participants were right-handed and all reported normal or corrected-to-normal vision, including normal color vision. They received 9 Euro per hour in compensation for their service. The study protocol was approved by the LMU Faculty of Pedagogics & Psychology Ethics Board. Informed consent was obtained from all participants prior to the experiment.

Apparatus. The experiment was conducted in a sound-reduced and moderately lit test room. Stimuli were presented on a CRT monitor at 1280×1024 pixels screen resolution and a refresh rate of 120 Hz. Stimuli were generated by Psychophysics Toolbox Version 3 (PTB-3) (Brainard, 1997) based on MATLAB R2016a (The MathWorks® Inc). Participants viewed the monitor from a distance of 60 cm (eye to screen) and gave their responses by pressing the leftward- (‘horizontal) or upward-pointing (‘vertical’) arrow on the keyboard with their right-hand index or middle fingers, respectively.

Stimuli. The (sparse) search displays used in Groups 1 and 2 (see the left panel of Figure 1 for an example display) were composed of eight colored outline shapes (circles or diamonds) equidistantly arranged around a virtual circle with a radius of 4° of visual angle. The display items consisted of either one circle (target) and seven diamonds (non-targets), or, alternatively, one diamond (target) and seven circles (non-targets). In a certain percentage of trials (see below), one of the non-target shapes (the distractor) differed in color from all the other shapes, being either green (CIE [Yxy]: 22.5, 0.32, 0.55) amongst homogeneous red shapes (CIE [Yxy]: 8.82, 0.54, 0.36), 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°of visual angle) in the center.

The (dense) search displays used in Groups 3 and 4 (see right-handed panel of Figure 1 for an example display) contained three times as many items: 24 instead of 8. These were arranged around three concentric circles: four items on an inner circle (radius of 1.8°), eight on a middle circle (radius of 4°), and twelve on an outer circle (radius of 6.5°). The diameter of the circle shapes and, respectively, the side length of the diamond shapes was 1.5° of visual angle.[7] Each outline shape contained a vertical or horizontal gray line inside (0.2° × 1.1°), with half of the internal lines being (randomly) vertical and half horizontal. Note that the target and singleton distractor appeared only on the middle circle of eight positions in these dense search displays.

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[7] Note that, in both display-density conditions, the stimulus sizes had be to reduced by 75% relative to those used by Wang & Theeuwes (2018a) and Zhang et al. (2019) in order to realize the dense displays without overlapping of the shapes on and across the three rings. To pilot these changes and to ascertain that the target is more salient and, thus, detected and responded to more efficiently in dense than in sparse displays, we conducted a within-participant ‘baseline’ experiment (with N=10 observers) in which the search displays never contained a distractor, but only an odd-one-out shape target (with the shape assignment to target and non-target items varying randomly across trials), under blocked and counterbalanced color-swapping and no-swapping conditions. As expected, the results depicted a significant main effect of display density (755 ms [dense] vs. 930 ms [sparse]; ($F(1,9) = 15.9$, $p = .003$, $\eta^2_p = .64$, BF > 1000), whereas the effect of color swapping was non-significant ($F(1,9) = 0.38$, $p=.55$, BF=0.33).

Design. The target, which was present on all trials, was a singleton, odd-one-out shape amongst the 7 (or 23) non-target shapes (either a circle or a diamond, randomly assigned on each trial). On trials without a distractor, the target was equally likely to appear at all 8 possible locations. On trials on which a distractor was present in the display, the target appeared equally frequently at all of the remaining 7 non-distractor locations. A singleton distractor, defined by a unique color (red or green, randomly assigned on each trial for Group 1 and 3 but consistent for Group 2 and 4), appeared in 66% of the trials. If a distractor was present, it appeared with 90% probability in one half (either the top or the bottom half) of the search display: the frequent region, and with 10% probability in the other half: the rare region. Which region was frequent and which rare was counterbalanced across participants within each group. Within each region, the distractor appeared at each of the four locations with equal probability (p = 90%/4 in the frequent region and p = 10%/4 in the rare region). The target also appeared at each location with equal probability, in both regions (p = 50%/4 and p = 50%/4, respectively). Note that the target and the distractor never appeared at the same location. Technically, this was achieved by first creating a random sequence of target positions in which the target appeared equally often at each position, and also a sequence of distractor positions with the statistical properties described above. This was done combinatorially, such that the target appeared equally often at each position (including the distractor position) for each of the distractor positions, and on distractor-absent trials. Then, for those (distractor-present) trials on which the target and distractor positions were the same, the target position was changed to a different, randomly selected position within the same (frequent or rare distractor) region. Since, within each region, the distractor appeared equally often at each of the positions in that region, this repositioning did not (on average) change the distribution of target positions[8]. Participants in each experimental group performed (at least) 960 trials[9], subdivided into 16 blocks of 60 trials each.

Procedure. Each trial began with the presentation of a fixation cross for 500 ms, followed by the search array, which was shown until the participant gave a response. The intertrial interval (ITI) ranged randomly between 500 and 750 ms. Participants were instructed to search

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[8] See the Appendix for a table with the actual distribution of target positions produced by this algorithm. Importantly, even when considering only the first 960 trials per group, as we did in most of our analyses, the target appeared very nearly equally often in the top and the bottom region, regardless of which region was the frequent distractor region (50.2% of targets in the bottom region when the bottom region was the frequent distractor region and 50.3% when the top region was the frequent distractor region).

[9] In the two ‘color swap’ groups, participants actually performed more than 960 trials, namely, 1440 trials in total. However, to ensure comparability across the four experimental conditions, we analyzed only the first 960 trials per group in all analyses in which all four groups were compared. The analysis of color-swapping effects involved only the color-swap conditions, and so for this we used the full set of 1440 trials.

for the target (the differently shaped item) and identify and respond to the orientation of the line inside – vertical or horizontal – as fast and as accurately as possible. For a vertical line, participants pressed the ‘up’ arrow on the keyboard; and for a horizontal line the ‘left’ arrow. At the end of the experiment, participants completed a post-experiment questionnaire, designed to determine whether they were aware of the frequent distractor region. This involved a three-stage procedure: first, participants had to indicate whether the distractor distribution was centered on one of four specific regions: top, bottom, left and right, or equal across the four different regions; second, (even when they had given an ‘equal’ response in stage 1), participants had to give a forced-choice response: indicating in which of the four regions the distractor had occurred most frequently (by marking the corresponding region on the ‘display’ depicted on the answer sheet); Finally, participants were to report how confident they were in the above answers using a seven-point rating scale, with a rating of 1 representing “Not at all confident” and 7 “Extremely confident”. Prior to the main experiment, participants performed 60 unrecorded practice trials to familiarize themselves with the task. Between trial blocks, participants could take a break of a self-determined length.

Bayes-Factor analysis. Bayesian analyses of variance (ANOVAs) and associated post-hoc tests were performed using JASP 0.9.2 (*http://www.jasp-stats.org*) with default settings. All Bayes factors reported for ANOVA main effects and interactions are ‘inclusion’ Bayes factors calculated across matched models. Inclusion Bayes factors compare models with a particular predictor to models that exclude that predictor. That is, they indicate the amount of change from prior inclusion odds (i.e., the ratio between the total prior probability for models including a predictor and the prior probability for models that do not include it) to posterior inclusion odds. Using inclusion Bayes factors calculated across matched models means that models that contain higher-order interactions involving the predictor of interest were excluded from the set of models on which the total prior and posterior odds were based. Inclusion Bayes factors provide a measure of the extent to which the data support inclusion of a factor in the model. Bayesian *t*-tests were performed using the ttestBF function of the R package ‘BayesFactor’ with the default setting (i.e., rscale =“medium”).

RESULTS

For all RT analyses reported below, trials with outlier RTs (defined as RTs being slower than 3,000 or faster than 150 ms, some 2% of trials) as well as trials on which participants made an incorrect response (some 3% of trials) were excluded. For the analyses of inter-trial effects, the very first trial in each block was additionally excluded, because of the break between that trial and the last trial in the preceding block.

Mean baseline RTs

We first examined whether the average RTs on distractor-absent trials differed between the different experimental groups (see Figure 2). Although RTs were numerically faster with dense as compared to sparse displays (961 ms vs. 1023 ms), an ANOVA with color swapping (swapping vs. no swapping) and display density (dense vs. sparse) as between-participant factors failed to reveal the main effect of display density to be significant: $F(1, 116) = 2.35$, $p = .13$, $\eta_p^2 = .020$, $BF = 0.5$. The main effect of color swapping ($F(1, 116) = 1.61$, $p = .21$, $BF = 0.40$) and the interaction ($F(1,116) = 0.841$, $p = .36$, $BF = 0.37$) were also non-significant.

Since a main effect of display density was predicted (see also the within-participant pilot reported briefly in footnote 6 above), based on the assumption that targets are more salient in dense displays, we further examined an alternative marker of saliency differences. In particular, Rangelov et al. (2017) had observed participants' RT variability to be increased with sparse displays, which (modeling work showed) was attributable to less consistent singleton target 'pop-out' across trials as compared to dense displays. Indeed, a very similar pattern obtained in a display density × color swapping ANOVA of intra-individual RT variability (i.e., standard deviations) on distractor-absent trials: RT variability was greater with sparse than with dense displays (391 ms vs. 352 ms, $F(1,116) = 4.11$, $p = .04$, $\eta_p^2 = .034$, $BF = 1.23$). The main effect of color swapping ($F(1, 116) = 1.91$, $p = .17$, $BF = 0.45$) and the interaction ($F(1,116) = 0.12$, $p = .73$, $BF = 0.27$) were non-significant.

Together with the faster RTs when the target shape was 'encircled', rather than just 'flanked', by homogeneous non-target shapes[10], we take this to mean that the target was more salient, and thus popped out more reliably, in dense displays.

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[10] Figure 2 suggests that the main effect of display density may have been obscured, to some extent, by a speed-accuracy trade-off, i.e.: nearly error-free responding (only) by the 'dense displays, with color swapping' group. Examining for the main effect in an ANOVA on a measure combining speed and accuracy (Balanced Integration Score; Liesefeld, Fu, & Zimmer, 2015; Liesefeld & Janczyk, 2019) yielded: $F(1,116) = 7.48$, $p = .007$, $\eta^2_p = .061$, $BF = 5.5$.

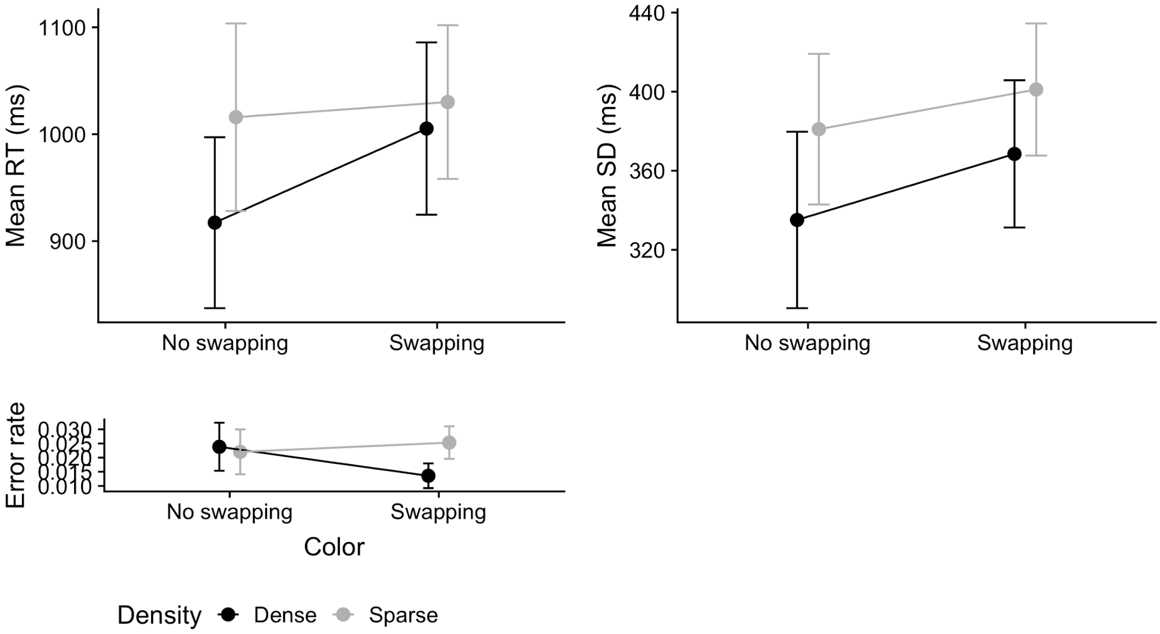

Figure 2. *Overall baseline (distractor-absent) response times (top left panel) and error rates (bottom left panel) and the within participant standard deviation of the baseline response times (top right panel) for all four – color-swapping (swapping, no swapping) × display-density (dense vs. sparse) – conditions (experimental groups). Error bars depict 95% confidence intervals.*

Distractor-position effects

Next we examined how distractor interference – defined as the difference between mean RTs on distractor-present trials, averaged over the frequent and rare distractor regions with equal weight given to each region (i.e., by first computing average RTs for each region separately and then taking the mean), and mean RTs on distractor-absent trials – differed across the four experimental groups (see Figure 3).

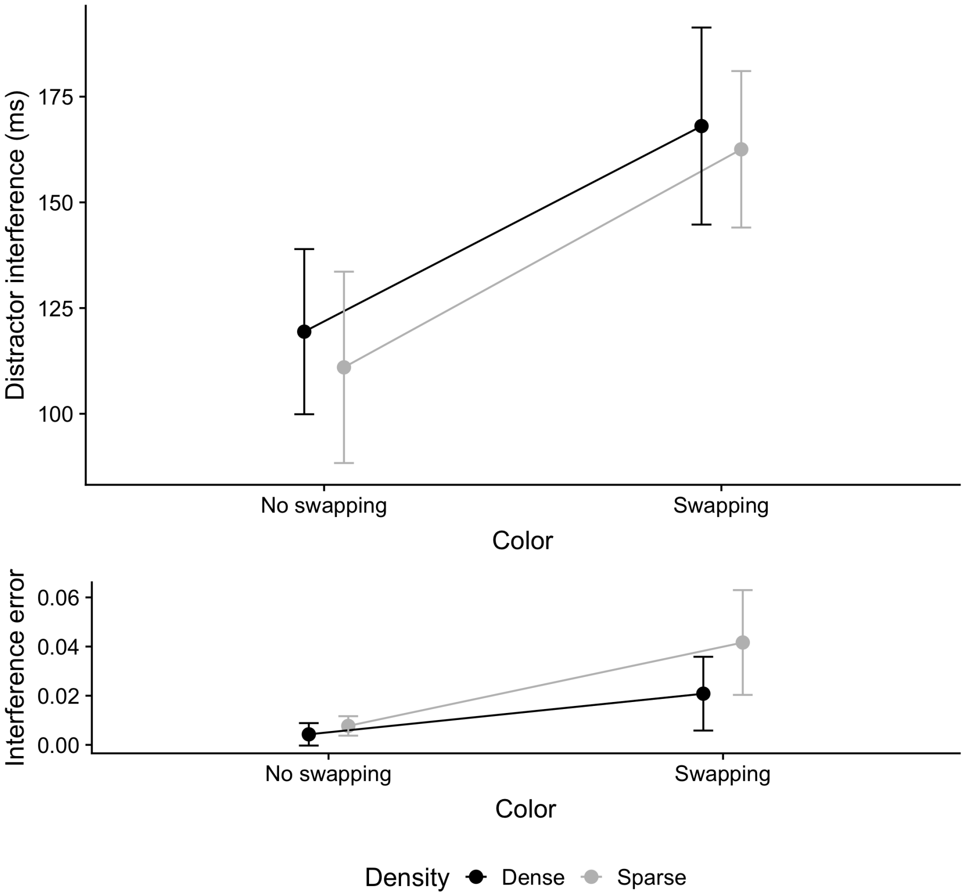

Figure 3. *Average distractor interference effect, calculated as the difference between mean RTs on distractor-present trials, averaged across the frequent and rare regions, and mean RTs on distractor-absent trials, for the two color swapping and display density conditions (experiments). Error bars depict 95% confidence intervals.*

An ANOVA of the amounts of (overall) distractor interference with color swapping (swapping vs. no swapping) and display density (dense vs. sparse) as between-participant factors revealed interference to be significantly lower for groups without color swapping versus groups with color swapping (mean: 115 vs. 165 ms; $F(1, 116) = 22.43$, $p < 0.001$, $\eta_p^2 = 0.162$, $BF > 1000$); neither the main effect of display density ($F(1, 116) = 0.43$, $p = .51$, $BF = 0.\ 23$) nor the color swapping × display density interaction ($F(1, 116) = 0.02$, $p = .89$, $BF = 0.27$) were significant. Of note, distractor interference was significantly greater than zero without color swapping ($t(59) = 15.5$, $p < 0.001$, $BF > 1000$) as well as with color swapping ($t(59) = 22.3$, $p < 0.001$, $BF > 1000$).

Next, we examined how the probability cueing (i.e., distractor-position) effect – defined as the difference in mean RTs between trials with a distractor in the rare region and trials with a distractor in the frequent region – differed across the experimental groups (see Figure 4).

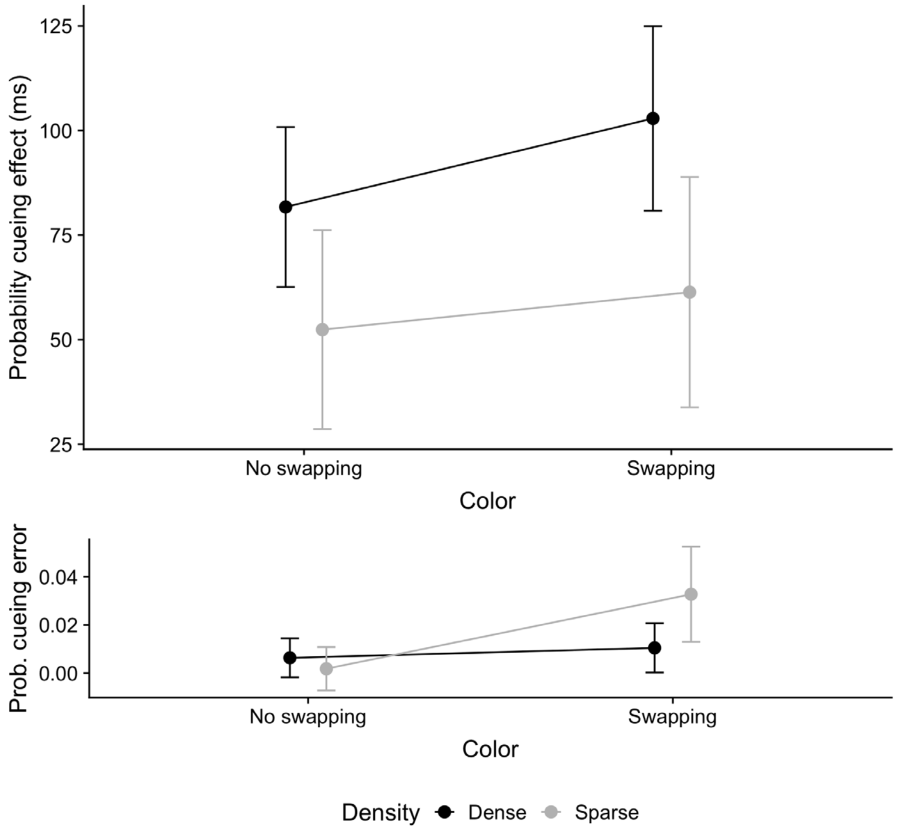

Figure 4. *Average probability-cueing effect, calculated as the difference in mean RTs between trials with a distractor in the rare region and trials with a distractor in the frequent region, for the two color swapping and display density conditions (experiments). Error bars depict 95% confidence intervals.*

An ANOVA of the size of the probability cueing effect with color swapping (swapping vs. no swapping) and display density (dense vs. sparse) as between-participant factors revealed the effect of display density to be significant: probability cueing was larger for dense than for sparse displays (92 ms vs. 57 ms), $F(1, 116) = 9.2, p = .003, \eta_p^2 = .073, BF = 11.3$. Numerically, probability cueing was also stronger with color swapping than without color swapping, but this effect was not statistically significant (82 vs. 67 ms), $F(1, 116) = 1.7, p = .20, BF = 0.41$. The interaction was not significant, $F(1,116) = 0.27, p = .60, BF = 0.30$. Of note, the probability cueing effect was significantly greater than zero for all groups (dense displays, with color swapping: $t(29) = 9.3$, $p < 0.001$, $BF > 1000$; sparse displays, with color swapping: $t(29) = 4.4$, $p < 0.001$, $BF > 1000$; dense displays, no color swapping: $t(23) = 8.5$, $p < 0.001$, $BF > 1000$; sparse displays, no color swapping: $t(29) = 4.4$, $p < 0.001$, $BF = 196$).

Target-position effects

In order to examine for any effects of the acquired distractor location probability cueing effect on the processing of the target, unaffected by interference resulting from a distractor being present in the search display, we assessed the target-position effects, defined as the difference in mean RT between trials with a target falling in the frequent region and trials with a target in the rare region, on distractor-absent trials. In order to rule out that any effect was due to (cross-trial) carry-over of inhibition of the location of the distractor on the preceding trial (Sauter et al., 2018; Zhang et al., 2019), we removed trials from the analysis on which the target appeared at the exact-same location as a distractor on the previous trials.

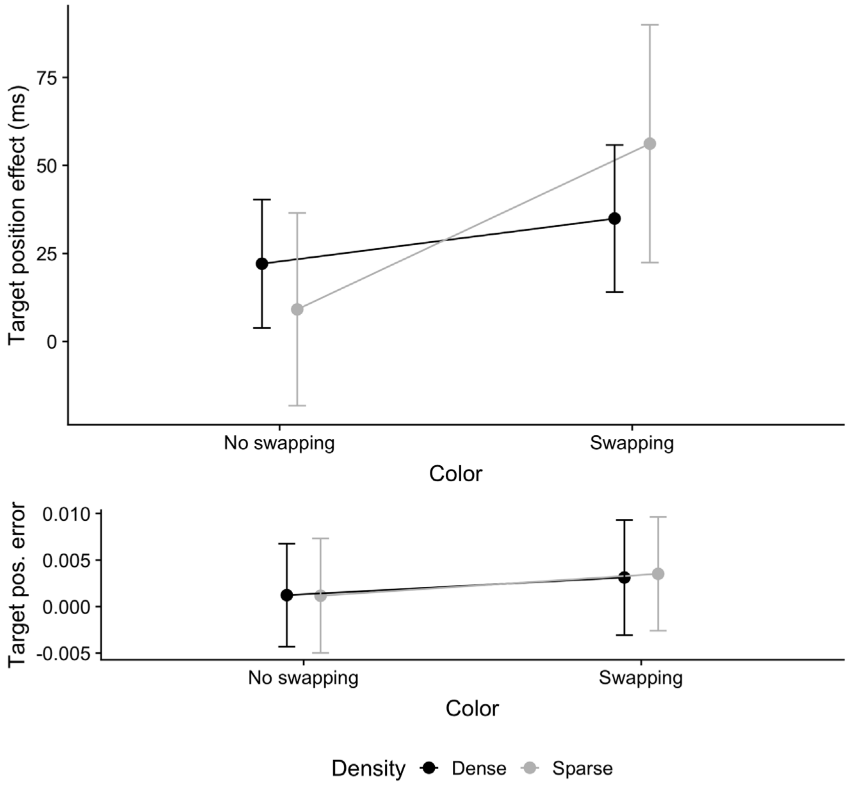

Figure 5. *Average target-position effect on distractor-absent trials, calculated as the difference in mean RTs between trials on which the target appeared in the frequent distractor region and trials on which the target appeared in the rare region. Error bars depict 95% confidence intervals.*

An ANOVA of the size of the target-position effect with color swapping (swapping vs. no swapping) and display density (dense vs. sparse) as between-participant factors revealed the effect of color swapping to be significant, F(1,116) = 5.4, p = .022, η_p^2 =.044, BF = 2.14: the target-position effect was larger with as compared to without color swapping (46 ms vs. 16 ms). Neither the main effect of display density, F(1, 116) = 0.10, p = .75, BF = 0.20, nor the interaction, F(1,116) = 1.75, p = .19, BF = 0.55, were significant. Of note, the target-position effect was significantly greater than zero with color swapping, *t*(59) = 4.6, *p* < .001, *BF* = 771, but at best marginal without color swapping, *t*(59) = 1.9, *p* = .06, *BF* = 0.76.

Color-swap effects

Conceivably, participants may try to suppress distractors based on their color, even in experimental conditions in which the color assignment was swapped randomly from trial to trial. To look for evidence of such feature-specific effects, following Wang and Theeuwes (2018a) and Zhang et al. (2019), we examined whether there would be any effects of color repetition versus swapping across consecutive trials for the two groups with random color swapping.[11] We first checked whether distractor interference or, respectively, the probability-cueing effect differed between trials (*n*) on which the color assignment was repeated vs. swapped from the preceding trials (*n*-1). An ANOVA with color repetition (repeat vs. switch) as within-participant factor and display density (sparse vs. dense) as between-participant factor revealed distractor interference to be significantly reduced, by some 30 ms, when the same color assignment was repeated rather than swapped (134 ms vs. 161 ms), *F*(1, 58) = 10.7, *p* =.002, η_p^2 =.16, *BF* = 19.9; this effect did not interact with display density, *F*(1, 58) = 0.024, *p* = .88, *BF* = 0.26. The probability-cueing (i.e., distractor-position) effect, by contrast, was not significantly diminished on color-repetition versus -swap trials (77 vs. 89 ms), *F*(1, 58) = 1.15, *p* = .29, *BF* = 0.34, whether the displays were dense or sparse (interaction: F(1, 58) = 0.006, p = .94, BF = 0.26).

In order to investigate the origin of the reduced interference on color-repetition trials, we performed a more detailed analysis of the color-repetition (vs. -swap) benefits, namely, as

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[11] Note that in this analysis (which involves examining for the effects of relatively rare cross-trial transition effects), we included the full available set of 1440 trials (rather than just the first 960 trials) per participant, so as to increase the reliability of the estimates for each condition compared. An equivalent analysis based on the partial data set (of 960 trials) revealed essentially the same pattern, except that the 'distractor condition on trial *n*' effect was not significant.

a function of distractor presence versus absence on both the current trial *n* and the preceding trial *n*-1 (as in Zhang et al., 2019). See Figure 6 for a depiction of the results.

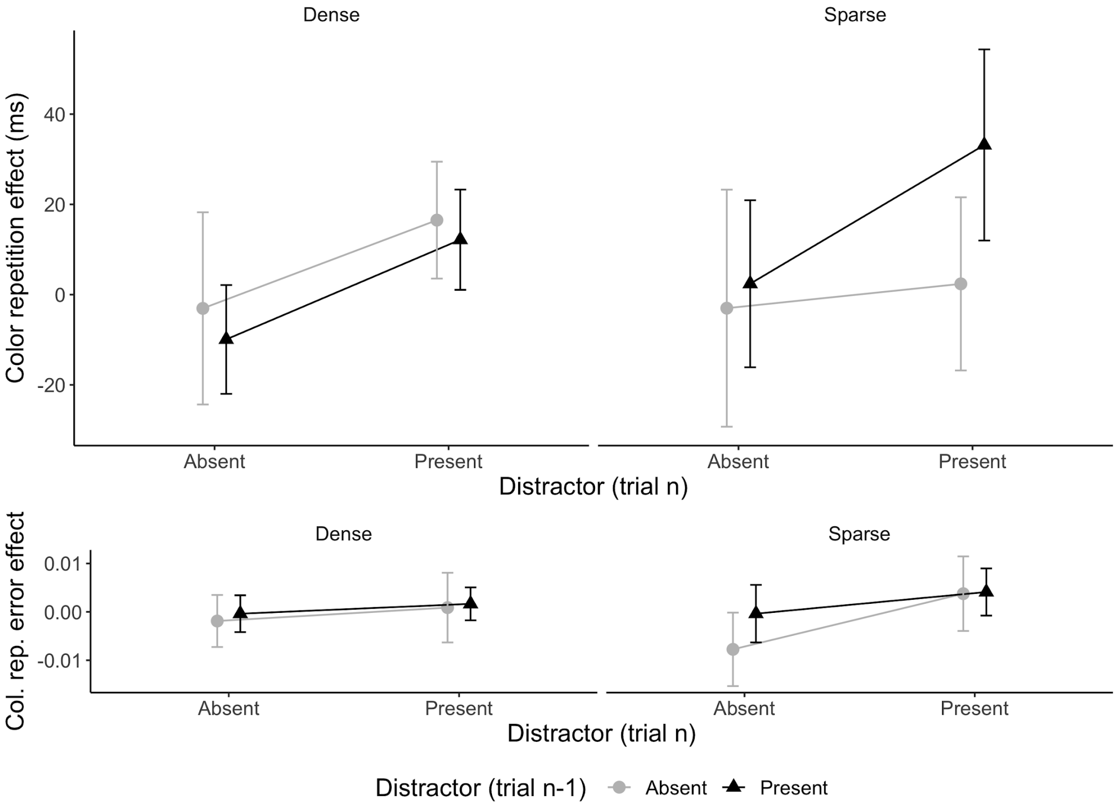

Figure 6. *Color-repetition effect (mean difference in RT between trials with a cross-trial change vs. repetition of the color assignment) as a function of the distractor condition (distractor absent vs. present) on trial n, dependent on the distractor condition on trial n-1, separately for dense and for sparse displays. Positive values mean RTs were faster when the same color was repeated (color-repetition benefits). Error bars depict 95% confidence intervals.*

An ANOVA on the color-repetition benefits with distractor condition on trial *n* (distractor present vs. absent) and distractor condition on trial *n*-1 as within-participant factors and display density as between-participant factor yielded a significant main effect of distractor condition on trial *n* (F(1,58) = 6.9, p = .011, η_p^2 =.11, BF = 14.3), reflecting larger color repetition benefits on distractor-present vs. distractor-absent trials (16 ms vs -3 ms), and a significant interaction between distractor condition on trial *n*-1 and display density (*F*(1, 58) = 4.5, *p* = .039, η_p^2 =.071, *BF* = 1.03). As suggested by post-hoc, Bonferroni-corrected t-tests, this interaction was, if anything, due to the color-repetition benefit on distractor present trials being larger on the trials following a distractor-present trial compared to on the trials following a distractor absent trial for sparse displays (33 ms vs. 2 ms; *t*(29) = 2.7, $p_{bonf} = 0.044$, *BF* = 4.1) but not for dense displays (12 ms vs. 17 ms; *t*(29) = -0.69, $p_{bonf} = 1$, *BF* = 0.24). There were significant differences in the color-repetition benefit based on distractor condition on trial n-1 on distractor absent trials (sparse displays: 2 ms vs. -3 ms; *t*(29) = 0.35, $p_{bonf} = 1$, *BF* = 0.21; dense displays: -10 vs. -3 ms; *t*(29) = -0.6, $p_{bonf} = 1$, *BF* = 0.23).

Awareness effects

To examine to what extent observers were aware of the spatial distractor distribution, we determined how many of them had correctly indicated the bias in the distribution in the post-experimental (four-alternative forced-choice) recognition test (see Method above). Overall, the distribution question was answered correctly by more participants than expected by chance (some 46% overall, as compared to a chance level of 25%), indicative of a level of awareness of the frequent distractor region (similar to Wang & Theewues, 2018a). There were no significant differences in awareness among the four groups ($\chi 2 = 0.761, p = .859$, 43%, 46%, 43%, and 53%, respectively).[12]

DISCUSSION

The present study was designed to re-examine at which hierarchical level, in the functional architecture of search guidance, suppression of display locations where a salient (different-dimension) distractor is encountered frequently is implemented and how this level depends on the particular experimental design employed. In contrast to many previous studies using similar stimuli, the distractor in the present study occurred with high probability in a particular region (region cueing; Goschy et al., 2014; Sauter et al., 2018, 2019), rather than at

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[12] However, the probability cueing effect, and its dependence on color swapping and display density, was somewhat different between participants who responded correctly to the forced-choice question ("aware" participants) and those who did not ("unaware" participants): awareness interacted significantly with color swapping (2-way interaction: F(1,105) = 6.36, p = 0.013, $\eta^2_p = .064$, BF = 2.8 and with both display density and color swapping (3-way interaction: F(1,105) = 4.70, p = 0.032, $\eta^2_p = .043$, BF = 1.9). With dense displays, the cueing effect was larger for aware than for unaware participants, irrespective of color swapping (color swapping: 109 ms vs. 99 ms; no color swapping: 92 ms vs. 70 ms). With sparse displays, by contrast, while cueing was pronounced for aware vs. unaware participants in the absence of color swapping (74 ms vs. 31 ms), it was less marked with color swapping (17 ms vs. 91 ms). There were no significant effects of awareness on overall distractor interference or on the target position effect. Thus, awareness appeared enhance the probability cueing effect generally with dense displays, i.e., under conditions of high (distractor) color feature contrast. With sparse displays, awareness appeared to enhance cueing under conditions of color consistency, but to impede it under conditions of color inconsistency. Apart from the need to replicate this (in the literature atypical) pattern, for interpreting it, it would likely be important to know whether 'aware' participants were also aware of the distractor manipulation, which was not tested.

a specific position (location cueing; Ferrante et al., 2018; Wang & Theeuwes, 2018a, b; Zhang et al, 2019). Replicating the pattern of (critical) results observed in a location-cueing paradigm (Zhang et al., 2019), here we observed a target-position effect (coupled with a distractor-position effect) only when the color assignment to the distractor and non-distractor items (the latter including the target) was changing unpredictably across trials (color swapping), but not when it was constant. By contrast, a distractor-position effect, indicative of distractor location probability learning, emerged both with color swapping and without it. This pattern was relatively uninfluenced by display density (though there were also interesting density effects discussed below). Thus, irrespective of whether the distractor is likely to occur in a larger region or at a particular location, observers may develop different strategies to suppress the likely distractor location(s) dependent on color swapping: with color swapping, suppression at the level of the (supra-dimensional) priority map, which produces a distractor-position effect (reduced interference from distractors in the frequent vs. the rare region) coupled with a target-position effect (impeded RTs to targets in the frequent vs. the rare region); without color swapping, dimension-based suppression, which produces only a beneficial distractor-position effect without the harmful target-position effect. This supports and reinforces the conclusion (Zhang et al., 2019) that color swapping is a, if not *the*, most critical factor making observers adopt one or the other strategy, irrespective of whether a single distractor location or a whole region (encompassing multiple locations) is likely to contain a distractor.

However, the total result pattern is more complex than this, so that, in what follows, we will discuss this main conclusion in the context of the other findings.

Baseline Performance: Mean baseline (distractor-absent) RTs to the target, uninfluenced by the presence of any distractor in the search array, were overall faster (and intra-individually less variable) with dense compared to sparse displays (961 ms vs. 1023 ms), while being little influenced by color swapping (a pattern confirmed in a within-participant control experiment – see footnote 6 above). It is well established that the exact same target is, on average, found faster in dense than in sparse displays, likely because the target is rendered more salient by the higher local feature (here: shape) contrast in dense displays, yielding more reliable ‘pop-out’ (see Bravo & Nakayama, 1992; Liesefeld et al., 2016; Nothdurft, 2000; Rangelov et al., 2017). We take this (together with the lack of a color-swap effect) to mean that observers performed the search task overall in a ‘singleton-detection’ search mode (cf. Bacon & Egeth, 1994).

Overall distractor interference: Overall distractor interference – the difference in mean RTs between distractor-present and distractor-absent trials – was significantly larger with color swapping than without color swapping (165 vs. 115 ms), while being uninfluenced by display density (144 ms [dense] vs. 137 ms [sparse]; the Bayes Factor, $BF = 0.23$, favors the null-hypothesis).

Considering the latter (null-) effect first: The lack of a density effect on distractor interference is of theoretical relevance in the context of the baseline effect considered above. Decreasing target saliency, through an increase in the similarity of the target and the non-targets, is known to result in increased distractor interference (Barras & Kerzel, 2017). One might therefore have expected that increasing target salience, by an increase in display density, would result in decreased distractor interference. The lack of a density effect on distractor interference suggests that the increased density of the display items (in dense arrays) did increase both the distractor and the target saliency commensurably, that is, without changing the relative saliency (i.e., the competition) of the distractor vis-à-vis the target singleton, effectively resulting in comparable amounts of distractor interference. (Making the non-targets more similar to the target, by contrast, would likely affect only the saliency of the target when the distractor singleton is defined in a different dimension.) In fact, a somewhat similar result had previously been reported by Theeuwes (2004).[13]

Turning to the color-swapping effect: Given that color swapping influenced only the overall distractor interference, but not the baseline RTs (see above), this would mean that specifically distractor interference (rather than target search as such) cannot generally be handled as effectively under conditions with color swapping as under conditions without swapping. As indicated by the differential target-position effects, without color swapping, observers are more likely to develop a dimension-based suppression strategy (while conceivably also being able to use feature-based suppression); in contrast, with color swapping, they are more likely to develop a priority-map-based strategy. Distractor interference may be greater with color swapping because the priority-map-based suppression, an inherently

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[13] Note, though, that Theeuwes (2004) had participants search for a diamond target in displays that contained other unique shape items (one square and one triangle, besides at least two non-singleton, circle, non-targets) to encourage the adoption of a ‘feature-search’, rather than a singleton-detection, mode (cf. Bacon & Egeth, 1994). Despite this, presentation of an additional color singleton (distractor) caused significant interference when the display size was rendered large (12 or 20 items) by adding more shape homogeneous non-singleton (circle) items to the search array, with little difference in the magnitude of interference between 12- and 20-item displays. Similar to our results, this could be explained by assuming that the additional filler items increased the saliency of the target and the distractor commensurably.

spatially selective suppression strategy, may be non-optimal for larger 'cued' regions (consisting of multiple locations). This contrasts with dimension-based suppression, which is inherently a spatially parallel suppression strategy (i.e., in the absence of spatial focusing, dimension-based suppression is assumed to operate in parallel across the whole display – see, e.g., Liesefeld, Liesefeld, & Müller, 2019; Liesefeld, & Müller, 2019a). Accordingly, the latter strategy would be better applicable with region cueing, where a stable color assignment to the distractor and non-distractor items is particularly conducive for the development of such a strategy.

As an aside, if strategy choice indeed depends on the absence versus presence of color swapping, this would call into question Gaspelin and Luck's (2018a) interpretation of their finding of an effect of (the presence vs. absence of) color swapping on inhibition strength, which they took as evidence for feature-specific (in their terms, 'first-order') and against dimension-based ('second-order') suppression (see also Liesefeld & Müller, 2019a, 2019b). Rather than probing which strategy is used (first- vs. second-order suppression), Gaspelin and Luck's introduction of color swapping might have discouraged the dimension-based suppression that is most readily available with constant distractor colors.

Since our color-swapping conditions involved swapping between the color of the singleton distractor and that of the other items, including the target, we cannot tell whether it is the uncertainty regarding the distractor color, the uncertainty regarding the target color, or the actual swapping between the distractor and the target color that is important. However, a recent study that compared a condition in which only the singleton distractor color swapped unpredictably between trials against a fixed-color condition failed to find any effect of color swapping (vs. no swapping) on the amount of distractor interference (Won, Kosoyan & Geng, 2019); and, in fact, all studies (that we are aware of) which did find an effect of color swapping on distractor interference used swapping between the singleton distractor color and the color of all the other items, including the target, like in the present study (Gaspelin & Luck, 2018a; Graves & Egeth, 2016; Kerzel & Barras, 2016). This suggests that it is not distractor color swapping per se, but rather the (combined) swapping between the distractor and the target color that drives the effect of color swapping on distractor interference.

Probability-cueing effect: Probability cueing – the reduced RT interference caused by distractors in the frequent as compared to the rare region – was significantly stronger for dense than for sparse displays (92 ms vs. 57 ms). Given that the overall amount of distractor interference (averaged across both distractor regions) was comparable between dense and sparse displays (see above), the finding of a significantly *stronger probability cueing effect for dense versus sparse displays* would suggest a trade-off relationship: increased inhibition applied to one, the frequent distractor region (in dense vs. sparse displays) goes along with reduced inhibition (in dense vs. sparse displays) of the other, rare region. And greater focusing of inhibition in dense (vs. sparse) displays would be required because of the increased saliency of the distractor (reflecting the increased local feature contrast).

Target-position effect: The target-position effect – the difference in mean RTs between trials with a target falling in the frequent versus the rare region, on distractor-absent trials – was significantly larger with as compared to without color swapping (46 ms vs. 16 ms); closer analysis revealed only the 46-ms effect to be significantly different from zero, but not the 16-ms effect. As already pointed out above, this pattern, in a way, replicates Zhang et al. (2019) and points to the importance of color swapping as a, if not *the*, crucial factor determining the suppression strategy that observers come to adopt: priority-map- versus dimension-based suppression. However, while there was a clear-cut dichotomy in Zhang et al. (2019; the Bayes Factor supported the null-hypothesis for conditions without color swapping, and for these conditions the target-position effect was significantly different from those with color swapping), the evidence appeared to be more mixed in the present study. In other words: some observers may adopt a dimension-based suppression strategy even with color swapping, and some a priority-map-based strategy even without color swapping. This may not be surprising (and, in fact, it might be odd to expect a clear-cut difference) given that both strategies are available to observers in principle (see also Liesefeld & Müller, 2019b).

Thus, taken together, even though it would appear that observers adopt a mixture of strategies under the same conditions, color-swapping promotes a priority-map-based strategy and no-swapping a dimension-based strategy. This supports our initial hypothesis (see also Zhang et al., 2019) that certainty with regard to the (dimensional/featural) nature of the distractor (when the distractor is consistently colored relative to the non-distractor-items) makes observers adopt a dimension-based suppression strategy (in parallel across the display), which – over the course of experience with the biased distractor distribution – becomes spatially tuned to the frequent distractor region. Adopting such a relatively ‘low-level’ suppression strategy would be overall beneficial: it would reduce distractor interference in the suppressed region without hampering the processing of targets (defined in a different dimension to the distractor) appearing in this region. In contrast, when there is uncertainty with regard to the nature of the distractor (i.e., when the distractor and non-distractor colors swap randomly across trials), the biased spatial distribution of distractors as such (i.e., whatever their precise properties) may become prominent, to which observer respond by adopting a global spatial – that is, priority-map-based – suppression strategy. This comes with a cost, however: slowed processing of targets appearing in the (globally) suppressed region.

Feature-based effects: One interesting question for the interpretation of the present results concerns whether, in conditions without color swapping, observers operated a dimension- or a feature-based suppression strategy. The latter would have been possible in principle because the distractor was defined by a consistent feature (and a consistent feature difference to the non-distractor items). Based on the present data alone, this possibility cannot be definitely ruled out. However, it would appear that observers adopted a 'singleton-detection' search mode in search for the variable target shape (see discussion of 'baseline performance' above). If so, then – assuming that singleton-detection mode applies to all odd-one-out items – it would appear unlikely that they adopted a feature-based set with regard to the distractor singleton. In any case, whatever the precise strategy they adopted under conditions of distractor color constancy, it would have impacted some representation/map specific to the distractor dimension (which may be a feature-specific representation/map) – because otherwise it would have produced a sizeable target-position effect. That is, at the least, our findings argue that without color swapping, acquired distractor location probability cueing operates at some level below the priority map.

However, some further clues to answering the question of feature- versus dimension-based suppression are provided by the pattern of color-repetition effects (observed for the groups performing the task under color-swap conditions). This pattern suggests that color repetition helped to reduce distractor interference overall, though it had little (i.e., only some numerical) impact on the probability-cueing effect. Possibly, when a certain-colored distractor captures attention, its color is encoded and suppressed, perhaps because this helps to disengage attention from the distractor and (re-)orient it to the target. Assuming that suppression of the distractor color is carried over across trials (perhaps in the form of a 'negative color template'; (e.g. Woodman & Luck, 2007), interference by a like-colored distractor would be reduced on the subsequent (color-repetition) trial. This interference reduction was not affected by whether the distractor (on trial *n*) appeared in the frequent versus the rare distractor region, suggesting that (carried-over) color-feature suppression is a display-wide (i.e., spatially non-selective) effect, operating on top of the probability-cueing effect and affecting both distractor regions equally. In addition, the (spatially *non-selective*) feature-specific effect, of at most 30 ms, is small relative to the (spatially *selective*) cueing effect, of some 70 to 80 ms. This effect pattern is consistent with Zhang et al.'s (2019) analysis of color swapping in a single-distractor-location probability-cueing paradigm, and confirms that the probability-cueing effect is not a feature-based effect (cf. Wang & Theeuwes, 2018a).

Interestingly, more detailed inter-trial analyses of the color-repetition effects confirmed that observing a color-repetition benefit (on a given trial *n*) depends (i) on the presence of a distractor on the preceding trial n-1 and (ii) on display density. Concerning point (i), there was little (no significant) benefit when there was no distractor on trial *n-1* – consistent with the idea that the benefit is driven by the distractor color, that is: the need to reject a distractor involves the setting-up of a negative distractor template that persists across trials (rather than a template for the non-distractor – including the target – color). Concerning point (ii), this distractor rejection dynamics was more pronounced for sparse than for dense displays – consistent with the idea that feature-based processing is more likely brought into the play with sparse than with dense displays, whereas dimension-based effects are seen with both sparse and dense displays (see, e.g., Rangelov, Müller, & Zehetleitner, 2013; for a recent discussion, see Liesefeld & Müller, 2019b).

Of note, the above-considered difference in the size of the feature-specific color suppression and the distractor-location probability-cueing effect (the latter being some two to three times larger), as well as the dissociative spatial non-specificity versus specificity of the two effects, is theoretically interesting: they argue that in the absence of color swapping, while spatially non-specific feature-based distractor would be at work consistently (perhaps increasing the color-repetition effect and thus reducing interference overall), it cannot explain the spatially specific probability-cueing effect. This would be the case unless one assumes that, for some reason, under no-color-swapping conditions, feature-based distractor suppression becomes spatially specific; this assumption may run counter to the notion that the feature-based suppression effect is based on a negative top-down distractor template held in visual working memory: templates may be featurally tuned (e.g. Geng, DiQuattro, & Helm, 2017), but are thought to work in parallel across the field (i.e., their top-down signals are not spatially tuned, but are rather 'broadcast' equally across the feature-detector layer); by contrast, bottom-up priority computations, e.g., as assumed in the DWA (weighting signal transmission from dimension-specific feature-contrast maps to the priority map), may be spatially tuned. Thus, on the balance of evidence, the probability-cueing effect under no-color-swap conditions is most likely dimensionally mediated.

This does, of course, not rule out that feature-based suppression may be tuned to particular locations under special conditions. In fact, this possibility is suggested by a very recent report, by Failing, Feldmann-Wüstefeld, Wang, Olivers, and Theeuwes (2019), that when two different (diagonally opposite) high-probability locations were statistically associated with two different distractor colors, suppression of a distractor at a particular (high-probability) location was stronger when it had the color associated with this position, as compared to the alternative color associated with the other position. Note, though, in another experiment in which two different distractor dimensions (one color and one shape) were associated with different high-probability locations, suppression at each high-probability location turned out to be completely specific to the associated dimension. Although not discussed by Failing, Feldmann-Wüstefeld, et al. (2019): this pattern of complete versus non-complete feature specificity of distractor suppression when distractors are defined within different versus the same dimensions is actually consistent with a core assumption of the DWA, namely: dimensionally coupled feature selectivity for signals defined within the same dimension (with regard to the color dimension, see Müller et al., 2003, and Zehetleitner, Goschy, & Müller, 2012, for prior evidence of dimensional coupling in relation to target selection and distractor de-selection, respectively).[14]

CONCLUSION

Thus, we conclude that even in distractor region probability cueing paradigms, in which a salient distractor is more likely to occur at one of multiple locations within a frequent sub-region of the display as compared to a rare region (e.g., Sauter et al., 2018), we observe similar patterns of distractor-position and target-positions effects as in paradigms in which a distractor is most likely to occur at one specific, 'frequent' location (e.g., Wang & Theeuwes, 2018a; Zhang et al., 2019). That is, with essentially the same paradigm: the distractor-position effect (reduced RT interference caused by distractors in the frequent vs. the rare region) may be

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[14] One related issue in this context concerns to what extent what looks like feature selectivity within the color dimension (e.g., in Failing, Feldmann-Wüstefeld, et al., 2019) is really a form of dimensional selectivity. In the search literature, feature-specific selection/de-selection effects have been demonstrated almost exclusively using color-defined targets/ distractors. However, there is evidence that 'color' is special (e.g., D'Zmura, 1991; Found & Müller, 1996; Lindsey et al., 2010; Müller et al., 2003) and may in fact be best conceived as consisting of a number of relatively independent (though coupled) 'sub-dimensions' (e.g., Found & Müller, 1996; for review, see Liesefeld, Liesefeld, Pollmann, & Müller, 2019). In any case, to corroborate general/genuine feature selectivity, at the very least, the critical color findings would need to be reproduced with other feature dimensions.

accompanied by a target-position effect (prolonged RTs to targets in the frequent vs. the rare region), arguing in favor of learned priority-map-based suppression of the likely distractor region (Wang & Theeuwes, 2018a; see also Ferrante at al., 2018); or the distractor-position effect may occur in the absence of target-position effect, arguing in favor of learned suppression at a level below the priority map, such as a dimension-based level (Sauter et al., 2018, 2019). Consistent with the single-location cueing paradigm (Zhang et al., 2019), the most important factor determining whether one or the other pattern is found is whether or not the distractor and non-distractor items (the latter including the target) swap colors randomly across trials: with color swapping, observers are more likely to acquire a priority-map-based suppression strategy; without color swapping, they are more likely to develop a dimension-based strategy (below the priority map). This difference likely arises because color swapping introduces uncertainty as to the nature of the distractor and so makes the distractor's (biased) spatial distribution more prominent relative to its perceptual definition. As a result, observers come to adopt and operate a purely space-based suppression strategy. Color consistency, by contrast, makes the perceptual definition of the distractor more prominent, invoking mechanisms of dimension-based suppression which are then spatially tuned according to the distractor distribution. In contrast to color swapping, display density (the second factor examined in the present study) as such has little influence on which specific strategy is being acquired.

Although, under conditions of color swapping, feature-based inhibition plays a significant role in distractor suppression (especially with sparse displays), it impacts distractors relatively equally whether they occur in the frequent or the rare region. That is, feature-based suppression appears to be spatially non-selective, which contrasts with the spatial modulation of priority-map-based and, we argue, dimension-based suppression. By implication, feature-based suppression could not explain the spatial modulation observed under color-no-swap conditions, which accordingly (given the absence of a target-position effect in the no-swap groups) would be attributable to dimension-based suppression. The proposed spatial non-selectivity of feature-based suppression (as compared to the selectivity of dimension-based suppression) requires corroboration, however, as it is based on analyses of complex inter-trial dynamics for which the database (in terms of the number of trials available for analysis) is, naturally, sparse.

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Appendix: Target position distribution

Table A: shows the frequency with which the target appeared at each position, for each group and each frequent distractor region within a group (there were 15 participants for each frequent distractor region in each group). Because most analyses were based on the first 960 trials, even in the groups in which participants performed more trials (to make the analyses based on an equal number of trials in each group), the table is also based on the first 960 trials in each group.

Table A: Target position distribution in the first 960 trials for each group and frequent distractor region. Each cell presents the percentage of trials, in one particular condition (a row in the table), in which the target appeared at a given position. The target position is given in degrees rotating clockwise from the ‘positive x-axis’, so that, e.g., 67.5 means the bottom right position on the circle.

		Angular target position (in degrees)							
Group	Frequent distractor region	22.5	67.5	112.5	157.5	202.5	247.5	292.5	337.5
1: sparse, swapping	Top	12.66	12.69	12.38	12.46	12.45	12.47	12.59	12.30
	Bottom	12.51	12.67	12.33	12.74	12.13	12.65	12.29	12.68
2: sparse, no swapping	Top	12.51	12.55	12.58	12.44	12.50	12.52	12.41	12.48
	Bottom	12.47	12.49	12.50	12.56	12.51	12.48	12.49	12.51
3: dense, swapping	Top	12.71	12.46	12.55	12.44	12.27	12.43	12.51	12.63
	Bottom	12.58	12.55	12.61	12.82	12.49	12.21	12.28	12.45
4: dense, no swapping	Top	12.64	12.61	12.46	12.54	12.40	12.35	12.42	12.58
	Bottom	12.67	12.34	12.57	12.62	12.45	12.30	12.51	12.55

2.3 Statistical learning of frequent distractor locations in visual search involves regional signal suppression in early visual cortex

CONTRIBUTIONS

HJM, BZ and RW conceived and designed the experiments. BZ, RW and SB collected the data. BZ analyzed data. BZ discussed the results with RW, FA, ZS and HJM. BZ and HJM interpreted the results and wrote the paper. RW and GRF commented on and revised the manuscript.

Statistical learning of frequent distractor locations in visual search involves regional signal suppression in early visual cortex

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ABSTRACT

Observers can learn salient distractors that occur frequently at particular locations, reducing their potential to cause interference. This effect has been attributed to a better suppression of distractors in more likely locations. However, how the suppression of distractors is neurally implemented remains largely unclear, specifically, whether visual-cortex signals at learned distractor locations would be down-modulated to reduce distractor interference and what specific role of the frontoparietal attention networks play in distractor handling. Using functional magnetic resonance imaging (fMRI) in regional distractor-location learning paradigm (Sauter et al. 2018, 2020) with two types of distractors defined in either the same- (e.g., orientation) or different- (e.g., color) dimension with the target, the fMRI results show that the BOLD signal in early visual cortex is significantly reduced for distractors (also target) occurring at the frequent distractor locations relative to the rare locations, mirroring the behavioral patterns. However, this reduction was more robust with same-dimension distractors. Crucially, behavioral interference was only correlated with distractor-evoked visual activity for same- (but not different-) dimension distractors. Moreover, with different- (but not same-) dimension distractors, a color-processing area within fusiform gyrus was activated more when the color distractor was present versus absent and with a distractor occurring in the rare versus the frequent region. These results support that statistical learning of frequent distractor locations involves regional suppression in early visual cortex, and potential differential neural mechanisms of distractor suppression between distractors defined in a different versus the same dimension to the target.

Key words: distractor suppression, early visual cortex, functional magnetic resonance imaging, statistical (distractor-location) learning

INTRODUCTION

In everyday life, and experimental scenarios such as the additional-singleton paradigm (Theeuwes 1992), attention is often distracted or ‘captured’ by salient but goal-irrelevant stimuli (Folk and Remington 1998; Hickey et al. 2006; Forster and Lavie 2008). However, with repeated exposure and practice (Kelley and Yantis 2009; Zehetleitner et al. 2012), distractor interference can be reduced via attentional control (Bacon and Egeth 1994; Leber and Egeth 2006; Müller et al. 2009; Gaspelin et al. 2017).

Moreover, observers can learn not only to prioritize locations for attention selection where task-relevant targets are regularly encountered (Shaw and Shaw 1977; Geng and Behrmann 2005), but also to deprioritize locations where salient but irrelevant distractors appear frequently (Goschy et al. 2014; Leber et al. 2016; Ferrante et al. 2018; Sauter et al. 2018; Wang and Theeuwes 2018). Typically, in the latter studies, a salient distractor occurs with higher likelihood at one, ‘frequent’ display location/subregion relative to the remaining, ‘rare’ locations/subregions. The consistent finding is that, over time, search becomes less impacted by distractors that appear at frequent, as compared to rare, locations. This effect is largely attributable to a proactive suppression of frequent distractor locations: oculomotor capture is less likely when distractors occur at frequent (vs. rare) locations (Di Caro et al. 2019; Wang et al. 2019; Sauter et al. 2020), and for frequent locations an anticipatory suppression-related event-related component (P_D) is observed (Wang, van Driel, et al. 2019). However, the way suppression of likely distractor locations is implemented is influenced by how distractors are defined relative to the target (Sauter et al. 2018; Allenmark et al. 2019; Failing et al. 2019; Zhang et al. 2019; Liesefeld and Müller 2020): if target and distractor are defined in the same dimension (e.g., target and distractor are both orientation-defined), suppression appears to work at a supra-dimensional level of ‘attentional-priority’ computation, impacting both distractor and target signals – as compared to a level of dimension-specific ‘feature-contrast’ computation when they are defined in a different dimension (orientation-defined target, color-defined distractor), in which case suppression typically impacts only distractor signals.

While a consensus is emerging as to the loci of learnt distractor-location suppression within the architecture of search guidance, how suppression is neurally implemented remains largely unclear. It is well-established that the frontoparietal network, including the inferior/superior parietal lobe (IPL/SPL), is involved in attentional control of distractor interference (de Fockert et al. 2004; Krueger et al. 2007), and top-down control can instigate preparatory activity to minimize capture by expected distractors (Serences et al. 2004; Ruff and Driver 2006; Munneke et al. 2011). For instance, presenting trial-by-trial precues indicating the likely target side as well as, on critical trials, the appearance of a distractor in the opposite hemifield, Ruff and Driver (2006) observed enhanced occipital-cortex activation in the hemisphere contralateral to the upcoming distractor during the cue period, and this was associated with reduced search costs later on. However, as regards top-down effects on distractor coding in early visual cortex, the evidence is mixed. For instance, Bertleff et al. (2016) found precuing of the target region to diminish distractor interference through increased activity in medial parietal regions involved in controlling spatial attention, rather than by down-modulating distractor signals in early visual cortex. In contrast, manipulating the overall likelihood with which a distractor could occur anywhere in the display, Won et al. (2020) reported distractor signaling in the visual cortex to be diminished when distractors occurred frequently, along with reduced distractor interference.

Thus, using functional magnetic resonance imaging (fMRI) in Sauter et al.'s (2018) distractor-location learning paradigm, the current study aimed to examine whether visual-cortex signals at learnt distractor locations would be down-modulated to reduce distractor interference, and the role the frontoparietal attention network plays in distractor handling. In particular, given the dissociative learning effects between distractors defined in the same versus a different dimension to the target, we examined for differences in neural mechanisms mediating distractor-location learning between the two distractor types.

MATERIALS and METHODS

Participants

32 volunteers (mean age: 27.47 years; age range: 20-45 years; 18 female) were recruited, 24 at Forschungszentrum Jülich and 8 at LMU Munich. Functional MRI data from 6 participants were excluded for the MRI analysis due to data quality (e.g. distortion) and/or head movements. Based on the effect size of significant preparatory visual activation of distractor suppression in Serences et al. (2004), with power of 0.80 and alpha 0.05 (G*Power analysis) (Erdfelder et al. 1996), the sample size was 24. We recruited 32 to get enough power. All participants were right-handed and reported normal or corrected-to-normal vision, including normal color vision, and none had been diagnosed with neurological or psychiatric disorders. Participants received 15 Euro per hour for their service. The study protocol was approved by the ethics committees of the German Society of Psychology (DGPs) and, respectively, the

Department of Psychology of LMU Munich, and written consent was obtained from all participants prior to the experiment.

Apparatus

In preparation for the fMRI experiment, participants received behavioral training outside the scanner to become familiarized with the task. The training was conducted in a sound-reduced and moderately lit test chamber. Stimuli were presented on a 24-inch Samsung SyncMaster 2233 (Samsung Electronics Co., Ltd., Seoul, South Korea) screen at *1280 × 1024* pixels screen resolution and a refresh rate of 120 Hz. Stimuli were generated by Psychophysics Toolbox Version 3 (PTB-3) (Brainard 1997) based on MATLAB R2019 (The MathWorks® Inc). Participants viewed the monitor from a distance of 60 cm (eye to screen); distance and fixation position were controlled by a forehead-and-chin rest and an EyeLink 1000 eye-tracker device. In the experiment proper (in the scanner), stimuli were presented on a 30-inch LCD screen mounted behind the scanner at a distance of 245 cm from the head coil. The stimuli settings and MRI data acquisition the parameters at Forschungszentrum Jülich and LMU Munich were the same. Participants viewed the monitor via an adjustable mirror positioned on top of the head coil.

Visual Search Task

Stimuli

The stimuli used were essentially the same as in Sauter et al. (2018, 2020). The visual search displays consisted of twenty-nine turquoise (CIE [Yxy]: 29.6, 0.23, 0.37, measured on an equivalent display outside the scanner) upright or inverted ‘i’ shaped bars (0.10° of visual angle wide, 0.50° high; see search display in Figure 1A). One bar was positioned in the center of the screen; the other bars were arranged on three imaginary concentric circles (around the center) with radii of 1.25°, 2.50°, and 3.75° of visual angle containing 4, 8, and 14 items, respectively. The target was an item defined by a unique orientation difference compared to the vertically oriented non-target items: it was tilted 12° to either the left or the right, with tilt direction randomized across trials. On a fraction of trials, one of the non-target items: the singleton distractor (simply referred to as ‘distractor’ hereafter) was defined by either a different color (red; CIE [Yxy]: 29.7, 0.30, 0.27; the *different-dimension distractor*) or a different orientation (a 90°-tilted, i.e., horizontally oriented ‘i’, the *same-dimension distractor*) compared with all the other items. The target and the singleton distractor only appeared at one of the eight positions on the middle circle, and they never appeared at the same location or adjacent to each other. The non-target items on the outer and inner rings served to equate local feature contrast amongst the various singleton positions. All search items were presented on a black screen background ($3.58\ cd/m^2$).

Note that the physical, bottom-up saliency of the two types of distractor was determined in a pilot study (with different participants) in which the color and, respectively, the orientation distractor were presented as response-relevant targets; that is, in separate blocks, they were the only singleton item in the display to which participants had to make an eye movement as fast as possible. Following Zehetleitner et al. (2013), we took the (saccadic) reaction time to be indicative of the physical saliency of a given distractor stimulus. Results revealed that a similar proportion of first saccades was directed to the red and the horizontal target, 92% vs. 90%. Latencies of the first saccade were somewhat shorter for the red compared to both the horizontal target, 166 ms vs. 184 ms, $t(8.06) = -2.93$, $p = .019$, $d_z = 1.69$. Thus, taking the two measures together: if anything, the physical saliency of the red singleton was somewhat higher than that of the horizontal singleton.

Design

The two types of singleton distractor were introduced as a session factor in a within-group design: participants encountered only one type of distractor, either a different-dimension (i.e., color) or a same-dimension (i.e., orientation) distractor, in either the first or the second experimental session (with order counterbalanced across participants). In each session, the singleton distractor was presented in 60% of trials, the remaining 40% being distractor-absent trials. If a distractor was present, it appeared with 80% probability in one half of the search display (i.e., at one of the four positions on the middle semicircle on either the left or the right side – henceforth referred to as the 'frequent' distractor region) and with 20% probability in the other half (the 'rare' distractor region) (see Figure 1A). In contrast to the distractor, the target (which was present on all trials) appeared equally often in both regions, with an equal probability for all eight possible positions.

Note that, for each participant, which distractor region was frequent was reversed between two experimental sessions (e.g., if the left half was frequent in session 1, the right half was frequent in session 2), so as to rule out carry-over of learning effects between the two types of distractor. The assignments of the frequent distractor region (left vs. right semicircle) and of the type of distractor (same dimension vs. different-dimension first) to the two sessions were counterbalanced across participants, thus avoiding possible confounds.

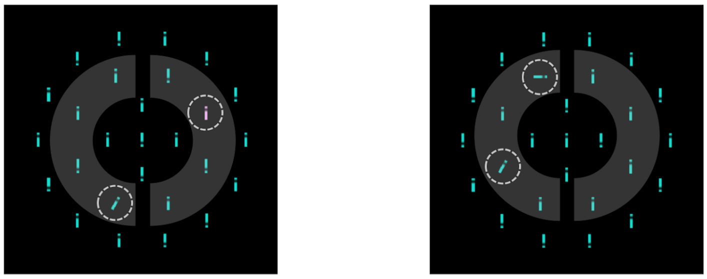
Further of note, distractor type was manipulated as a within-subject factor in the present study, that is: our participants had to learn the spatial distribution of one type of distractor first and then, after an unlearning phase, the opposite distribution with the other type of distractor. In previous studies (Sauter et al. 2018, 2019, 2020), we had used a between-subject design, to avoid carry-over of acquired suppression strategies from one distractor type to the other. Based on finding dissociative target-location effects between same- and different-dimension distractors, we had proposed that statistical learning of distractor locations normally involves different levels of priority computation: the supra-dimensional priority map with same-dimension distractors (producing both a distractor- and a target-location effect) versus a level specific to the distractor dimension with different-dimension distractors (producing only a distractor-location effect). Despite possible carry-over effects potentially weakening dissociative effects between the two distractor types, for the present fMRI study, we opted for a within-subject design to examine statistical distractor-learning effects within the same brain. Also note that with different-dimension distractors, both dimension- and priority-map-based suppression are in principle feasible, though even if observers start out with a priority-map-based strategy (as indicated by them displaying a target-location effect), most will revert to dimension-based strategy (as indicated by observers losing the target-location, but not the distractor-location, effect) over extended practice on the task (Zhang et al. 2019).

Procedure

Each trial began with the presentation of a fixation cross in the middle of the screen for 500 ms, followed by the search display for a fixed duration of 300 ms (see Figure 1B). Participants were instructed to respond to the top versus bottom position of the dot in the target ‘i’ by pressing the corresponding (left-/right-hand) response button (with stimulus-response assignment counterbalanced across participants) with two hands. Responses were to be made within 900 ms of search display onset; otherwise, the trial was ‘timed out’. Following the response or time-out, feedback was provided in the shape of a colored dot (0.4° of visual angle in diameter) presented in the screen center: a green dot (RGB: 0, 255, 0) following a correct response and a red dot (RGB: 255, 0, 0) following an incorrect response or a time-out (i.e., too slow a response). A total time of 1200 ms was fixed for response and feedback: a maximum of 900 ms for response and a minimum of 300 ms for feedback (i.e., the duration of the feedback depended on the response time on a given trial). The intertrial interval (ITI) was 1000 ms or 3000 ms, randomly determined on each trial. Each experimental session consisted of 440 trials in total, subdivided into 8 blocks of 55 trials. Blocks were separated by breaks of 6 s duration. Prior to the MRI scanning, participants performed three training blocks outside the scanner (with the same type of distractor as in the first experimental session), to practice the task (i.e., finding the target 'i' and responding to the dot position within it) and start learning the biased (80%/20%) spatial distractor distribution (so as to increase the power to determine the brain regions involved in statistical distractor location learning in the scanner). In addition, prior to practicing the second session (also outside the scanner), participants completed four blocks (40 trials in each block) in which the singleton distractor was the same as in the first session but appeared equally often at two distractor regions (50%/50% distribution), to unlearn the spatial bias acquired for the first type of distractor. The number of unlearning trials was based on Ferrante et al. (2018), who found the distractor-location learning effect to be near-abolished within 144 'extinction' trials.

In all experimental phases, participants were instructed to maintain fixation on the center of the screen from the appearance of the fixation cross appeared to the end of the trial. During practice (outside the scanner), compliance with this instruction was checked by monitoring participants' eye movements using an eye-tracker device. In the scanner, eye movements could not be recorded, but participants reported that they had successfully maintained fixation on the vast majority of trials. Note also that making eye movements would have been counterproductive given the brief (300-ms) display duration.

A. Stimulus display



(a) Different-dimension distractor session

(b) Same-dimension distractor session

B. Trial procedure

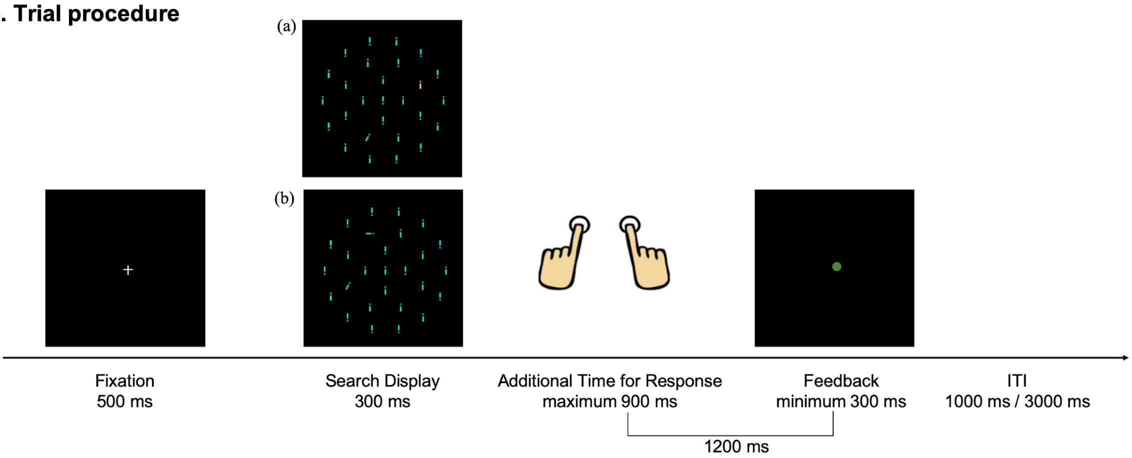


Figure 1. *A. Example of a search display in (a) the different-dimension distractor session: the search target is the 12-°titled item (here, outlined by a white dashed circle, bottom-left of the middle ring), and the distractor is a red color singleton (outlined by white dashed circle, top-right of the middle ring); (b) the same-dimension distractor session: the search target is again the 12°-titled item (outlined by white dashed circle, bottom-left of the middle ring), and the distractor is a horizontal singleton (outlined by a white dashed circle, top-left of the middle ring). Gray depicted areas indicate the eight potential target and distractor locations, and the left and right gray semicircles the frequent and, respectively, rare distractor regions. Note that the dashed lines and gray areas are for illustration purposes only; they were not shown in the experiment. B. Example of the trial procedure, described in more detail in the text.*

Position Localizer Task

To functionally identify the visual cortical representations corresponding to different target and singleton distractor locations, a separate position localizer run was performed either before or after experimental session 1 (counterbalanced across participants). Participants were instructed to fixate the cross in the screen center. They were then exposed to a contrast-reversing flickering checkerboard pattern that consisted of black and white mini-tiles (RGB: 0, 0, 0 and RGB: 255, 255, 255, respectively) flickering counter-phase at 8 Hz, with a height and width of 2.5°, which was presented successively in each quadrant of the visual field (see Figure 2a). Note that the size of the localizer covered two adjacent (target/distractor) locations in the search display. The localizer stimuli cycled through the four quadrants in clockwise direction, appearing at each location for 16 s with a 16 s break in-between, for two full rounds, so that the localizer run took 4.27 min to complete.

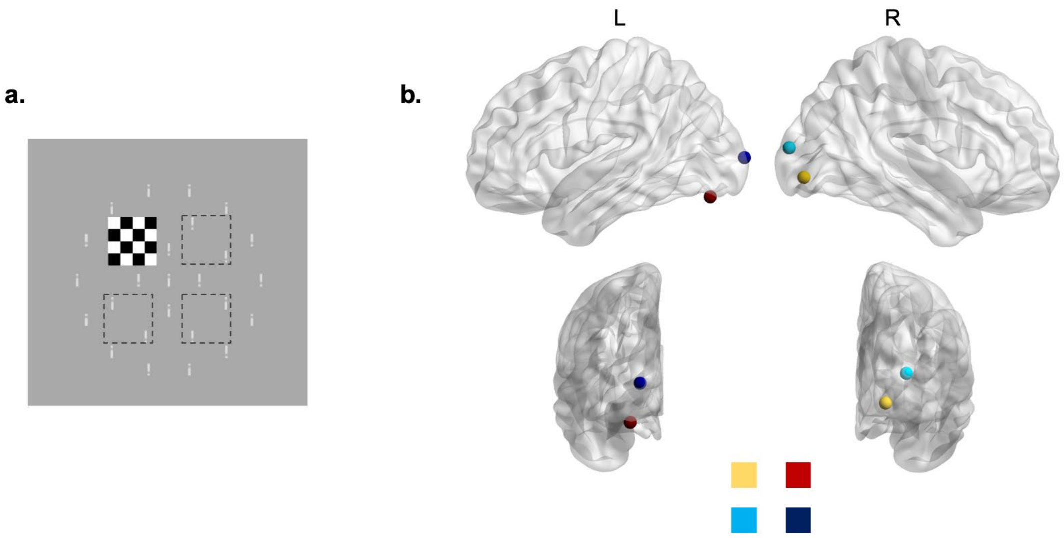


Figure 2. *(a) An example of checkerboard stimuli (here, top-left) in the positional localizer that correspond to possible target and distractor locations; Note that the black dash line and gray 'i' items of the inner and outer ring here were only depicted for illustration purpose and not shown to the observers in the experiment. (b) Four VOIs induced by four different position localizers coded by four colors are projected onto a surface rendering.*

MRI Measurement and Analysis

Data acquisition

MRI data were acquired on a 3.0 T TRIO Prisma MRI (Siemens, Erlangen, Germany) whole-body MRI system equipped with a 64-channel head matrix coil. To help stabilize the head position, each subject was fitted with a cushion in the head coil. Functional images were obtained using a blood oxygenation level-dependent (BOLD) contrast sensitive gradient-echo echo-planar sequence. A total of 1355 images were acquired in each experimental session and, respectively, 244 images in each positional localizer run; scanning parameters: TR = 1200 ms, TE = 30 ms, flip angle = 70 degree, FOV = 192×192 mm, voxels size = 2 × 2 × 3 mm, slices number = 36, slice thickness = 3 mm. Structural MRI images (T1-weighted) were acquired from the sagittal plane a using three-dimensional magnetization-prepared rapid gradient-echo (MP-RAGE) pulse sequence; scanning parameters: TR = 1780 ms, TE = 2.51 ms, flip angle = 8 degree, FOV = 256 × 256 mm, voxel size = 0.9 × 0.9 × 0.9 mm, slice thickness = 0.9 mm.

Preprocessing

Functional imaging data were processed with SPM12 (r7771) (Wellcome Centre for Human Neuroimaging, London, United Kingdom; https://www.fil.ion.ucl.ac.uk/spm/software/spm12) based on MATLAB R2019a. Functional images acquired in each experimental session were corrected for interslice time differences for every participant first. Next, the functional images from the main experiment, as well as those from the position localizer functional images, were corrected for head movement by affine registration in a two-pass procedure realigning individual functional images to their mean image. Participants who exhibited translation head motion of more than 3 mm or rotations of more than 3 degrees were excluded from further analysis. The mean image for each participant was then spatially normalized to a standard Montreal Neurological Institute (MNI) template using the 'unified segmentation' approach and the resulting deformation field was applied to the individual functional images. The resultant images were smoothed with a 6-mm full width at half maximum (FWHM) Gaussian kernel to improve the signal-to-noise ratio and to compensate for residual anatomical variations.

fMRI Analysis

Due to data quality issues (e.g., distortion) and/or large head movements during the visual search task, six out of the thirty-two participants were excluded from the functional MRI data analysis. To maximally use the available data, we included their good-quality behavioral and positional localizer data in the analysis.

Whole-brain analysis The first-level (individual-participant) analysis involved the application of a general linear model (GLM), with the following regressors for each distractor-type session. There were four primary regressors, one for each of the four basic experimental conditions of theoretical interest: two regressors for distractor-present trials, namely, singleton distractor in the frequent region and singleton distractor in the rare region; and two regressors for distractor-absent trials, namely, target in the frequent region and target in the rare region. In addition, the two manual-response conditions (left button press, right button press) were included as regressors to avoid a high implicit baseline (Monti 2011), along with an extra regressor for unused trials (the first trial in each block and trials with incorrect/missing responses). The hemodynamic response related to neural activity in each of the above conditions was modeled by the canonical hemodynamic response function and its first derivative, which can capture the late negative dip of empirical BOLD responses (Henson et al. 2002). Finally, six head-movement parameters were considered as covariates in the model to reduce potential confounding effects (Lund et al. 2005). Based on the GLM, combining the same regressors across the two experimental sessions, we defined and calculated four contrast images at the first level, in order to examine the effects of distractor interference (distractor present > distractor absent, and vice versa) and of distractor-location learning (distractor in the rare region > distractor in the frequent region, and vice versa). Importantly, the four contrast images were also calculated separately for two experimental sessions (i.e., the different- and the same-dimension distractor condition).

In the second-level group analysis, we first identified brain regions that were generally, across the two sessions, involved in a specific condition and then used these as masks for performing the respective test within the two (distractor-type) sessions, since we were interested in condition-specific differential responses within the ‘distraction network’. That is, we first submitted the four individual contrast images that combined the same regressors across the two sessions (e.g., distractor present > distractor absent) to one-sample t-tests in order to determine common brain regions activated in one particular condition at a height threshold of $p < .001$ (uncorrected). Next, we used those activated regions as a mask for examining the same condition separately in each experimental session (e.g., distractor present > distractor absent in the different- and, respectively, the same-dimension session) on the group level. Restated, the four individual contrast images within the different- and, respectively, the same-dimension session were taken to the group level and subjected to a one-sample t-test based on the corresponding mask, with family-wise error (FWE) corrected at a cluster-defining voxel-level cut-off of $p < 0.05$ and a minimum cluster size of 5 contiguous voxels.

Volume-of-Interest (VOI) analysis Functional MRI data of the localizer stimuli (checkerboards) at the four positions corresponding to potential target/distractor locations were used to identify localized activation in early visual cortex (see Figure 2). The first-level GLM model was estimated with four experimental regressors defined by the onset of visual stimulation at each of the four localizer positions, with a duration of 16 seconds. The hemodynamic response was again modeled by the canonical hemodynamic response function and its first derivative. Six head-movement parameters were included as covariates. Four individual contrast images were calculated by comparing each positional regressor with the other three regressors, and then taken to the group level for one-sample t-tests at an extent threshold of $p < 0.05$ (FWE corrected) with a minimum cluster size of 5 contiguous voxels (Bertleff et al. 2016). The significantly activated clusters thus obtained turned out somewhat different in volume size for the four position localizers. To ensure identical volume sizes for the subsequent VOI analysis, the four localizer VOIs were defined as four spheres, with the center point of each sphere placed on the peak coordinate defined by the group maximum t value within the respective cluster and with a radius of 9 mm (see Figure 2b). The spheres' radius was determined based on the minimum volume size – consisting of 116 voxels – identified in a group-level analysis of the four localizer positions. In the next step, another set of first-level GLM models were estimated with four experimental regressors each representing a *distractor* occurring at one of the localizer positions, separately for two distractor-type sessions. The hemodynamic response related to neural activity in each of the four distractor regressors was modeled by the canonical hemodynamic response function and its first derivative, with six head-movement parameters considered as covariates in the model. Analogous GLM models were developed with four regressors each representing a *target* appearing at one of the four positions, separately for two distractor-type sessions. Beta values of experimental regressors were extracted within the corresponding localizer VOIs for further examination.

RESULTS

Behavioral Results

The first trial in each block was excluded from analysis, as were response-error trials in the response-time (RT) analysis.

The error rate was overall higher in the same-dimension than in the different-dimension session (14.47% vs. 12.66%), and compared to the distractor-absent baseline (10.7%), more errors were made on trials in which a distractor was present (in the rare region: 16.3%; in the frequent region, 15.7%). Further, the increased error rates caused by distractor presence were more marked with same- than with different-dimension distractors (see Figure 3a). This effect pattern was confirmed by a repeated-measures ANOVA with the factors Distractor (absent, in the frequent region, in the rare region) and Distractor Type (different-dimension distractor, same-dimension distractor), which revealed all effects to be significant: Distractor, $F(2, 62) =$

32.49, $p < .001$, $\eta_p^2 = .109$; Distractor Type, $F(1, 31) = 6.41$, $p = .017$, $\eta_p^2 = .034$; interaction, $F(2, 62) = 11.24$, $p < .001$, $\eta_p^2 = .032$.

This (interactive) effect pattern was mirrored in the RT results (Figure 3a), effectively ruling out differential speed-accuracy trade-offs. An analogous ANOVA of the mean RTs again revealed all effects to be significant: Distractor, $F(2, 62) = 122.6$, $p < .001$, $\eta_p^2 = .082$; Distractor Type, $F(1, 31) = 59.9$, $p < .001$, $\eta_p^2 = .131$; interaction, $F(2, 62) = 59.4$, $p < .001$, $\eta_p^2 = .054$. Response speed was overall slower with same- than with different-dimension distractors, and the presence of a distractor slowed RTs to the target (relative to the distractor-absent baseline). This slowing was more marked in the same- than in the different-dimension distractor condition, as depicted in Figure 3b, the interference effect was only some 8 ms with different-dimension distractors, $t(31) = 3.15$, $p = .004$, but ten times as high (81 ms) with same-dimension distractors, $t(31) = 14.0$, $p < .001$. This differential interference effect was significant ($t(31) = -12.2$, $p < .001$). Thus, even though the two types of distractor were balanced in terms of bottom-up saliency, same-dimension distractors caused considerably more RT interference than different-dimension distractors – in line with previous findings (e.g., Sauter et al. 2018, 2019; Liesefeld and Müller 2020).

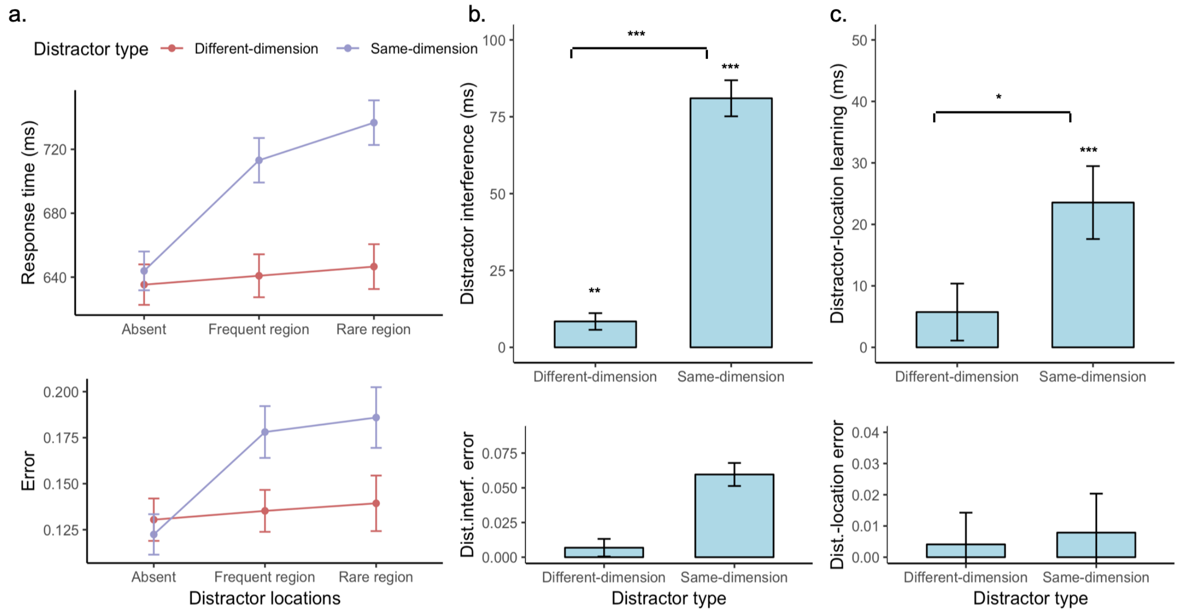


Figure 3. *Response-time (upper panels), and analogous error-rate (lower panels) for the two distractor-type conditions. (a) Averaged RTs and error-rate of three distractor locations, separately for the different- and same-dimension distractors. (b) Distractor-interference effect, calculated as the difference between distractor-present and -absent trials, separately for the*

*different- and same-dimension distractors. (c) Distractor-location learning effect, calculated as the difference between trials with a distractor in the rare vs. frequent region, separately for the different- and same-dimension distractors. Error bars depict 95% confidence intervals. * denotes p < .05, ** p < .01, *** p < .001.*

To quantify the effect of distractor-location learning, we calculated the difference in RT performance between trials with a distractor in the rare region versus trials with a distractor in the frequent region. As depicted in Figure 3c, when a distractor appeared in the frequent region, RTs to the target were generally faster than with a distractor appearing in the rare region. Importantly, this difference was greater with same-dimension distractors, evidenced by a significant distractor-location effect in the same-dimension session (24-ms benefit, $t(31) = 4.03$, $p < .001$), but not in the different-dimension condition (6-ms benefit, $t(31) = 1.26$, $p = .218$). In any case, the larger (frequent- vs. rare-region) RT benefits obtained with same- than with different-dimension distractors ($t(31) = -2.04$, $p = .05$) closely replicate our previous findings (e.g., Sauter et al. 2018, 2019; Liesefeld and Müller 2020).

Of note, even though the target occurred with equal likelihood in both distractor regions, targets appearing at a location in the frequent region were responded to slower than targets in the rare region, the RT costs amounting to some 9-ms (combined across distractor-present and -absent trials) with different-dimension distractors ($t(31) = 2.61$, $p = .014$) and 18-ms with same-dimension distractors ($t(31) = 4.31$, $p < .001$). Although the cost was double the size in the same- versus the different-dimension condition, the difference was non-significant ($t(31) = -1.23$, $p = .228$). Thus, while statistical learning of distractor locations reduces the interference caused by distractors in the frequent region, this is associated with a cost: slowed processing of targets appearing in the frequent (distractor) region. Consistent with our previous behavioral studies, this cost effect is more marked, at least numerically, with same-dimension distractors. [In previous studies, there was either no cost with different-dimension distractors (e.g., Liesefeld and Müller 2020), or there was some cost initially, which however disappeared over the course of extended practice on the task (Zhang et al. 2019).]

VOI results

Based on human probabilistic cytoarchitectonic maps within the Anatomy Toolbox (Eickhoff et al. 2005), the group peak coordinates of the maximum *t*-values associated with each of the four flickering checkerboard localizers – that is, potential target/distractor positions – were localized to early visual cortex (V1 – V4; Figure 2b).

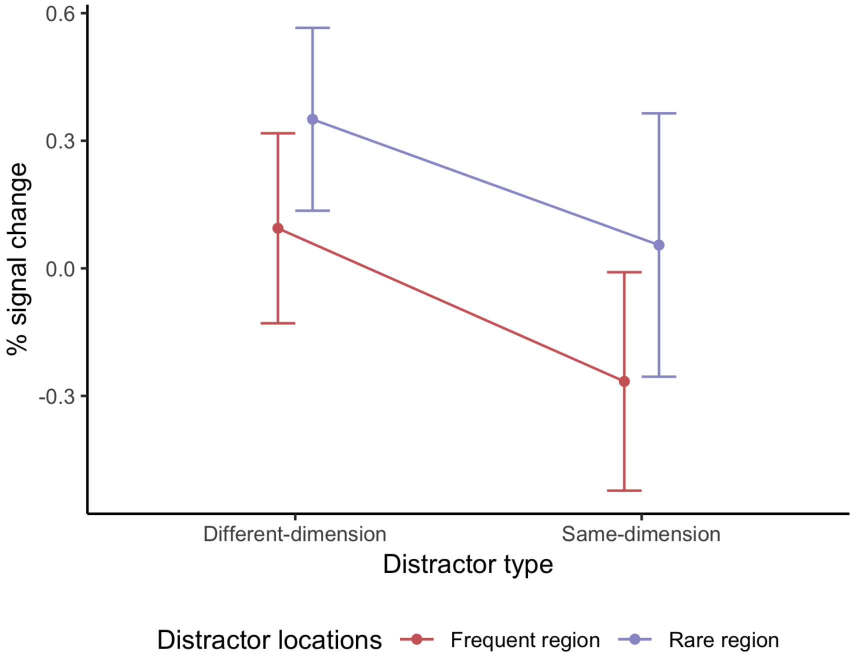


Figure 4. *Mean percentage signal change (beta values) representing early visual activation by singleton distractors appearing in the frequent vs. the rare distractor region, separately for the different- and same-dimension distractor conditions. Error bars depict 95% confidence intervals.*

We first examined for changes in the beta values representing activation at the specific localizer positions (VOIs) when the distractor appeared at a location in the frequent and, respectively, the rare region, for the two distractor types. To start with, we submitted the beta values to a three-way ANOVA with the within-subject factors Distractor Region (frequent region, rare region) and Distractor Type (different-, same-dimension distractor) and the between-subject factor Frequent Hemisphere (Group 1 with different-dimension distractors appearing frequently in the left region, i.e., the right VOIs, and same-dimension distractors appearing frequently in the right region, i.e., the left VOIs, Group 2 with the reversed frequent hemisphere relative to Group 1 for two distractor types). As the effect of the distractor-frequency manipulation did not differ between the two groups (non-significant main effect of Frequent Hemisphere, non-significant Frequent Hemisphere x Distractor Region or Frequent Hemisphere x Distractor Type interactions, all *p*s > .07), we collapsed the beta values from different assignments of frequent regions.

Figure 4 depicts the resulting beta values for distractor locations in the frequent and, respectively, rare distractor regions, separately for each distractor type. By visual inspection, and as was confirmed by repeated-measures ANOVA of Distractor Type and Distractor Region, the beta values were overall lower for distractors appearing in the frequent versus the rare region (significant main effect of Distractor Region, $F(1, 25) = 7.57$, $p = .01$). This pattern is consistent with the idea that statistical learning of distractor locations is associated with stronger signal suppression in early visual areas coding frequent versus rare distractor locations. However, in contrast to the RT results, the beta values turned out little influenced by the factor Distractor Type (main effect, $F(1, 25) = 1.24$, $p = .28$); in particular, the effect of (frequent, rare) distractor region did not appear to be reduced in the different-, as compared to the same-, dimension distractor condition (non-significant Distractor Type x Distractor Region interaction, $F(1, 25) = 0.09$, $p = .76$). However, as a weaker effect was expected from the RT pattern, we conducted paired t-tests comparing the beta values between the frequent and rare distractor regions, separately for the two distractor types. These revealed the difference to be significant for the same-dimension condition (rare vs. frequent region: 0.06 vs. -0.27, $t(25) = 2.45$, $p = .022$), but not for the different-dimension condition (0.35 vs. 0.09, $t(25) = 1.57$, $p = .13$). Thus, while early visual-cortex activation was generally reduced when a distractor occurred in the frequent (vs. the rare) region, this effect was statistically robust (i.e., consistent across participants) only with same-dimension distractors, but not with different-dimension distractors.

Given this, we further examined whether the early visual-cortex modulations play a role in generating the behavioral effects. To this end, we analyzed the relationships between the beta values and the RT interference caused by distractors occurring in the frequent and, respectively, the rare region, for each of the two distractor-type conditions. The correlations are illustrated in Figure 5. As can be seen, the beta values were predictive of RT-interference magnitude only in the same-dimension condition (Frequent region: $r = .517$, $p = .007$; Rare region: $r = .466$, $p = .016$), but not the different-dimension condition (Frequent region: $r = .094$, $p = .646$; Rare region: $r = -.052$, $p = .800$). This pattern points to a critical role of the early visual signal modulations for behavioral distractor interference only with same-dimension distractors; in contrast, some other, or additional, distractor-handling mechanism must come into play with different-dimension distractors (see whole-brain results below).

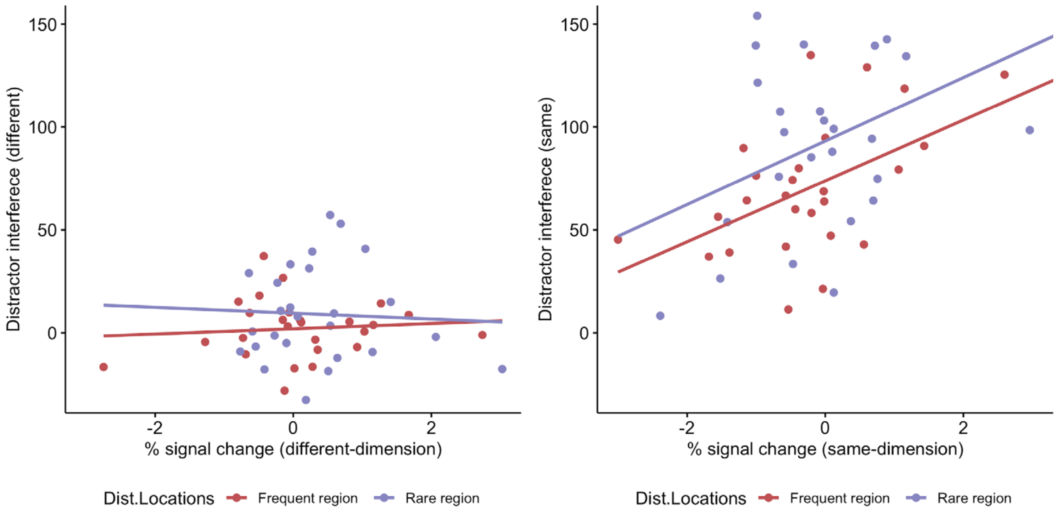


Figure 5. *Correlation between behavioral distractor interference effect (RTs) in the frequent region and the rare region with the respective percentage signal changes for distractors in the frequent and rare region, separately for the different- (left panel) and the same-dimension distractor conditions (right panel).*

Of note, the beta values were not only reduced when a distractor occurred in the frequent (vs. the rare) region (see above), but also when a target appeared there (significant main effect of Target Location in frequent vs. rare region: $F(1, 25) = 6.90, p = .015$). Although the beta values were numerically more negative overall in the same-dimension condition, the main effect of Distractor Type was non-significant ($F(1, 25) = 0.51, p = .48$). Finally, the reduction was comparable between the two distractor-type conditions (Target-Location × Distractor-Type interaction: $F(1, 25) = 0.008, p = .93$), even though it tended to be more robust in the same-dimension (rare vs. frequent region: 0.09 vs. -0.22, $t(25) = -2.42, p = .023$) than in the different-dimension distractor condition (0.33 vs. 0.01, $t(25) = -1.85, p = .077$). This pattern is similar to the distractor-location effects (see above), and so likely reflecting the same mechanisms underlying statistical distractor-location learning.

Whole-brain results

Whole-brain results showed that the presence of a singleton distractor defined in a different dimension (namely color) to the target (orientation) invoked a BOLD response in left fusiform gyrus (FWE corrected, $p < .05$, see Figure 6 and Table 1). Furthermore, compared to a (color) distractor appearing in the frequent region, a distractor in the rare region induced stronger activation in the right superior parietal lobule (Brodmann area, BA 7), left fusiform gyrus, as well as large parts of occipital cortex (FWE corrected, $p < .05$, see Table 1, Figure 7).

In contrast to the different-dimension distractor, the presence of a distractor defined in the same dimension as the target was associated with more robust activation in the right superior parietal lobule (BA 7) as well as the left superior parietal lobule extending to left middle occipital regions (FWE corrected, $p < .05$, see Table 1, Figure 6). Critically, however, no significant clusters were found when comparing (same-dimension) distractors in the rare region versus the frequent region. This pattern suggests that distractor handling in general and statistical distractor-location learning in particular operates more in early visuo-cortical areas with same-dimension (orientation-defined) distractors (see VOI results above), whereas some higher-level mechanism comes into play with different-dimension (color-defined) distractors.

Table 1. List of activations associated with contrasts defined by (A) Distractor present > Absent, (B) Distractor in the rare region > Frequent region, (C) Distractor in the frequent region > Rare region, separately for the different-dimension session and the same-dimension session.

Contrast	*Side*	*Region*	*Cluster size*	*Cluster peak coordinates*	*T value*
Different-dimension session					
(A) Distractor present > Absent	L	Fusiform gyrus	7	-33, -57, -12	4.70
(B) Distractor in the rare region > Frequent region	L	Superior occipital lobule	16	-21, -63, 30	4.92
	R	Middle occipital gyrus	26	30, -69, 24	4.67
	R	Inferior occipital lobe	6	36, -66, -12	4.61
	L	Fusiform gyrus	30	-36, -60, -12	4.63
	R	Superior parietal lobule (BA 7)	17	30, -57, 51	4.59
(C) Distractor in the frequent region > Rare region	No significant brain activation				
Same-dimension session					
(A) Distractor present > Absent	L	Superior occipital lobule	68	-21, -60, 51	5.20
	L	Superior occipital lobule	10	-24, -69, 27	5.03
	R	Superior parietal lobule (BA 7)	26	27, -63, 45	4.02
(B) Distractor in the rare region > Frequent region	No significant brain activation				
(C) Distractor in the frequent region > Rare region	No significant brain activation				

Coordinates (x, y, z) were defined in MNI space. Activations were all significant at $p < 0.05$ (FWE corrected) at the cluster level (based on $p < 0.001$, at the voxel level).

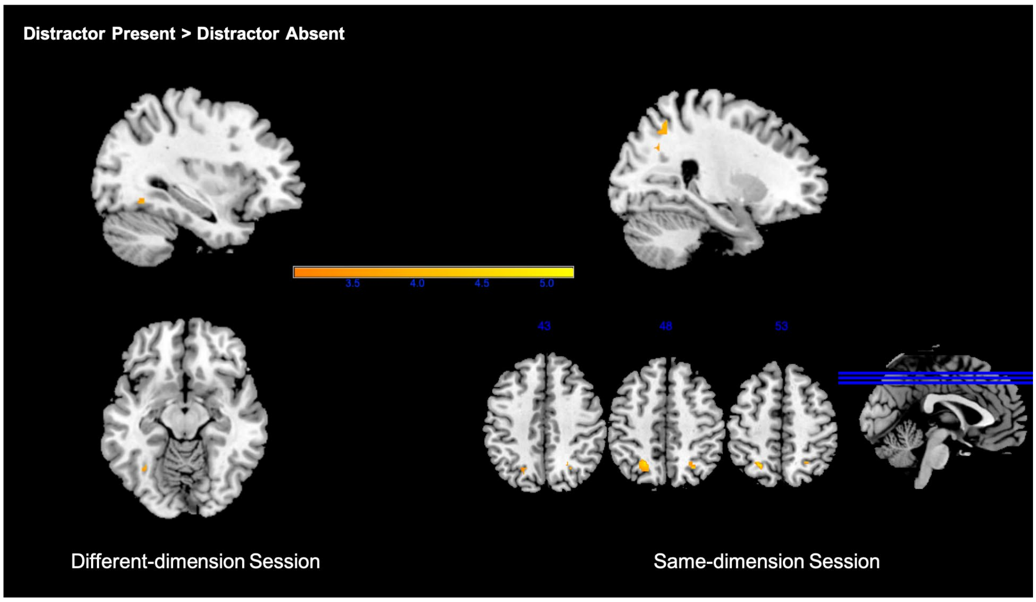


Figure 6. *Whole brain activation patterns colored in yellow reflect invoked BOLD signals mainly driven by the presence of a salient distractor defined by the different-dimension (color-defined) with target (left, different-dimension session), and the presence of a salient distractor defined by the same-dimension (orientation-defined) with target (right, same-dimension session) at $p < .05$, FWE corrected at the cluster level.*

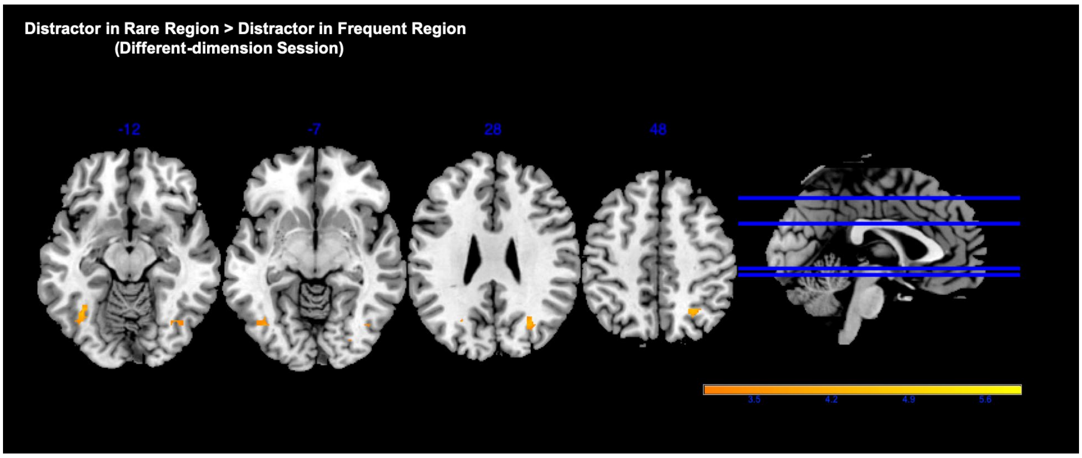


Figure 7. *Whole brain activation patterns colored in yellow showed increased BOLD signals when the salient distractor defined by the different-dimension (color-defined) appeared in the rare region relative to in the frequent region, at $p < .05$ FWE corrected at the cluster level.*

DISCUSSION

Combining fMRI with a statistical distractor-location learning paradigm, we manipulated whether the singleton distractor was defined within the same dimension (orientation) or a different dimension (color) relative to the target. The behavioral results replicated previous findings: interference by a salient distractor was reduced when it appeared within the frequent, versus the rare, distractor region – evidencing adaptation of attentional guidance to the biased distractor distribution. Further, despite being equally (if not more) salient, different-dimension distractors produced substantially less interference than same-dimension distractors, associated with a less marked frequent versus rare distractor-region effect. These behavioral effects were, to some extent, reflected in the fMRI results. BOLD signals in the early visual cortex were reduced for distractors occurring in the frequent, versus the rare, region. While the reduction was numerically similar in the two distractor conditions, it was more robust with same-dimension distractors, and, crucially, behavioral interference correlated with distractor-evoked VOI activity exclusively for this type of distractor. A similar activity pattern was evident when (spatially unbiased) targets appeared in the frequent versus rare distractor region, mirroring an analogous effect in the RTs. Whole-brain analysis revealed involvement of parietal parts of the fronto-parietal attention network in distractor handling. Importantly, though, in the different- (but not same-) dimension distractor condition, fusiform gyrus was activated more when a distractor was present versus absent, and more with a distractor occurring in the rare versus the frequent region. This suggests that distractors defined in a different dimension to the target (namely, color) are, in crucial respects, handled differently by the brain to same-dimension distractors.

The behavioral signature of statistical distractor-location learning has been well documented recently: RT interference is reduced for distractors occurring at frequent versus rare locations, and this is associated with reduced capture of the first saccade by distractors at frequent locations (Di Caro et al. 2019; Wang et al. 2019a; Sauter et al. 2020). Together with an ERP component interpreted in terms of distractor suppression (Wang et al. 2019b), this has been taken as evidence that observers learn to down-modulate the attentional priority signals (Itti and Koch 2001; Fecteau and Munoz 2006; Wolfe and Gray 2007) generated by distractors at frequent locations, thus reducing their potential to capture attention and cause interference. In line with this, we found that early visual-cortex signaling was reduced for distractors occurring in the frequent, versus the rare, region. Assuming that the attentional priority map is situated at some superordinate level in the visual system – such as the pulvinar thalamus, which is thought to integrate saliency signals from LIP, FEF, etc. (e.g., Bundesen et al. 2005) – reduced distractor signaling in early visual cortex might reflect learnt top-down inhibition of feature coding in early visual areas. The fact that this is observed generally (with both types of distractor) is consistent with Won et al. (2020), who found reduced visual-cortex signaling when different-dimension distractors (i.e., color singletons that varied in the specific color feature) occurred with 80%, but not 25%, frequency anywhere in the search display. In contrast, the reason why Bertleff et al. (2016) did not find evidence of down-modulated distractor signaling (when comparing blocks with 100% vs. 0% distractor presence) in early visual areas may be that they varied the spatial-attentional setting (focused vs. distributed) for the *target* (rather than the *distractor*), along with the use of different-dimension (color) distractors.

Neurally, input coding in early visual cortex is thought to constitute the first computational stage of salience processing: the generation of local feature-contrast, or 'saliency', signals (Knierim and van Essen 1992; Nothdurft 2000; Li 2002) within the various feature dimensions, which are subsequently integrated across dimensions into an 'overall-saliency' map determining the priorities for the allocation of attention. Stimuli that contrast more strongly with their surround (i.e., are more bottom-up salient) generate higher peaks on the priority map and so have a higher likelihood to summon attention (Treue 2003; Töllner et al. 2011; Kamkar et al. 2018). Accordingly, if distractors are more salient than targets, they are more likely to capture attention inadvertently. Thus, our finding of a reduction of distractor signals in early visual cortex (especially at frequent locations) would be indicative of a general down-modulation of feature-contrast signals, broadly consistent with Gaspelin and Luck's (2019) 'signal-suppression' hypothesis.

Of note, if anything, our color distractors were more salient than our orientation distractors (see Method), and so, on a purely bottom-up account, they should *not* have produced less interference than the orientation distractors. However, the fact that they did produce substantially less (rather than more) behavioral interference, coupled with (i) a less marked frequent versus rare distractor-region RT effect and (ii) and the absence of a correlation of early visuo-cortical BOLD activity with the magnitude of RT interference, suggests that distractor-signal suppression, and in particular enhanced suppression in the frequent versus the rare region, involved some other, or additional, mechanism with different-dimension distractors.

According to the Dimension-Weighting Account (Found and Müller 1996; Müller et al. 2003, 2009; Liesefeld and Müller 2020), such a mechanism is provided by dimension-based signal suppression (also referred to as ‘second-order feature suppression’ by Gaspelin and Luck 2018; Won et al. 2019). That is, with distractors defined in a different dimension to the target (here: color distractors, orientation targets), suppression might operate at the level of the distractor dimension, selectively down-modulating the contribution of color signals to (supra-dimensional) priority computation without impacting the contribution of orientation signals. This strategy is unavailable with same-dimension distractors. Consistent with a filtering stage specific to the distractor dimension is the finding from the whole-brain analysis that the left fusiform gyrus is generally involved in dealing with our color-defined different-dimension distractors **(**whereas it was not activated by orientation-defined same-dimension distractors**)**. Previous neuropsychological, electrophysiological, and neuro-imaging studies have revealed the (left) fusiform gyrus to play a role in color processing (Allison et al. 1993; Chao and Martin 1999; Pollmann et al. 2000; Simmons et al. 2007). Of note, Simmons et al. (2007) considered the left fusiform gyrus to be “a high-level color perception region” that is activated not only during color perception (responding more strongly to color than to grayscale stimuli), but also during the top-down-controlled retrieval of conceptual color knowledge (i.e., during verifying whether a named color is true of a named object). In the present study, the left fusiform gyrus was generally activated by color distractors, compared to when no distractors were present in the display. This pattern is consistent with fusiform gyrus playing a role in color-based stimulus filtering: reducing the weight of color-based feature-contrast signals in the computation of attentional priority. Previous studies have shown that color-based distractor filtering can operate quite effectively across all display locations (e.g., Müller et al. 2009; Won et al. 2019), so tuning of the filter to a region where color distractors occur frequently might yield little extra benefits. Spatially uniform filtering could explain why the correlation between distractor-generated BOLD activity in early visual areas and behavioral (RT) distractor interference was effectively abolished for color-defined distractors (while it was robust for orientation-defined distractors). Additionally, the *dimensional* filter might itself be modified by statistical distractor-location learning, up-modulating the suppression weights for color signals in the frequent, relative to the rare, distractor region. Consistent with this, fusiform gyrus was activated less strongly by color distractors in the frequent versus the rare region. – Given this general sketch of learnt distractor suppression, at least two questions arise:

The first is: How does the adaptation, in early visual cortex, to the spatial distractor distribution come about? The reduced response to distractors in the frequent versus the rare region might reflect a form of low-level ‘habituation’ (e.g., Turatto et al. 2018). Of note, though, VOI activity was reduced not only to distractor signals in the frequent region, but also to target signals (despite targets occurring with equal frequency in both regions). Behavioral work has demonstrated *facilitation* of locations at which *targets* appear frequently, analogous to *inhibition* of positions where *distractors* occur frequently (Ferrante et al. 2018) – suggesting that behavioral facilitation (target-location learning) is the flipside of inhibition (distractor-location learning). Thus, if inhibition involves a top-down-mediated reduction of neural responsivity in early visual cortex, owing to the status of 'distractors' as task-irrelevant, to-be-rejected items, one would expect facilitation to be associated with *higher* beta values for targets at frequent versus rare *target* locations – at variance with habituation accounts which would predict the beta values to be *lower* (as for distractors at frequent versus rare *distractor* locations). To our knowledge, these contrasting predictions have not yet been tested for statistical *target*-location learning. However, assuming that *distractor*-location inhibition is top-down mediated (tied to the status of distractors as 'distractors'), the fact that target signals, too, were reduced in early visual cortex would argue in favor of the inhibition at the lower level originating from some higher level. One likely source is the priority map, that is: inhibition of salient distractors that captured attention at the priority-map level feeds back to and adapts ('habituates') neuronal responsivity in feature-coding areas. Consistent with the notion of the priority map being a 'feature-blind' representation, this feeding-back of inhibition appears to be feature-unspecific: it impacts not only coding of the distractor feature, but also of the target feature, even if the latter belongs to a different dimension. Of note, though, the feedback tended to be generally weaker in the different (vs. the same-) dimension condition, as reflected by the beta values being numerically more positive for VOIs in both the frequent and rare distractor regions (this pattern was seen both with a distractor and a target appearing in a given VOI). Weaker feedback is also consistent with a reduced target-location effect in the different- (vs. the same-) dimension condition.

A second question concerns why the beta-value gradient between the frequent- and rare-distractor-region VOIs was not noticeably reduced for different- as compared to same-dimension distractors in the present study, given that different-dimension distractors permitted efficient, dimension-based filtering of distractor signals. One possibility is that the gradient is learnt early on during practice (e.g., already in the first trial block, because distractors in the frequent region capture attention more often than distractors in the rare region) and then simply persists, while the strategy of dimension-based filtering is 'discovered' only later on, once the early-level gradient has been established (Zhang et al. 2019). That is, capture prevention by dimension-based filtering does not lead to unlearning of the originally acquired gradient. Consistent with this are indications that statistical distractor-learning effects are quite resistant to unlearning (Turatto et al. 2018). Alternatively, even after a different-dimension distractor seizes to capture attention (due to efficient dimension-based filtering), the presence of a distractor may still be registered and responded to with top-down inhibitory feedback, reinforcing the gradient at the lower level; that is, the gradient reflects distractor frequency in the two regions, independently of whether or not the distractor is potent enough to capture attention. In other words, the low-level gradient represents the basic distractor-region 'prior'.

Whole-brain analysis also revealed the right SPL to be more strongly activated by different-dimension distractors appearing in the rare versus the frequent region (an effect not seen with same-dimension distractors). The right SPL, which has long been considered critical for visuo-spatial attentional control (Shapiro et al. 2002; Thakral and Slotnick 2009), is engaged not only in shifts of spatial attention (Corbetta et al. 1995; Behrmann et al. 2004), but also in shifting attention between separable dimensions of the input (Yantis and Serences 2003). The stronger SPL activation by different-dimension distractors in the rare region might reflect a higher incidence of attentional capture by such distractors, which may require combined dimensional and spatial shifting of attention to a target defined in a different dimension. Dimensional shifting would not be required with same-dimension distractors, which might explain why no distractor-region-specific SPL activation was seen in the same-dimension distractor condition.

In summary, the current results show that statistical learning of distractor locations involves (acquired) suppression down to the level of the early visual cortex. In addition, with different-dimension (color) distractors, higher-level, dimension-specific filtering mechanisms can come into play. Color-based filtering, involving the right fusiform gyrus and SPL, substantially reduces the interference caused by color distractors, whether they occur in the frequent or rare region. A dimension-based filtering strategy does not seem to be available with distractors defined in the same dimension as the target (orientation), in which case interference reduction relies solely on spatially tuned lower-level signal suppression.

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3 General Discussion

The current dissertation investigated the cognitive and neural mechanisms underlying the spatial distractor suppression based on statistical learning of distractor locations, focusing on the locus of distractor location suppression within the functional architecture of search guidance and how the learned suppression of distractors in the frequent location(s) is neurally realized in the early visual cortex and the frontoparietal attention networks. I will briefly summarize the results of the three studies, discuss how they contribute to the current framework and point out potential future directions.

3.1 Summary of results

3.1.1 Spatial distractor suppression within cognitive framework

Recall what the dissertation described in the general introduction, regarding at which stage the suppression operated, the theoretical conflict between Sauter et al. (2018) and Wang and Theeuwes (2018a) arises from the question that, with different-dimension defined distractors, whether the distractor-location learning effect is coupled with a *target-position effect* (measured by a significant slow response to the target appeared at the frequent location relative to the rare locations in the absence of the singleton distractor). In other words, the critical result is whether the learned spatial distractor suppression also impairs the processing of different-dimension-defined targets: priority-map based suppression predicts an impact of the processing of both target and distractor in the frequent region, while dimension-based suppression predicts that the suppression is only limited to the distractor processing, leaving the target processing unaffected. Thus, in the synopsis results of the cognitive framework, I mainly focused on whether the target processing is impaired by the spatial distractor suppression.

The first study (Chapter 2.1) adopted the original paradigm used by Wang and Theeuwes (2018a) with shape-defined target and color-defined singleton distractor (different-dimension distractors) and designed three psychophysical experiments to investigate three potentially 'confounding' factors that might be the critical factors dissociated results of Sauter-et-al and Wang-&-Theeuwes. First of all, all three experiments showed typical distractor-location learning effects, revealed by shorter response time when a singleton distractor appeared at the frequent distractor location relative to rare distractor locations, which were highly consistent with previous studies showing an effective suppression in the frequent distractor location (Goschy et al., 2014; Leber et al., 2016; Ferrante et al., 2018; Sauter et al., 2018; Wang & Theeuwes, 2018a). In addition, in Experiment 1, we examined a potential confounding factor in Wang and Theeuwes (2018a), namely the carry-over of positional inhibition of the distractor location from one distractor-present trial (e.g., trial n-1) to the next distractor-absent trial (e.g., trial n), which was ruled out in Sauter-et-al (2018). The results revealed that, after removing those cross-trials, the target location effect was still robust with significantly stronger interference for targets appearing in the frequent distractor location compared to the rare locations, suggesting the cross-trial positional inhibition made little contribution to the finding of target location effect observed in Wang and Theeuwes (2018a). This experiment ruled out the possibility of carry-over inhibition resulting in different results between two studies and supported the conclusion that suppression of the frequent distractor location operated at the level of the priority map.

Subsequently, Experiment 2 examined whether the observed target location effect was influenced by the target location probability due to the fact that the target appeared three times more likely in the frequent location relative to any of other rare locations on distractor-present trials in Wang and Theeuwes (2018a). After balancing the probabilities of the target positions, the significant pattern of target location effect was observed in the first experimental session (the first half of the experiment), but disappeared in the second session. The latter is consistent with the results observed by Sauter et al. (2018). Therefore, the experiment concluded, over the course of learning, observers shift their strategy of the spatial distractor inhibition from the level of priority map to the level below the priority map at a potential dimension-based level in the paradigm of Wang and Theeuwes' (2018a; see also Wang & Theeuwes, 2018b).

In Experiment 3, the color assigned to the distractor and non-distractor items were consistent across the whole experiment, which was similar to the design of Sauter et al. (2018), instead of randomly swapping across trials as the paradigm of Wang and Theeuwes (2018a). Consistent with the initial prediction, this time, the typical distractor-location learning effect was no longer accompanied by a target location effect. That is, search performance was not impaired when targets occurred at the frequent relative to the rare distractor locations in both first and second experimental sessions. The results supported that the color swapping assignment for the distractor and non-distractor items was a critical factor that drove different results of the target location effect and ensured a theoretical conflict between the two studies (Sauter-et-al and Wang & Theeuwes): when the color of the singleton distractor (relative to non-distractor items) is predictable across tirals, observers adopted a dimension-based suppression assumed by Sauter et al. (2018). By contrast, observers prefer a priority-based suppression when the color of the singleton distractor is non-predictable. Therefore, combining the above three experiments, the current dissertation concludes in the first study that, to reduce interference from distractors appearing at the frequent location, both priority-based suppression strategy and dimension-based suppression strategy are feasible, and which one is adopted depends on the various, distractor and target probability cues acquired over the course of practice on the task.

To further examine other factors that potentially contribute to the differential results of two studies and determine the level of spatial distractor suppression within the functional architecture of search guidance, the second study (Chapter 2.2) combined the distractor-location learning paradigm of Sauter-et-al and Wang-&-Theeuwes, in which the color-defined distractor was more likely to appear in a subregion within the search display as the design in Sauter-et-al's, instead of a location in the paradigm of Wang-&-Theeuwes. More importantly, two factors - display density (dense vs. sparse search display) and random color swapping between the distractor and non-distractor items (color swapping vs. no color swapping) - were orthogonally varied in the design bringing in four manipulation groups. The results first showed similar patterns of distractor-location learning effects among all groups as in paradigms in which a distractor was more likely to occur at one specific location (e.g., Wang & Theeuwes, 2018a). More importantly, the results replicated the pattern observed in Experiment 3 of the first study (Chapter 2.1) and revealed that a target-position effect was only significantly observed when the color assignment to the distractor and non-distractor items was randomly changing unpredictably across trials (color swapping), but not when it was constant (no color swapping). In addition, the factor of display density made little contribution to the observed target location effect. These findings support and reinforce the conclusion in the first study that, no matter the salient singleton distractor is more likely to appear in a whole region or a location within the search display, color swapping is a critical factor that influences observers to adopt one or the other strategy. In other words, observers may develop different strategies to suppress more (vs. less) likely distractor location(s) based on the color assignment of the distractor/non-distractor: with color swapping, suppression operates at the level of the priority map, which produces a distractor-location learning effect coupled with a target-position effect; without color swapping, suppression implemented in the dimension-based level, which produces only a beneficial distractor-location effect without the harmful target-position effect.

3.1.2 Spatial distractor suppression within neural framework

The third study (Chapter 2.3) used functional magnetic resonance imaging (fMRI) techniques in regional distractor-location learning paradigm (Sauter et al., 2018) with two types of distractors defined in the same- (e.g., orientation) and different- (e.g., color) dimension relative to the target. The behavioral results replicated previous findings with distractor-location learning effects for two types of distractors: less interference by a salient distractor when it appeared at the frequent relative to the rare region. Significantly, mirroring the behavior pattern, BOLD signals in the early visual cortex were also reduced for the two types of distractors occurring in the frequent versus the rare region. These results supported that statistical learning of distractor locations involves (acquired) suppression down to the level of the early visual cortex and top-down inhibition of feature coding in early visual areas to reduce distractor interference.

Crucially, the study also found that the reduction of visual activation of the distractor in the frequent (vs. rare) region was larger for the same-dimension distractor relative to the different-dimension distractor, and behavioral interference caused by the distractor was correlated with distractor-evoked visual activity only for the same-dimension distractor but not for the different-dimension distractor. Further, whole-brain results indicated that in the different-dimension distractor condition, the color processing brain areas - fusiform gyrus - was activated more when a distractor was present versus absent, and also more (together with superior parietal lobule) when a distractor occurred at the rare versus the frequent region. In contrast, no frontoparietal brain areas showed significant activation when the same-dimension distractor appeared in the frequent region relative to the rare region (or vice versa). These results potentially demonstrated different neural mechanisms of spatial distractor suppression between distractors defined in the different and the same dimension to the target. With different-dimension distractors (here: color distractors, orientation targets), suppression might operate at the level of the distractor dimension, with the help of the left fusiform gyrus and superior parietal lobule, selectively down-modulating the contribution of color signals to supra-dimensional priority computation. With same-dimension distractors (here: orientation targets and distractors), this strategy is not possible, but observers rely more on the spatial reduction of lower-level sensory signals to reduce interference from distractors.

3.2 Future directions

In the distractor-location learning paradigm, the current dissertation revealed a critical factor - whether the distractor and non-distractor items swap colors randomly across trials or not - determines the level of distractor suppression: at the level of the priority-map or at the dimension level. However, how the two different expectations about distracting information (that is, a distractor is predictable or not in the whole experiment) are implemented at the neural level to reduce the distractor interference remains mostly unknown. Thus, it is worth exploring the neural dissociation of two suppression strategies using EEG techniques. Also, the finding suggests that participants may adopt priority-map suppression when the distractor swaps color with the target, it remains unclear that the key factor behind the priority-based suppression is sharing a feature between the distractor and the target or is varying features of the distractor during the whole experiment. Further studies are needed to clarify these questions.

Moreover, the current dissertation focuses on which stage the spatial distractor suppression is potentially implemented within search guidance's functional architecture. However, the nature of the suppression mechanism itself is still an open question. To be more specific, whether the spatial suppression is functioning as a limited cognitive resource or as a habituation mechanism remains unclear. The former predicts attention is optimally distributed across the frequent and rare distractor region based on the statistical distribution of distractor, while the latter is only determined by how often distractors appear inside each region (e.g., Chelazzi et al., 2019). Further studies are required to disassociate the two possible accounts.

In addition, Study 3 of the dissertation shows that the distractor coding in the early visual cortex was significantly reduced when both types of distractors occurred at the frequent versus the rare region, indicating a suppression on the early visual cortex. However, it is unclear whether this suppression is already implemented in the visual cortex prior to or after the search display onset. Previous studies observed enhanced cortex activation in the hemisphere contralateral to the upcoming distractor during the cue period (e.g., Ruff & Driver, 2006), and a baseline increase of visual activation for directing attention to targets in the absence of stimulation (Kastner et al., 1999), suggesting preparatory modulations in the visual cortex even without the presenting of targets/distractors. Also, with similar distractor-location learning paradigms, recent ERP studies hold a dispute on whether there was a stronger enhancement in alpha power band for contra- versus ipsi-lateral relative to the high-probability location during the pre-stimuli (van Moorselaar et al., 2020; Wang, van Driel, et al., 2019). Therefore, combining fMRI techniques in a similar distractor-location learning paradigm may potentially answer whether (if yes, how) the visual cortex is modulated during the pre-stimuli period to prepare an inhibition mechanism for the later post-stimuli stage.

Finally, attention deficit hyperactivity disorder (ADHD) is characterized by an ongoing pattern of inattention and/or hyperactivity-impulsivity that interferes with functioning or development. Previous studies documented impairments of selective attention in ADHD (Brodeur & Pond, 2001; Mason et al., 2003; e.g., for a review, Mueller et al., 2017), with abnormal processing of irrelevant information (Carter et al., 1995; Friedman-Hill et al., 2010). Investigating the potential neural dysfunction of attention control in ADHD, typically on distractor inhibition processing, would contribute to the better understanding of neural deficits of ADHD and potentially lead to more targeted and effective treatment approaches for these individuals.

3.3 Conclusions

Taken above three studies together, the current dissertation explores cognitive and neural mechanisms of spatial distractor suppression based on statistical learning of distractor locations. On the one hand, the dissertation reveals the critical factors between the two studies (Sauter et al., 2018; Wang and Theeuwes, 2018a) that result in the different theoretical conclusions, and concludes the locus of learned spatial distractor suppression within the functional architecture of search guidance. Specifically, in the distractor-location learning paradigm, irrespective of whether a salient singleton distractor is more likely to occur at multiple locations within a subregion of the display (e.g., Sauter et al., 2018) or at a specific location (e.g., Wang and Theeuwes, 2018a), observers are both likely to adopt the priority-map-based suppression strategy and dimension-based suppression strategy (below the priority map) to reduce interference of distractor in the frequent region. Notably, a critical factor determining which strategy is adopted is whether the distractor and non-distractor items swap colors randomly across trials: without color swapping, observers are more likely to acquire a dimension-based suppression; with color swapping, they prefer to develop a priority-map-based suppression in the first beginning, and potentially shift to dimension-based suppression later with the course of learning.

On the other hand, at the neural level, the dissertation shows that statistical learning of frequent distractor locations involves suppression down to the level of the early visual cortex, and potential differential neural mechanisms of spatial distractor suppression between distractors defined in a different versus the same dimension to the target: with different-dimension distractors (e.g., color), higher-level, dimension-specific filtering mechanisms (the right fusiform gyrus and superior parietal lobule) plays a role to reduce the interference from distractors; with same-dimension distractors, interference reduction relies on cutting down lower-level sensory signals.

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Conference Abstracts

Zhang B, Allenmark F, Liesefeld HR, Shi Z, Müller HJ. Flexible Suppression on Probability Cueing of Distractor. The 42nd edition of the European Conference on Visual Perception, August 25th - 29th, 2019, in Leuven, Belgium

Wang X, Lin P, **Zhang B**, Öngür D, Levitt JJ. Altered Frontostriatal Connectivity Related to Clinical Severity in First Episode, Treatment-naive Schizophrenia. The Society of Biological Psychiatry’s 69th Annual Meeting, May 8-10, 2015 in Toronto, Ontario, Canada.

Deutsche Zusammenfassung

Visuelle Suche ist im Alltag allgegenwärtig, etwa um die Lieblingsschokolade im Supermarkt zu finden oder einen Freund in einer Menschenmenge zu erkennen. Angesichts der überwältigenden Menge an Informationen in der komplexen Umgebung, mit der wir ständig interagieren, ist eine effiziente Auswahl des visuellen Inputs entscheidend für ein an verschiedene Umgebungen und Ziele angepasstes Verhalten. Mit anderen Worten, wir müssen unsere begrenzten Ressourcen (z. B. Aufmerksamkeit) auf relevante. Informationen fokussieren und Informationen, die uns ablenken, ignorieren. Die Aufmerksamkeitsselektion ist jedoch nicht immer unter willentlicher Kontrolle und richtet sich auf relevante Objekte, die mit unseren Zielen übereinstimmen, sondern kann manchmal auch auf auffällige, aber zielirrelevante Objekte in der Umgebung gelenkt werden. Verwandte Arbeiten im visuellen Bereich wurden erforscht und es wurden mehrere theoretische Erklärungen formuliert. Die stimulusgesteuerte Aufmerksamkeitserfassung (Theeuwes, 1991, 1992) geht zum Beispiel davon aus, dass die Aufmerksamkeit automatisch von dem auffälligsten Objekt in der Umgebung ergriffen wird und die Aufmerksamkeitsselektion rein von unten nach oben erfolgt. Und der "contingent attentional capture account" (Folk et al., 1992) argumentiert, dass die Aufmerksamkeitserfassung durch irrelevante Reize davon abhängt, ob die irrelevanten Reize dem Top-Down-Suchziel entsprechen. Andere Erklärungen (z. B. die Suchmodus-Annahme, Bacon & Egeth, 1994, und die Signalunterdrückungshypothese, Gaspelin et al., 2015, 2017; Sawaki & Luck, 2010) beziehen diese beiden Prozesse mit ein. Zusammenfassend kann man man sagen, wird im Allgemeinen angenommen, dass der auffällige, aber aufgabenirrelevante Distraktor potenziell unsere Aufmerksamkeit von unten nach oben fesseln und die Verhaltensleistung beeinträchtigen könnte, aber die durch den Distraktor verursachte Störung kann auch durch Top-down-Aufmerksamkeitskontrolle reduziert werden.

Die visuelle Suche kann durch Ausnutzung der räumlichen Verteilung von Objekten in der Umgebung erleichtert werden. Beobachter können die Aufmerksamkeitsselektion auf bestimmte Orte priorisieren, an denen relevante Informationen regelmäßig anzutreffen sind (Geng & Behrmann, 2002, 2005). Ebenso können Orte, an denen saliente, aber irrelevante Objekte häufig auftauchen, durch Aufmerksamkeitssteuerung depriorisiert werden. Der Effekt, dass Beobachter aus Erfahrung die räumliche Verteilung von salienten, aber aufgabenirrelevanten Distraktoren in der visuellen Umgebung zu lernen scheinen, um die durch solche Distraktoren verursachte Interferenz zu reduzieren, wurde als "Distractor Location

Probability Cueing" bezeichnet (z. B. Goschy et al., 2014, Ferrante et al., 2018; Leber et al., 2016; Sauter et al., 2018; Wang & Theeuwes, 2018a). In jüngster Zeit stimmten neue Studien darin überein, dass die beobachtete Reduktion der Distraktorinterferenz größtenteils auf eine bessere Unterdrückung von Distraktoren an häufigen Orten zurückzuführen ist (Di Caro et al., 2019; Sauter et al., 2020; Wang, Samara, et al., 2019; Wang, van Driel, et al., 2019), aber hinsichtlich der Frage, wie diese räumliche Distraktorunterdrückung innerhalb der funktionellen Architektur der Führung der Suche zur Reduktion der Interferenz implementiert wird (d.h. zu welchem Zeitpunkt die Unterdrückung wirkt), sind die Schlussfolgerungen noch in der Debatte. Zum Beispiel haben Sauter und Kollegen (2018) die dimensionsbasierte Suppression angesprochen, da in der Bedingung der Abwesenheit des Distraktors ein durch die Orientierung definiertes Ziel nicht durch die räumliche Suppression des Distraktors beeinträchtigt wurde, wenn der saliente Distraktor durch die Farbe definiert war (aber beeinträchtigt wurde, wenn der saliente Distraktor durch die Orientierung definiert war), während Wang & Theeuwes (2018a) eine verlangsamte Verarbeitung des formdefinierten Ziels fanden, wenn der farbdefinierte Distraktor an der wahrscheinlicheren im Vergleich zur weniger wahrscheinlichen Distraktorposition erschien (als "Zielort-Effekt" bezeichnet), konsistent mit prioritätsbasierter Suppression. Wie die Unterdrückung des Distraktors im Gehirn verarbeitet wird, um die Interferenz an wahrscheinlichen Distraktorpositionen zu reduzieren, ist noch wenig verstanden worden. Die Studienreihe der aktuellen Dissertation untersucht daher die kognitiven und neuronalen Mechanismen, die der räumlichen Distraktorunterdrückung auf der Basis des Wahrscheinlichkeits-Cueing (oder statistischen Lernens) von Distraktorpositionen zugrunde liegen. Konkret verwenden wir zunächst klassische Verhaltensuntersuchungen, um den Ort der räumlichen Distraktorunterdrückung innerhalb der funktionellen Architektur der Führung der Suche zu bestimmen, und untersuchen dann, wie die erlernte räumliche Unterdrückung von Distraktoren auf neuronaler Ebene, durch funktionelle Magnetresonanztomographie (fMRI), implementiert wird.

In der ersten Studie (Kapitel 2.1) wurde das ursprüngliche Paradigma von Wang und Theeuwes (2018a) übernommen und drei psychophysikalische Experimente durchgeführt, um drei potenziell "verwirrende" Faktoren zu untersuchen, die zu dem in Wang und Theeuwes (2018a) beobachteten Zielort-Effekt führen könnten und die im Design von Sauter-et-al systematisch ausgeschlossen wurden. Experiment 1 untersuchte einen potentiellen konfundierenden Faktor in Wang und Theeuwes (2018a) - den Carry-Over-Effekt der Positionshemmung des Distraktorstandortes von einem Trial, in dem der Distraktor vorhanden war (z.B. Trial n-1) zum nächsten Trial, in dem der Distraktor abwesend war (z.B. Trial n). Die Ergebnisse zeigten, dass der Zielort-Effekt nach dem Entfernen dieser Cross-Trials immer noch robust war, mit einer signifikant stärkeren Interferenz für Ziele, die an der häufigen Distraktorposition erscheinen, im Vergleich zu den seltenen Positionen, was darauf hindeutet, dass die Cross-Trial-Positionshemmung wenig zu dem in Wang und Theeuwes (2018a) beobachteten Zielort-Effekt beigetragen hat. In Experiment 2 wurde untersucht, ob der beobachtete Zielort-Effekt durch die Wahrscheinlichkeit des Zielortes beeinflusst wurde, da das Ziel in den Versuchen mit präsentem Distraktor in Wang und Theeuwes (2018a) dreimal wahrscheinlicher an dem häufigen Ort erschien als an einem der anderen seltenen Orte. Nach dem Ausgleich der Wahrscheinlichkeiten der Zielpositionen wurde das signifikante Muster des Zielort-Effekts in der ersten experimentellen Sitzung beobachtet, verschwand aber in der zweiten Sitzung. Letzteres stimmt mit den von Sauter et al. (2018) beobachteten Ergebnissen überein. Wichtig ist, dass in Experiment 3 die Farbe des Distraktors und des Nicht-Distraktors über das gesamte Experiment konsistent gehalten wurde, wie von Sauter et al. (2018) entworfen, anstatt die Farbe in jedem Versuch zu vertauschen, wie im ursprünglichen Paradigma. Die Ergebnisse zeigten, dass der Zielort-Effekt vollständig aufgehoben wurde. Basierend auf den obigen drei Studien kamen wir daher in der ersten Studie zu dem Schluss, dass zur Verringerung der Interferenz durch Distraktoren, die an der häufigen Position erscheinen, sowohl die prioritätsbasierte Unterdrückungsstrategien als auch die dimensionsbasierte Unterdrückungsstrategien denkbar sind, und dass die Wahl der Strategie von den verschiedenen Distraktor- und Zielwahrscheinlichkeitshinweisen abhängt, die im Laufe der Übung der Aufgabe erworben wurden.

Um weitere Faktoren zu untersuchen, die möglicherweise zu den unterschiedlichen Ergebnissen der beiden Studien beitragen und das Ausmaß der räumlichen Distraktorunterdrückung bestimmen könnten, wurde in der zweiten Studie (Kapitel 2.2) das Distraktor-Ort-Lernparadigma von Sauter-et-al und Wang-&-Theeuwes kombiniert, bei dem der farbdefinierte Distraktor mit größerer Wahrscheinlichkeit in einer Subregion innerhalb des Suchdisplays wie bei Sauter-et-al auftauchte (statt an einem Ort im Paradigma von Wang-&-Theeuwes). Noch wichtiger ist, dass zwei Faktoren - Displaydichte (dichtes vs. spärliches Suchdisplay) und zufälliger Farbtausch zwischen dem Distraktor und den Nicht-Distraktor-Items (Farbtausch vs. kein Farbtausch) - orthogonal im Design variiert wurden, was zu vier Manipulationsgruppen führte. Die Ergebnisse zeigten zunächst in allen Gruppen ähnliche Muster von Distraktor-Orts-Lerneffekten wie in Paradigmen, in denen ein Distraktor mit höherer Wahrscheinlichkeit an einem bestimmten Ort auftritt (z.B. Wang & Theeuwes, 2018a). Wichtiger noch, die Ergebnisse replizierten das Muster, das in Experiment 3 der ersten Studie (Kapitel 2.1) beobachtet wurde, und zeigten, dass ein Target-Positions-Effekt nur dann signifikant beobachtet wurde, wenn sich die Farbzuordnung zu den Distraktor- und Nicht-Distraktor-Items über Trials hinweg unvorhersehbar änderte (Color Swapping), aber nicht, wenn sie konstant war (kein Color Swapping). Darüber hinaus trug der Faktor der Anzeigedichte nur wenig zum beobachteten Zielort-Effekt bei. Diese Ergebnisse unterstützen und verstärken die Schlussfolgerung aus der ersten Studie, dass unabhängig davon, ob der singuläre Distraktor eher in einer ganzen Region oder an einem Ort innerhalb des Suchdisplays auftauchte, Farbvertauschung ein kritischer Faktor war, der die Beobachter beeinflusste, die eine oder die andere Strategie zu wählen. In anderen Worten entwickeln Beobachter möglicherweise unterschiedliche Strategien zur Unterdrückung wahrscheinlicher (vs. weniger wahrscheinlicher) Distraktorpositionen, basierend auf der Farbzuordnung des Distraktors/Nicht-Distraktors: mit Farbvertauschung funktioniert die Unterdrückung auf der Ebene der Prioritätskarte; ohne Farbvertauschung wird die Unterdrückung auf der dimensionsbasierten Ebene implementiert.

In der dritten Studie (Kapitel 2.3) wurden fMRT-Techniken mit dem Distraktor-Lokalisierungs-Lernparadigma von Sauter et al. (2018) mit zwei Arten von Distraktoren eingesetzt, die entweder in der gleichen oder in einer anderen visuellen Dimension relativ zum Ziel definiert wurden, um zu untersuchen, (i) ob Signale des visuellen Kortex an gelernten Distraktorpositionen heruntermoduliert werden, um Distraktorinterferenzen zu reduzieren, (ii) welche spezifische Rolle das frontoparietale Aufmerksamkeitsnetzwerk bei der Distraktorverarbeitung spielt, sowie (iii) Unterschiede in den neuronalen Mechanismen, die zwischen den beiden Distraktortypen vermitteln. Die Verhaltensergebnisse replizierten frühere Befunde mit Distraktor-Lokalisierungs-Lerneffekten für zwei Arten von Distraktoren. Wichtig ist, dass die BOLD-Signale im frühen visuellen Kortex für Distraktoren, die in der häufigen Region auftraten, im Vergleich zur seltenen Region ebenfalls reduziert waren, was das Verhaltensmuster widerspiegelt. Entscheidend war, dass die Reduktion der visuellen Aktivierung des Distraktors in der häufigen (vs. seltenen) Region für gleichdimensionale Distraktoren größer war als für verschiedendimensionale Distraktoren, und dass die Verhaltensinterferenz mit der durch den Distraktor hervorgerufenen visuellen Aktivität nur für gleichdimensionale Distraktoren korreliert war, nicht aber für verschiedendimensionale Distraktoren. Weitere Ganzhirn-Ergebnisse zeigten, dass in der Bedingung mit verschiedendimensionalen Distraktoren der Gyrus fusiformis stärker aktiviert wurde, wenn ein Distraktor anwesend war, als wenn er nicht anwesend war, und auch stärker (zusammen mit dem Lobulus parietalis superior), wenn ein Distraktor in der seltenen Region auftrat, als in der häufigen Region, während keine frontoparietalen Hirnareale eine signifikante Aktivierung zeigten, wenn der gleichdimensionale Distraktor in der häufigen Region im Vergleich zur seltenen Region erschien (oder umgekehrt). Diese Ergebnisse unterstützten, dass statistisches Lernen von Distraktorpositionen eine (erworbene) Suppression bis hinunter zur Ebene des frühen visuellen Kortex und eine Top-Down-Inhibition der Merkmalskodierung in frühen visuellen Arealen beinhaltet, um die Distraktorinterferenz zu reduzieren, was möglicherweise unterschiedliche neuronale Mechanismen der räumlichen Distraktorunterdrückung zwischen Distraktoren, die in einer anderen und der gleichen Dimension zum Ziel definiert sind, darstellt. Bei Distraktoren unterschiedlicher Dimension (hier: Farbdistraktoren, Orientierungsziele) könnte die Suppression auf der Ebene der Distraktordimension mit Hilfe des linken Gyrus fusiformis und des superioren Parietallappens wirken, indem sie den Beitrag der Farbsignale zur überdimensionalen Prioritätsberechnung selektiv heruntermoduliert. Bei gleichdimensionalen Distraktoren (hier: Orientierungsziele und Distraktoren) ist diese Strategie nicht möglich, sondern der Beobachter verlässt sich eher auf die räumliche Reduktion von sensorischen Signalen niedrigerer Ebene, um Störungen durch Distraktoren zu reduzieren.

Die drei oben genannten Studien zusammengenommen, enthüllten in der aktuellen Dissertation kognitive und neuronale Mechanismen der räumlichen Distraktorunterdrückung, die auf dem statistischen Lernen von Distraktorpositionen basieren. Einerseits haben wir die kritischen Faktoren aufgedeckt, die zu den unterschiedlichen theoretischen Schlussfolgerungen der beiden Studien geführt haben, und den Ort der räumlichen Distraktorunterdrückung innerhalb der funktionellen Architektur der Führung der Suche bestimmt. Konkret bedeutet dies, dass Beobachter im Paradigma zum Erlernen von Distraktor-Standorten unabhängig davon, ob ein salienter Distraktor mit höherer Wahrscheinlichkeit an mehreren Orten innerhalb einer Subregion des Displays (z. B. Sauter et al., 2018) oder an einem bestimmten Ort (z. B. Wang und Theeuwes, 2018a) auftritt, sowohl die prioritätsbasierte Unterdrückungsstrategie als auch die dimensionsbasierte Unterdrückungsstrategie anwenden, um die Interferenz des Distraktors in der häufigen Region zu reduzieren. Wichtig ist, dass der kritischste Faktor, der bestimmt, welche Strategie angenommen wird, darin besteht, ob die Distraktor- und Nicht-Distraktor-Items die Farben zufällig über die Trials hinweg tauschen: ohne Farbswapping erwerben die Beobachter eher eine dimensionsbasierte Strategie (unterhalb der Prioritätskarte);

mit Farbswapping bevorzugen sie zu Beginn eine prioritätskartenbasierte Unterdrückungsstrategie und wechseln möglicherweise später im Verlauf des Lernens zur dimensionsbasierten Unterdrückung. Auf der anderen Seite haben wir auf der neuronalen Ebene aufgedeckt, dass das statistische Lernen von häufigen Distraktorpositionen eine Suppression bis hinunter zur Ebene des frühen visuellen Kortex beinhaltet, sowie mögliche unterschiedliche neuronale Mechanismen der Distraktorunterdrückung zwischen Distraktoren, die in einer anderen als der gleichen Dimension zum Ziel definiert sind: Bei Distraktoren unterschiedlicher Dimension (Farbe) spielen übergeordnete, dimensionsspezifische Filtermechanismen (rechter fusiformer Gyrus und superiorer parietaler Lobulus) eine Rolle, um die Interferenz von Distraktoren zu reduzieren; bei gleichdimensionalen Distraktoren beruht die Interferenzreduktion auf der Reduktion von sensorischen Signalen niedrigerer Ebene.